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Implications of Climate Change for Bioassessment Programs and Approaches to Account for Effects

United States Environmental Protection Agency
Office of Research and Development, National Center for Environmental Assessment

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Global Change Research Program
National Center for Environmental Assessment
Office of Research and Development
U.S. Environmental Protection Agency
Washington, DC 20460

DISCLAIMER

ABSTRACT

Climate change will affect stream ecosystems directly, indirectly, and through interactions with other stressors. Biological responses to these changes include altered community composition, interactions, and functions. Effects will vary regionally and present heretofore unaccounted influences on biomonitoring, which water-quality agencies use to assess the status and health of ecosystems as required by the Clean Water Act. Biomonitoring, which uses biological indicators and metrics to assess ecosystem condition, is anchored in comparison to regionally established reference benchmarks of ecological condition. Climate change will affect responses and interpretation of these indicators and metrics at both reference and nonreference sites and, therefore, has the potential to confound the diagnosis of ecological condition. This report analyzes four regionally distributed state biomonitoring data sets to inform on how biological indicators respond to the effects of climate change, what climate-specific indicators may be available to detect effects, how well current sampling detects climate-driven changes, and how program designs can continue to detect impairment. Results can be used to identify methods that assist with detecting climate-related effects and highlight steps that can be taken to ensure that programs continue to meet resource protection goals.

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LIST OF ABBREVIATIONS AND ACRONYMS

ANOVA	Analysis of variance
BCG	Biological Condition Gradient
CCA	Canonical Correspondence Analysis
cfs	cubic feet per second
CWA	Clean Water Act
DEP	Department of Environmental Protection
DEQ	Department of Environmental Quality
ECBP	Eastern Corn Belt Plain
EDAS	Ecological Data Application System
EMAP	Environmental Monitoring and Assessment Program
ENSO	El Niño/Southern Oscillation
EPA	U.S. Environmental Protection Agency
EPT	Ephemeroptera, Plecoptera, Trichoptera
EWH	exceptional warmwater habitat
GCM	general circulation models
GIS	geographic information system
HAB	harmful algal blooms
HBI	Hilsenhoff Biotic Index
IBI	Index of Biotic Integrity
ICI	Invertebrate Community Index
ICLUS	Integrated climate and land use scenarios
IHA	Indicators of Hydrologic Alteration
IPCC	Intergovernmental Panel on Climate Change
MBI	Midwest Biodiversity Institute
MIwb	Modified Index of Well-Being
MMI	multimetric index
MWH	modified warmwater habitat
NAO	North Atlantic Oscillation
NCAR	National Center for Atmospheric Research
NCBI	North Carolina Biotic Index
NCDENR	North Carolina Department of the Environment and Natural Resources
NMDS	nonmetric multidimensional scaling
NPDES	National Pollutant Discharge Elimination System
O/E	observed to expected ratio
OCH	Odonata, Coleoptera, Hemiptera
OTU	Operational Taxonomic Unit
PDO	Pacific Decadal Oscillation
PRISM	Parameter-elevation Regressions on Independent Slopes Model
QHEI	Qualitative Habitat Evaluation Index
RA	relative abundance
RBI	Richards-Baker flashiness Index
RIVPACS	River InVertebrate Prediction and Classification System
SD	standard deviation
TMDL	total maximum daily load

LIST OF ABBREVIATIONS AND ACRONYMS (continued)

USGS	United States Geological Service
WSV	Weighted Stressor Values
WWH	warmwater habitat

PREFACE

This report was prepared by Tetra Tech, Inc. and the Global Change Research Program in the National Center for Environmental Assessment of the Office of Research and Development at the U.S. Environmental Protection Agency (U.S. EPA). It is intended for managers and scientists working on biological indicators, bioassessment, and biocriteria, particularly in the EPA's Office of Water and Regions, and also at state agencies. The results presented in this report are based on data primarily from four U.S. states: Maine, North Carolina, Ohio, and Utah. The main findings of interest to managers and policymakers, the supporting evidence, and management responses are presented in a separate summary at the beginning of this report. The remainder of the report provides more detail to substantiate each of the findings. Descriptions of specific analysis methods, underlying data, and supporting analyses are in the appendices to this report.

AUTHORS, CONTRIBUTORS, AND REVIEWERS

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EXECUTIVE SUMMARY

Bioassessment is used for resource management to determine the ecological consequences of environmental stressors. All states utilize some form of bioassessment as part of their implementation of the Clean Water Act (CWA). This assessment identifies the components of state and tribal bioassessment programs that may be affected by climate change. The study investigates the potential to identify biological response signals to climate change within existing bioassessment data sets, analyzes how biological responses can be categorized and interpreted, and assesses how they may influence decision-making processes. This study focused on benthic macroinvertebrates, which are important indicators used in bioassessments of wadeable rivers and streams. The ultimate goals of the report are to provide a foundation for understanding the potential climatic vulnerability of bioassessment indicators and advancing the development of specific strategies to ensure the effectiveness of monitoring and management plans under changing conditions.

We selected four regionally distributed state bioassessment data sets from Maine, North Carolina, Ohio, and Utah for this analysis. Bioassessment data were analyzed to determine the relative sensitivity of benthic community characteristics and traits to historical trends in temperature, precipitation, and other environmental drivers. The analysis allowed community characteristics and traits to be classified as either sensitive or insensitive to climate change effects.

Bioassessment programs rely on reference sites, often the most natural or pristine sites available, to help provide a basis for comparison with impaired sites. However, climate change will impact all sites in a region. Consequently, it will be necessary to understand the potential impacts of climate change for the use of reference sites in bioassessments. We examined the vulnerability of reference conditions to changes in climate and interactions between climate change and other landscape-level stressors, especially land use.

This study describes biological responses to changes in temperature, precipitation, and flow that will, in the long term, affect the metrics and indices used to define ecological status. Not all regions are equally threatened or responsive because of large-scale variability in climate and other environmental factors. We found that climatically sensitive components of bioassessment programs include

- Assessment design (e.g., multimetric indices [MMIs], selection of reference sites, determination of reference condition)
- Implementation (e.g., data collection and analysis)
- Environmental management (e.g., determination of impairment and water-quality standards)

Ecological traits are useful tools for these analyses because traits are not location specific, unlike some species. This facilitates comparisons among the state data sets used. This study mainly focuses on traits related to temperature and hydrologic sensitivities. Effective bioassessment designs rely on MMIs and predictive models to detect impairment. The effectiveness of widely used MMIs and predictive models may be undermined by changing climatic conditions through the ecological trait of temperature sensitivity. Taxa with cold water- and warm water-preferences are used in many MMIs and predictive models. The climate responsiveness of these traits groups varies between states and ecoregions; however, they are generally found to be sensitive to changing temperature conditions. Consequently, MMIs and predictive models, which rely on these sensitive taxa are likely to be influenced by climate change. In many cases, it may be feasible to develop new MMIs and modify variables in predictive models to partition sensitive taxa and reduce the potential for changing conditions to confound efforts to detect impairment.

Another widespread and related finding is the moderate but significant relationship between temperature sensitivity and sensitivity to organic pollution. These findings show that metrics selected because the composite taxa are considered to be generally sensitive to conventional pollutants also have demonstrable sensitivities to climate-related changes in temperature and flow conditions. These sensitivities remain difficult to tease apart, although approaches to modify metrics using temperature- and possibly flow-sensitive traits show some promise in helping separate the influence of climate change from other stressors when combined with appropriate study designs.

The implementation of bioassessment programs often involves flexible sampling systems, such as rotating basin designs. These systems ensure statistically adequate sampling over 5-year periods, often at the expense of continuous monitoring of specific locations. Consequently, states may have many reference locations but lack enough stable, long-term stations needed to detect climate-driven changes in biotic condition. In order to account for climate change effects in the interpretation of station conditions, consistent long-term monitoring of a site or a region will be needed. At the least, monitoring network designs will need to consider incorporation of a few specific locations for detection of trends over time or include more extensive probabilistic monitoring of a watershed or region in a manner that supports climate-related trend detection.

Climate change can cause other problems for reference-based bioassessment systems. We note that climate change can drive shifts in community composition that vary by location, potentially further compounded by nonclimatic landscape stressors. The result is variation in responses between locations that can confound efforts to establish statistically significant relationships or detect impairment. For example, our results show that high-flow metrics (e.g., flashiness, high pulse-count duration, 1-day maximum flow) tend to reflect urbanization, swamping climate change effects; whereas low-flow metrics (e.g., short-duration minimum flows, low pulse-count duration) respond to climate change effects more so than to land use.

Some of the long-term stations in our study showed increasing trends in benthic inferred temperatures, though not all trends were significant. These correspond well with the magnitude of air temperature increases observed for the period, suggesting that the estimates of benthic invertebrate temperature optima were generally appropriate, and that using benthic invertebrate occurrence and abundance coupled with temperature preferences provides evidence of benthic community changes over time related to long-term changes in temperature. With a large enough data set, this type of analysis could be informative of long-term trends that are more widely applicable than our analyses that were limited to data from single sites. Inferred temperature responses are evidence of climate change-related increases in temperature, in that they reflect a progressive shift over time in composition of temperature preferences integrated across the entire benthic community. The response over time of any one taxon with a particular temperature preference (e.g., a cold water taxon) may or may not be significant despite the expectation, but it is informative if the community as a whole is reflecting an overall progressive shift in temperature preferences.

A synthesis of results leads to several recommendations for bioassessment programs in terms of modifying assessment design, implementation, and environmental management. With respect to metrics and indices, it may be useful to partition climatically vulnerable indicators into new metrics that account for temperature preferences of the component taxa. Analyzing bioassessment data according to temperature preferences will facilitate tracking climate change-related taxa losses and replacements. This traits-based approach for detecting and tracking climate change effects is promising, given that there were few specific species that showed consistent climate-related trends across multiple sites and states analyzed. It may also be useful to identify particular sensitive taxa by region that can be tracked for climate change responses.

Although data limitations prevent explicit differentiation between interannual, cyclical, and long-term directional climate effects, the net response of benthic community metrics to climate-sensitive variables (i.e., water temperature, hydrologic patterns) provides useful information. The responses can be used to (1) define the direction and nature of effects expected due to climate change; (2) identify the most sensitive indicators to climate change; and (3) understand implications to MMIs or predictive models and their application by managers to characterize condition of stream resources for decision making.

The limited long-term data also illustrate that annual monitoring at least at some fixed reference locations would be valuable to account for climate change effects and to further our understanding of natural variability. The ability to detect a real trend is affected by signal-to-noise ratio and by the amount of data available to account for this variation. Evidence from this study of the high among-site variability within ecoregions illustrates the trade-off in sampling effort between sampling many stations using a probability-based design to understand regional variations and sampling selected locations more frequently to document long-term trends. A mixture of targeted reference sites that can be maintained over the long term along with probabilistic sampling may be more appropriate for monitoring the effects of climate change. This more comprehensive monitoring design will increase the robustness of water program assessments to the confounding effects of climate change.

Long-term monitoring also requires that these reference locations are as protected as possible from other stressors and landscape influences. Our analyses show that reference conditions may be more vulnerable than impaired sites to climate change effects, a result that undermines the current methods of condition assessment. Two approaches that can assist with condition assessments in the context of climate change are to (1) implement the Biological Condition Gradient (BCG) framework, within which changes in condition of both high quality and impaired locations can be more rigorously defined and tracked; and (2) promote protection of high quality stream reaches that define reference conditions. Protection should focus on minimization, mitigation, and/or buffering from nonpoint source runoff, erosion, and hydrologic changes.

Documenting existing land use conditions surrounding established reference locations is also important to establish a baseline for tracking future changes. Urbanization surrounding reference stations will interfere with the ability to detect climate change and separate climate responses from conventional stressors; this can interfere with managing aquatic resources, setting permit limits, and meeting Clean Water Act requirements. Our results show that hydrologic monitoring, especially using low-flow parameters, can assist with distinguishing changes due to urbanization versus climate.

Reference sites that remain unprotected from stressors or land use changes are vulnerable to deterioration due to conventional stressors as well as climate change. The deterioration of reference conditions and climate impacts on biological indicators, metrics, and indices together can affect the determination of stream reach impairment. In vulnerable watersheds, this may lead to fewer listings of impaired stream reaches and progressive under-protection of water resources, unless the management framework is adjusted to better account for expected climate change effects. Adaptations that should be considered include modification of metrics so that climate effects can be tracked, re-evaluation of thresholds for defining impairment, and actions to document and protect reference station conditions.

Actions that are associated with the listing of a stream reach as impaired, including stressor identification and development of total maximum daily loads (TMDLs), are also affected by climate changes. Stressor identification should include biological responses to climate change effects. Climate-related changes to flow may also need to be integrated into loading calculations and limits for new or revised TMDLs.

Water-quality standards that are resilient to changes in climate-related variables will remain protective and should be identified. Climate change can be expected to alter some designated uses and their attainability, especially in vulnerable streams or regions. Refinement of aquatic life uses can be applied to guard against lowering of water quality protective standards.

The results from the analyses conducted as part of this assessment illustrate plausible mechanisms through which climate change can affect many of the activities in bioassessment programs. Our results also identify methods that can assist with detecting these effects and controlling for them analytically. Implementing these recommendations will allow programs to continue to meet their resource protection and restoration goals in the context of climate change.

1. INTRODUCTION

Water-quality agencies use biomonitoring to assess the status and health of aquatic ecosystems as required by the Clean Water Act; however, a major environmental driver—climate—is changing in ways that have heretofore been largely unaccounted in terms of its influences on biomonitoring and bioassessment. There is growing information on the effects of climate change on aquatic ecosystems (e.g., Doledec et al., 1996; Durance and Ormerod, 2007; Buisson et al., 2008; Chessman, 2009; Flenner et al., 2010; Britton et al., 2010), with the clear potential for these to affect many activities associated with biologically based assessment programs. It is, therefore, important to consider the influence of climate change effects on bioassessment approaches, and to adapt these programs accordingly. This project was implemented with the goal of contributing to the foundation for understanding how potential climate changes affect bioassessment indicators and for advancing the development of specific strategies to ensure the long-term effectiveness of monitoring and management plans. The study focuses on biological responses to climate change and on biological indicators, with the main objectives of (1) investigating whether biological response signals to climate change are discernible within existing bioassessment data sets; (2) analyzing how responses of a variety of biological indicators can be categorized and interpreted with regard to apparent climate sensitivity or robustness; and (3) assessing how changes in biological responses may influence decision-making processes that are based on comparative interpretation of combined indicator responses.

The study objectives make this a 'data mining' study. It attempts to use existing, long-term biomonitoring data sets, which were collected for another purpose (i.e., to monitor the status of stream biota using reference-based comparisons) to address a new question for which the original collection programs were not designed. While there are certainly some questions about climate change effects that can be addressed using spatial comparisons, for the most part, climate change is a long-term temporal question, requiring trend analysis to investigate long-term patterns in temperature, precipitation, flow, other habitat variables, and biologic response variables. Given that at least some state biomonitoring programs have been in place for long periods of time (e.g., 2+ decades), and that outside of this arena, long-term biological data sets are relatively rare, it is an attractive opportunity to apply these long-term biological data set to the climate change-related questions that are the focus of this study.

This type of postfacto analysis of historic data sets is widely used to determine whether climate change effects are already discernible in ecosystem responses (e.g., Daufresne et al., 2004; Durance and Ormerod, 2007; Burgmer et al., 2007; Murphy et al., 2007). However, this data mining approach has several pitfalls. One is the contrast between the focus of most biomonitoring designs on spatial comparisons (i.e., between reference and nonreference sites), and the fundamentally temporal comparisons that are needed to answer climate change questions (e.g., evaluation of long-term trends). Other new objectives with respect to existing biomonitoring design are the need to separate climate change effects from responses to conventional stressors, and the need to be able to apply any observed results to a regional scale (e.g., an ecoregion, a province, or a class of stations). As a result, for mined biomonitoring data to ideally address the goals of this study would require not only having long-term data from a few sites, but having such data at reference sites that are minimally affected by other major anthropogenic stressors, and having such data from a number of regionally distributed, representative locations. As is often the case with the opportunistic use of mined data, the existing biomonitoring data sets available for analysis in this study do not always meet the criteria that would have allowed the most rigorous evaluation of the study questions.

1.1. DECISION CONTEXT

In order to understand the implications of climate change impacts on bioassessment programs, it is useful to consider the regulatory framework to which bioassessment programs contribute. The U.S. Clean Water Act (CWA) of 1972 identifies the restoration and maintenance of physical, chemical, and biological integrity as a long-term goal (Barbour et al., 2000). Biological assessment, or ‘bioassessment,’ is applied worldwide as a valuable and necessary tool for resource managers in achieving this goal (Norris and Barbour, 2009), and one that has been found to be more effective than sampling only chemical parameters (Karr, 2006). This is largely due to the recognition that biological indicators reflect an integrated response to all environmental conditions to which they are exposed over time (Moog and Chovanec, 2000; Barbour et al., 2000) and, thus, can provide information that may not be revealed by measurement of concentrations of chemical pollutants or toxicity tests (Barbour et al., 1999;

Rosenberg and Resh, 1993; Resh and Rosenberg, 1984). Biological assessment, coupled with multimetric or predictive modeling analyses, is a strong approach for diagnosing diminished ecological integrity, and minimizing or preventing degradation of river systems (Karr and Chu, 2000).

In the United States, biological assessment plays a central role in numerous water quality programs that are components of the CWA. Bioassessment data are used to assess water quality, identify biologically impaired waters, and develop National Water Quality Inventory reports. Bioassessment is used to develop biocriteria and set aquatic life use categories, which represent different protection standards. Bioassessment data are used to determine whether conditions of the waterbody support designated uses, and if not, to develop total maximum daily load (TMDL) limitations for the pollutant(s) contributing to the impairment. Bioassessment results are used to help identify causes of observed impairments, based on the assumption that various components of aquatic communities will respond differently to different types of stressors. Bioassessment is used to determine the impacts of point source discharges as well as of episodic spills, defining the extent of damage, responses to remediations, and supporting enforcement actions. Other CWA programs that depend on bioassessment data include permit evaluation and issuance, tracking responses to restoration actions, and other components of watershed management.

A variety of biological metrics and indices have been developed as ecological indicators that are mainly applied to gauge the condition of aquatic ecosystems but also to judge causes of degradation (Niemi and McDonald, 2004). They can serve as early warnings of degradation and often simplify extensive and complex environmental data. Biological indicators should be selected at appropriate spatial and temporal scales, incorporate natural variability, and be sensitive to the range of stressors expected in a system (Niemi and McDonald, 2004). The concept of linkage between biological indicators and the stressors on a system is crucial to the interpretation of bioassessment results. It also means that all stressors impacting a resource must be considered to achieve valid stressor identification and attribution of causes that can lead to effective ecosystem management. "All stressors" must now go beyond conventional pollutants to include climate change, as well as other global changes in land and water use (Hamilton et al., 2010a).

It is clear that if interpretations of biological response patterns are compromised by not accounting for the potentially important stressor of climate change, this could have wide-ranging consequences. To address the goals of this study, expectations for climate change effects on stream ecosystems are briefly outlined, and these are illustrated in a simplified conceptual model (see Figure 1-1). A subset of effects that are relevant to bioassessment programs and that can be tested using biomonitoring data are identified and are the focus of this study. These effects include shifts in community composition, relative abundances of component taxa, and richness of various taxa components, biological metrics that are typically measured and relied on in biomonitoring programs. The mechanisms through which climate changes can translate to changes in stream conditions and biological responses are used to define hypotheses for responses of various biological metrics that were tested to address study objectives.

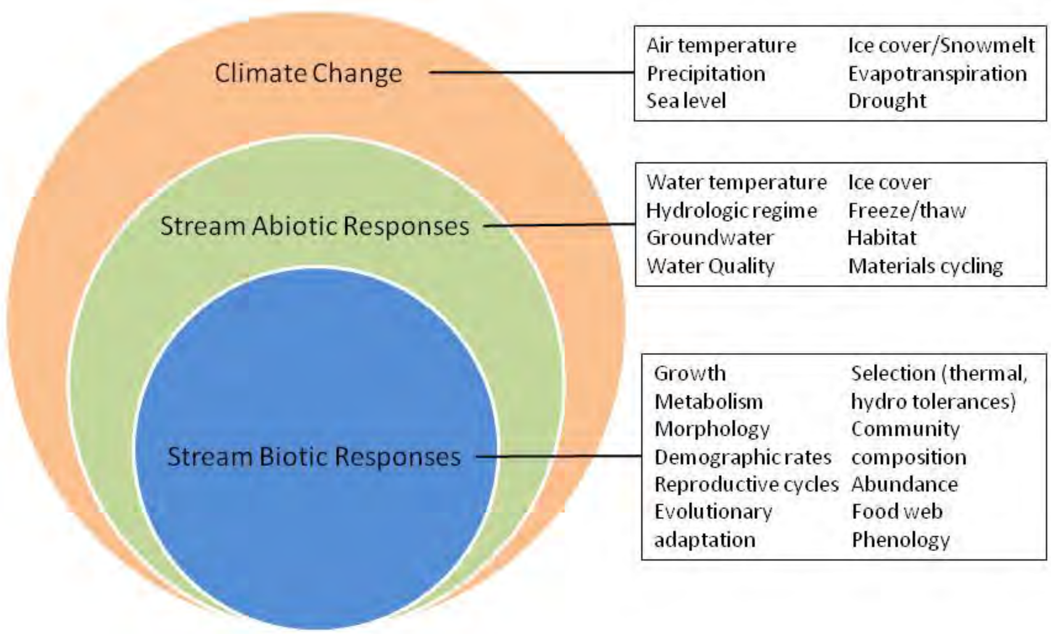

Figure 1-1. Conceptual model of the linkages between climate forcings, climate system changes, stream habitat changes (abiotic), and the subsequent individual-, population- and community-level responses to these changes.

1.2. CLIMATE CHANGE EFFECTS AND ECOLOGICAL RESPONSES

Changing patterns of climate forcing are expected to alter spatial and temporal patterns of air temperature and precipitation and drive changes in sea level rise, ice cover, timing and magnitude of snow melt, evapotranspiration, drought, flooding magnitude and frequency, and other extreme events (see Figure 1-1). Changes in air temperature and precipitation are two principal factors that will impact stream and river ecosystems through direct effects on water temperature and hydrologic regimes, and through indirect effects on dissolved oxygen (DO), pH, nutrients, and other dissolved constituents, changing the assimilation capacity of pollutants into receiving waters, sediment erosion and deposition, and habitat structure (see Figure 1-1).

Global or large-scale regional projections for changes in air temperature and precipitation patterns are the most readily available climate change projections and are important because they bound our expectations for overall magnitude and direction change. Multiple general circulation models (GCMs) provide us with an ensemble of projected changes in temperature and precipitation patterns (Intergovernmental Panel on Climate change [IPCC], 2007a). Global average projections of temperature increases over the next century range from 1.1−2.9^{o}C for the lowest emissions scenario to 2.4–6.4^{o}C for the highest emissions scenario (IPCC, 2007a). This represents a higher rate of increase (about 0.2^{o}C per decade) than the last 50 years (0.13^{o}C per decade), and further rate increases are considered possible (IPPC, 2007b; Ramstorf et al., 2007; Hansen et al., 2006).

The ensemble of GCM results are more uncertain in their projections for precipitation than for temperature and are variable among major geographic regions of the United States. Details of precipitation projections for regions that correspond to study areas of this project are presented in subsequent chapters. However, general projections include increased frequency of heavy precipitation events, more precipitation in winter and less precipitation in summer, more winter precipitation as rain instead of snow, earlier snow-melt, earlier ice-off in rivers and lakes, longer periods of low flow, and more frequent droughts in summer (IPCC, 2007a; Barnett et al., 2005; Hayhoe et al., 2007; Fisher et al., 1997). Changes in air temperature and precipitation patterns will drive changes in stream thermal and hydrologic regimes, which in turn will directly and indirectly influence biota (see Figure 1-1). As a result, available measures of stream thermal and hydrologic conditions (highlighted in Figure 1-1), as well as surrogates thereof, were the focus of climate change analyses in this study.

Freshwater ecosystems are considered sensitive to climate change impacts, because of their fundamental dependence on hydrology and thermal regimes, their dominance by poikilotherms, and the risks of interactions with other stressors (Durance and Ormerod, 2007). Documentation of aquatic biological responses to climate change on a basis that is meaningful to water quality and resource managers has been slow in coming, with much early attention focused on terrestrial ecosystems (e.g., Root et al., 2003; Thuiller, 2004; Walther et al., 2002, 2005; Parmesan, 2006; Tobin et al., 2008; Suding et al., 2008; Zuckerberg et al., 2009). However, there is an increasing body of information of aquatic ecosystem responses to climate change. Table 1-1 summarizes several salient examples of observed changes in aquatic community structure that are relevant in a bioassessment framework, though a broader range of biological responses is included in the conceptual model (see Figure 1-1). These can have potentially major consequences both for ecosystem function and for the interpretation of biomonitoring results relative to an assessment of ecosystem health. Expectations for the types, direction, and magnitude of biological responses should be linked to the magnitude and direction of climate change projections for each region, and potentially ameliorated by local factors. That is, biological responses are likely to be species- and/or trait-group-specific, and may vary regionally. The literature results in Table 1-1, comprising a range of observed and expected biological responses, are used to develop hypotheses for testing potentially sensitive trait and taxonomic groups of invertebrates for responses to changes in stream temperature and flow conditions.

A study of possible biological responses to climate change suggests we are not only documenting biological responses over time or to climate-related habitat conditions (e.g., stream temperature or flow metrics), but making causal linkages between climate change trends and biological responses. Causal attribution requires several logical linkages: (1) that long-term changes in climate factors (e.g., air temperature, precipitation metrics) have in fact occurred in the regions being studied; (2) that those climate changes can be associated with changes in stream conditions (e.g., in stream temperature and flow metrics); and (3) that observed biological trends and responses are associated with those changes in stream temperature and/or flow. In fact, to attribute observed biological responses to long-term climate change to the exclusion of other potential contributing causes, such as multidecadal climate oscillations, landscape stressors

Table 1-1. Examples of observed changes in aquatic community structure related to climate change that are relevant in a bioassessment framework

Examples of aquatic community changes	Reference
Increases in abundance, species richness, and proportion of southern and warm-water species of fish in large rivers	Daufresne and Boet, 2007
Loss of cold-water fishes from headwater streams, but also extension of more tolerant, thermophilic fishes from larger streams and rivers into newly suitable habitat	Buisson et al., 2008
Increases in fish species richness with increasing temperatures at higher latitudes	Hiddink and Hofstede, 2008
Displacement of upstream, cold-water invertebrate taxa with downstream, warm-water taxa	Daufresne et al., 2004
Increase in lentic and thermophilic invertebrates with increasing temperature	Doledec et al., 1996
Reductions of spring abundance of dominant taxa, shifts in invertebrate assemblage composition from cooler to warmer water taxa, and possible losses (local extinctions) of scarcer taxa with increasing temperatures	Durance and Ormerod, 2007
Significant long-term trends related to the thermophily and rheophily of benthic taxa, with groups preferring cold waters and higher flows declining	Chessman, 2009
Changes in stability and persistence	Collier, 2008
Changes in species composition in lakes	Burgmer et al., 2007
Changes in structure and diversity of riverine mollusk communities with reduction in community resilience during hot years	Mouthon and Daufresne, 2006

such as urbanization, nutrient enrichment, sedimentation, habitat alteration, or others, would require biological responses to be highly specific to climate change trends. This puts demands on a study design that are not entirely achievable using data collected in a biomonitoring framework, and especially using data mined from design parameters focused on dissimilar study objectives. For example, the length of available biological records is seldom more than about 2 decades, and because this is well within the duration of a single multidecadal climate oscillation, it is not possible to analytically separate potential contributions of such climate cycles from those of long-term directional climate change using the bioassessment data sets analyzed in this study. In addition, the interactions between climate cycles such as the Pacific Decadal or North Atlantic Oscillations (NAOs) can act synergistically or antagonistically with climate change, depending on their phases (e.g., Seager and Vecchi, 2010), potentially enhancing or obscuring the types and magnitudes of biological responses that might be expected over the long term. In this perspective, 'climate change' can be considered the long-term, average directional changes that span multiple climate cycle oscillations. However, recognition of the types and directions, and with caution, the magnitudes of biological responses to changes in climate-associated factors, and the identification of biological metrics that are sensitive to such climate-associated changes, can be inferred from linkages between changes in climate factors, associated changes in stream conditions, and associated changes in biological metrics, even in the absence of the ability to partition long-term direction and cyclic climate patterns.

In the strictest sense, establishing cause and effect may require controlled experimental design. However, it is common practice to infer probable sources of cause by clear associations between types and sources of stressors present and responses of biota whose autecology characteristics are known (Norris and Barbour, 2009; Cormier and Suter, 2008). This study used various approaches to strengthen inferences drawn in relation to the main questions. When available, we obtained long-term records of temperature, precipitation, and/or streamflows to place data from the period of record into an historic perspective and assessed the plausibility of the magnitude of stream temperature increases estimated for the biological periods of record in comparison to literature study results. We cross-checked the calculation of temperature optima for taxa used as a basis for defining thermal preference trait categories for examination and attribution of climate change-related biological responses with other classifications when possible, and confirmed the temperature optima through the estimation of benthic-inferred temperature trends. Though truly pristine reference conditions are rarely available, this study examined long-term biological trends and responses at minimally or least-impacted long-term monitoring stations, to limit known confounding by anthropogenic factors aside from climate-related alterations. In addition, we validated the success of this approach to the extent possible with available data on covariates that might also explain observed trends.

1.2.1. Expectations for Thermal Regime Changes and Associated Biological Responses

Changes in the thermal regimes of streams and rivers in response to climate change have been documented from long-term river temperature data sets around the country (e.g., Kaushel et al., 2010). Stream water temperature patterns closely follow air temperature patterns (e.g., Mohseni et al., 2003; Pilgrim et al., 1998; Stephan and Preudhomme, 1993). They are not directly driven by air temperature, but rather solar radiation as the primary heat source influences changes in stream temperature regimes (Allan and Castillo, 2007; Ward, 1985); other influences, including variations in flow volume and snow melt, ground water influence, aspect, riparian shading, presence of deep pools, meteorology, river conditions, and geographic setting also influence stream temperatures (Allan and Castillo, 2007; Caissie, 2006; Mohseni et al., 2003; Daufresne et al., 2004; Hawkins et al., 1997; Ward, 1985). These factors contribute to regional differences in stream water temperature responses to climate change forcing. The effects of water temperature can also interact with stream flow alterations, with higher temperatures and higher warming rates during low flow conditions (van Vliet and Zwolsman, 2008; Zwolsman and Van Bokhoven, 2007; Sinokrot and Gulliver, 2000). As a result, influences of stream temperatures and flow conditions cannot always be separated in terms of their effects on biota.

It is clear that water temperature is an important ecosystem driver, affecting water quality and the distribution of aquatic species (Caissie, 2006). Temperature regimes determine the distribution and abundance of aquatic species through temperature tolerances and evolutionary adaptations, along with competitive interactions, effects on food supply, and other factors (e.g., Matthews, 1998; Hawkins et al., 1997; Vannote and Sweeney, 1980; Sweeney and Vannote, 1978). A variety of individual-, population- and community-level changes ensue, including altered phenology (Gregory et al., 2000; Harper and Peckarsky, 2006); changes in the number and/or timing of reproductive periods (Hogg et al., 1995; Flanagan et al., 2003; Hampton, 2005); and selection for new thermal or hydrological tolerances (Rahel et al., 1996; Stefan et al., 2001; Golladay et al., 2004; Gibson et al., 2005) (see Figure 1-1).

Many of these categories of biological responses to climate change are difficult or impossible to discern using the types of data (i.e., collection methods, timing and frequency of collections, metrics measured) typically obtained from biomonitoring programs. Changes in phenology, timing, or number of reproductive cycles, and altered utilization of food resources are examples. Instead, biomonitoring programs are designed to characterize community structure, composition, abundance, and richness usually on an annual basis during a selected index period. It is change in metrics related to these community characteristics that this study assessed for possible responses to changing climate-related conditions.

Changes in the thermal regime of a stream/river can result in decreases in sensitive taxa or increases in tolerant taxa. For many taxa, summer temperatures can represent upper bounds of temperature preferences (although not necessarily true thermal maxima). However, winter temperatures or the seasonal timing of some thermal cues or thresholds may also be important in controlling distributions. One paradigm is that as climate change alters the spatial distribution of the ‘climate envelope’ that represents the appropriate thermal regime for a taxon that the taxon will shift its distribution accordingly. This can include range shifts northward or to higher elevations for cold-preference taxa as, for instance, the more southerly or lower elevation portions of their historic range become warmer, and some temperature tolerances are exceeded. On the other hand, warm preference or more broadly tolerant taxa might increase in abundance or extend their range abundance (e.g., Hamilton et al., 2010b). Because taxa are likely to respond at different rates, altered abundances and distributions of temperature (or hydrologically) sensitive and tolerant taxa will result in new species interactions and community compositions.

1.2.2. Expectations for Hydrologic Changes and Associated Biological Responses

Some of the major impacts of projected climate changes on stream systems will be to their hydrologic characteristics. The IPCC (2007a) projects average annual runoff to increase by 10−40% at high latitudes and some tropical areas, but to decrease by 10−30% over some midlatitudes dry regions and the dry tropics. In North America, projected changes in average stream flow range from an increase of 10−40% at high latitudes to a decrease of about 10−30% in midlatitude western North America by 2050 (Milly et al., 2005). In western/southwestern snow-pack dominated regions, the combination of warming temperatures, a shift toward less winter precipitation falling as snow, and snow-melt occurring earlier will shift the peak runoff from spring to late-winter/early spring, accompanied a by reduced magnitude of snowpack (Barnett et al., 2005, Clow, 2010). Typical projections are for peak runoff to shift from about 2 weeks up to 1 month earlier by the end of the century (Dettinger et al., 2004, Hayhoe et al., 2007). Stewart et al. (2005) has already found evidence for shifts of this magnitude (1−4 week earlier timing of snow melt and runoff based on data from 1948 to 2002) for several montane catchments in the western United States.

Numerous studies have demonstrated the importance of hydrologic changes on biological responses (Webb et al., 2009; Dewson et al., 2007; Suren and Jowett, 2006; Lind et al., 2006; Poff, 2002; Extence et al., 1999; Stanley et al., 1994). Significant associations between hydrologic variables and trait modalities also have been documented in a number of other studies (e.g., Horrigan and Baird, 2008). Dewson et al. (2007), Poff and Zimmerman (2009), and McManamay et al. (2011) reviewed the literature documenting a broad range of biological responses to changes in hydrologic conditions. Hydrologic regime of a stream is not a singular variable, and the range of hydrologic alterations that can result from the combination of increasing magnitude and variability of temperatures combined with a range of projected changes in precipitation and drought conditions is great. As examples, these may include longer duration and lower summer low flows, decreases in average discharge, greater incidence of floods, greater flashiness, and many others. Dewson et al. (2007) found that invertebrate abundances changed (increased or decreased based on flow preferences as well as habitat availability) in response to decreases in discharge, whereas invertebrate richness decreased with flow changes that resulted in decreased habitat diversity. Flow alterations affecting food resources were also important in affecting invertebrate responses. Carlisle et al. (2010) found that reduced stream discharge was the best predictor of reduced integrity of invertebrate and fish communities. Under reduced flow conditions, fish and invertebrates that increased tended to have traits typical of nonflowing (e.g., lake) environments, such as preferences for fine-grained substrates and slow-moving currents, and also traits that allow escape during parts of the life cycle.

Some of these studies are particularly relevant because they document responses to extreme and variable hydrologic conditions, similar to those that are projected to occur as a result of climate change. Several were conducted in streams in Mediterranean-climate regions, where the harsh and variable climatic conditions strongly influence biological assemblages, and we utilized this information during metric development. Results show that organisms with resilience or resistance trait modalities, such as high dispersion and colonization capabilities, resistance to desiccation and aerial breathing, were generally prevalent in drier, harsher climatic conditions (Béche et al., 2006; Bonada et al., 2007b; Diaz et al., 2008). Trait modalities that confer resilience to extreme conditions were also prevalent in macroinvertebrate communities recovering from severe drought conditions in Georgia, United States (Griswold et al., 2008). Organisms that recovered most rapidly generally had short life cycles, resistance to desiccation, small body size, armoring, and abundance in drift. As flow increased and habitat conditions stabilized, larger, soft-bodied organisms that are rare in drift became more prevalent (Griswold et al., 2008).

1.3. CONCEPTUAL MODEL LINKAGES STRUCTURING THE STUDY APPROACH

Figure 1-1 is a conceptual model that highlights the linkages between the changing components of the climate system and various aspects of aquatic ecosystems. There are numerous interacting pathways that link climate factors that help form regional ecosystem characteristics with other environmental drivers, to yield a range of biological responses in stream and river ecosystems. Projections for changes in air temperature and precipitation patterns are the main climate drivers that are linked to stream and river habitat conditions (see Figure 1-1). Other closely related predictions, such as for earlier snowmelt or increased drought frequency or duration, expand the picture of climate-related alterations that are likely to influence stream ecosystem characteristics. These changing regional climate conditions will alter stream environments through direct and indirect processes that will lead to altered thermal and hydrologic regimes, changes in groundwater conditions and baseflow, changes in waterborne chemical constituents and water quality conditions, and changes in physical habitat characteristics, such as stream morphology and substrate type (see Figure 1-1). Interactions among these abiotic characteristics, as well as with other existing pollutants and stressors on the stream, will contribute to changes in stream biota at every level of organization—individual, population, community, and ecosystem. Though not intended to be exhaustive, Figure 1-1 lists numerous anticipated and observed biotic responses that link mechanistically to the range of climate-driven abiotic changes shown. Many of the biological responses in Figure 1-1 are not typically measured as part of a biomonitoring program but could contribute to outcomes of community structure that are used to characterize condition. For example, changes in number of reproductive cycles per year for a species is not a typical bioassessment metric; however, changes in reproductive patterns and success can alter the community composition and relative abundance measured at any time. Some other types of biological responses, such as genetic adaptation, are only tangentially relevant to bioassessment measurements.

The strategy for this study was to consider how the multiple mechanisms through which climate-related changes impacting streams (alterations in thermal regimes, hydrologic regimes, water quality, nutrient status, habitat conditions, and essential interactions with food supply, competitors, and predators) could combine to yield changes in commonly measured metrics of community composition, abundance and richness, and then use this information to postulate what types of biological metrics might best capture the predicted responses. Changes in the thermal and hydrologic regimes of streams are the most direct links between the climate drivers of air temperature and precipitation. Changes in ice cover and snowmelt patterns and expectations for increasing drought conditions contribute to changes in hydrologic regime. Changing thermal and hydrologic characteristics of a stream can contribute directly to alterations in community composition, abundance, and richness through numerous direct as well as indirect mechanisms. Mechanisms of action can be through traits related to temperature and flow preferences and tolerances, as well as traits that confer ability to adapt to droughts or flood disturbances, or to recover from increased stress, including greater variability in temperature and flow conditions. Other expectations from this model include potential responses of taxonomic groups considered sensitive to other perturbations and responses of feeding guilds through indirect effects of altered availability of food resources. Accordingly, this study explores and develops temperature and flow preference trait groups, and examines the responses of these, as well as trait groups related to habit, feeding type, size, and mobility. Taxonomic groups considered sensitive or tolerant to conventional stressors and metrics that are commonly utilized in biomonitoring programs are also investigated. Boxes outlined in bold in Figure 1-1 identify the climate, stream condition, and biological components on which this study focused.

The effects of global change on bioassessment programs will vary regionally. Land and water use effects are largely driven by locations of and projected future changes in major population and agricultural centers. Differences in the severity of climate change impacts are instead driven by regional variability in climate, as well as regional differences in the vulnerability of aquatic ecosystems. Differences in regional climate and disturbance regimes are important contributors to species sensitivities to environmental changes (Helmuth et al., 2006). Many factors can influence susceptibility to changing water temperature or hydrologic regime due to climate change, such as elevation (Chessman, 2009; Diaz et al., 2008; Cereghino et al., 2003), stream order (Cereghino et al., 2003; Minshall et al., 1985), degree of ground water influence, or factors that affect water depth and flow rate, such as water withdrawals (Chessman, 2009; Poff et al., 2006a; Poff, 1997). To the extent possible, factors such as these that can affect the sensitivity of biota to overarching climate change influences, including elevation, ecoregion, and stream size, are examined in this study.

This study uses four regionally distributed state bioassessment data sets from Maine, North Carolina, Ohio, and Utah to examine historical trends in relation to temperature, precipitation, flow, and other environmental drivers. We use community and traits analyses to identify potential indicators, both sensitive and insensitive (robust) to climate change effects. Examination of climate-sensitive traits facilitates transfer of analysis results to other places. Additional analyses focusing on the vulnerability of reference conditions and the interactions between climate change and other landscape-level stressors, especially land use, supplement these results. This study builds on the results of a preliminary analysis (U.S. EPA, 2008) and feedback from a workshop convened in 2009 with state and tribal scientists and resource managers, academic and agency experts, and decision makers to explore the following issues: the effects of climate change on endpoints of concern; methods for integrating climate change into existing state and tribal water quality programs; and ways to create opportunities for adaptation.

Study findings are summarized in the beginning of this report in the Summary for Managers and Policymakers. The body of the report expands on the analyses that support these findings. Section 2 describes methods used, including types and sources of data; data preparation; biomonitoring station characteristics; climate conditions and climate change projections for regions analyzed; thermal, hydrologic, and combined indicator development; methods used for trend, categorical, and spatial analyses; and approaches for assessing impacts to biomonitoring program decisions. Sections 3, 4, 5, and 6 apply these methods and summarize results for each of the four state biomonitoring data sets evaluated. Section 7 integrates results across regions, analyzes implications to environmental management, and discusses design considerations for a monitoring network to detect climate change effects. While all primary analysis results are summarized in the main report, some detailed results and supporting materials are compiled in appendices.

2. METHODS

2.1. DATA GATHERING

2.1.1. Exposure Data

We gathered regional and state-specific data on historic and future projected climatic changes. Our goals were to evaluate the direction and rate of change in temperature and precipitation patterns in each state and region, to examine differences in spatial patterns of change within each state (i.e., identify 'hot spots'), and to compare the magnitude and direction of future projected changes. We based summaries of regional projections on results from literature searches. For the state-specific summaries, we obtained annual and seasonal air temperature and precipitation data from the Climate Wizard Web site (http://www.climatewizard.org/). We ran linear trend analyses on these data for two historic time periods: 1901−2000 and 1971−2000. The base data for these historic trend analyses came from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) Group, Oregon State University (http://www.prismclimate.org, Gibson et al., 2002). PRISM data are modeled data that utilize a digital elevation model and point measurements of climate data to generate estimates of annual, monthly, and event-based climatic elements with a 4-km resolution. In addition to running linear trend analyses, we generated maps for each state based on 1971−2000 averages to evaluate spatial differences in temperature and precipitation patterns.

We also used the Climate Wizard Web site to gather data on projected changes in annual and seasonal air temperature and precipitation for high (A2) and low (B1) emissions scenarios for mid (2040−2069) and late (2070−2099) century compared to an historic (1961−1990) time period. Data from 15 different GCM were evaluated (see Table 2-1). We used these data to calculate ensemble minimum, maximum, and average values. In addition, we calculated standard deviations (SDs) to assess levels of uncertainty across models.

2.1.2. Temperature and Streamflow Data

Water temperature is the most proximate measure of thermal change in streams. Efforts were made to acquire all available site-specific water temperature data for the biological monitoring sites in each state. The available data were primarily instantaneous measurements taken at the time of each biological sampling event. In only a few instances, where the

Table 2-1. Future projection data from 16 GCMs were evaluated. These data were obtained from the Climate Wizard Web site (http://www.climatewizard.org/)

GCM	Country	Institution
BCCR-BCM2.0	Norway	Bjerknes Centre for Climate Research
CGCM3.1(T47)	Canada	Canadian Centre for Climate Modelling & Analysis
CNRM-CM3	France	Météo-France/Centre National de Recherches Météorologiques
CSIRO-Mk3.0	Australia	CSIRO Atmospheric Research
GFDL-CM2.0	USA	U.S. Department of Commerce/NOAA/Geophysical Fluid Dynamics Laboratory
GFDL-CM2.1	USA	U.S. Department of Commerce/NOAA/Geophysical Fluid Dynamics Laboratory
GISS-ER	USA	NASA/Goddard Institute for Space Studies
INM-CM3.0	Russia	Institute for Numerical Mathematics
IPSL-CM4	France	Institut Pierre Simon Laplace
MIROC3.2(medres)	Japan	Center for Climate System Research (The University of Tokyo), National Institute for Environmental Studies, and Frontier Research Center for Global Change (JAMSTEC)
ECHO-G	Germany/Korea	Meteorological Institute of the University of Bonn, Meteorological Research Institute of KMA, and Model and Data group.
ECHAM5/MPI-OM	Germany	Max Planck Institute for Meteorology
MRI-CGCM2.3.2	Japan	Meteorological Research Institute
CCSM3	USA	National Center for Atmospheric Research
PCM	USA	National Center for Atmospheric Research
UKMO-HadCM3	UK	Hadley Centre for Climate Prediction and Research/Met Office

site happened to be located near a United States Geological Service (USGS) gage, we were able to find continuous water temperature data, and even then, it was for a limited number of years. Continuous data are preferable over instantaneous measures because they capture more aspects of the true thermal regime, such as timing, duration, and frequency of extremes. We made similar efforts to acquire site-specific streamflow data, but these data were only available for a limited number of sites. If sites were colocated with USGS gages, we downloaded daily streamflow data from the USGS real-time flow data Web site (http://waterdata.usgs.gov/nwis/rt). In other instances, state biomonitoring programs were able to provide instantaneous streamflow measurements that were taken at the time of the biological sampling event.

2.1.3. Biological Data

Routine biomonitoring data from Maine, Utah, and North Carolina were compiled into Ecological Data Application System (EDAS) databases, which are custom database applications that are used with Microsoft Access. For Ohio, data were originally obtained from STORET; however, interactions with the Ohio Environmental Protection Agency (EPA) revealed that data generation, database development, and management, as well as ongoing analyses for Ohio are conducted by Ed Rankin and Chris Yoder of Midwest Biodiversity Institute (MBI). Therefore, data manipulation and analyses for Ohio were conducted by MBI under subcontract to Tetra Tech. The Ohio database included both fish and macroinvertebrate data. The Maine, Utah, and North Carolina databases contained macroinvertebrate data only.

Taxonomic data were screened in order to minimize the chance of detecting false trends due to changes in field and laboratory protocols (e.g., differences in collection methods, differences in sample processing/subsampling methods, changes in taxonomists, and/or taxonomic keys). In the Maine, Utah, and North Carolina data sets, preliminary iterative data summaries, and screening procedures included

- Tabulating numbers of samples by station (e.g., station name, station ID number, and/or sample ID number) and date. Results were examined for consistent number of samples by station/date and for breaks in sample collection at stations across years. Problems discovered through this approach included changes over time in collection methods and/or reporting of replicates and errors or changes in station naming that resulted in data for the same location appearing under different station names. It also helped identify locations with long-term data records.

- Tabulating total abundance and total number of taxa by station and collection date. Results were examined for discontinuities in magnitude or trends in values between stations and across dates. Problems discovered through this approach included changes in reporting of abundances (e.g., from number per sample to number per square meter); whether replicates were averaged, summed, or reported separately and changes or errors in whether subsampling was applied during sample analysis and how it was accounted for in the data.

- Tabulating taxa (at the lowest levels reported) by collection date. For these, either taxa abundance or occurrence was tabulated, and these were either averaged over all stations within the state, or within each ecoregion and/or other appropriate subset (e.g., river basin or watershed). For this purpose, the tabulations of taxa were placed in phylogenetic order, and some higher-level phylogenetic structure (e.g., order and family names, or others as needed) was included for reference. Results were examined for many types of patterns, including
    - changes in taxonomic naming over time (e.g., changes in genus- or higher-level names, changes in placement within families). This not only revealed changes in systematics over time, but also caught changes in taxonomists and/or labs used to analyze samples.
    - changes in level of attribution over time (e.g., increasing use of species names in recent years where individuals were typically left at the genus or family level in earlier samples);
    - changes in other types of naming conventions (e.g., changes in level of placement for taxa such as water mites).

Problems identified through these procedures included extensive changes in taxonomic knowledge and systematics over the decades of sample analysis. For illustration, one example is changes in the mayfly genus *Ephemerella*, including changes in the inclusion of various species of *Ephemerella* between *Ephemerella* and *Drunella*. In addition, we found many instances of changes in the higher-level groups under which various taxa would be reported, so that in the database, the same genus (or species, or family) would appear in more than one place. The effect of this was that these would act like separate taxa when a taxa ID name or number was invoked for trend analysis. Many associated corrections were applied to the phylogenetic structuring and naming conventions in the databases.

To address issues associated with changes in taxonomic naming of genera and/or species, or greater prevalence of species identifications in recent years, we followed the guidelines of Cuffney et al. (2007) to develop OTUs for the Maine, Utah, and North Carolina data sets. OTU development involved summing species to the genus level (or similar procedures at other levels), or combining two or more genera that could not always be reliably separated. The intent of OTUs is to exclude ambiguous taxa from analyses and include only distinct/unique taxa. Because a complete and correct master taxa list is required before OTUs can be established, the master taxa lists in each of the databases were first verified through several iterative procedures.

Next, three levels of OTUs were established: lowest taxonomic unit (generally species), genus, and family. Rules were developed based on a general procedure of Remove Parent/Merge Children (retain the Child taxa [finer level of detail] and remove the Parent taxon or merge the Child taxa into the Parent taxon). According to Cuffney et al. (2007), this appears to be the most robust method for retaining taxa richness and abundance information for further analysis. All decisions were data set dependent. Rules were created on the data set as a whole and then applied to individual samples prior to analysis. The last step in the process was to manually review the list of OTU designations and make final corrections where necessary. Genus-level OTUs were generally found to be most appropriate, although there were some exceptions (e.g., in the Utah database, a family-level OTU had to be used for Chironomidae due to inconsistencies arising from a change in taxonomy labs).

In the Ohio data set, MBI developed a program to scan for changes in taxonomy over time that could affect calculations of Ohio EPA's Invertebrate Community Index (ICI) (DeShon, 1995). The program provided a listing of the first and last occurrence of each taxon in the Ohio EPA database. MBI used this to extract a list of possible taxa that could affect ICI scoring via taxonomic refinement (splitting or lumping of taxa). MBI then conferred with senior Ohio EPA taxonomists to determine how to best address these changes. Their efforts primarily resulted in "lumping" individual taxa designations of mayflies back to "*Baetis* sp." or "*Pseudocloeon* sp." Table A-1 in Appendix A lists the mayfly taxa that appeared earlier and then "disappeared" or those that "appeared" later, mostly at resampled sites.

In the Maine, North Carolina, and Utah data sets, we used Nonmetric Multidimensional Scaling (NMDS) to evaluate whether the database 'fixes,' and in particular the taxonomic corrections and application of OTU rules, were effective in minimizing changes over time due to taxonomic identification procedures rather than actual community changes. NMDS is an ordination that takes the taxa in the samples and shows in ordination space how closely related the samples and stations are based on their species composition. Grouping variables (e.g., year, month, collection method, taxonomy lab, ecoregion, watershed, etc.) can be overlaid to look for trends. The NMDS ordinations were performed only on least-disturbed sites in order to eliminate differences due to other disturbances. The NMDS ordinations were run before and after generating genus-level OTUs. Patterns were examined for distinct shifts that might indicate changes in taxonomists or labs during the sampling period of record, as well as ineffective OTU procedures. Section A.2 in Appendix A contains the NMDS plots.

In addition to taxonomic data, we compiled life history, mobility, morphology, habitat, and resource acquisition traits data for North American macroinvertebrate taxa found in lotic systems. Advantages of using traits data are that they are less susceptible to taxonomic ambiguities or inconsistencies in long-term data sets; they can detect changes in functional community characteristics; and they vary less across geographical areas, which allows for larger-scale trend analyses across regional species pools. Traits data for 3,857 North American macroinvertebrate taxa were compiled into the Freshwater Biological Traits database (U.S. EPA, 2012).

2.1.4. Site Information

In addition to water temperature, streamflow, and biological data, we gathered all available water chemistry, habitat, and land-use data from the state biomonitoring programs. These data allowed us to screen for potential nonclimatic factors that may have influenced trends in the biological data over time. The amount and type of data available for each state varied. Because of this, we used a Geographic Information System (ArcGIS 9.2) to obtain a standardized set of parameters for each biological sampling site. These included 2001 National Land Cover Data (Vogelmann et al., 2001) within a 1-km buffer zone, site-specific elevation, and EPA Level 3 and 4 ecoregions. The 1-km distance for the land-use buffer was arbitrary and was intended to provide a measure of potential anthropogenic stressors in the surrounding area. We aggregated land-use classifications into broad categories (e.g., urban and agricultural).

2.2. DERIVATION OF INDICATORS

2.2.1. Thermal Preferences

We used weighted-average modeling or related approaches (e.g., maximum likelihood estimates, general linear modeling) to develop lists of candidate taxa in each state that could potentially serve as indicators of thermal change. The methods described in Yuan (2006) were used to estimate the optima values and ranges of occurrence (tolerances) for temperature for OTUs that had a sufficient distribution and number of observations to support the analysis.

Weighted averaging is a simple, robust approach for estimating the central tendencies of different taxa, or in our case, temperature optima and tolerance values (ter Braak and Looman, 1986). The basic approach is a straightforward weighted average—the temperature at each site in a state at which the species is observed, multiplied by the relative abundance of the species at that site, with the sum over all sites of the weighted temperatures divided by the sum of the abundances of that species from all sites. This mean temperature is taken as the preferred temperature for the taxon, and the breadth of the distribution (size of the standard deviation or other measure of spread) represents an estimate of the tolerance or sensitivity of the taxon. Table 2-2 and Figure 2-1 illustrate the approach.

Table 2-2. Example of how a weighted average model temperature optimum (weighted mean) estimate is calculated

Species A temperature preference			
Station ID	**Relative abundance**	**Observed temperature**	**RA × temp.**
A	0.10	22	2.20
B	0.02	33	0.66
C	0.02	12	0.24
D	0.04	14	0.56
Sum	*0.18*		*3.66*

Weighted average = 3.66/0.18 = 20.3333, RA = relative abundance, temp. = observed temperature.

When using weighted averages, a wide distribution of samples across the environmental gradient results in a more robust estimate of temperatures of occurrence and, therefore, of inferred preference. For a given state data set, weighted-average tolerance values for each OTU are computed using the same set of environmental data; therefore, any bias arising from an uneven distribution of data will be the same for all OTUs, and their relative placement along the temperature gradient will generally be preserved.\

The generalized linear model is also used to estimate taxon-environment relationships for each combination of taxon and environmental variable. In addition to providing a means of computing tolerance values, regression estimates of the taxon-environment relationship quantify

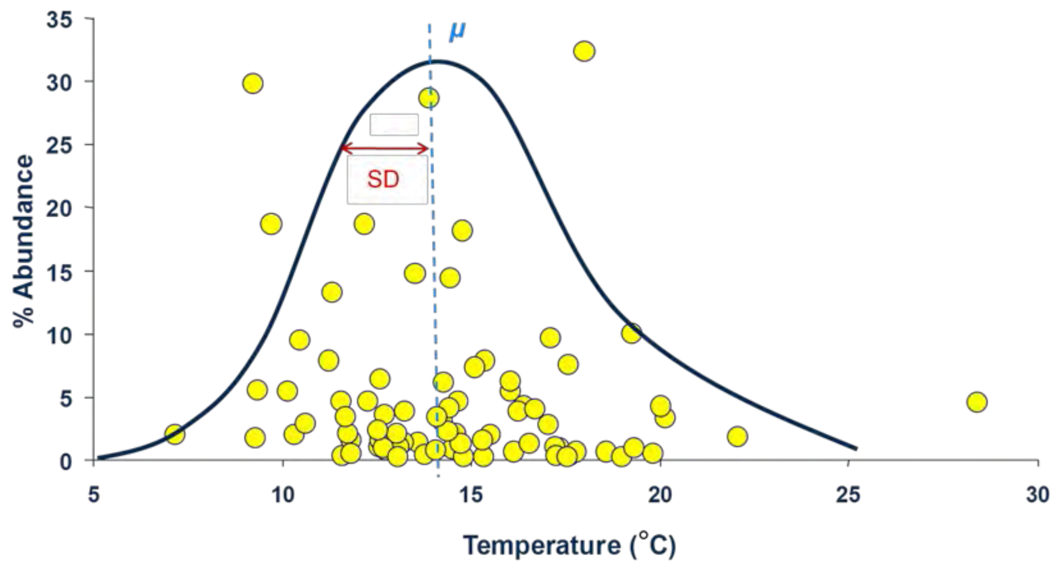

Figure 2-1. Illustration of weighted average temperature distribution, where the weighted average mean (μ) is taken as the temperature optimum (preference) for the taxon, and the magnitude of SD is taken as an estimate of the temperature sensitivity or tolerance.

the strength of the association between a given environmental gradient and changes in the occurrence probability or abundance of a taxon. In the case of presence/absence data, the response variable is modeled as a binomial distribution; in the case of abundance data, a negative binomial distribution is often assumed (maximum likelihood estimates).

Weighted-average calculations were used for the states that had absolute (noncategorical) abundance data by taxon. If only presence/absence (categorical or qualitative abundance) data were available, a generalized linear model was used. Calculations were made separately for each state. For the Maine, North Carolina, and Utah analyses, stations across all ecoregions were grouped together, and data were subset to account for seasonal variation (when needed), as well as for variation associated with different sampling methods. For example, in Utah, only samples collected during the fall index period were used. In North Carolina, only samples collected using a certain method were analyzed. OTUs that occurred in fewer than 20 samples were excluded, as low sample size affects the regression model and biases the optima and breadth values for rare taxa, especially under extreme conditions.

Because the specific characteristics of each state data set varied (e.g., range of collection dates, station locations, elevation), and because the methods used to derive the thermal optima and tolerance estimates also varied in some cases, we developed an arbitrary ranking scheme to make results more comparable across data sets. For the Maine, North Carolina, and Utah data sets, we assigned taxa rankings ranging from 1 to 7 based on percentage within each data set. We designated taxa with rankings ≤3 (<40th percentile) as preliminary cold-water taxa and taxa with rankings ≥5 (>60th percentile) as preliminary warm-water taxa (see Table 2-3). Thermal optima and tolerance values were not available for all taxa, so we used literature, primarily the traits matrix in Poff et al. (2006b) and the USGS traits database (Vieira et al., 2006), as a basis for making some additional initial designations.

Table 2-3. Example taken from Utah analysis results to illustrate development of ranking for temperature (or other environmental parameter) preference and tolerance rankings from weighted-average or generalized linear model temperature distribution results. Ranks 1–3 are cold stenotherms; Ranks 5–7 are warm eurytherms

Rank	Percentage	Optimum	Tolerance
1	0-0.1	4.6-6.7	2.0-2.7
2	0.1-0.25	6.8-7.6	2.8-3.2
3	0.25-0.4	7.7-8.3	3.3-3.5
4	0.4-0.6	8.4-9.1	3.6-3.7
5	0.6-0.75	9.2-9.6	3.8-3.9
6	0.75-0.9	9.7-10.4	34.0-4.3
7	0.9-1.0	10.5-15.7	4.4-5.1

After making these preliminary cold- and warm-water designations, we refined the lists based on case studies and best professional judgment from regional advisory groups. We felt these additional considerations were necessary because some taxa occurred with greater frequency in warm- or cold-water habitats but were not present exclusively in one or the other. For example, some taxa initially designated as cold-water taxa also were present at sites that had the hottest recorded water temperatures. During the refinement process, we removed these taxa from the cold-water list.

For the Ohio data set, MBI used the same general procedures described in Yuan (2006) when making weighted-average calculations to derive optima and tolerance values (which the author termed weighted stressor values [WSVs]). However, there were some differences in the data they used, how they prepared their data sets for analysis and how they ranked taxa. Instead of instantaneous water temperature measurements, MBI's calculations were based on maximum temperature recorded from summer-fall grab samples collected during the same period within which the biological data were collected. Before running the analyses, MBI divided the data into different stream size categories—headwater (drainage area ≤20 mi^2) and wadeable (drainage area >20 to 300 mi^2)—and analyzed these data sets separately. Taxa rankings, which they termed "Taxa Indicator Values," were derived using the methodology of Meador and Carlisle (2007) and were based on an ordinal scale of 1 (most sensitive) to 10 (most tolerant). MBI did not formally designate lists of cold and warm-water taxa but did note which taxa occurred at the extremes of the distributions.

In addition to estimating thermal optima and tolerance values, we also examined the relationship between these values and organic enrichment tolerance values for each state. Overlap between these sensitivities means that it will be difficult to tease out whether the thermal indicator taxa are responding to changes associated with warming temperatures or whether they are responding to other stressors, such as enrichment.

2.2.2. Hydrologic Indicators

We attempted to develop lists of candidate taxa in each state that could potentially serve as indicators of hydrologic change. The types of analyses that were conducted for each state varied depending on the amount and type of hydrologic data that were available. For the Maine, North Carolina, and Utah data sets, we used a geographic information system (GIS) to associate biological sampling sites with USGS flow gages. Sites and gages were considered to be matches if they were located on the same stream reach and were within 500 m of one another. For the sites that had gages, all available hydrologic data were downloaded from the USGS real-time flow data Web site. Indicators of Hydrologic Alteration (IHA) software (Version 7.0.4.0, TNC, 2007) was then used to calculate a suite of nonparametric IHA parameters for each site (see Table 2-4). The Richards-Baker Flashiness Index (RBI, Baker et al., 2004), which uses flow data to quantify the frequency and rapidity of short-term changes in stream flow, was also calculated for each site. IHA and RBI data were then paired with biological data from each site. In general, these data sets had limited sample sizes, but if sufficient data existed, we used weighted averaging to calculate taxa optima and tolerance values for hydrologic variables that showed the strongest relationships with the biological data.

Table 2-4. Summary of IHA parameters used in the analyses. High flow events refer to flows above the 75th percentile of all flows. Low flow events refer to flows less than or equal to the 50th percentile of all flows. Extreme low flow events refer to flows less than the 10th percentile of all low flows

Annual IHA parameters	Description
Monthly	Median discharge (cfs)
1-day min	Annual minima, 1-day mean (cfs)
3-day min	Annual minima, 3-day means (cfs)
1-day max	Annual maxima, 1-day mean (cfs)
3-day max	Annual maxima, 3-day means (cfs)
Date min	Julian date of each annual 1-day minimum
Date max	Julian date of each annual 1-day maximum
Lo pulse #	Number of low pulses within each water year
Lo pulse L	Median duration of low pulses (days)
Hi pulse #	Number of high pulses within each water year
Hi pulse L	Median duration of high pulses (days)
Environmental flow components	
Xlow1 peak	Minimum ('peak') flow (cfs) during extreme low flow event (within each year)
Xlow1 dur	Duration of extreme low flow event (days)
Xlow1 time	Julian date of peak flow
Xlow1 freq	Frequency of extreme low flows during water year
High1 peak	Maximum ('peak') flow (cfs) during extreme high flow event (within each year)
High1 dur	Duration of extreme high flow event (days)
High1 time	Julian date of peak flow
High1 freq	Frequency of extreme high flows during water year
Baseflow index	7-day minimum flow/mean flow for year
Number of reversals	Number of hydrological reversals

For the Ohio data set, instead of using IHA and RBI data, MBI calculated weighted-average estimates based on a subset of habitat measures from the Qualitative Habitat Evaluation Index (QHEI), which is a visual assessment of substrate, cover, channel, riparian, pools, riffle, and stream gradient (Rankin, 1995, 1989). Since its inception, the QHEI has been collected by trained professionals at Ohio EPA. Recent signal/noise ratio analyses of variation from sites with multiple QHEI values indicate the index is precise, and the subcomponents are moderately precise to precise (Miltner and Rankin, 2009). The subset of QHEI attributes that MBI analyzed (which they termed the Hydro-QHEI), are responsive either directly (current speed components) or indirectly (stream depth measures) to alterations of the flow regime. As with the thermal preference calculations, MBI calculated these weighted average estimates separately for headwater (drainage area $\leq$20 mi^2) and wadeable streams (drainage area >20 to 300 mi^2).

In addition to the weighted averaging, there were sufficient data in the North Carolina and Utah data sets to further examine associations between taxonomic data and hydrologic variables using NMDS. We performed the NMDS ordinations to evaluate which IHA parameters had the strongest influence on taxonomic composition. We overlaid grouping variables such as season and ecoregion to determine how much (if any) influence these variables had on the biological assemblage. For the Utah data set, we had sufficient data to also run a Canonical Correspondence Analysis (CCA). In Maine, we lacked sufficient data to run these types of analyses. However, we were able to run correlations analyses to look for associations between biological data and IHA parameters at one site that had over 20 years of data. We were also able to do this type of analysis at seven sites in Utah.

2.2.3. Traits-Based Indicators in Future Scenarios

For the Maine, North Carolina, and Utah data sets, we conducted exploratory exercises to develop lists of taxa that may be most and least sensitive to projected changes in temperature and streamflow based on combinations of traits. We used relevant literature and best professional judgment to develop lists of traits modalities likely to be “functionally” linked to projected changes in temperature and streamflow. These included traits such as voltinism, adult ability to exit, ability to survive desiccation, dispersal ability, adult flying strength, occurrence in drift, swimming ability, armoring, shape, respiration, size at maturity, habit, functional feeding group, and thermal preference.

When assessing sensitivity to future climatic changes, we focused on a generalized scenario in which temperatures are increasing, and flows are decreasing during the low flow periods when state biomonitoring programs typically collect their samples. These low flow conditions can be stressful to organisms due to loss of habitat, limited food resources, and altered water chemistry. We acknowledge that using this type of generalized scenario is an oversimplification, and that regions may experience both extreme low flow and high flow events in a given year. A common theme across potential future scenarios is that organisms are likely to be exposed to more extreme and unpredictable conditions. We kept this in mind when deciding which traits and trait modalities to consider when developing the lists of candidate indicator taxa, and when assessing whether trait modalities were favorable or unfavorable in the face of changing climatic conditions. Table 2-5 contains a list of the traits and trait modalities that we used. Taxa that had the most number of favorable trait modalities were placed on the least sensitive list, while those with the most number of unfavorable trait modalities were placed on the most sensitive list.

Table 2-5. List of traits and trait modalities that were considered when developing lists of traits-based indicator taxa for future conditions of warming temperatures and lower flows. The list was developed based on relevant literature and best professional judgment and consists of trait modalities likely to be "functionally" linked to the changes in temperature and streamflow

Traits	Favorable	Unfavorable
Voltinism	Bi- or multivoltine (>1 generation/yr)	Semivoltine (<1 generation/yr)
Adult ability to exit	Present	Absent
Ability to survive desiccation	Present	Absent
Dispersal ability (adult)	High	Low
Adult flying strength	Strong	Weak
Swimming ability	Strong	None
Armoring	Good, heavily sclerotized	None
Occurrence in drift	Abundant, common	Rare
Respiration	Plastron or spiracle (aerial)	Tegument
Size at maturity	Small	Large
Rheophily	Depositional	Erosional
Habit (primary)	Skater, swimmer	Clinger
Functional feeding group (primary)	Collector-gatherer, predator	Scrapers, collector-filterer
Thermal preference	Warm	Cold

We acknowledge that there are many limitations associated with this methodology. There are many factors other than temperature and hydrological variability that control the distribution of species in lotic environments. Also, all traits do not have the same importance and influence on adaptation to particular environmental conditions, so focusing on just the number of favorable or unfavorable traits is an oversimplification and will not necessarily define a taxon's ability to adapt to climate change. Moreover, there are phylogenetic constraints to the combination of traits (and number of "favorable" traits) that could be found in a given taxon, and it is possible that different combinations of traits (including different numbers of traits) can provide similar "protection," just via a different strategy. These issues are largely problematic for the field of trait-based ecology in general. Knowing this, we included results from these exploratory analyses as a first step towards developing more robust lists of traits-based indicator taxa. In the future, as more data become available and we learn more about which traits are in fact advantageous or not in the face of changing temperatures and/or hydrology, these lists should be refined.

2.3. LEAST-DISTURBED LONG-TERM BIOLOGICAL MONITORING SITES

We focused primarily on analyses of least-disturbed sites in each state so that trends in biological data were as free from confounding nonclimatic factors as possible. We relied upon guidance from the respective state agencies when selecting least-disturbed sites. Of the four states evaluated, only Ohio has a formal statewide long-term monitoring network for least-disturbed sites, and MBI focused their analyses on this network of sites. The Maine, North Carolina, and Utah data sets were better suited for analyses of individual least-disturbed sites that had the longest-term biological data. In these states, we performed exploratory analyses to evaluate whether least-disturbed sites could be grouped together to create longer term data sets, but site-specific differences were evident within these grouped data sets, so we focused on individual sites. At some of these sites, anthropogenic influences are higher than desired (i.e., >5% urban or >10% agricultural within a 1-km buffer), but the data were analyzed anyway because they represent the best-available long-term data in each state data set.

2.4. EVIDENCE OF TRENDS AT LEAST-DISTURBED LONG-TERM MONITORING SITES

2.4.1. Temporal Trends in Climatic and Biological Variables

We examined year-to-year variability in climatic (temperature, streamflow, precipitation) and biological variables at least disturbed biological sampling sites with the longest-term biological data. In Ohio, MBI looked at the amount and direction of change in state bioassessment ratings (based on ICI and Index of Biotic Integrity [IBI] scores) at a group of about 300 least disturbed "reference" sites that were sampled at 10-year intervals. Scores from the initial sampling period (1980−1989) were compared to data from resampling periods in 1990−1999 and 2000−2006.

The Maine, North Carolina, and Utah data sets were better suited for analyses of individual sites. We focused our analyses on least-disturbed sites that had the longest-term biological data. When evaluating long-term temperature trends at these sites, we lacked sufficient water temperature data, so we used air temperature as a surrogate. While water temperature data are obviously preferable, air temperatures can closely track water temperatures if there are no large effects from evaporative cooling, warm-water additions, or groundwater damping (Caissie, 2006). Stephan and Preudhomme (1993) estimated a linear relationship (factor of 0.86 in ºC) between weekly average water and air temperatures for 11 streams in the Mississippi River Basin. While a similar linear relationship has been applied by others (e.g., Pilgrim et al., 1998; Eaton and Scheller, 1996), Mohseni et al. (2003) suggest the relationship between air and water temperatures is better explained by an S-curve, such that at higher air temperatures, stream temperature increases level off due to evaporative cooling.

For each of the selected sites, we gathered daily observed maximum and minimum air temperature data for the full period of record from the nearest active weather reporting station (or inactive station that had data for the biological period of record). These data were obtained for all three states from the Utah Climate Center Web site (http://climate.usurf.usu.edu/products/data.php). First, to screen the data, we removed missing values (recorded as 999s) and excluded data from years for which there were 2 or more months of missing data and/or fewer than 200 total measurements. Next, we averaged maximum and minimum air temperature values to obtain daily mean annual air temperature. We then calculated annual averages and plotted these data against year. We fitted these data with a linear trend line and calculated r^2 and p-values to test for significance. At each of the selected sites, we also determined which month was hottest (on average), based on mean monthly maximum air temperatures, and calculated the mean maximum air temperature for the hottest month to get a sense of how much thermal stress the organisms may have been exposed to during a given year.

In addition to the temperature data, we gathered flow data by matching the biological sampling sites with the closest USGS gages. We performed desktop screening to assess whether the flow data from the gages were representative of flow conditions at the biological sampling site. To supplement the flow data (which we lacked for some sites), we gathered daily observed precipitation data from the closest weather reporting stations, once again using the Utah Climate Center Web site (http://climate.usurf.usu.edu/products/data.php). First, we removed the missing values. Next we summed the daily values to obtain annual precipitation for the full period of record. We plotted flow and precipitation data against year, fit the data with linear trend lines, and calculated r^2 and *p*-values. At each of the selected sites, we also looked at hydrographs to determine when the lowest flows typically occurred at each site. The intent was to get a sense of how much stress the organisms may have been exposed to during a given year due to extremes in flow conditions. We found that the low-flow periods generally corresponded with the index periods that state biomonitoring programs use for collecting biological samples. Therefore, we calculated mean monthly flow and precipitation values for each state's index period and evaluated trends in these data over time.

In addition to analyzing the observed data from the nearest weather stations, we used a GIS to obtain PRISM annual air temperature and precipitation data from 1974 to 2006 for the selected sites in Maine, North Carolina, and Utah. We selected this time period because it corresponds to the minimum and maximum years for which biological data were available in the state biomonitoring databases. Where there were periods of overlap, the modeled PRISM data were compared to the observed weather station data. Although values sometimes differed, especially when biological sampling sites and weather stations were located in areas of differing topography (i.e., at different elevations), there was generally good correspondence in patterns.

At each of the selected sites, we looked for temporal trends in the biological data. More specifically, we analyzed year-to-year variability in state bioassessment scores and the following metric values: number of EPT taxa, HBI, and thermal preference metrics. The thermal preference metrics are based on the lists of cold and warm-water taxa that were developed for each state (as described in Section 2.2.1). When we calculated the biological variables, if multiple samples were collected in a given year, values were averaged to derive one value per year. We also accounted for seasonal variation by limiting samples to those collected during a single season or index period. We plotted the biological data against year and presented the data in a way that allows for comparison with trends in temperature and streamflow.

For each site, we reported the range of temperature, precipitation, and flow values that occurred during the period of biological record. In addition, we reported ranges of water chemistry values and/or habitat measures (depending on what type of data were available for each state) for the period of biological record. We did this to evaluate whether trends in the biological data may have been influenced by potential confounding factors that were not related to climate.

2.4.2. Associations Between Biological Variables and Climatic Variables

In the Maine, North Carolina, and Utah data sets, we performed correlation analyses on data from least-disturbed sites that had the longest-term biological data. We used Statistica software (Version 10, Copyright StatSoft, Inc., 1984−2011) to run Kendall tau nonparametric correlation analyses on state bioassessment scores, selected biological metrics, year, temperature, flow, and precipitation variables. When deciding which biological metrics to evaluate, we considered the list of commonly used metrics in Barbour et al. (1999) and also looked at which metrics are most commonly used by state biomonitoring programs. We based our selection of thermal and hydrologic indicator metrics on literature searches and best professional judgment. Table 2-6 shows the biological metrics that were evaluated at each site. When reporting results, we noted which biological variables had strong associations ($r \geq 0.5$) with year or climatic parameters. We also noted whether the direction of these relationships was in keeping with expectations, as described in Table 2-5.

2.4.3. Groupings Based on Climatic Variables

In the Maine, North Carolina, and Utah data sets, we grouped data based on extremes in climate variables, using these groupings as proxies for future climate conditions. These analyses were done at the least-disturbed sites that had the longest-term biological data. For the temperature analyses, we partitioned data into years characterized by hotter (>67th percentile of the temperature distribution during years of biological collections), colder (<33rd percentile of

Table 2-6. List of biological metrics/traits evaluated at each site considering commonly used metrics summarized in Barbour et al. (1999) and those used by state biomonitoring programs

Biological metric/trait[a]	Predicted response to…	Source
…increasing stress		
Total number of taxa (richness)	Decrease	Table 7-1 in Barbour et al., 1999 (compiled from DeShon, 1995, Barbour et al., 1996, Fore et al., 1996, Smith and Voshell, 1997)
Number of EPT taxa (Ephemeroptera [mayflies], Plecoptera [stoneflies], and Trichoptera [caddisflies])	Decrease	
Number of Ephemeroptera (mayfly) taxa	Decrease	
Number of Plecoptera (stonefly) taxa	Decrease	
Number of Trichoptera (caddisfly) taxa	Decrease	
Number of intolerant taxa (sensitive to perturbation)	Decrease	
Percentage EPT individuals	Decrease	
Percentage Ephemeroptera individuals	Decrease	
Percentage dominant taxon	Increase	
Percentage tolerant individuals	Increase	
Hilsenhoff Biotic Index (tolerance toward organic enrichment, Hilsenhoff, 1987)	Increase	Commonly used, based on inventory of multimetric indices used by state biomonitoring programs
Shannon-Wiener Diversity Index	Decrease	
Percentage noninsect individuals	Increase	
…warming temperatures		
Number of cold-water taxa	Decrease	Cold- and warm-water taxa derived from weighted-average modeling or related approaches performed on each state data set, with refinements literature searches, and best professional judgment of regional taxonomic experts
Percentage cold-water individuals	Decrease	
Number of warm-water taxa	Increase	
Percentage warm-water individuals	Increase	
…changing streamflow conditions		
Collector filterer	Decrease during low flow conditions	Bogan and Lytle, 2007
Collector gatherer	Increase during slow velocity conditions	Heino, 2009

Table 2-6. List of biological metrics evaluated at each site considering commonly used metrics summarized in Barbour et al. (1999) and those used by state biomonitoring programs (cont.)

Scraper/herbivore	Increase during conditions of stable flow and habitat availability; decrease during drought conditions	Fenoglio et al., 2007, Griswold et al., 2008, Diaz et al., 2008
Predator	Increase during low flow conditions	Bogan and Lytle, 2007
Swimmer	Comprise higher proportion of assemblage during drier, harsher climatic conditions	Béche et al., 2006, Bonada et al., 2007a, Diaz et al., 2008
Rheophily—depositional	Increase during low flow/slow velocity conditions	Best professional judgment
Rheophily—erosional	Increase during high flow/fast velocity conditions	
Odonata/Coleoptera/Hemiptera (OCH)	Expected to be more prevalent during summer, low flow (more pool-like) periods	Bonada et al., 2007b

[a]Trait assignments were based primarily on the Poff et al. (2006b) traits matrix and Vieira et al. (2006).

temperature), and normal (33rd to 67th percentile) temperatures based on PRISM mean annual average air temperatures. When flow data were available, a similar partitioning of high, low, and normal flow years was applied based on mean annual flow. When flow data were not available, we based the partitioning on PRISM mean annual precipitation. Gaps in the biological data prevented us from designating groupings based on the full range of temperature, flow, and/or precipitation values, which would have been preferable. For the temperature analyses, temperatures in the hottest-year samples were generally 1−2°C higher than for the coldest-year samples, a difference that corresponds well with future climatic projections for midcentury.

After samples were grouped based on these environmental variables, Statistica software (Version 10, Copyright StatSoft, Inc., 1984−2011) was used to run one-way analysis of variance (ANOVA) tests to evaluate whether significant differences existed among state bioassessment scores, number of total taxa, number of EPT taxa, and thermal preference metrics from the different year groupings. Differences were considered significant if $p < 0.05$ based on the Tukey honest significant difference test for unequal sample size (n) (Spjotvoll/Stoline).

In addition to the ANOVAs, at the three sites that had the longest-term biological data (15 or more years), we used PCOrd® software (Version 4.41, McCune and Mefford, 1999) to perform NMDS ordinations. The intent was to evaluate differences in taxonomic composition among samples collected during the different year groupings, and to determine which environmental variables explained the greatest amount of variation on each of the ordination axes. We examined the following environmental variables: PRISM mean annual air temperature and precipitation**,** PRISM mean annual air temperature and precipitation from the previous year (lag effects), and the absolute difference between the PRISM mean annual air temperature and precipitation from the sampling year and the previous year (year-to-year variability).

2.5. SENSITIVITY OF BENTHIC MACROINVERTEBRATES TO TEMPERATURE

In the Maine, North Carolina, and Utah data sets, we examined the spatial distributions of cold and warm-water taxa to gain insights into which areas in each state are likely to be most and least sensitive to projected changes in temperature and stream flow. We based our analyses on the premise that streams with greater numbers and abundances of cold-water taxa will be more sensitive to warming temperatures and decreasing precipitation patterns. We performed one-way ANOVAs to determine whether significant differences existed in the distributions of cold and warm-water taxa across different ecoregions and stream size categories (based on Strahler order). Although our premise makes intuitive sense, it may be that cool water taxa in transitional areas, where species are expected to be closer to their tolerance limits, will be most sensitive and will experience the greatest amount of change.

In the Ohio data set, MBI examined the amount and direction of change in the bioassessment scores across different site types (stratified by stream size), habitat categories (modified warmwater [MWH], warmwater [WWH], and exceptional warmwater [EWH]), and ecoregions, and looked for general concordances between intolerant and sensitive species as categorized for the IBI and ICI and species sensitive to temperature and habitat features indicative of altered flow conditions. Trends they documented were most attributable to reduced pollution from point sources, mostly due to municipal wastewater treatment plant upgrades after 1988 (Yoder et al., 2005), not to climate-related changes. Sensitivities in Ohio may be best monitored by tracking changes in the distributions of candidate indicator taxa that were identified through MBI's weighted-averaging analyses and by carefully monitoring the habitats that those taxa occur in.

2.6. IMPLICATIONS FOR STATE BIOMONITORING PROGRAMS

Our discussions of implications of climate change on state biomonitoring programs vary depending on the type of data available for each state, and also on how each state assesses the biological integrity of its streams. Utah uses a River InVertebrate Prediction and Classification System (RIVPACS) model. Maine uses linear discriminant models with over 20 model input metrics to classify station condition. North Carolina typically calculates bioclassification scores based on two metrics: EPT richness and the North Carolina Biotic Index (NCBI), while Ohio uses multimetric indices for fish (IBI) and macroinvertebrates (ICI) to rate streams. For each state, we synthesized results from the analyses of existing temperature, flow, precipitation, and biological data. For Utah and North Carolina, in addition to analyzing existing data, we performed exploratory analyses by manipulating data to gain further insights into how future projected climatic changes might impact each state's assessment methods. In Utah, this involved manipulating the climate-related predictor variables in the Utah RIVPACS model in a way that would simulate future projected changes. We assessed how much this might affect Utah's bioassessment scores. In North Carolina, we looked at how the loss of cold-water taxa at least-disturbed sites in the Piedmont and Blue Ridge Mountain ecoregions would affect bioclassification scores. Table 2-7 provides a summary of the types of analyses that were conducted in each state.

Table 2-7. Summary of types of analyses that were conducted on the Maine, North Carolina, Utah, and Ohio data sets

Analyses	Maine	North Carolina	Utah	Ohio
Derivation of indicators				
Thermal				
Weighted-average modeling or related approaches	x	x	x	x
Hydrologic				
Weighted-average modeling or related approaches			x	x
NMDS		x	x	
CCA			x	
Correlation analyses	1 site		7 sites	
Traits-based	x	x	x	
Temporal trends				
Temperature, flow, and/or precipitation variables	3 sites	5 sites	4 sites	
State bioassessment scores	3 sites	5 sites	4 sites	statewide
Biological metrics (individual sites)	3 sites	5 sites	4 sites	
Correlation analyses				
Biological variables vs. temperature, flow, and/or precipitation variables	3 sites	1 site	4 sites	
Year groupings (hot/cold/normal, etc.)				
ANOVA	3 sites	1 site	4 sites	
NMDS	1 site		2 sites	
Future exploratory analyses		x	x	

3. UTAH

3.1. EXPOSURES

3.1.1. Regional Projections for the Southwestern United States

In coming years, the landscape of the Southwestern United States will be impacted by increases in temperature, drought, wildfire, and invasive species, as well as by an increased frequency and altered timing of flooding (Karl et al., 2009). Temperature increases in the southwest are expected to be greater than the global average (Gutzler et al., 2006), though projections are not substantially higher than for other regions of the United States. Projections using different models and emissions assumptions show seasonal and annual temperature increases of 3−4°C per century (Christensen and Lettenmeier, 2006; Gutzler and Robbins, 2011) (see Table 3-1).

Table 3-1. Projections for temperature and precipitation changes in the Southwest to 2100

Temperature change	Precipitation change	Change in precipitation frequency	Citation
3−4◦C		N/A	Gutzler et al., 2006
3−4◦C	−2 to +1%	N/A	Christensen and Lettenmeier, 2006
	Decrease	N/A	Schoof et al., 2010
	No change to slight increase	N/A	Gutzler and Robbins, 2011

Climate model projections for precipitation show small changes, ranging from slight decreases to slight increases for the southwestern United States among the numerous GCM model outputs used to generate the ensemble projections (National Center for Atmospheric Research [NCAR] Web site, http://rcpm.ucar.edu; Christensen and Lettenmeier, 2006; Schoof et al., 2010; Gutzler and Robbins, 2011) (see Table 3-1). Many ensemble modeling results show small decreases in summer precipitation but small increases in winter precipitation (Christensen and Lettenmeier, 2006), though some show the reverse (e.g., Gutzler and Robbins, 2011). Schoof et al. (2010) projected an increase in the intensity of wintertime precipitation.

The impacts of projected changes in temperature and precipitation on stream hydrologic conditions are of particular interest to the assessment of effects on freshwater systems. Changes have already been observed (as well as modeled) in the magnitude, timing, frequency, and duration of stream flow events, as well as in timing and amount of snow melt (e.g., Hayhoe et al., 2007). The IPCC (2007a) projects average annual runoff to decrease by 10−30% over midlatitude regions, including the southwestern United States. Average runoff is projected to decrease in the Colorado River Basin by 8−11% over a century under the B1 and A2 scenarios, respectively (Christensen and Lettenmeier, 2006). Hurd et al. (2004) modeled a greater range of future runoff changes for the Colorado River, ranging from a 38% decrease to a 24% increase comparing baseline and nine different combinations of future changes in temperature (+1.5, 2.5, and 5°C) and precipitation (−10, +5, and +1%). The biggest increase in runoff corresponded with the biggest percentage increase in precipitation combined with the smallest increase in temperature, while the modeled decreases in average annual runoff were associated with the largest modeled decrease in annual precipitation for all of the modeled temperature increases (Hurd et al., 2004).

In western/southwestern snow-pack dominated regions, the combination of warming temperatures, a shift toward less winter precipitation falling as snow, and snow-melt occurring earlier will change peak runoff from spring to late-winter/early spring (Barnett et al., 2005; Clow, 2010). Typical projections are for peak runoff to shift from about 2 weeks up to 1 month earlier by the end of the century (Dettinger et al., 2004; Hayhoe et al., 2007). Stewart et al. (2005) found evidence for shifts to earlier timing of snow melt and runoff averaging 1−4 weeks based on evaluation of data from 1948 to 2002 for several montane catchments in the western United States. In evaluations of snow-pack dominated streams in Colorado, Clow (2010) found that snowmelt and the timing of peak stream runoff has shifted 2−3 weeks earlier over the 29 years from 1978−2007 (median change 4.8 days per decade). This was accompanied by a decline in April and maximum snow-water equivalent (SWE) of 4.1 and 3.6 cm per decade, respectively. Decreases in total snow pack also contribute to the earlier onset of snow melt and the corresponding earlier spring runoff in western and southwestern high elevation systems.

In addition, increasing air temperatures are projected to increase the likelihood of winter/early spring precipitation as rain instead of snow. Rain-on-snow events, as well as rain during winter months when cold to frozen ground conditions can decrease the infiltration of rain, can increase the likelihood of severe episodic flooding (IPCC, 2007a).

An additional projection for the southwestern United States is for increased aridity, increased severity of summer droughts, associated decreased stream discharge, and extended periods of summer low flows (Gutzler et al., 2006; Gutzler and Robbins, 2011; Seager and Vecchi, 2010; Seager et al., 2007). Most models for the region project increases in evapotranspiration—due to increased temperature rather than changes in summer precipitation—leading to a net decrease in soil moisture and a greater likelihood of late-summer drought (NAST, 2001). This scenario of decreasing soil moisture, increasing evapotranspiration, and higher summer temperatures leading to increasing summer dry periods was specifically modeled in New Mexico (Gutzler et al., 2006), with expectations for decreasing summer stream discharge. Gutzler and Robbins (2011) also projected increases in the severity of droughts over the next century in the southwest, based on modeling of the Palmer drought index. But unlike historic droughts, projected increases in future temperature are also expected to inhibit natural recovery from severe droughts. Seager et al. (2007) projects more arid conditions and more persistent drought for New Mexico, beginning in the late 20th and early 21st centuries. Seager and Vecchi (2010) suggest this pattern is driven by reduced winter precipitation, and will reach the amplitude of historic droughts by midcentury. Though with high uncertainty, they estimate this pattern will be augmented by natural multidecadal oscillations of the Pacific and Atlantic, which are currently in phases that augment drought condition in the southwestern United States.

3.1.2. Historic Climate Trends and Climate Change Projections for Utah

Utah has a semiarid to arid climate. Its diverse landscape consists of a mix of mountains, valleys, and low lying areas. The Wasatch and Uinta Mountains, which run through the central part of the state, are high, precipitous mountains with narrow crests and valleys flanked in some areas by dissected plateaus and open high mountains (U.S. EPA, 2002). The Colorado Plateaus ecoregion, which comprises much of the eastern and southern part of the state, has a mix of large low-lying areas and rugged tableland topography with sharp changes in local relief. The Central Basin and Range ecoregion, which makes up much of western Utah, consists of dry basins, scattered high and low mountains, and salt flats (U.S. EPA, 2002). Temperature and precipitation patterns are influenced by topography, as shown in Figure 3-1, with the Wasatch and Uinta Mountains having the coolest mean annual temperatures (see Figure 3-1A) and the greatest amount of annual precipitation (see Figure 3-1B).

There is a great deal of year-to-year variability in temperature and precipitation patterns, but overall, temperatures in Utah have been increasing over the last century and are projected to continue to increase. A historic trend analysis of Utah PRISM data shows that mean annual air temperature has increased at a rate of 0.01°C/year ($p < 0.01$) from 1901−2000 (see Figure 3-2). This trend has been steeper in more recent decades, with a change rate of 0.04°C/year from 1971−2000 (see Table 3-2). The long-term rate, netting a change of almost 1°C over century, is lower than the future model projections for changes of 2.7−4.4°C over the coming century (see Section 3.1.1 above). However, the more recent rate of increase estimate for the 1971−2000 period (approximately 4°C per century) is quite consistent with future projected rates. Seasonal trends over the last century have been similar to the annual change rate of 0.01 °C/year (see Table 3-2 and Figure 3-3). In recent decades, steeper trends (0.05−0.07 °C/year) have been occurring during the winter and spring (see Table 3-2). Table 3-3 summarizes future projections for mid- and late-century for high (A2) and low (B1) emissions scenarios. Based on an ensemble average across 15 models, mean annual air temperatures are projected to increase by up to 2.9°C by midcentury and up to 4.8°C by the end of the century compared to a historic time period (1961−1990). These future projections are consistent with the literature values summarized in Section 3.1.1 above. The greatest increases are projected to occur during the summer and fall (see Table 3-3).

Precipitation patterns in Utah have been highly variable. Overall, mean annual precipitation has increased at a rate of 0.347 mm/year from 1901−2000 (see Figure 3-4 and Table 3-4). In more recent decades, this rate has increased to 1.28 mm/year (see Table 3-4). However, due to the high degree of year-to-year variability, none of the historic trends in precipitation are significant ($p > 0.05$). The same holds true with seasonal change rates; the amount and direction of change vary depending on season and time period, and no trends are significant (see Table 3-4 and Figure 3-5). Table 3-5 summarizes future projections for mid- and late-century for high (A2) and low (B1) emissions scenarios. The future projections are highly variable across models and emissions scenarios. Under the high emissions scenario, the

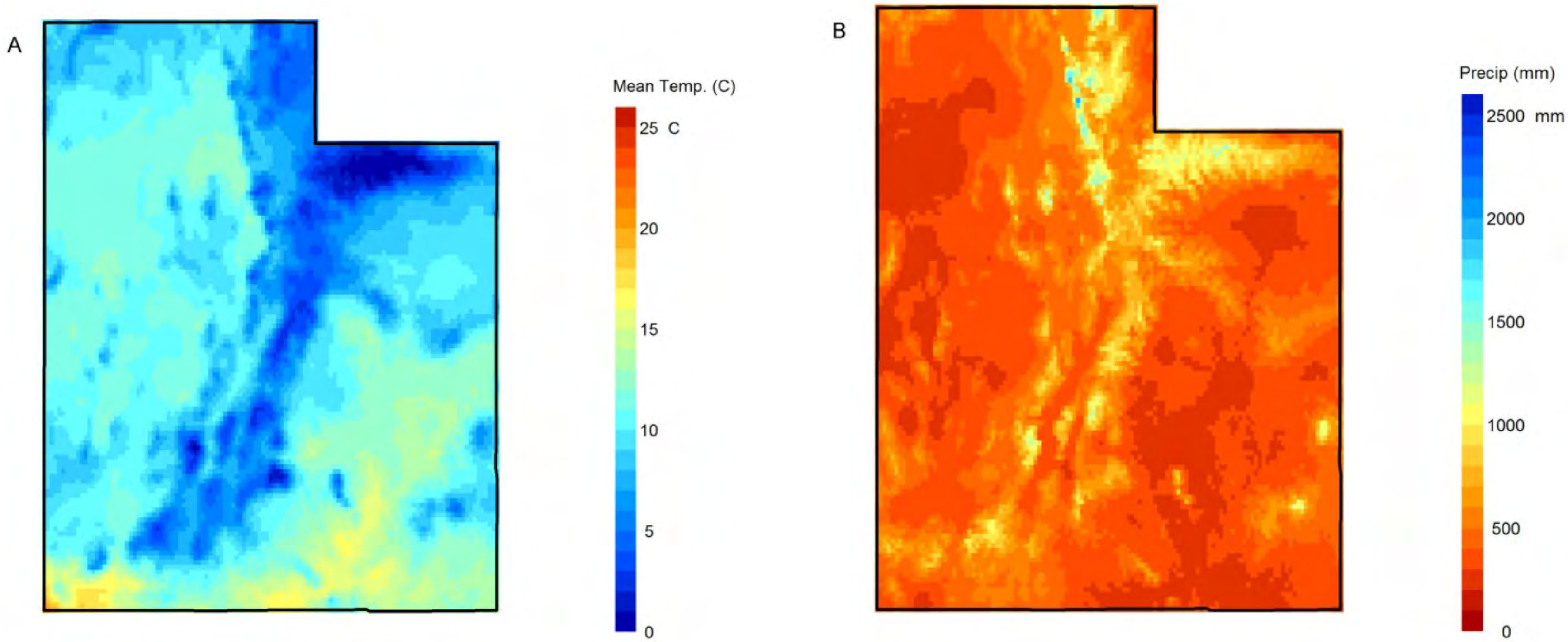

Figure 3-1. Utah's temperature and precipitation patterns. (A) Mean annual air temperature (°C) from 1971−2000 for the state of Utah; (B) Mean annual precipitation (mm) 1971−2000 for the state of Utah. Map produced using the Climate Wizard Web site (http://www.climatewizard.org/). Base climate data from the PRISM Group, Oregon State University, http://www.prismclimate.org.

Table 3-2. Change rates in Utah PRISM mean annual air temperature compared across two time periods: 1971–2000 versus 1901–2000. Entries in bold text are significant (p < 0.05). Data were derived from the Climate Wizard Web site (http://www.climatewizard.org/). Base climate data came from the PRISM Group, Oregon State University, http://www.prismclimate.org

Time period	Air temperature (°C/yr)				
	Annual	**DJF**	**MAM**	**JJA**	**SON**
1901−2000	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**
1971−2000	**0.04**	0.07	**0.05**	0.01	0.02

DJF = December, January, and February; MAM = March, April, and May; JJA = June, July, and August; SON = September, October, and November.

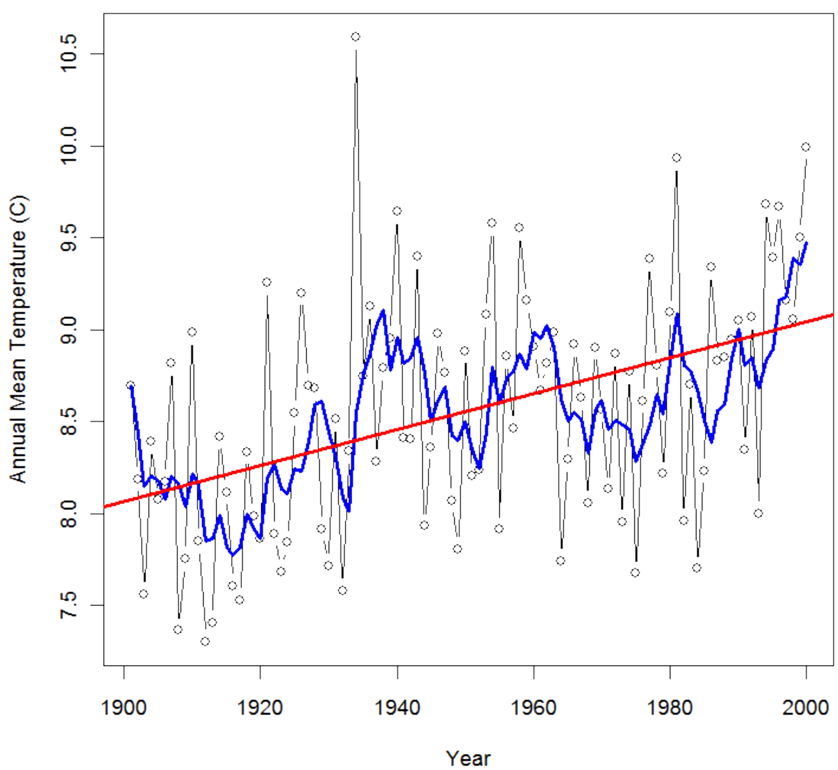

Figure 3-2. Trends in annual mean air temperature in Utah from 1901–2000. Change rate = 0.01°C/year, p-value < 0.01. Figure produced using Climate Wizard Web site (http://www.climatewizard.org/). Base climate data from the PRISM Group, Oregon State University, http://www.prismclimate.org.

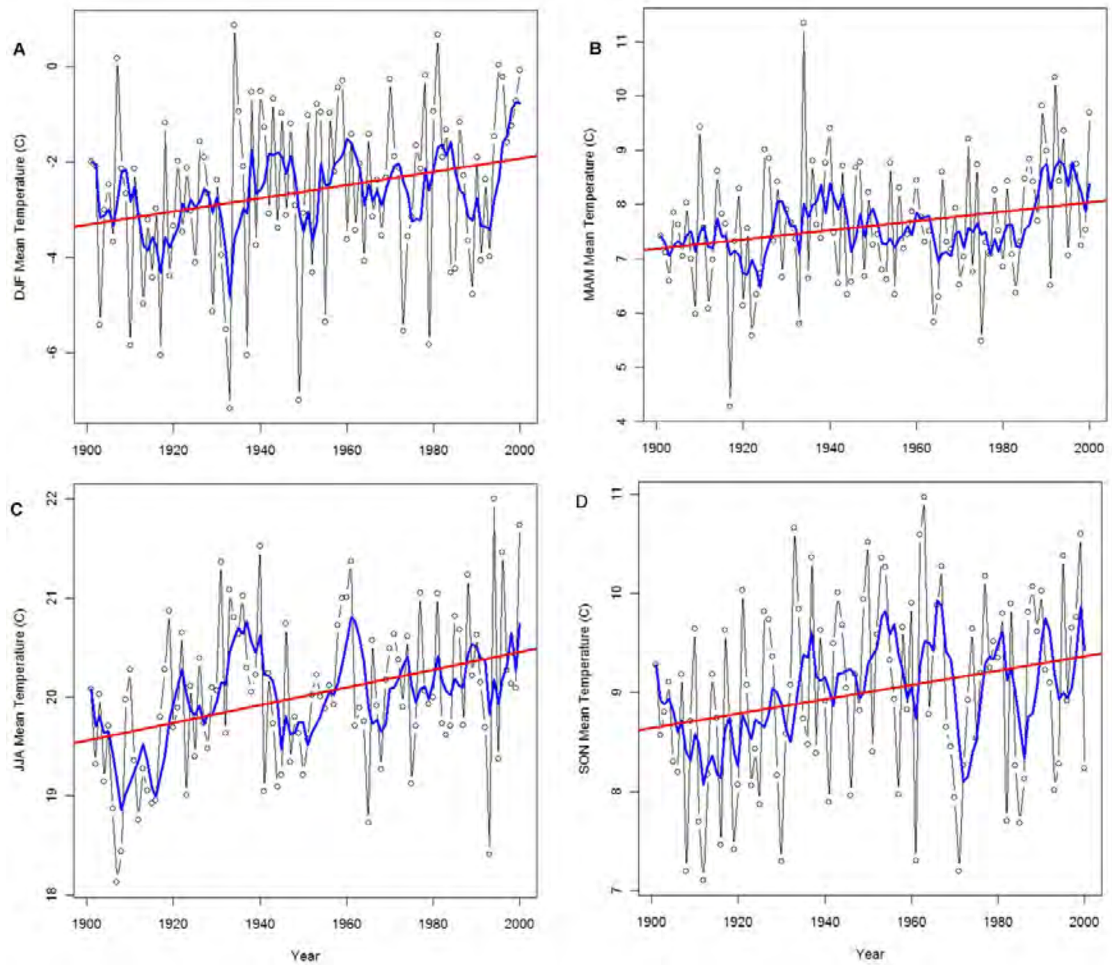

Figure 3-3. Trends in seasonal mean air temperature in Utah from 1901–2000. (A) DJF = December, January, and February, change rate = 0.014°C/year, *p*-value = 0.01; (B) MAM = March, April, and May, change rate = 0.009°C/year, *p*-value = 0.01; (C) JJA = June, July, and August, change rate = 0.009°C/year, *p*-value < 0.01; (D) SON = September, October, and November, change rate = 0.007°C/year, *p*-value = 0.04. Figure produced using Climate Wizard Web site (http://www.climatewizard.org/). Base climate data from the PRISM Group, Oregon State University, http://www.prismclimate.org.

Table 3-3. Projected departure from historic (1961–1990) trends in annual and seasonal air temperature (°C) in Utah for mid- (2040–2069) and late-century (2070–2099) for high and low emissions scenarios. Values represent the minimum, average, maximum, and standard deviations from 15 different climate models. Data were derived from the Climate Wizard Web site (http://www.climatewizard.org/)

	A2 (high) emissions scenario					**B1 (low) emissions scenario**				
Model	**Annual**	**DJF**	**MAM**	**JJA**	**SON**	**Annual**	**DJF**	**MAM**	**JJA**	**SON**
Ensemble low	1.7	1.4	1.2	1.8	2.0	1.0	0.5	0.7	1.3	1.3
Ensemble average	2.9	2.6	2.6	3.3	3.3	2.3	2.1	2.1	2.6	2.3
Ensemble high	4.1	4.1	4.6	4.4	4.2	3.5	3.7	3.9	3.6	3.0
SD	0.7	0.9	1.0	0.8	0.7	0.7	0.9	0.8	0.7	0.6
Late-Century (2070–2099) vs. historic (1961–1990)										
Ensemble low	3.0	2.3	2.1	3.4	3.5	1.8	1.6	1.4	1.8	1.6
Ensemble average	4.8	4.3	4.3	5.4	5.5	3.0	2.8	2.8	3.4	3.0
Ensemble high	6.7	7.1	8.0	7.1	6.9	4.4	4.8	5.4	4.4	4.0
SD	1.1	1.3	1.6	1.2	1.1	0.8	1.0	1.0	0.8	0.8

DJF = December, January, and February; MAM = March, April, and May; JJA = June, July, August and SON = September, October, and November.

Table 3-4. Change rates in Utah PRISM mean annual precipitation compared across two time periods: 1971–2000 versus 1901–2000. No trends are significant ($p < 0.05$). Data were derived from the Climate Wizard Web site (http://www.climatewizard.org/). Base climate data came from the PRISM Group, Oregon State University, http://www.prismclimate.org

Time period	Precipitation (mm/yr)				
	Annual	DJF	MAM	JJA	SON
1901−2000	0.35	−0.05	0.11	0.11	0.2
1971−2000	1.28	0.61	0.27	0.69	−0.14

DJF = December, January, and February; MAM = March, April, and May; JJA = June, July, and August; SON = September, October, and November.

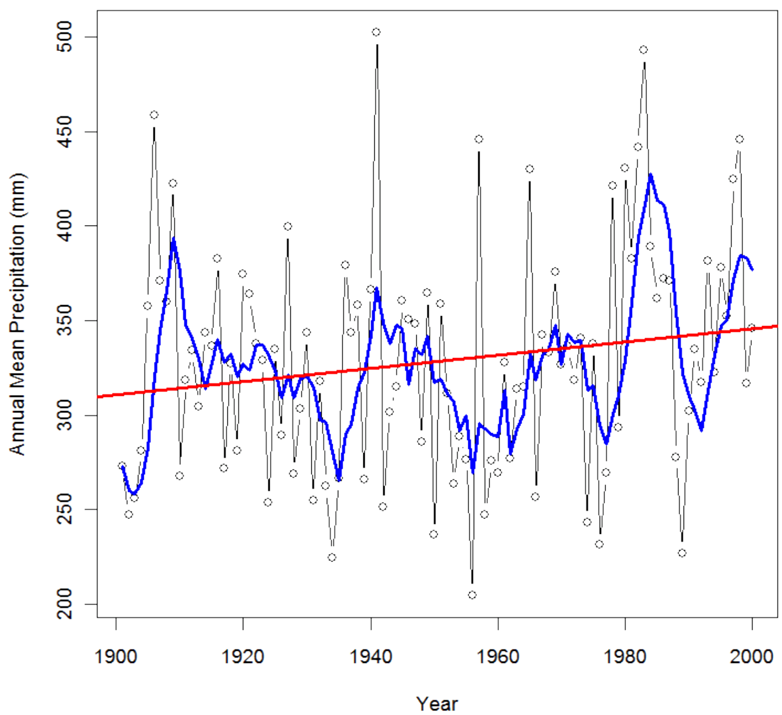

Figure 3-4. Trends in annual mean precipitation in Utah from 1901–2000. Change rate = 0.347 mm/year, *p*-value = 0.15. Figure produced using Climate Wizard Web site (http://www.climatewizard.org/). Base climate data from the PRISM Group, Oregon State University, http://www.prismclimate.org.

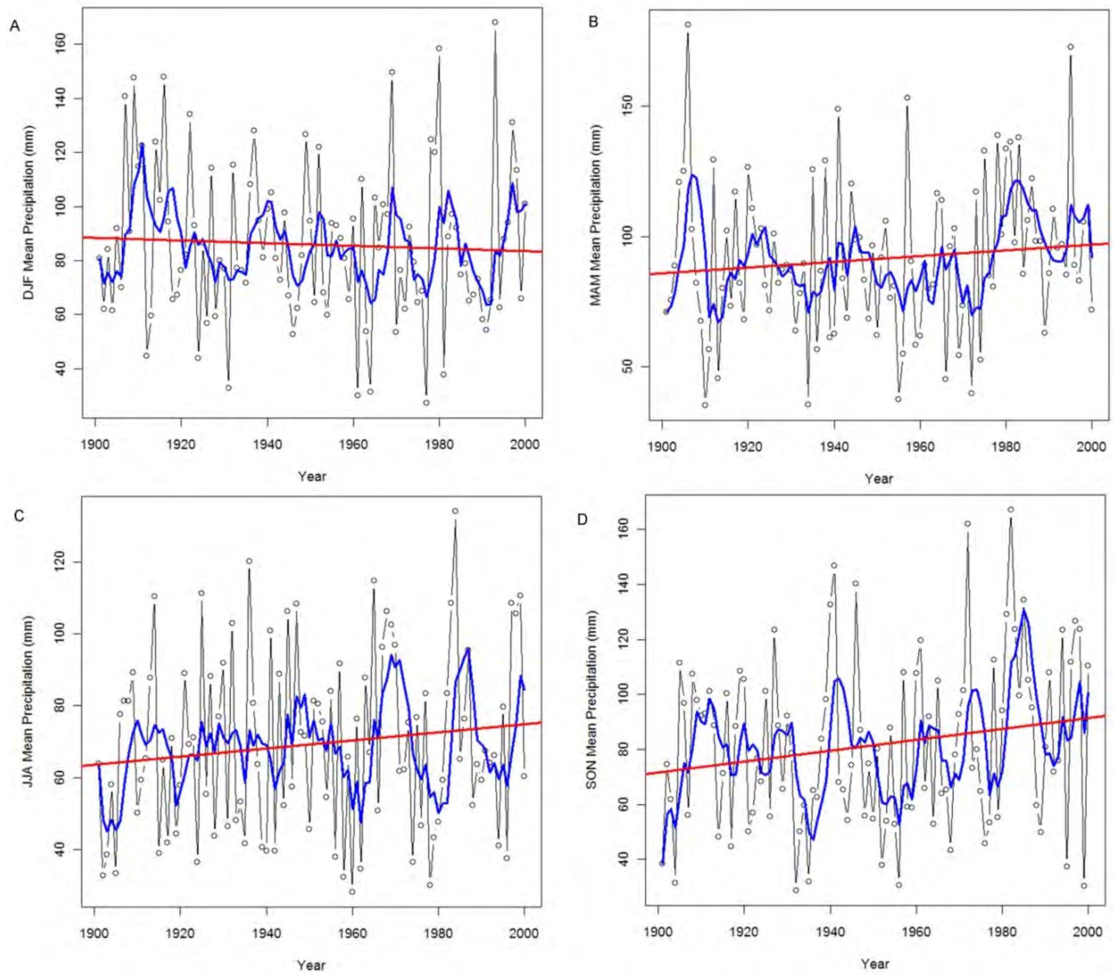

Figure 3-5. Trends in seasonal mean precipitation in Utah from 1901–2000. (A) DJF = December, January, and February, change rate = –0.05 mm/year, *p*-value = 0.62; (B) MAM = March, April, and May, change rate = 0.11 mm/year, *p*-value = 0.27; (C) JJA = June, July, and August, change rate = 0.11 mm/year, *p*-value = 0.15; (D) SON = September, October, and November, change rate = 0.20 mm/year, *p*-value = 0.12. Figure produced using Climate Wizard Web site (http://www.climatewizard.org/). Base climate data from the PRISM Group, Oregon State University, http://www.prismclimate.org.

Table 3-5. Projected departure from historic (1961–1990) trends in annual and seasonal precipitation (mm) in Utah for mid- (2040–2069) and late-century (2070–2099) for high and low emissions scenarios. Values represent the minimum, average, maximum, and standard deviations from 15 different climate models. Data were derived from the Climate Wizard Web site (http://www.climatewizard.org/)

Midcentury (2040−2069) vs. historic (1961−1990)										
	A2 (high) emissions scenario					B1 (low) emissions scenario				
Model	Annual	DJF	MAM	JJA	SON	Annual	DJF	MAM	JJA	SON
Ensemble low	–74.7	−12.0	−48.9	−19.4	−10.7	−28.9	−42.9	−26.8	−16.1	−9.2
Ensemble average	−2.7	10.3	−8.5	−6.9	2.3	22.3	0.8	3.3	16.8	4.2
Ensemble high	50.6	50.5	9.9	6.5	24.1	255.9	38.0	92.1	211.6	35.2
SD	33.4	16.1	14.8	7.9	11.6	71.8	18.5	28.4	58.9	11.4
Late-century (2070−2099) vs. historic (1961−1990)										
Ensemble low	−62.1	−14.5	−55.1	−27.5	−23.0	–51.5	–54.5	–45.7	−19.3	–18.5
Ensemble average	–5.8	14.9	–16.0	–4.4	2.8	50.7	1.6	10.7	32.8	12.3
Ensemble high	37.0	66.8	15.4	24.3	49.9	376.9	36.9	127.6	261.3	63.1
SD	30.3	18.9	15.1	13.6	17.6	125.4	24.2	44.9	84.8	21.8

DJF = December, January, and February; MAM = March, April, and May; JJA = June, July, August and SON = September, October, and November.

ensemble average projects that mean annual precipitation will decrease by 2.7 mm by midcentury and 5.8 mm by the end of the century compared to a historic time period (1961−1990). Under the high emissions scenario, the greatest changes are projected to occur during the winter and spring (see Table 3-5).

3.2. DATA INVENTORY AND PREPARATION

The Utah database contains data for 2,337 biological samples from 615 unique stations, with sampling dates ranging from 1977 to 2005. Water chemistry data (nutrients, metals, alkalinity, and turbidity) and in situ measurements are available for many of these sites. No habitat data are available. Most sites have fewer than 5 years of data, but there are 30 sites that have 10 or more years of data (see Table 3-6). Utah Department of Environmental Quality (DEQ) considers four of these long-term sites to be in reference (highest quality) condition. Utah DEQ's reference designations are based on a combination of a reference scoring sheet (multiple lines of scoring) and independent ranking of sites from field crew/scientists. Only sites that are consistently ranked as reference are included on the list. Figure 3-6 shows the spatial distribution of biological sampling sites.

Table 3-6. Distribution of reference and total stations, categorized by duration of sampling

	Utah	
Years sampled	**Reference**	**Total**
1 to 4	61	482
5 to 9	1	41
≥10	4	26
Total	**66**	**549**

When preparing the biological data for long-term trend analyses, genus-level OTUs were generally found to be most appropriate for the Utah data set. However, a family-level OTU had be to be used for Chironomidae, as subfamily- and/or genus-level identifications only occurred in later years in the Utah data set. "Fixes" also had to be made to OTU assignments for *Ephemerella* and *Drunella* due to changes in taxonomic systematics. Additionally, there was some uncertainty as to the consistency of how abundance data were recorded over the years.

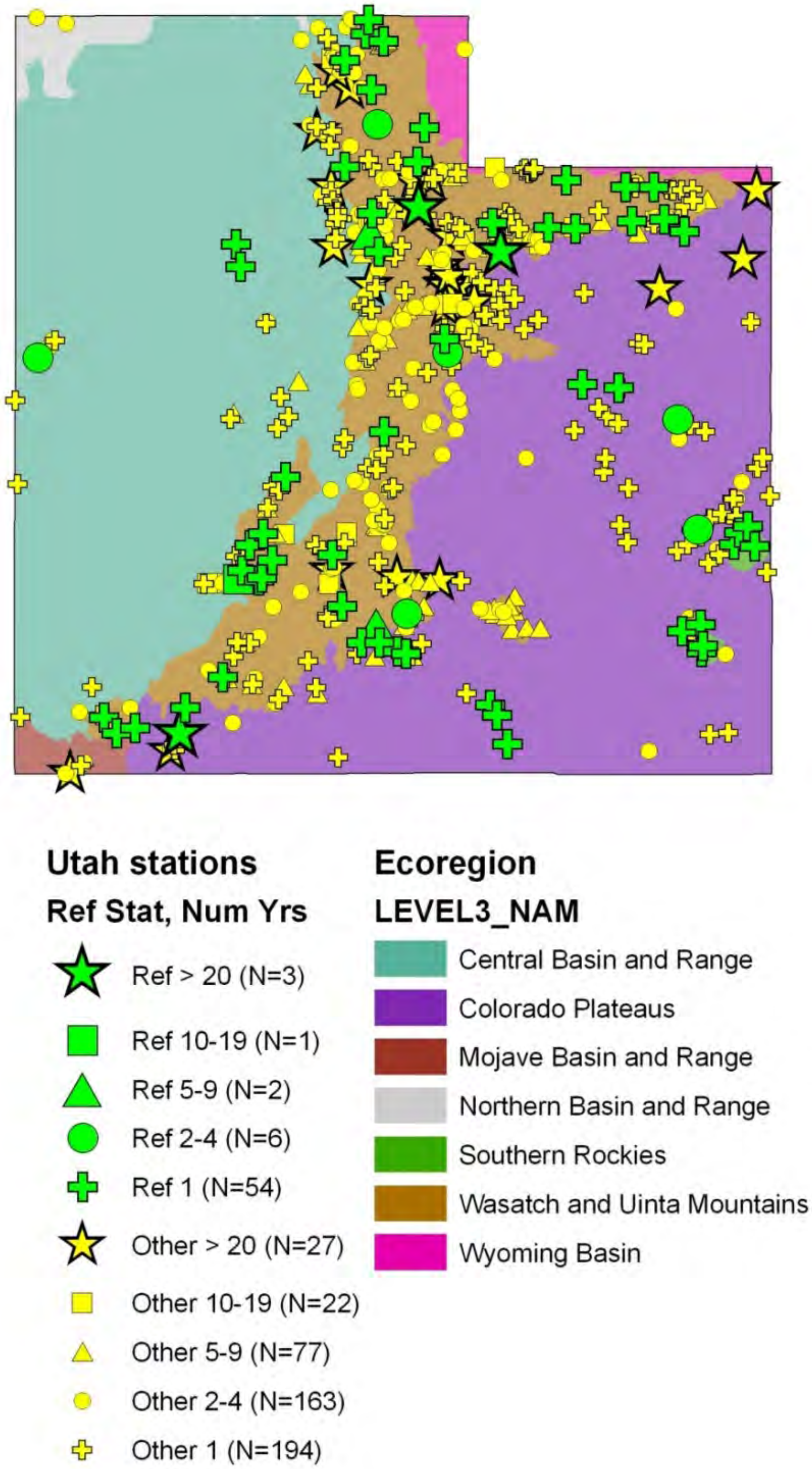

Figure 3-6. Utah biomonitoring stations, coded by reference status and duration of data.

These questions related to whether recorded abundances were corrected for subsampling in the laboratory, area sampled, and/or replication. These questions could not be fully resolved based on institutional knowledge of Utah DEQ scientists or from extant database metadata or other documentation. Because of this uncertainty, where possible, we based our calculations and analyses on relative abundance data. If calculations required the use of abundance data, we interpreted results with caution.

3.3. UTAH DEQ METHODS

For the period of analyses used in this report (prior to 2006), Utah DEQ collected samples from riffle habitats using a Hess sampler. Starting in 2006, quantitative riffle habitat samples were collected using the Environmental Monitoring and Assessment Program (EMAP) kick method; therefore, any future long-term trend analyses would have to examine comparability between these sampling methods. Samples are typically collected during a September/October index period, but the Utah data set includes samples collected throughout the year. For most analyses, only fall samples were used to minimize variation associated with seasonal differences in taxonomic composition.

In recent years, Utah started using a RIVPACS model (fall samples) to assess wadeable streams (Ostermiller, unpublished presentation titled "Development of a biological assessment framework", Appendix B). The model was calibrated based on reference data collected from 1999−2005. The random forests method was used to select predictor variables that best discriminated among the site groups (Breiman and Cutler, 2009). The model has 15 predictor variables, 7 of which are related to climate (e.g., temperature, precipitation, freeze dates). Samples are scored based on the ratio of observed to expected (O/E) assemblages (expected assemblages are established based on reference site data). If a sample receives an O/E score of ≥0.74, Utah DEQ considers the beneficial use of the waterbody to be fully supported.

3.4. INDICATORS

3.4.1. Thermal Preference

As described in Section 2, we used the guidelines of Yuan (2006) to calculate thermal optima and tolerance values. For the Utah data set, we based our calculations on a subset of data collected during the fall season (n = 572). These data, along with weighted-average inferences derived from Idaho (Brandt, 2001), California (Herbst and Silldorff, 2007), and Oregon (Yuan, 2006; Huff et al., 2008) data sets, were used to develop lists of cold- and warm-water taxa for the Utah data set. These lists are the basis of the region-specific thermal-preference richness and relative-abundance metrics used in some analyses.

The Utah cold-water taxa list is composed of 33 taxa, and the warm-water taxa list is composed of 16 taxa. The relatively low number of warm-water taxa is partially a consequence of the need to use a family-level OTU for Chironomidae. Tables 3-6 and 3-7, respectively, list the cold- and warm-water taxa, along with abundance and distribution information[1]. Ten of the cold-water taxa are Plecopterans, eight are Dipterans, seven are Trichopterans, and six are Ephemeropterans (see Table 3-7). Five of the warm-water taxa are Trichopterans, three are Coleopterans, and two are Dipterans and Ephemeropterans (see Table 3-8).

The most abundant cold-water taxa are two Ephemeropterans, *Ephemerella* and *Cinygmula*, which comprise 1.85 and 1.03% of the total individuals, respectively. Of the cold-water taxa, Chloroperlidae occurs at the highest percentage of sites (49%), followed by two Ephemeropterans (*Ephemerella* and *Cinygmula*), which occur at 44 and 46% of the sites, respectively. Asellidae and Leptohyphidae are the most abundant warm-water taxa, with overall abundances of 3.12 and 1.42%. Among the warm-water taxa, Leptohyphidae occurs at the highest percentage of sites (31%), followed by Coenagrionidae (18%) and *Cheumatopsyche* (17%). Many of the taxa on the cold- and warm-water lists have low overall abundances (less than 0.1%) and occur at less than 10% of the sites.

Most of the taxa on the cold-water list are intolerant to enrichment, while most of the warm-water taxa are tolerant or have intermediate tolerance to enrichment (see Figure 3-7). Because of this, it is difficult to tease out whether organisms are responding to changes associated with warming temperatures or whether they are responding to other stressors, such as enrichment.

3.4.2. Hydrologic Indicators

We attempted to develop a list of candidate taxa in Utah that could potentially serve as indicators of hydrologic change. We were able to match USGS gage data with biological data

[1]There are some noteworthy genera that were excluded from the Utah cold-water taxa list. These include *Zapada, Epeorus, Drunella, Brachycentrus*, and *Rhyacophila*. These taxa were excluded because of variations in thermal preferences among species within these genera.

from 43 sampling sites, and calculated IHA parameters and the RBI per the methods described in Section 2.2.2. The data set, which included samples from both disturbed and least-disturbed sites, had some limitations. It had a relatively small sample size, and some sites had many more years of data than others (i.e., one site had 19 years of data, others had 1 year of data). Despite

Table 3-7. List of Utah cold-water-temperature indicator taxa, sorted by order, family, then Final ID. Distribution and abundance information is also included. Sum_Individuals = the total number of individuals from that taxon in the Utah database; Pct_Abund = percentage of total individuals in the database composed of that taxon; Num_Stations = number of stations in the database that the taxon occurred at; Pct_Stations = percentage of stations in the database at which the taxon occurred

Order	Family	Final ID	Sum_individs	Pct_abund	Num_stations	Pct_stations
Coleoptera	Elmidae	*Heterlimnius*	16,463.0	0.0	50.0	7.9
Diptera	Blephariceridae	*Bibiocephala*	2,257.0	0.0	15.0	2.4
Diptera	Ceratopogonidae	*Bezzia*	109,267.1	0.2	232.0	36.5
Diptera	Empididae	*Chelifera*	94,014.1	0.2	261.0	41.1
Diptera	Empididae	*Oreogeton*	228.5	0.0	13.0	2.1
Diptera	Empididae	*Wiedemannia*	458.0	0.0	13.0	2.1
Diptera	Psychodidae	*Pericoma*	145,582.7	0.3	210.0	33.1
Diptera	Tipulidae	*Dicranota*	35,439.2	0.1	220.0	34.7
Diptera	Tipulidae	*Rhabdomastix*	8.0	0.0	1.0	0.2
Dorylaimida	Dorylaimidae	Nematoda	141,425.3	0.3	249.0	39.2
Ephemeroptera	Ameletidae	*Ameletus*	13,157.6	0.0	137.0	21.6
Ephemeroptera	Ephemerellidae	*Ephemerella*	859,335.8	1.9	292.0	46.0
Ephemeroptera	Heptageniidae	*Cinygma*	606.2	0.0	6.0	0.9
Ephemeroptera	Heptageniidae	*Cinygmula*	479,866.5	1.0	278.0	43.8
Ephemeroptera	Heptageniidae	*Ironodes*	551.6	0.0	6.0	0.9
Ephemeroptera	Heptageniidae	*Rhithrogena*	198,501.8	0.4	243.0	38.3
Plecoptera	Capniidae	Capniidae	113,578.8	0.2	228.0	35.9
Plecoptera	Chloroperlidae	Chloroperlidae	203,579.9	0.4	309.0	48.7

Table 3-7. List of Utah cold-water-temperature indicator taxa, sorted by order, family, then Final ID. Distribution and abundance information is also included. Sum_Individuals = the total number of individuals from that taxon in the Utah database; Pct_Abund = percentage of total individuals in the database composed of that taxon; Num_Stations = number of stations in the database that the taxon occurred at; Pct_Stations = percentage of stations in the database at which the taxon occurred (cont.)

Order	Family	Final ID	Sum_individs	Pct_abund	Num_stations	Pct_stations
Plecoptera	Leuctridae	Leuctridae	21,176.5	0.1	106.0	16.7
Plecoptera	Nemouridae	*Visoka*	50.0	0.0	1.0	0.2
Plecoptera	Pelecorhynchidae	*Glutops*	91.0	0.0	4.0	0.6
Plecoptera	Peltoperlidae	*Yoraperla*	72.7	0.0	5.0	0.8
Plecoptera	Perlodidae	*Cultus*	20,419.7	0.0	97.0	15.3
Plecoptera	Perlodidae	*Kogotus*	1,288.7	0.0	14.0	2.2
Plecoptera	Perlodidae	*Megarcys*	7,129.9	0.0	65.0	10.2
Plecoptera	Taeniopterygidae	*Taenionema*	79,949.8	0.2	87.0	13.7
Trichoptera	Apataniidae	*Apatania*	20,154.3	0.0	39.0	6.1
Trichoptera	Glossosomatidae	*Anagapetus*	42.0	0.0	2.0	0.3
Trichoptera	Hydropsychidae	*Parapsyche*	3,552.5	0.0	40.0	6.3
Trichoptera	Lepidostomatidae	*Lepidostoma*	353,679.8	0.8	240.0	37.8
Trichoptera	Limnephilidae	*Ecclisomyia*	1,262.8	0.0	14.0	2.2
Trichoptera	Uenoidae	*Neothremma*	129,853.8	0.3	100.0	15.8
Trichoptera	Uenoidae	*Oligophlebodes*	147,256.9	0.3	101.0	15.9

Table 3-8. List of Utah warm-water-temperature indicator taxa. Distribution and abundance information is also included. Sum_Individuals = the total number of individuals from that taxon in the Utah database; Pct_Abund = percentage of total individuals in the database composed of that taxon; Num_Stations = number of stations in the database that the taxon occurred at; Pct_Stations = percentage of stations in the database at which the taxon occurred

Order	Family	Final ID	Sum_individs	Pct_abund	Num_stations	Pct_stations
Coleoptera	Elmidae	*Microcylloepus*	114,016	0.24	50	7.87
Coleoptera	Elmidae	*Ordobrevia*	360	0	5	0.79
Coleoptera	Psephenidae	*Psephenus*	65.8	0	4	0.63
Diptera	Psychodidae	*Maruina*	1,140.2	0	16	2.52
Diptera	Stratiomyidae	*Caloparyphus*	9,652	0.02	26	4.09
Ephemeroptera	Caenidae	*Caenis*	567	0	11	1.73
Ephemeroptera	Leptohyphidae	Leptohyphidae	659,670.3	1.42	197	31.02
Hemiptera	Naucoridae	*Ambrysus*	25,879.7	0.06	39	6.14
Isopoda	Asellidae	Asellidae	1,450,840.4	3.12	81	12.76
Odonata	Coenagrionidae	Coenagrionidae	45,144.1	0.1	117	18.43
Plecoptera	Perlidae	*Calineuria*	245	0	9	1.42
Trichoptera	Hydropsychidae	*Cheumatopsyche*	172,233.9	0.37	105	16.54
Trichoptera	Hydroptilidae	*Ochrotrichia*	6,768.2	0.01	29	4.57
Trichoptera	Leptoceridae	*Nectopsyche*	8,434.7	0.02	35	5.51
Trichoptera	Leptoceridae	*Oecetis*	28,993.3	0.06	90	14.17
Trichoptera	Psychomyiidae	*Tinodes*	12,774.6	0.03	34	5.35

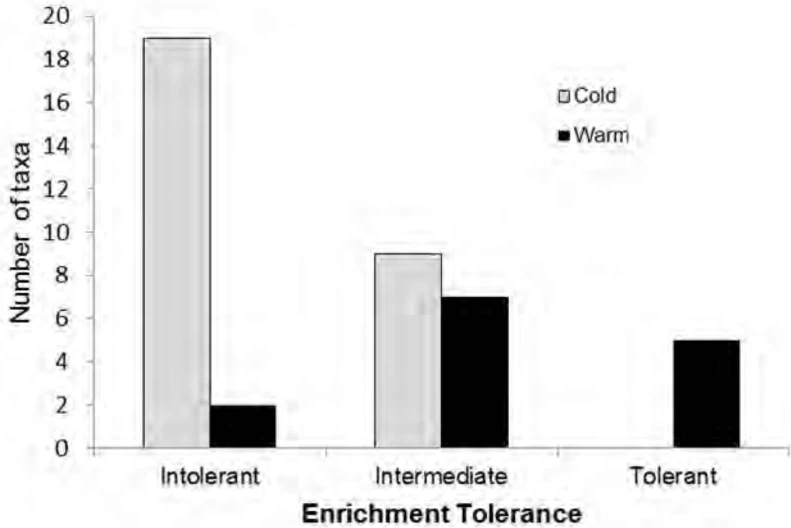

Figure 3-7. Relationship between Utah cold and warm-water-preference taxa and Utah enrichment tolerance scores (tolerance scores based on the Utah data set were not available, so scores were based on assignments used by New Mexico Environment Department). Taxa with enrichment tolerance scores of 0–3 were categorized as Intolerant, those with scores of 4–6 were Intermediate, and those with scores of 7–10 were Tolerant.

these limitations, we ran several different types of analyses in search of linkages between biological and hydrologic data.

One of the analyses run was weighted-average modeling. We found that year had a stronger influence on taxonomic composition than the hydrologic variables. The hydrologic variable that showed the strongest influence was the 3-day mean of the annual minima (cfs). Of the taxa that were evaluated, Leuctridae, Asellidae, and *Zapada* had the lowest 3-day minima optima values, while *Hyalella* and *Helicopsyche* had the highest. Leuctridae and *Zapada* had relatively low tolerance ranges, while *Hyalella* and *Helicopysche* had large tolerance ranges. This suggests that Leuctridae and *Zapada* are better adapted to low flow conditions than other taxa in Utah, perhaps due in part to their smaller sizes. For the full set of weighted average results for 3-day annual minima, see Table B-1 in Appendix B.

In addition to the weighted-average modeling, we also performed ordinations (NMDS and CCA analyses). Results were similar. Year had the strongest influence on taxonomic composition. Of the hydrologic parameters evaluated, 3-day annual minima and number of high pulses per water year were the strongest drivers. Appendix B contains ordination plots from these analyses. The last set of analyses that we ran were correlation analyses on data from seven sites that had more than 10 years of data. Table B-2 of Appendix B lists these sites. Only one of these sites is considered to be least disturbed based on Utah DEQ's reference criteria. There were a number of significant correlations at each site, but none of the taxa or biological metrics showed consistent patterns across sites, so we were unable to develop candidate indicator taxa. Results from these analyses are available upon request.

3.4.3. Traits-Based Indicators in a Warmer Drier Scenario

- As discussed in Section 3.1.2, the climate in Utah is projected to become warmer and drier. We developed a list of taxa that may be most and least sensitive to these projected changes based on the suite of trait modalities considered in Section 2.2.3. The taxa in Table 3-9 that are deemed most sensitive, or most likely to be adversely affected by these projected climatic changes, are mostly EPT taxa.

Two taxa, a Coleopteran and a Hemipteran, were included on the least sensitive list. These taxa have the ability to exit (as adults), have high dispersal ability, strong flying strength, strong swimming ability, and breathe through plastron-spiracles.

3.5. LEAST DISTURBED LONG-TERM BIOLOGICAL MONITORING SITES

Utah does not have a formal statewide long-term reference network. We explored grouping least-disturbed sites together to create a statewide data set that could be analyzed for long-term trends, but site-specific differences were evident within the data set, and the sample size was relatively low; therefore, we focused on individual sites. We performed trend analyses at the four reference stations in Utah that had 10 or more years of data. Figure 3-8 shows the locations of these stations. Table 3-10 briefly summarizes site characteristics. Two are located in the Wasatch and Uinta Mountains ecoregion, and the others are located in the Colorado Plateaus ecoregion. Anthropogenic influences are higher than desired (>5% urban or >10% agricultural) at two of the sites, but data were analyzed from these sites because they represented the best-available long-term data in the state database. Table 3-11 lists the time periods for which biological data are available for these sites. Data used in these analyses were limited to fall (September−November) kick-method samples.

Table 3-9. List of taxa that may be most and least sensitive to a warmer and drier future scenario based on a combination of traits

Order	Family	Final ID	Sensitivity to warmer drier scenario
Diptera	Blephariceridae	*Bibiocephala*	most
Ephemeroptera	Ephemerellidae	*Ephemerella*	most
Ephemeroptera	Heptageniidae	*Cinygma*	most
Ephemeroptera	Heptageniidae	*Cinygmula*	most
Ephemeroptera	Heptageniidae	*Ironodes*	most
Ephemeroptera	Heptageniidae	*Rhithrogena*	most
Plecoptera	Chloroperlidae	Chloroperlidae	most
Plecoptera	Perlodidae	*Cultus*	most
Plecoptera	Perlodidae	*Kogotus*	most
Plecoptera	Perlodidae	*Megarcys*	most
Trichoptera	Apataniidae	*Apatania*	most
Trichoptera	Hydropsychidae	*Parapsyche*	most
Trichoptera	Lepidostomatidae	*Lepidostoma*	most
Trichoptera	Limnephilidae	*Ecclisomyia*	most
Coleoptera	Dytiscidae	Dytiscidae	least
Hemiptera	Corixidae	Corixidae	least

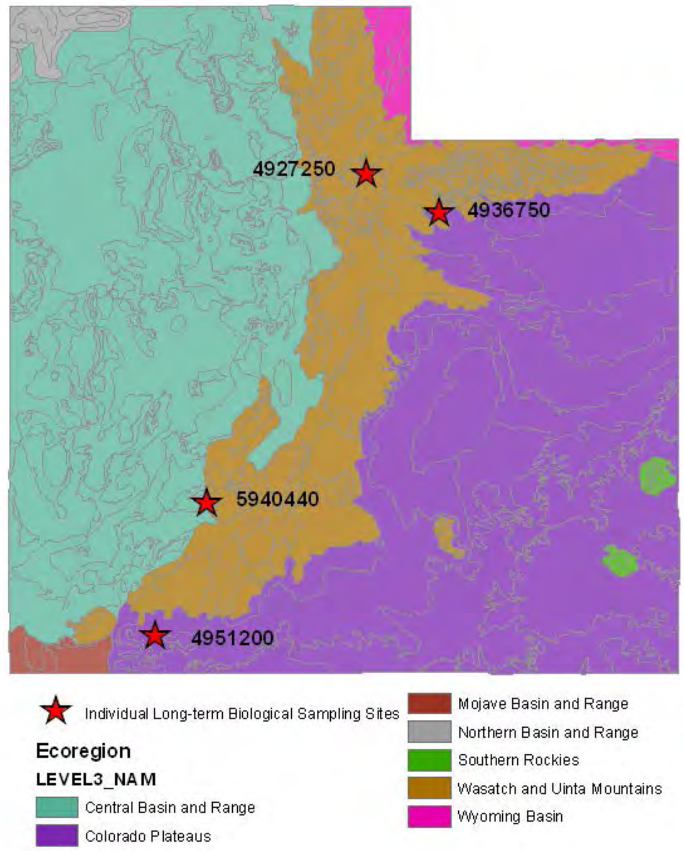

Figure 3-8. Locations of the four least disturbed long-term biological monitoring sites (4927250 = Weber; 4951200 = Virgin; 4936750 = Duchesne; 5940440 = Beaver).

Table 3-10. Site characteristics for the long-term biological monitoring stations in Utah. Percentage urban and percentage agricultural (Ag) apply to a 1-km buffer zone around each site and are based on 2001 National Land Cover Data

Site ID	Water body	Longitude (DD)	Latitude (DD)	EPA Level 3 ecoregion	Elevation (m)	Drainage area (km^2)	% Urban	% Ag
UT 4927250[a]	Weber	111.37358	40.75294	Wasatch and Uinta Mountains	1,846.6	740.7	4.5	21.1
UT 4951200	Virgin	112.94808	37.28483	Colorado Plateaus	1,369.2	756.3	3.4	0.5
UT 4936750	Duchesne	110.83	40.46139	Colorado Plateaus	2,123.5	489.5	10.3	1.1
UT 5940440	Beaver	112.56711	38.28	Wasatch and Uinta Mountains	1,904.8	236.2	0	0

[a]Site is 0.8 km above a reservoir.

DD = decimal degrees.

Table 3-11. Time periods for which biological data were available at the long-term monitoring sites in Utah. Data used in these analyses were limited to fall (September–November) kick-method samples

Station ID	Water body	Number of years of data analyzed	Years
UT 4927250	Weber	17	1985–1995, 1998, 2000, 2001, 2003–2005
UT 4951200	Virgin	14	1985–1993, 1996, 2000–2002, 2004
UT 4936750	Duchesne	12	1985–1993, 1995, 2000, 2001
UT 5940440	Beaver	9	1996–1998, 2000–2005

3.6. EVIDENCE OF TRENDS AT LEAST DISTURBED LONG-TERM MONITORING SITES

3.6.1. Weber River (UT 4927250)

The Weber River site (UT 4927250) is located approximately 0.8 km above Rockport Reservoir in Summit County in the Wasatch Uinta Mountains/Mountain Valleys ecoregion. It has a drainage area of 740.7 km^2 and an elevation of 1,847 m. Its highest maximum monthly temperatures occur during July, and it lowest average flows (<100 cfs) occur from September through March. This station has 19 years of data, ranging from 1985 to 2005, with spring, summer, and fall sampling events. When limited to fall samples only, 17 years of data are available. Daily temperature and precipitation data from 1955 to 2010 were gathered from the Wanship Dam weather station (SiteID 429165, Latitude: 40.7908, Longitude: 111.408), which is located approximately 5 km northwest of the biological sampling site, below Wanship dam. Seven months of data were missing in 1955, so we used 1956 as the start date for our analyses. Flow data from 1904−2011 were gathered from USGS gage 10128500 (Weber River near Oakley, Latitude: 40.7371721, Longitude: 111.247965). The gage is located 10.6 km east of the biological sampling site. Figure 3-9 shows an aerial photograph of the site, along with the nearest weather station and active USGS gage.

3.6.1.1. *Temporal Trends in Climatic and Biological Variables*

Since 1956, mean annual air temperatures at the Weber River (UT 4927250) site have ranged from 5 to 9.5°C. There is a great deal of year-to-year variability, but overall, temperatures have been increasing over time (when fit with a linear trend line, $r^2 = 0.51$, $p < 0.01$) (see Figure 3-10). When PRISM air temperature data are compared to observed data, there is good correspondence in pattern, but PRISM data are generally 1−2°C lower than observed values, perhaps because the weather station is at a slightly lower elevation than the biological sampling site. Mean annual flow and mean annual precipitation patterns have been highly variable over time (see Figure 3-11). Since 1904, mean annual flow values have ranged from 77 to 417 cfs (when fit with a linear trend line, $r^2 = 0.05$, $p = 0.03$). Precipitation patterns generally show good correspondence with flow patterns (see Figure 3-11).

Figure 3-9. Locations of the Weber River (UT 4927250) biological sampling site, USGS gage 10128500 (Weber River near Oakley) and Wanship Dam weather station. Image from Google Earth.

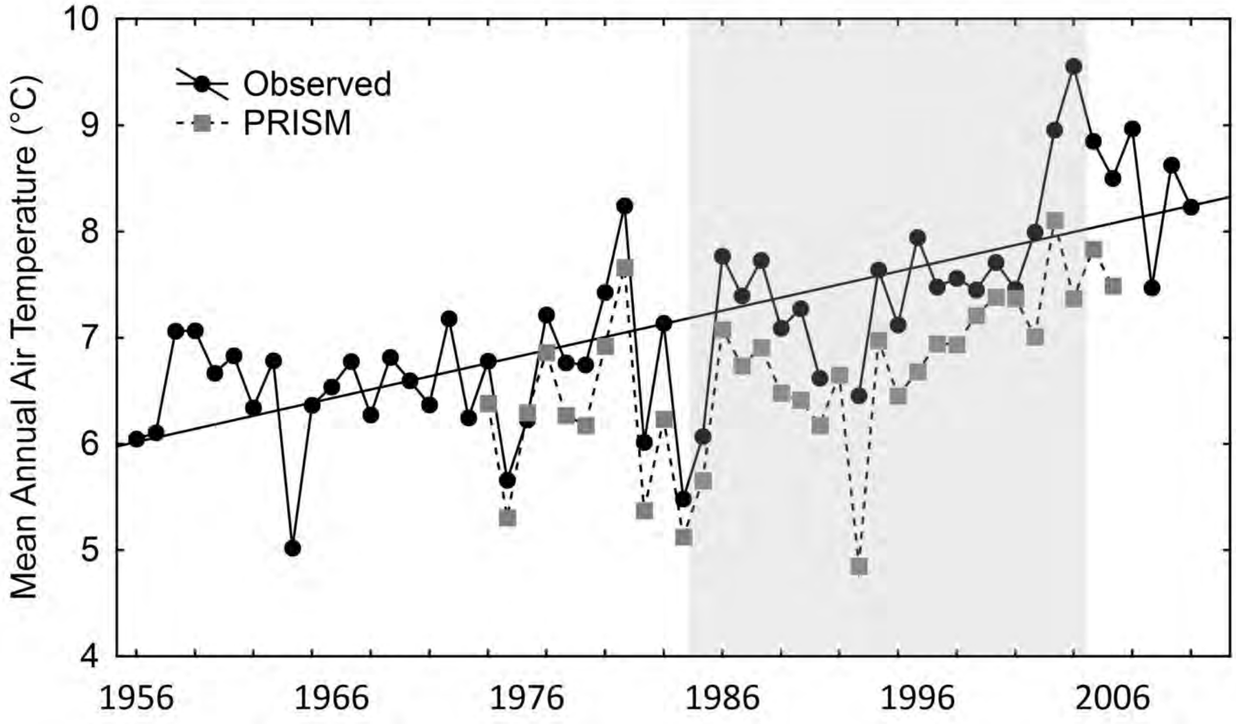

Figure 3-10. Yearly trends in annual observed air temperature (°C) at the Weber River site (UT 4927250) from 1955–2010, based on data from the Wanship Dam weather station. For comparative purposes, PRISM annual air temperature data associated with the biological sampling site are also included from 1975–2005. The area shaded in grey corresponds to the period of biological record. When the observed data are fitted with a linear trend line, $r^2 = 0.51$, $p < 0.01$, and $y = 0.0412x + 5.9756$.

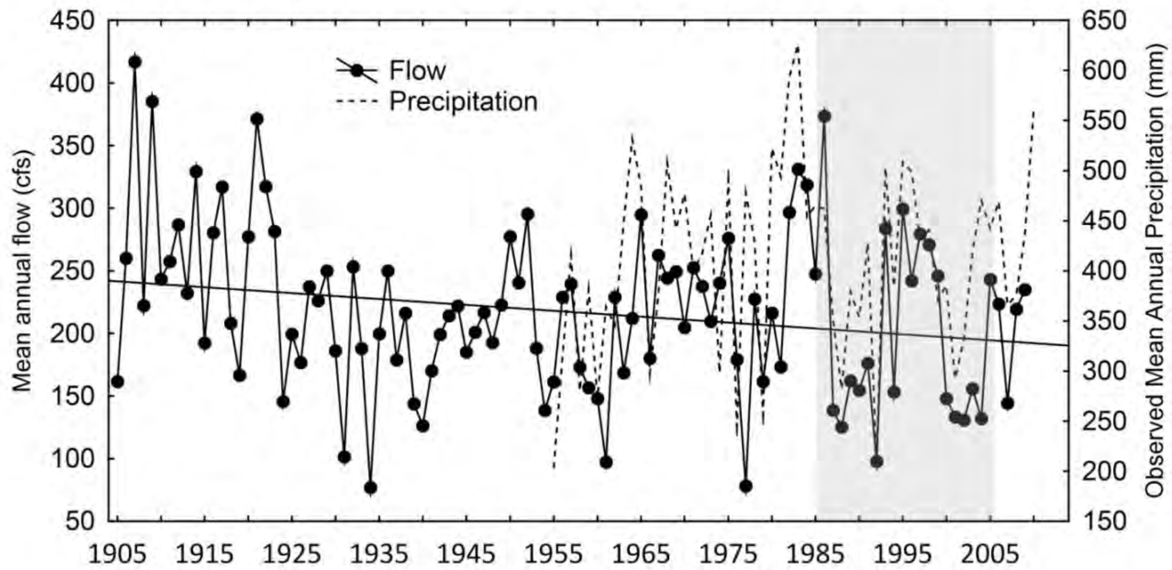

Figure 3-11. Yearly trends in mean annual flow (cfs) at the Weber River site (UT 4927250) from 1904–2011, based on data from USGS gage 10128500. For comparative purposes, observed annual precipitation data from the Wanship Dam weather station are also included from 1955–2010. The area shaded in grey corresponds to the period of biological record. When the observed data are fitted with a linear trend line, $r^2 = 0.05$, $p = 0.03$, and $y = 242.043 - 0.4707 \times x$.

In addition to mean annual values, mean maximum July temperature and mean fall flow values were also evaluated, as these are likely to be physiologically stressful time periods for the biological organisms. During the period of biological record (1985−2005), mean maximum July air temperatures ranged from 26.9−34.3°C, and mean fall flow values ranged from 97.8 to 373.5 cfs (see Table 3-12). O/E scores range from a low of 0.57 in 1986 to values of 1.0 or higher during the early 1990s and 2000 (see Figure 3-12A). The number of EPT taxa was highest in the early 1990s and dropped dramatically from 2000−2005 (see Figure 3-12B). This decline corresponds with a period of higher than normal temperatures and lower than normal flows (see Figure 3-12C). HBI scores were highly variable over time (see Figure 3-12B); because the HBI is calculated based on abundance data (vs. relative abundance data), results should be interpreted with caution due to reasons cited in Section 3.2. The cold-water taxa metrics also showed a sharp decline from 2000−2005 (see Figures 3-13A and B).

Table 3-12. Range of temperature, precipitation, and flow values that occurred at the Weber River site (UT 4927250) during the period of biological record. SON = September, October, November

Parameter	Min	Max
Year	1985	2005
PRISM mean annual air temperature (°C)	4.9	8.1
Observed mean maximum July air temperature (°C)	26.9	34.3
Mean annual flow (cfs)	276.8	474.4
Mean SON flow (cfs)	97.8	373.5
PRISM mean annual precipitation (mm)	35.5	120.0

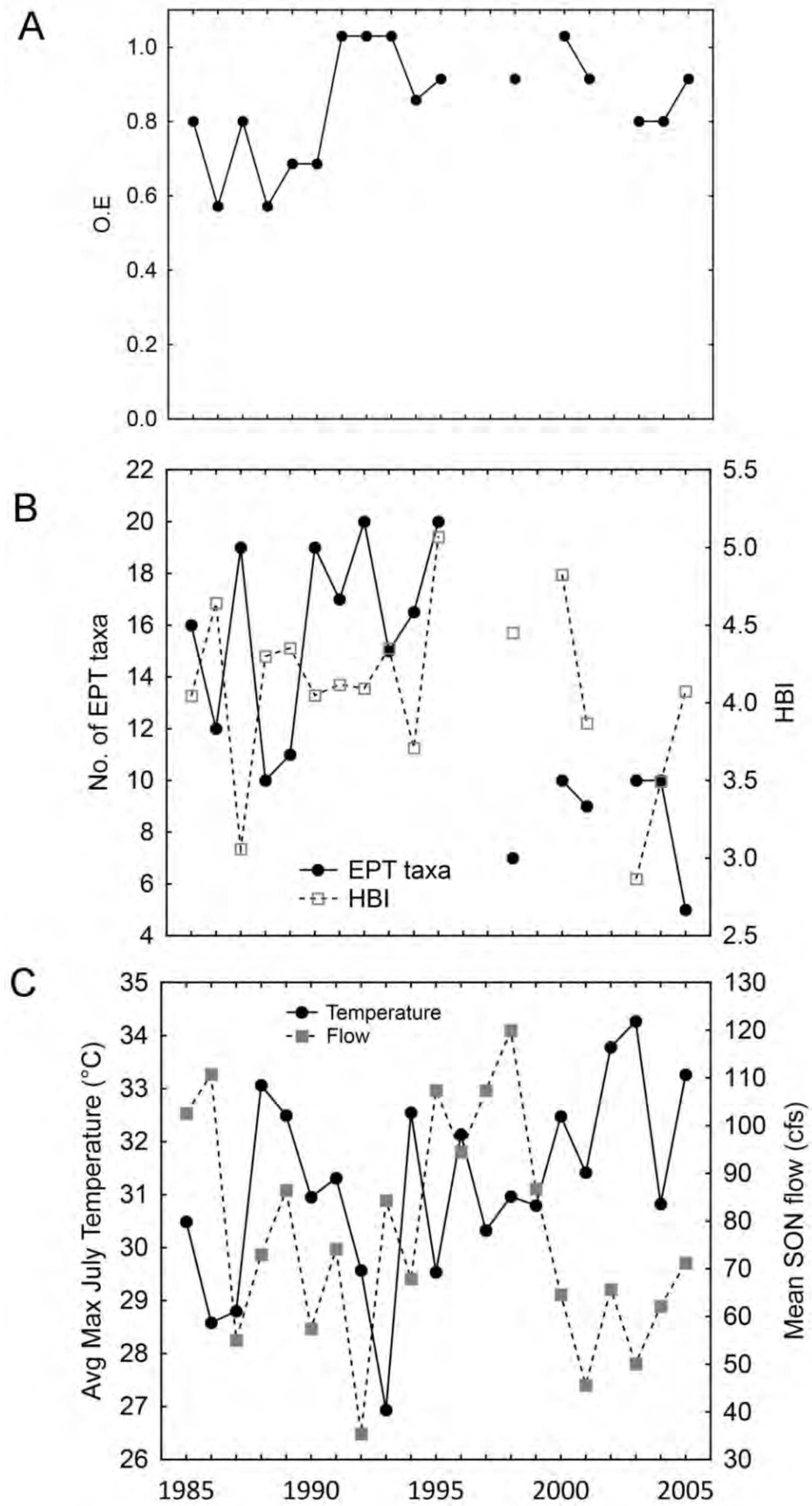

Figure 3-12. Yearly trends at the Weber River site (UT 4927250) in (A) O/E, (B) number of EPT taxa and HBI; (C) mean maximum July temperature (°C) and mean September/October/November (SON) flow (cfs).

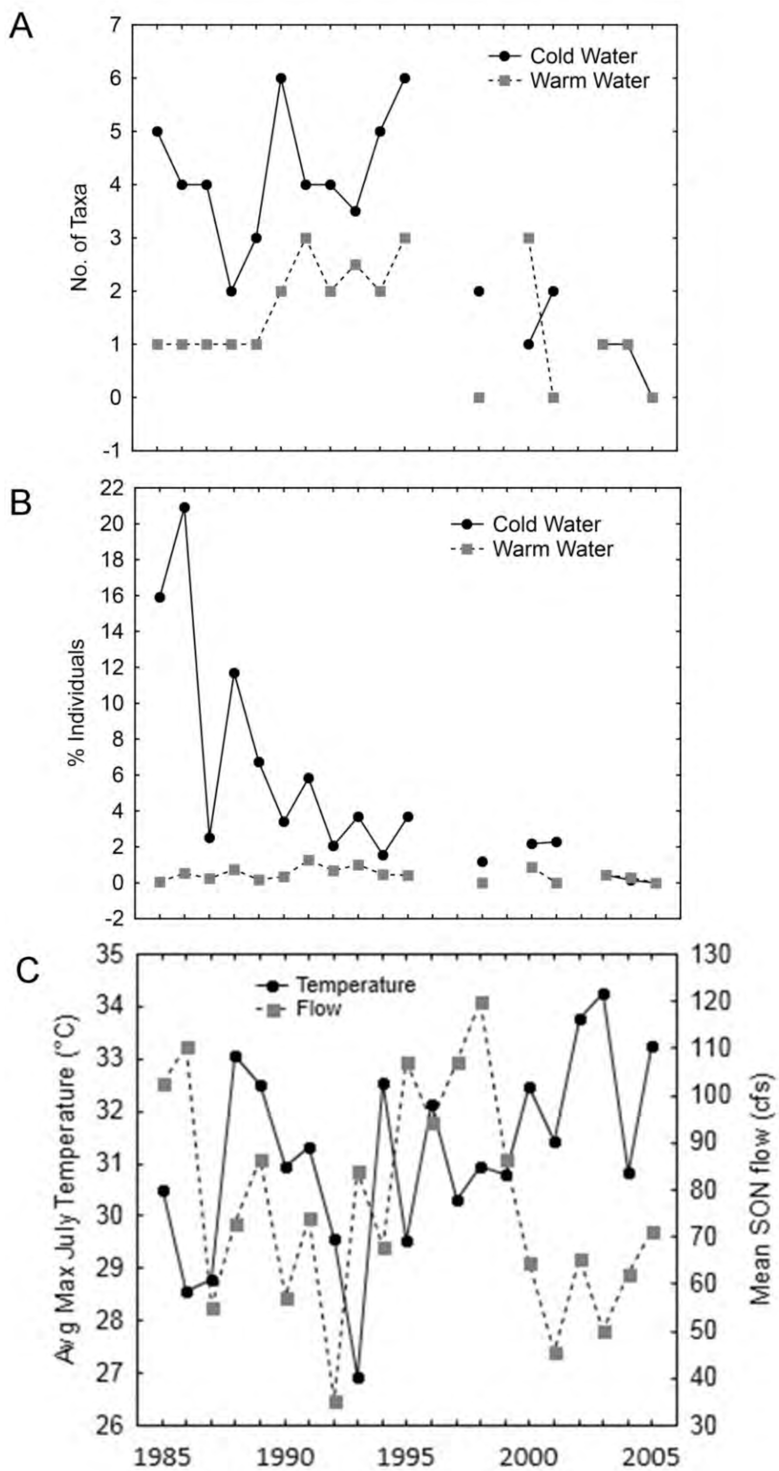

Figure 3-13. Yearly trends at the Weber River site (UT 4927250) in (A) number of cold and warm-water taxa; (B) percentage cold and warm-water individuals; and (C) mean maximum July temperature (°C) and mean September/October/November (SON) flow (cfs).

Confounding factors related to water chemistry were not evident. From 1985−2005, parameter values[2] were within the following ranges:

- DO: 9 to 12.2 mg/L
- pH: 7.8 to 8.7
- Chloride: 4.4 to 24 mg/L
- Nitrite (NO_2) + nitrate (NO_3): 0.15 to 0.36 mg/L
- Total phosphorus: 0.02 to 0.09 mg/L
- Specific conductance: 306 to 444 µmho/cm
- Turbidity: 1.7 to 10.3 NTU

3.6.1.2. *Associations Between Biological and Climatic Variables*

Kendall tau nonparametric correlations analyses allow examination of associations between commonly used biological metrics, year, temperature, flow, and precipitation variables at the Weber River (UT 4927250) site. Five of the 13 biological metrics showed strong associations ($r \geq 0.5$) with year or the environmental parameters (see Table 3-13). Three of the metrics (number of Ephemeroptera taxa, number of Plecoptera taxa, and number of intolerant taxa) were negatively correlated with PRISM mean annual air temperature, number of Plecoptera taxa was negatively correlated with year ($r = -0.62$), and the HBI was positively correlated with mean fall flow ($r = 0.51$) (see Table 3-13). The HBI was originally developed to reflect organic enrichment but is generally expected to increase with increasing perturbation (Barbour et al. 1999, Table 2-2). Based on this, the positive correlation of HBI with flow was somewhat surprising, if lower low flows are assumed to be more stressful (i.e., decreasing fall low flows would represent increasing stress, leading to an expectation for a negative relationship with HBI). Similarly, the responses of diversity and dominance to mean fall flow, though $r < |0.5|$, were counter to expectation, assuming decreasing fall low flows are more stressful (see Table 3-13). Per reasons cited in Section 3.2, results for the HBI and Shannon-Wiener Diversity

[2]Up to four samples were collected per year; the values shown here represent an average of these samples.

Table 3-13. Kendall tau nonparametric correlations analyses performed to examine associations between commonly used biological metrics, year, and climatic variables at the Weber River site (UT 4927250). Results are based on 17 years of data. Entries are in bold text if *r* ≥ ±0.5 and are highlighted in gray if they are in a direction opposite of what is expected. Ranges of biological metric values are also included. SON = September, October, November. Per reasons cited in Section 3.2, results for the HBI and Shannon-Wiener Diversity Index should be interpreted with caution because they are calculated based on abundance data (vs. relative abundance data)

Biological metric	Range of metric values		*r* values (based on Kendall Tau correlations)					
				Air temperature (°C)		Flow (cfs)		
	Min	Max	Year	PRISM mean annual	Observed mean maximum July	Mean annual	Mean SON	PRISM mean annual precipitation (mm)
Total no. taxa	12	33	–0.10	–0.32	–0.25	0.01	–0.16	–0.16
No. EPT taxa	5	20	–0.35	–0.45	–0.38	0.00	–0.05	–0.18
No. Ephemeroptera taxa	2	8	–0.41	**–0.55**	–0.38	0.16	–0.01	–0.10
No. Plecoptera taxa	0	6	**–0.62**	**–0.51**	–0.44	0.04	0.09	–0.15
No. Trichoptera taxa	2	9.5	–0.02	–0.23	–0.24	–0.08	–0.10	–0.02
No. Intolerant taxa	5	15	–0.37	**–0.51**	–0.29	0.05	–0.06	–0.17
Percentage EPT individuals	27.5	77.7	0.00	0.07	0.10	–0.22	–0.25	–0.21
Percentage Ephemeroptera individuals	1.5	54.7	–0.37	–0.36	–0.35	0.26	0.26	0.07
Shannon-Wiener Diversity Index	1.4	3.4	0.13	–0.04	0.03	–0.26	–0.47	–0.40
Percentage noninsect individuals	0.7	9.4	–0.06	–0.02	0.04	–0.37	–0.34	–0.41
Percentage dominant taxon	20.4	70.7	–0.10	–0.04	–0.06	0.44	0.44	0.40
Percentage tolerant individuals	0.0	5.5	0.19	0.00	–0.17	–0.17	–0.35	–0.04
Hilsenhoff Biotic Index	2.9	5.1	–0.09	–0.14	–0.16	0.34	**0.51**	0.18

Index should be interpreted with caution because they are calculated based on abundance data (vs. relative abundance data).

Similar analyses were performed on the thermal preference metrics. The cold-water metrics showed strong negative associations with year, and number of cold-water taxa was negatively correlated with PRISM mean annual air temperature (see Table 3-14). A subset of biological metrics that have shown responsiveness to hydrologic variables in other studies (see Section 2, Table 2-2) were also examined (see Table 3-15). Three of the metrics showed strong associations with year. Two of these, Odonata, Coleoptera, Hemiptera (OCH) taxa, and depositional taxa, occurred in low numbers, so results for these metrics should be interpreted with caution. Five of the percentage individuals metrics showed strong associations with mean fall flow. Four of these went against expectations (see Table 2-2), with collector-gatherers showing a positive correlation with mean fall flow, and percentage scraper/herbivores and erosional individuals having negative correlations.

3.6.1.3. *Groupings Based on Climatic Variables*

Samples were partitioned into hottest/coldest/normal year groups and lowest/normal/highest flow year groups. At the Weber River site (UT 4927250), on average, the hottest years were 1.7°C warmer than the coldest years, and highest flow years had 170 more cfs than lowest flow years. When samples were grouped based on temperature, there were significant ($p < 0.05$) differences between mean metric values for total number of taxa, number of EPT taxa, and number of cold-water taxa in hottest and coldest years samples (see Table 3-16). There were no significant differences in mean metric values across the flow groups (see Table 3-17).

NMDS was used to evaluate differences in taxonomic composition among samples collected during hottest, coldest, and normal years. "Hottest year" samples formed a distinct cluster from the "coldest" and "normal" year samples (see Figure 3-14). PRISM mean annual air temperature from the year the sample was collected, PRISM mean annual air temperature from the year prior to sample collection, and the difference between PRISM mean annual precipitation from the sample collection year and the year prior were important drivers along Axes 1 and 2. Figure 3-15 shows which taxa are the strongest drivers along these axes. *Pteronarcys*, Chloroperlidae, and *Ephemerella* have the strongest positive correlations with Axis 2, and

Table 3-14. Kendall tau nonparametric correlations analyses performed to examine associations between thermal preference metrics, year, and climatic variables at the Weber River site (UT 4927250). Results are based on 17 years of data. Entries are in bold text if *r* ≥ ±0.50. Ranges of biological metric values are also included. SON = September, October, November

Biological metric	Range of metric values: Min	Range of metric values: Max	*r* values (based on Kendall Tau correlations): Year	Air Temperature (°C): PRISM mean annual	Air Temperature (°C): Observed mean maximum July	Flow (cfs): Mean annual	Flow (cfs): Mean SON	PRISM Mean annual precipitation (mm)
No. cold-water taxa	0	6.0	**–0.50**	**–0.57**	–0.36	0.19	0.14	–0.05
Percentage cold-water individuals	0	20.9	**–0.71**	–0.46	–0.28	0.22	0.34	–0.06
No. warm-water taxa	0	3.0	–0.03	–0.38	–0.22	0.03	0.02	–0.02
Percentage warm-water individuals	0	1.3	–0.14	–0.15	–0.13	–0.07	–0.01	–0.08

Table 3-15. Kendall tau nonparametric correlations analyses performed to examine associations between a subset of biological metrics, year, flow, and precipitation variables at the Weber River site (UT 4927250). The subset of biological metrics were selected per the criteria outlined in Section 2 and have shown responsiveness to hydrologic variables in other studies (see Section 2, Table 2-2). Results are based on 17 years of data. Entries are in bold text if $r \geq \pm 0.5$ and are highlighted in gray if they are in a direction opposite of what is expected. Ranges of biological metric values are also included. SON = September, October, November

Biological metric		Range of metric values		*r* values (based on Kendall Tau correlations)			
					Flow (cfs)		
		Min	Max	Year	Mean annual	Mean SON	PRISM mean annual precipitation (mm)
Richness	Collector filterer	2.0	5.0	–0.08	–0.08	–0.16	0.04
	Collector gatherer	3.0	9.0	–0.20	0.13	–0.01	–0.06
	Scraper/herbivore	1.0	8.0	0.00	–0.06	–0.23	–0.09
	Predator	2.0	9.0	–0.18	0.07	–0.04	–0.12
	Swimmer	1.0	3.0	–0.12	0.24	0.03	0.03
	OCH	0.0	3.0	**0.56**	0.09	–0.01	0.36
	Depositional	0.0	1.0	**–0.51**	0.25	0.16	–0.02
	Erosional	4.0	10.0	–0.03	–0.16	–0.22	–0.03
Percentage individuals	Collector filterer	3.2	60.2	0.32	–0.37	–0.34	–0.18
	Collector gatherer	13.3	94.2	–0.35	0.49	**0.57**	0.26
	Scraper/herbivore	0.2	31.0	0.43	–0.26	**–0.53**	–0.10
	Predator	1.8	10.9	–0.15	–0.28	–0.25	–0.35
	Swimmer	0.7	34.2	–0.04	0.12	0.06	–0.04
	OCH	0.0	29.5	**0.53**	–0.32	**–0.55**	–0.12
	Depositional	0.0	0.9	–0.36	0.23	0.14	0.07
	Erosional	4.0	81.6	0.34	**–0.50**	**–0.59**	–0.28

Table 3-16. Mean metric values (±1 SD) for the Weber River site (UT 4927250) in coldest, normal, and hottest year samples. Year groups are based on PRISM mean annual air temperature values. One-way ANOVA was done to evaluate differences in mean metric values. Groups with no superscripts are not significantly different ($p < 0.05$). Entries with superscripts have significant differences across year groups; those entries with different superscripts are significantly different from each other (e.g., coldest total no. taxa vs. normal and hottest total no. taxa)

Year group	O/E	Total no. taxa	No. EPT taxa	No. cold-water taxa	No. warm-water taxa	% Cold-water individuals	% Warm-water individuals
Coldest	0.9 ± 0.2	27.5 ± 3.5^{A}	17.4 ± 2.1^{A}	4.9 ± 1.1^{A}	2.3 ± 0.8	6.5 ± 5.4	0.6 ± 0.5
Normal	0.8 ± 0.2	21.5 ± 7.8^{AB}	13.6 ± 4.9^{AB}	3.4 ± 1.1^{A}	1.1 ± 0.7	6.7 ± 7.4	0.4 ± 0.3
Hottest	0.9 ± 0.1	17.2 ± 3.3^{B}	8.8 ± 2.2^{B}	1.0 ± 0.7^{B}	1.0 ± 1.2	1.0 ± 1.1	0.3 ± 0.4

Table 3-17. Mean metric values (±1 SD) for the Weber River site (UT 4927250) in driest, normal, and wettest flow year samples. Year groups are based on mean annual flow values from USGS gage 10128500. One-way ANOVA was done to evaluate differences in mean metric values. None of the year groups are significantly different ($p < 0.05$)

Year group	O/E	Total no. taxa	No. EPT taxa	No. cold-water taxa	No. warm-water taxa	% Cold-water individuals	% Warm-water individuals
Driest	0.8 ± 0.2	21.0 ± 7.8	13.6 ± 5.4	2.6 ± 1.3	1.0 ± 0.7	3.7 ± 4.5	0.4 ± 0.3
Normal	0.9 ± 0.1	22.5 ± 7.1	12.6 ± 5.0	2.9 ± 2.3	1.7 ± 1.1	2.9 ± 2.6	0.5 ± 0.4
Wettest	0.8 ± 0.2	22.3 ± 6.6	14.0 ± 4.8	4.1 ± 1.5	1.5 ± 1.2	9.1 ± 8.8	0.4 ± 0.4

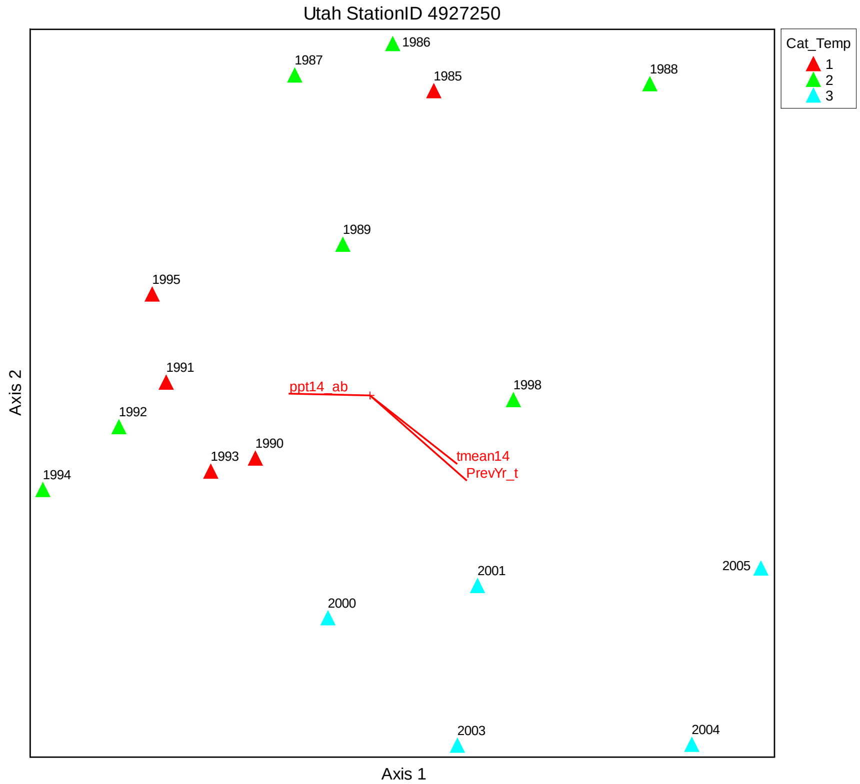

Figure 3-14. NMDS plot (Axis 1-2) for the Weber River site (UT 4927250), shown in Figure 3-8. Cat_Temp refers to the temperature categories, which are: 1 = coldest years; 2 = normal years; 3 = hottest years. Samples are labeled by collection year. tmean14 = PRISM mean annual air temperature from the year the sample was collected, PrevYr_t = PRISM mean annual air temperature from the year prior to sample collection, and ppt14_ab = absolute difference between the PRISM mean annual precipitation value from the year of the sample collection and the year prior.

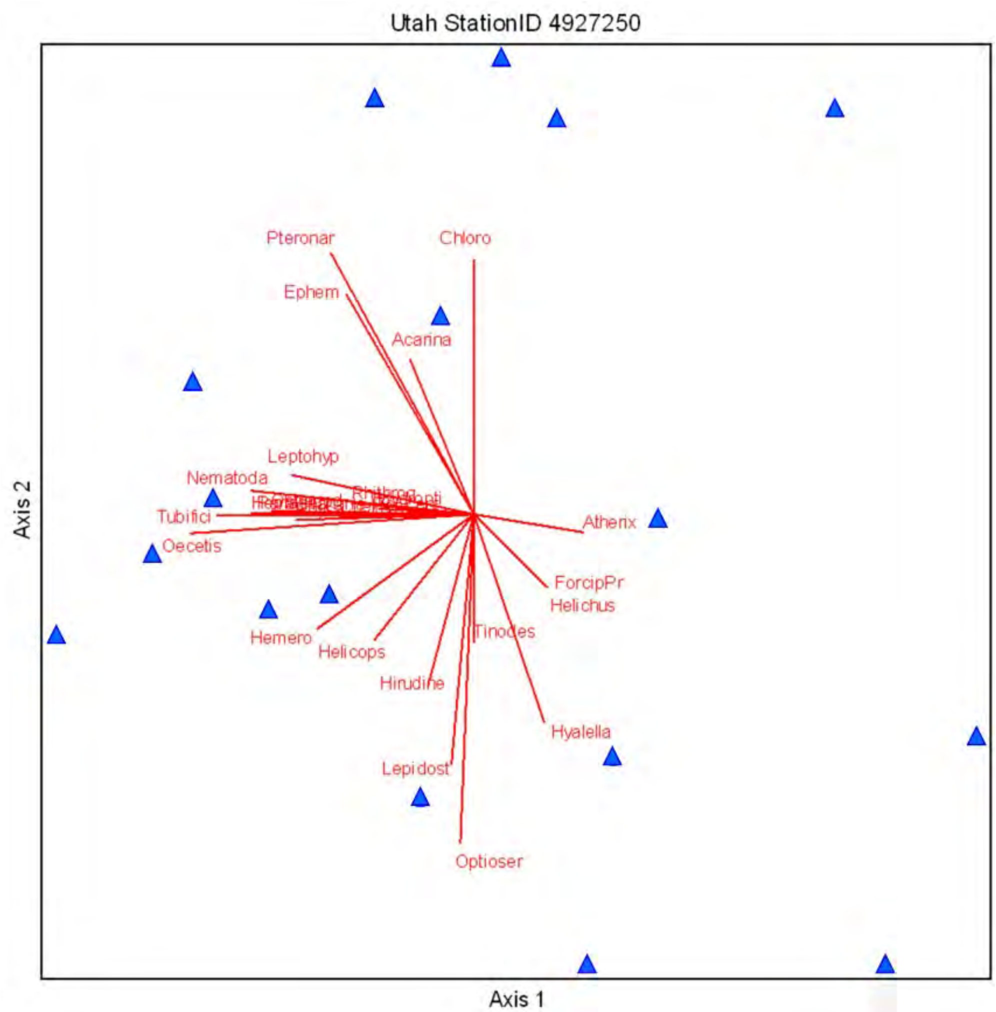

Figure 3-15. NMDS plot (Axis 1-2) for the Weber River site (UT 4927250) showing which taxa are most highly correlated with each axis.

Optioservus, *Lepidostoma,* and *Hyallela* have the strongest negative correlations with Axis 2. The three taxa positively associated with Axis 2 tend toward cold-water-preference—Chloroperlidae and *Pteronarcys* are absent from the "hottest year" samples, and *Ephemerella* is present in all the "coldest year" and "normal year" samples and is only present in one "hottest year" sample. Some additional taxa that occurred during multiple years and were not found in "hottest year" samples include *Rhithrogena*, Nematoda, and Tubificidae. Warm-water-preference taxa that are present in the majority of "hottest year" samples include *Optioservus*, *Lepidostoma,* and *Hyallela*, though they also are present in "coldest year" and/or "normal year" samples.

3.6.2. Virgin River (UT 4951200)

The Virgin River site (UT 4951200) is located near Zion National Park (NP), on the Virgin River below Zion Narrows in the Colorado Plateaus/Escarpments ecoregion. It has a drainage area of 756 km^2 and is at an elevation of 1,369 m. Its highest maximum monthly temperatures occur during July, and it lowest average flows (approximately 50 cfs) occur from July through February. This station has 15 years of data, ranging from 1985−2004. Temperature and precipitation data dating from 1904 to 2010 were gathered from the Zion NP weather station (SiteID 429717, Latitude: 37.2083, Longitude: 112.984). The weather station is located approximately 9 km southwest of the biological sampling site. Flow data from 1991−1994 were gathered from USGS gage 9405490 (North Fork Virgin River above Big Bend near Springdale, Latitude: 37.27859, Longitude: 112.94466). The gage is located on a tributary 0.8 km south of the biological sampling site. Figure 3-16 shows an aerial photograph of the site, along with the nearest weather station and active USGS gage.

3.6.2.1. *Temporal Trends in Climatic and Biological Variables*

Since 1904, observed mean annual air temperatures at the weather station closest to the Virgin River site (UT 4951200) have ranged from 12.1 to 18.6°C. Over time, year–to-year variability has decreased, and temperatures have shown a slight increase (when fit with a linear trend line, $r^2 = 0.16$, $p < 0.01$) (see Figure 3-17). When PRISM air temperature data are compared to observed data, the PRISM temperatures are 3.5−6°C lower, perhaps due to the differences in the locations and elevations of the weather station versus the biological sampling sites (the elevation of the biological sampling is about 137 m higher than the weather station).

Because flow data are not available for most of the biological sampling period, precipitation data were used as a surrogate. Since 1904, observed mean precipitation values have ranged from 87 to 679 mm. There is a great deal of year-to-year variability, but overall, mean annual precipitation has increased slightly over time (when fit with a linear trend line, $r^2 = 0.01$, $p = 0.32$) (see Figure 3-18). When PRISM precipitation data are compared to observed data, there is close correspondence (see Figure 3-18).

During the period of biological record (1985−2004), mean maximum July air temperatures ranged from 35.6−40.6°C, and mean fall precipitation values ranged from 2.5 to 80.2 mm (see Table 3-18). O/E scores increased over time, ranging from a low of 0.42 in 1985−1986 to 0.94 in 2001 (see Figure 3-19A). The number of EPT taxa increased to a high of 18 in the early 1990s, before dropping off to a low of 4 in 2000 (see Figure 3-19B). The year 1999 was extremely dry (see Figure 3-19C), and this may have contributed to the low numbers in 2000. Conditions in 1989 and 2003 were hotter and drier than normal (see Figure 3-19C), and this may also have influenced the biological assemblage.

Figure 3-16. Locations of the Virgin River (UT 4951200) biological sampling site, N. Fork Virgin River USGS gage, and Zion NP weather station. Image from Google Earth.

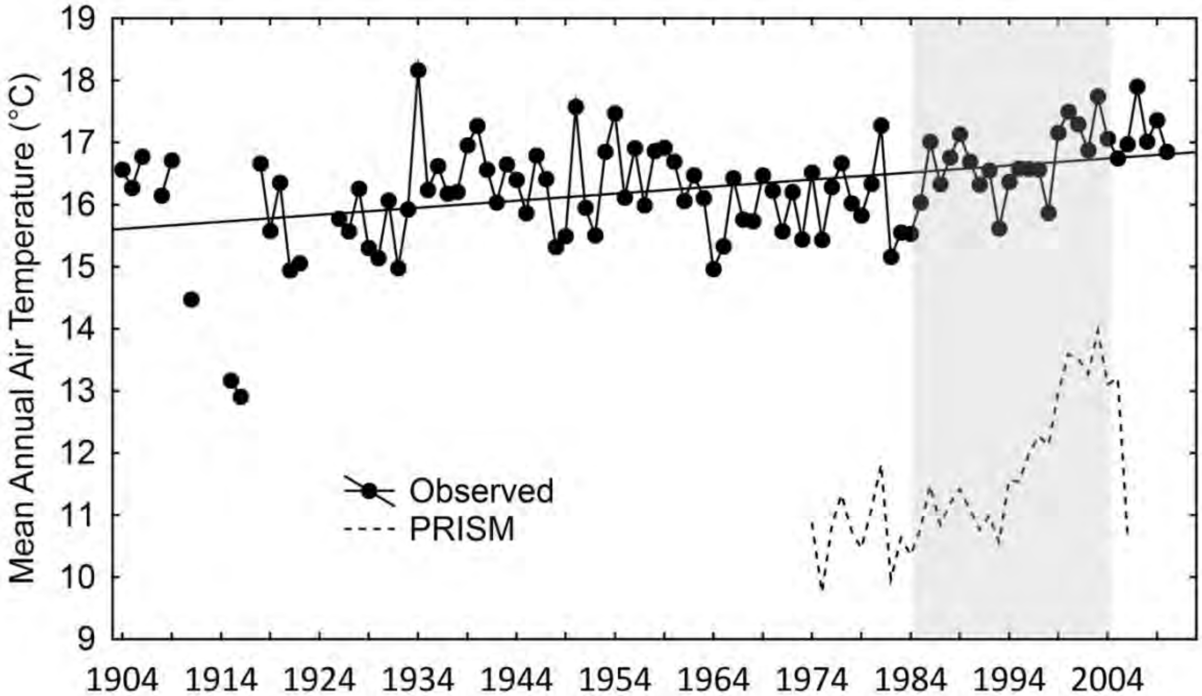

Figure 3-17. Yearly trends in annual observed air temperature (°C) at the Virgin River site (UT 4951200) from 1904–2010, based on data from the Zion NP weather station. For comparative purposes, PRISM annual air temperature data associated with the biological sampling site are also included from 1975−2005. The area shaded in grey corresponds to the period of biological record. When the observed data are fitted with a linear trend line, $r^2 = 0.16$, $p < 0.01$, and $y = –6.0313 + 0.0114 \times x$.

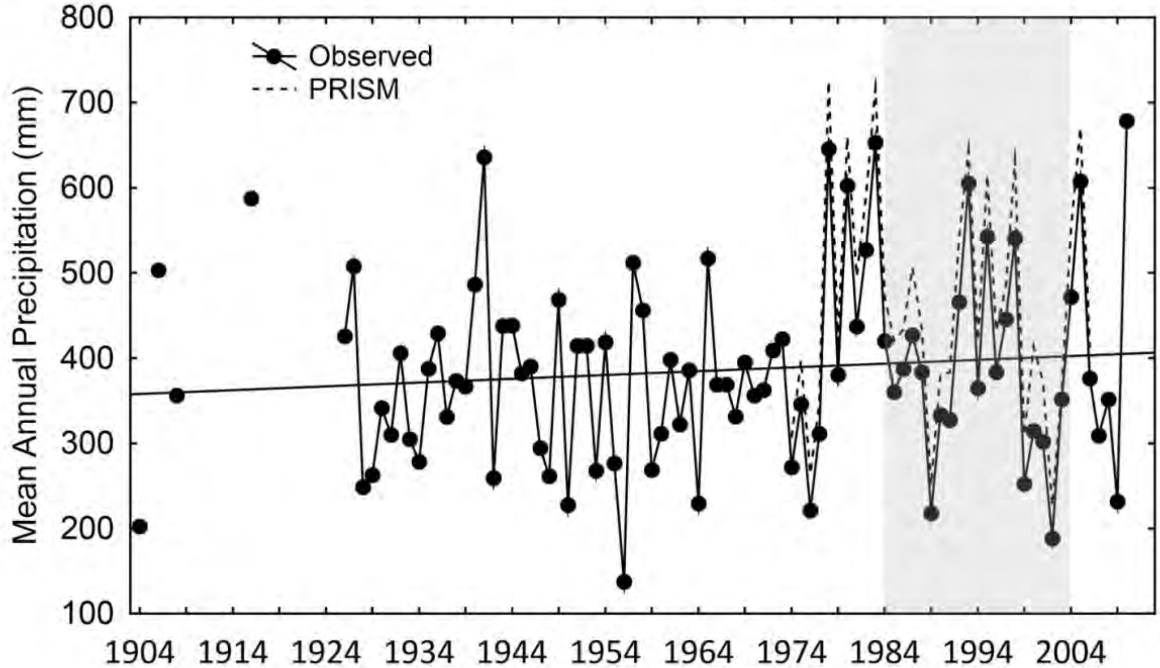

Figure 3-18. Yearly trends in mean annual precipitation (mm) at the Virgin River site (UT 4951200) from 1904–2011, based on data from the Zion NP weather station. For comparative purposes, PRISM annual precipitation data associated with the biological sampling site are also included from 1975–2005. The area shaded in grey corresponds to the period of biological record. When the observed data are fitted with a linear trend line, $r^2 = 0.01$, $p = 0.32$, and $y = -497.0505 + 0.449 \times x$.

Table 3-18. Range of temperature, precipitation, and flow values that occurred at the Virgin River site (UT 4951200) during the period of biological record. SON = September, October, November

Parameter	Min	Max
Year	1984	2004
PRISM mean annual air temperature (°C)	10.4	14.0
Observed mean maximum July air temperature (°C)	35.6	40.6
Mean SON precipitation (mm)	2.5	80.2
PRISM mean annual precipitation (mm)	226.9	644.5

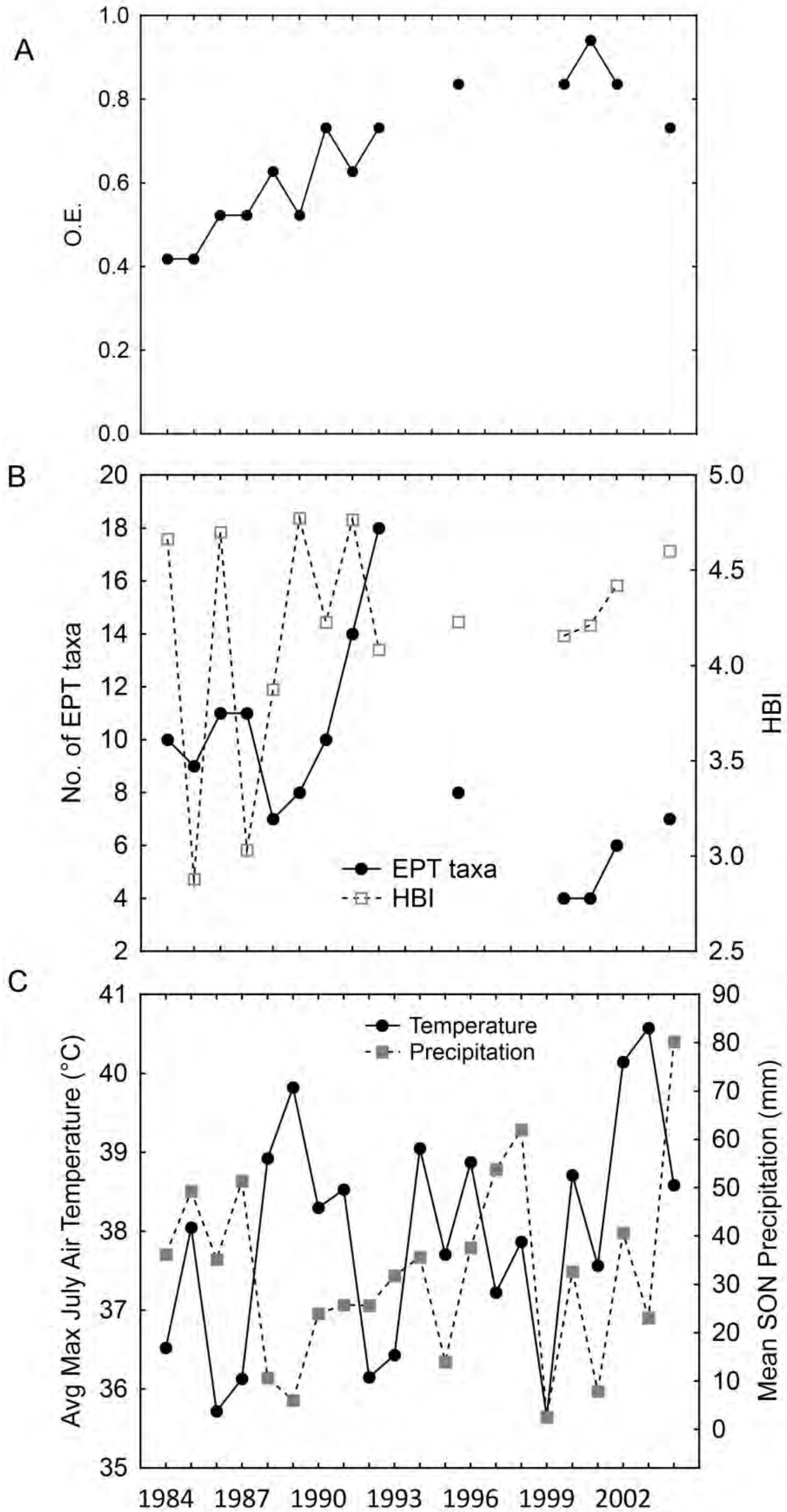

Figure 3-19. Yearly trends at the Virgin River site (UT 4951200) in (A) O/E, (B) number of EPT taxa and HBI; (C) mean maximum July temperature (°C) and mean observed September/October/November (SON) precipitation (mm).

HBI scores were highly variable (see Figure 3-19B) and reflect large changes in the abundances of certain taxa from year to year, in particular Chironomidae and *Ephemerella*. Because the HBI is calculated based on abundance data (vs. relative abundance data), results should be interpreted with caution due to reasons cited in Section 3.2. From 2000 onward, cold-water taxa were absent or occurred in extremely low numbers, while the number of warm-water taxa increased by 2−3 taxa starting in 2001 (see Figures 3-20A and B).

Confounding factors related to water chemistry were not evident during the time period for which water chemistry data were available. From 1985−2002, parameter values[3] were within the following ranges:

- DO: 8.9 to 10.1 mg/L
- pH: 7.9 to 8.6
- Chloride: 29.0 to 43.7 mg/L
- Nitrite (NO_2) + nitrate (NO_3): 0.06 to 0.29 g/L
- Nitrogen, Kjeldahl: 0.10 to 1.00 mg/L
- Total phosphorus: 0.01 to 0.04 mg/L
- Specific conductance: 511 to 618 µmho/cm
- Total suspended solids (TSS): 6 to 218 mg/L

3.6.2.2. *Associations Between Biological Variables and Climatic Variables*

Kendall tau nonparametric correlations analyses were performed to examine associations between 13 commonly used biological metrics, year, temperature, and precipitation variables at the Virgin River site (UT 4951200). Five of the biological metrics (total number of taxa, number of EPT taxa, number of Ephemeroptera taxa, number of Plecoptera taxa, and number of intolerant taxa) had strong ($r \geq 0.5$) negative associations with PRISM mean annual air temperature (see Table 3-19). Two metrics were strongly associated with precipitation variables.

[3]Up to four samples were collected per year; the values shown here represent an average of these samples.

Table 3-19. Kendall tau nonparametric correlations analyses performed to examine associations between commonly used biological metrics, year, and climatic variables at the Virgin River site (UT 4951200). Results are based on 15 years of data. Entries are in bold text if $r \geq \pm 0.5$ and are highlighted in gray if they are in a direction opposite of what is expected. Ranges of biological metric values are also included. SON = September, October, November. Per reasons cited in Section 3.2, results for the HBI and Shannon-Wiener Diversity Index should be interpreted with caution because they are calculated based on abundance data (vs. relative abundance data)

Biological metric	Range of metric values		*r* values (based on Kendall Tau correlations)				
				Air temperature (°C)		Precipitation (mm)	
	Min	Max	Year	PRISM mean annual	Observed mean maximum July	PRISM mean annual	Observed SON
Total no. taxa	12.00	32.00	–0.09	**–0.72**	–0.20	0.32	–0.05
No. EPT taxa	4.00	18.00	–0.32	**–0.72**	–0.34	**0.57**	0.05
No. Ephemeroptera taxa	2.00	10.00	**–0.53**	**–0.79**	–0.44	0.32	0.01
No. Plecoptera taxa	0.00	4.00	–0.44	**–0.56**	–0.09	0.36	–0.19
No. Trichoptera taxa	1.00	7.00	0.17	–0.24	–0.19	0.38	0.40
No. Intolerant taxa	0.00	13.00	–0.46	**–0.66**	–0.32	0.48	–0.11
Percentage EPT individuals	34.82	89.16	0.01	0.27	0.08	0.10	–0.10
Percentage Ephemeroptera individuals	29.41	86.63	0.27	0.41	0.12	0.05	–0.05
Shannon-Wiener Diversity Index	1.72	3.19	–0.16	–0.43	0.03	0.10	–0.36
Percentage noninsect individuals	1.41	9.20	–0.14	–0.49	0.05	0.25	–0.21
Percentage dominant taxon	24.57	53.72	0.16	0.34	–0.03	–0.01	**0.54**
Percentage tolerant individuals	0.00	6.28	0.20	–0.20	0.04	0.00	–0.04
Hilsenhoff Biotic Index	2.88	4.77	0.16	–0.10	–0.12	0.03	0.27

Number of EPT taxa was positively correlated ($r = 0.57$) with PRISM mean annual precipitation, and the percentage dominant taxon metric was positively correlated ($r = 0.54$) with mean fall precipitation (see Table 3-19). The direction of the relationship of the taxa dominance metric with fall flow is counter to expectation, if decreasing fall low flows are considered more stressful, and dominance is expected to increase (and diversity decrease) as lower more stressful flows eliminate sensitive taxa (see Table 2-2). One metric, number of Ephemeroptera taxa, was negatively correlated with year ($r = -0.53$).

When similar analyses were performed on the thermal preference metrics, percentage of warm-water individuals was positively correlated ($r = 0.56$) with PRISM mean annual air temperature, and the number of warm-water taxa had a strong positive association ($r = 0.67$) with year (see Table 3-20).

The biological metrics in Table 3-21 have shown responsiveness to hydrologic variables in other studies (see Section 2, Table 2-2). None had strong associations with mean annual or mean fall precipitation variables. One metric, percentage OCH individuals, showed a strong positive association ($r = 0.50$) with year (see Table 3-21).

3.6.2.3. *Groupings Based on Climatic Variables*

Samples were partitioned into hottest/coldest/normal year groups and driest/normal/wettest flow year groups. At the Virgin River site (UT 4951200), on average, the hottest years were 2.7°C warmer than the coldest years, and wettest years had approximately 250 more millimeters of precipitation than driest years. When samples were grouped based on temperature, there were significant ($p < 0.05$) differences between mean metric values for total number of taxa, number of EPT taxa, number of cold-water taxa, and number of warm-water taxa in hottest and coldest/normal years samples, with the lowest mean metric values occurring in the hottest year samples for all but the number of warm-water taxa, which were higher in the hottest years (see Table 3-22). The percentage of cold-water individuals metric was significantly lower in hottest versus normal year samples. One metric showed significant differences across the precipitation groups (see Table 3-23). Mean number of EPT taxa was significantly higher in the wettest versus driest year samples.

NMDS was used to evaluate differences in taxonomic composition among samples collected during hottest, coldest, and normal years. “Hottest year” samples formed a distinct

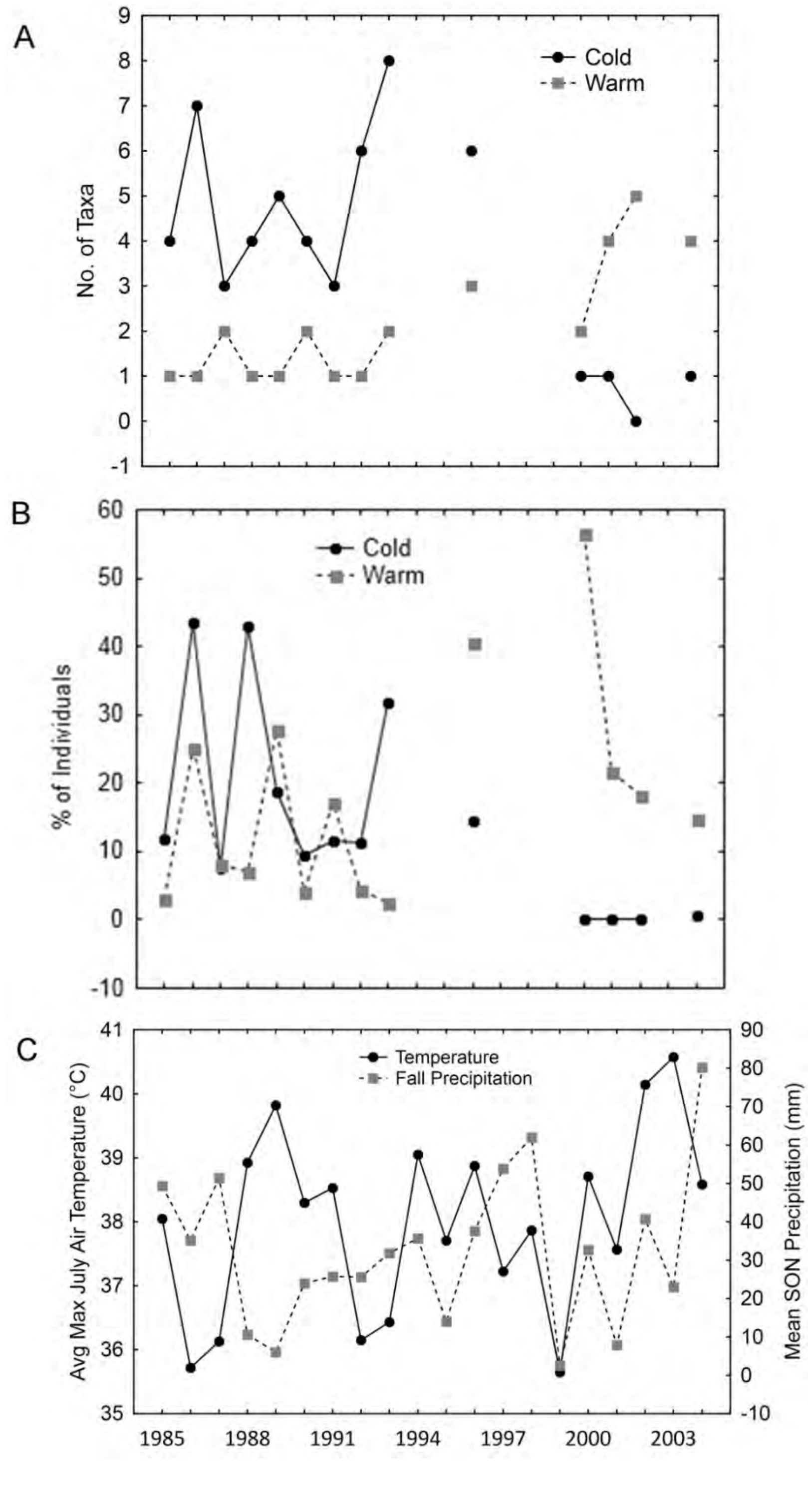

Figure 3-20. Yearly trends at the Virgin River site (UT 4951200) in (A) number of cold and warm-water taxa; (B) percentage cold and warm-water individuals; and (C) mean maximum July temperature (°C) and mean observed September/October/November (SON) precipitation (mm).

Table 3-20. Kendall tau nonparametric correlations analyses performed to examine associations between thermal preference metrics, year, and climatic variables at the Virgin River site (UT 4951200). Results are based on 15 years of data. Entries are in bold text if $r \geq \pm 0.5$. Ranges of biological metric values are also included. SON = September, October, November

Biological metric	Range of metric values		*r* values (based on Kendall Tau correlations)				
				Air temperature (°C)		Precipitation (mm)	
	Min	Max	Year	PRISM mean annual	Observed mean maximum July	PRISM mean annual	Observed SON
No. cold-water taxa	0.0	8.0	–0.33	–0.31	–0.29	0.33	–0.17
Percentage cold-water individuals	0.0	43.5	–0.45	–0.36	–0.12	0.25	–0.16
No. warm-water taxa	1.0	5.0	**0.67**	0.42	0.19	–0.11	0.29
Percentage warm-water individuals	2.6	56.6	0.16	**0.56**	0.23	–0.32	–0.08

Table 3-21. Kendall tau nonparametric correlations analyses performed to examine associations between a subset of biological metrics, year, flow, and precipitation variables at the Virgin River site (UT 4951200). The subset of biological metrics were selected per the criteria outlined in Section 2 and have shown responsiveness to hydrologic variables in other studies (see Section 2, Table 2-2). Results are based on 15 years of data. Entries are in bold text if $r \geq \pm 0.5$. Ranges of biological metric values are also included. SON = September, October, November

Biological metric		Range of metric values		*r* values (based on Kendall tau correlations)		
					Precipitation (mm)	
		Min	Max	Year	PRISM mean annual	Observed SON
Richness	Collector filterer	2.0	4.0	0.13	0.33	0.21
	Collector Gatherer	3.0	11.0	0.14	0.28	0.19
	Scraper/herbivore	1.0	7.0	–0.35	0.35	–0.07
	Predator	2.0	9.0	–0.02	0.15	–0.30
	Swimmer	1.0	3.0	0.06	0.19	–0.06
	OCH	0.0	3.0	0.44	–0.01	–0.24
	Depositional	1.0	2.0	–0.05	–0.09	–0.27
	Erosional	3.0	8.0	0.06	0.14	–0.01
Percentage individuals	Collector filterer	1.3	40.4	–0.25	0.32	–0.01
	Collector Gatherer	37.2	95.8	0.05	0.36	0.30
	Scraper/herbivore	0.2	50.3	0.03	–0.41	–0.34
	Predator	1.8	21.3	–0.45	0.16	–0.12
	Swimmer	1.9	47.1	0.49	–0.08	0.08
	OCH	0.0	8.1	**0.50**	–0.17	0.10
	Depositional	2.4	53.9	0.16	–0.32	–0.08
	Erosional	1.3	57.0	0.08	–0.23	–0.16

Table 3-22. Mean metric values (±1 SD) for the Virgin River site (UT 4951200) in coldest, normal, and hottest year samples. Year groups are based on PRISM mean annual air temperature values. One-way ANOVA was performed to evaluate differences in mean metric values. Groups with no superscripts are not significantly different (*p* < 0.05). Entries with superscripts have significant differences across year groups; those entries with different superscripts are significantly different from each other (e.g., coldest and normal total no. taxa vs. hottest total no. taxa)

Year group	O/E	Total no. taxa	No. EPT taxa	No. cold-water taxa	No. warm-water taxa	% cold-water individuals	% warm-water individuals
Coldest	0.6 ± 0.2	22.8 ± 6.6^{A}	12.3 ± 3.9^{A}	4.5 ± 2.4^{A}	1.5 ± 0.6^{A}	15.7 ± 10.9^{AB}	7.7 ± 6.7
Normal	0.6 ± 0.1	19.8 ± 3.2^{A}	9.5 ± 2.6^{A}	5.3 ± 1.2^{A}	1.5 ± 0.8^{A}	23.4 ± 15.6^{A}	18.1 ± 15.3
Hottest	0.8 ± 0.1	14.5 ± 1.9^{B}	5.3 ± 1.5^{B}	0.8 ± 0.5^{B}	3.8 ± 1.3^{B}	0.2 ± 0.2^{B}	27.8 ± 19.4

Table 3-23. Mean metric values (±1 SD) for the Virgin River site (UT 4951200) in driest, normal, and wettest flow year samples. Year groups are based on mean annual flow values from USGS gage 10128500. One-way ANOVA was performed to evaluate differences in mean metric values. Groups with no superscripts are not significantly different (*p* < 0.05). Entries with superscripts have significant differences across year groups; those entries with different superscripts are significantly different from each other (e.g., driest no. EPT taxa vs. normal and wettest no. EPT taxa)

Year group	O/E	Total no. taxa	No. EPT taxa	No. cold-water taxa	No. warm-water taxa	% cold-water individuals	% warm-water individuals
Driest	0.7 ± 0.2	16.8 ± 2.5	6.3 ± 1.7^{A}	2.5 ± 2.4	3.0 ± 1.8	7.1 ± 8.9	17.9 ± 10.0
Normal	0.6 ± 0.2	18.3 ± 3.9	8.7 ± 2.5^{AB}	4.2 ± 2.1	1.5 ± 0.8	20.7 ± 18.1	24.9 ± 20.5
Wettest	0.7 ± 0.1	14.5 ± 7.3	12.5 ± 4.7^{B}	4.5 ± 3.1	2.3 ± 1.3	12.8 ± 13.4	7.4 ± 5.4

cluster from the "coldest" and "normal" year samples (see Figure 3-21). PRISM mean annual air temperature from the year the sample was collected, PRISM mean annual air temperature from the year prior to sample collection, and PRISM mean annual precipitation from the year prior to sample collection were important drivers along Axis 1, while the difference between PRISM mean annual precipitation from the sample collection year and the year prior is a strong driver along Axis 2. Figure 3-22 shows which taxa are the strongest drivers along these axes. *Ephemerella*, Nematoda, and *Heptagenia* have the strongest negative correlations with Axis 1, and appear to tend toward a cold-water-preference. Nematoda are absent from the "hottest year" samples, and *Ephemerella* and *Heptagenia* are present in all "coldest year" samples, six of the seven "normal year" samples and only one of the "hottest year" samples. *Forcipomyia/Probezzia*, *Microcylloepus*, *Caloparyphus,* and *Chimarra* have the strongest positive correlations with Axis 1, and appear to be warm tolerant. These taxa are present in at least two of the four "hottest year" samples and are absent from the "coldest year" and/or "normal year" samples.

3.6.3. Beaver River (UT 5940440)

The Beaver River site (UT 5940440) is located in the Wasatch Uinta Mountains/Semiarid Foothills ecoregion. It has a drainage area of 236 km^2 and is at an elevation of 1,905 m. Its highest maximum monthly temperatures occur during July, and its lowest average flows (<30 cfs) occur from September through March. This station has 11 years of data, ranging from1994−2005, with a mix of spring and fall sampling events. When limited to fall samples only, 9 years of data are available. Precipitation data from 1939 to 2010 were gathered from the Beaver Canyon PH weather station (SiteID 420527, Latitude: 38.2681, Longitude: 112.481). Temperature data became available from this station starting in 1997. The weather station is located approximately 7 km east of the biological sampling site. USGS gage 10234500 (Beaver River near Beaver, Latitude: 38.28052, Longitude: 112.56827) is colocated with the biological sampling site and has flow data dating back to 1914. Figure 3-23 shows an aerial photograph of the site, along with the nearest weather station and active USGS gage.

3.6.3.1. *Temporal trends in Climatic and Biological Variables*

Since 1974, PRISM mean annual air temperatures at the Beaver River site (UT 5940440) have ranged from 5.8 to 9.4°C. Temperatures have varied from year to year, but overall, have

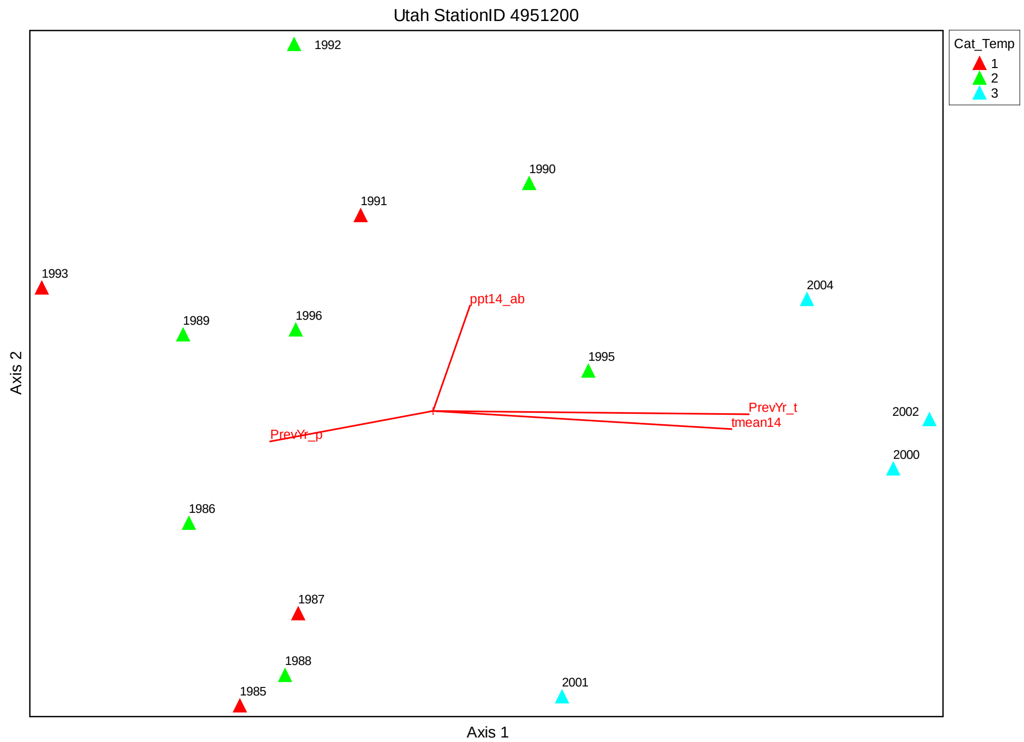

Figure 3-21. NMDS plot (Axis 1-2) for the Virgin River site (UT 4951200). Cat_Temp refers to the temperature categories, which are 1 = cold years; 2 = normal years; 3 = hot years. Samples are labeled by collection year. tmean14 = PRISM mean annual air temperature from the year the sample was collected, PrevYr_t = PRISM mean annual air temperature from the year prior to sample collection, ppt14_ab = absolute difference between the PRISM mean annual precipitation value from the year of the sample collection and the year prior, and PrevYr_p = PRISM mean annual precipitation from the year prior to sample collection.

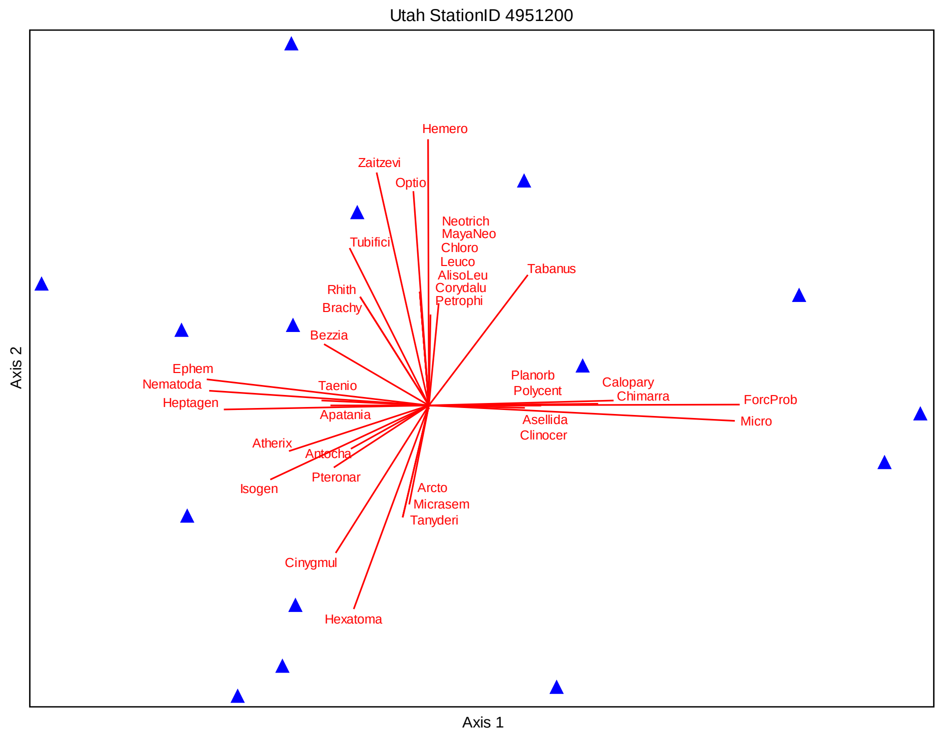

Figure 3-22. NMDS plot (Axis 1-2) for Utah Station 4951200 (Virgin) that shows which taxa are most highly correlated with each axis.

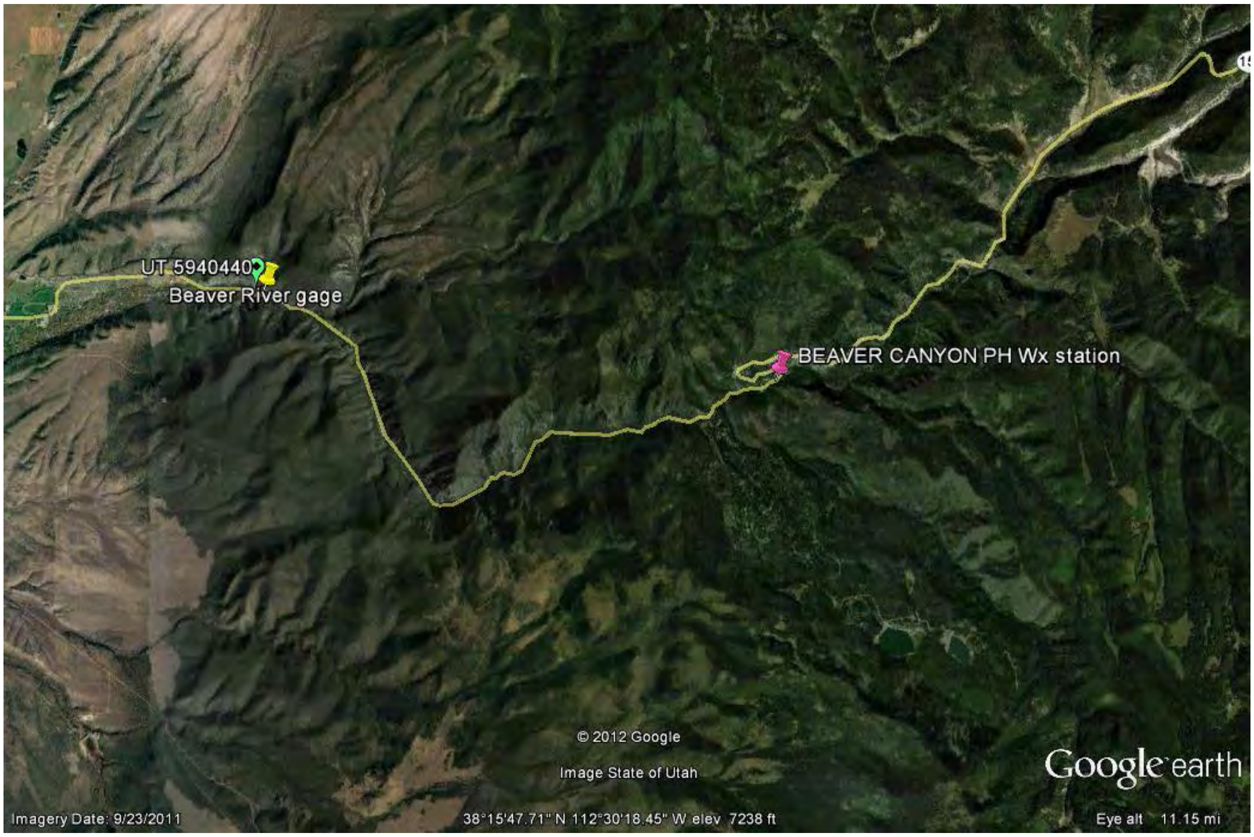

Figure 3-23. Locations of the Beaver River (UT 5940440) biological sampling site, Beaver River USGS gage, and Beaver Canyon pH weather station. Image from Google Earth.

increased over time (when fit with a linear trend line, $r^2 = 0.52$, $p < 0.01$) (see Figure 3-24). When observed air temperature data from the nearest weather station (available starting in 1997) are compared to PRISM data, there is close overlap, with less than a 1°C difference in values (see Figure 3-24). Mean annual flow and mean annual precipitation patterns have been highly variable over time (see Figure 3-25). Since 1914, mean annual flow values have ranged from 16 to 122 cfs (when fit with a linear trend line, $r^2 = 0.01$, $p = 0.26$). Precipitation patterns generally show good correspondence with flow patterns (see Figure 3-11).

During the period of biological record (1996−2005), mean maximum July air temperatures ranged from 26.5−31.1°C, and mean fall flow values ranged from 20.5 to 100.7 cfs (see Table 3-24). O/E scores have fluctuated over time, ranging from 0.73 to 1.06 (see Figure 3-26A). HBI scores were also variable (see Figure 3-26B); because the HBI is calculated based on abundance data (vs. relative abundance data), trends in this metric should be interpreted with caution due to reasons cited in Section 3.2. The highest number of EPT taxa occurred in 1996, then declined and remained at lower levels through 2005 (see Figure 3-26B). The drop in EPT taxa in 1997 and 1998 corresponded with higher than normal fall flows and only low to average July temperatures (see Figure 3-26C). In 2002 and 2003, conditions were hotter and drier than normal. During this time, the percentage of cold-water individuals metric dropped to its lowest levels (3−5%) (see Figure 3-27B). No warm-water taxa were present at this site.

From 1996−2005, water chemistry parameter values[4] were within the following ranges:

- DO: 9.1 to 10.8 mg/L
- pH: 8.1 to 8.6
- Chloride: 3.5 to 83.2 mg/L
- Nitrite (NO_2) + nitrate (NO_3): 0.07 to 0.69 mg/L
- Total phosphorus: 0.03 to 0.07 mg/L
- Specific conductance: 107 to 153 µmho/cm
- Turbidity: 2.3 to 6.3 NTU
- Aluminum: 56.4 to 500 µg/L

[4]Up to four samples were collected per year; the values shown here represent an average of these samples.

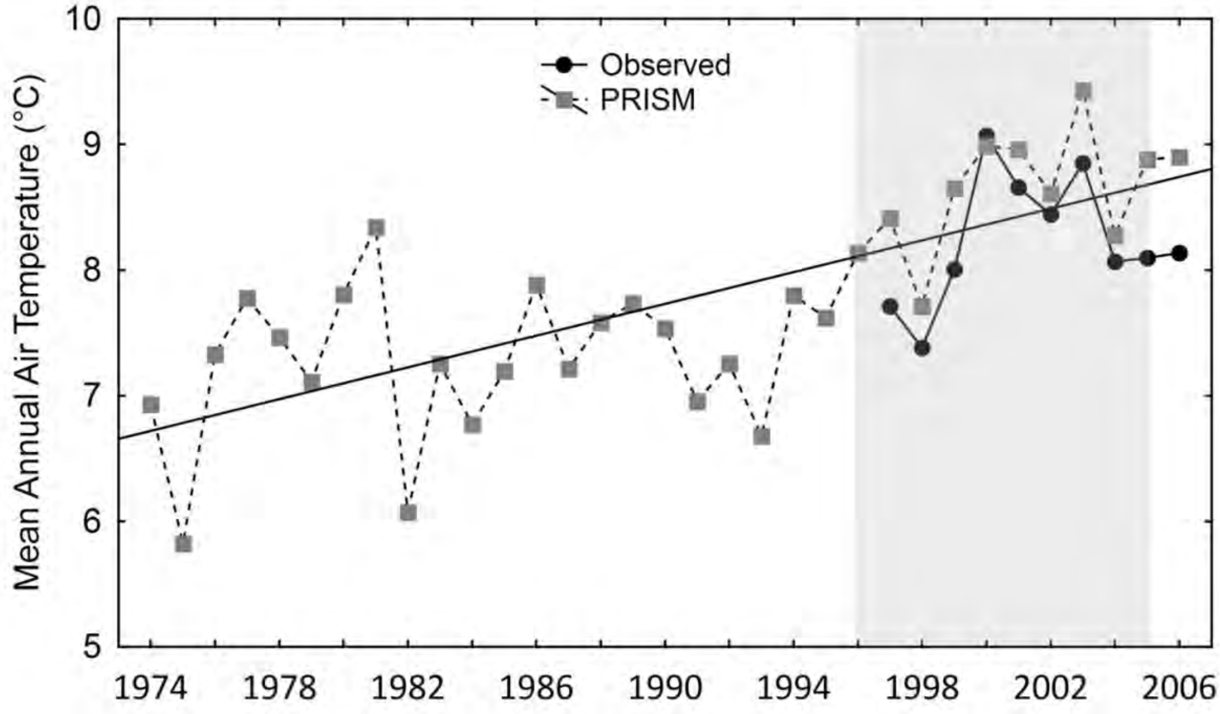

Figure 3-24. Yearly trends in PRISM annual air temperature data associated with the Beaver River site (UT 5940440) from 1975–2005. Also included are annual observed air temperature (°C) data from 1997–2006 based on data from the Beaver Canyon PH weather station. The area shaded in grey corresponds to the period of biological record. When the PRISM data are fitted with a linear trend line, $r^2 = 0.52$, $p < 0.01$, and $y = 0.0632x + 6.6556$.

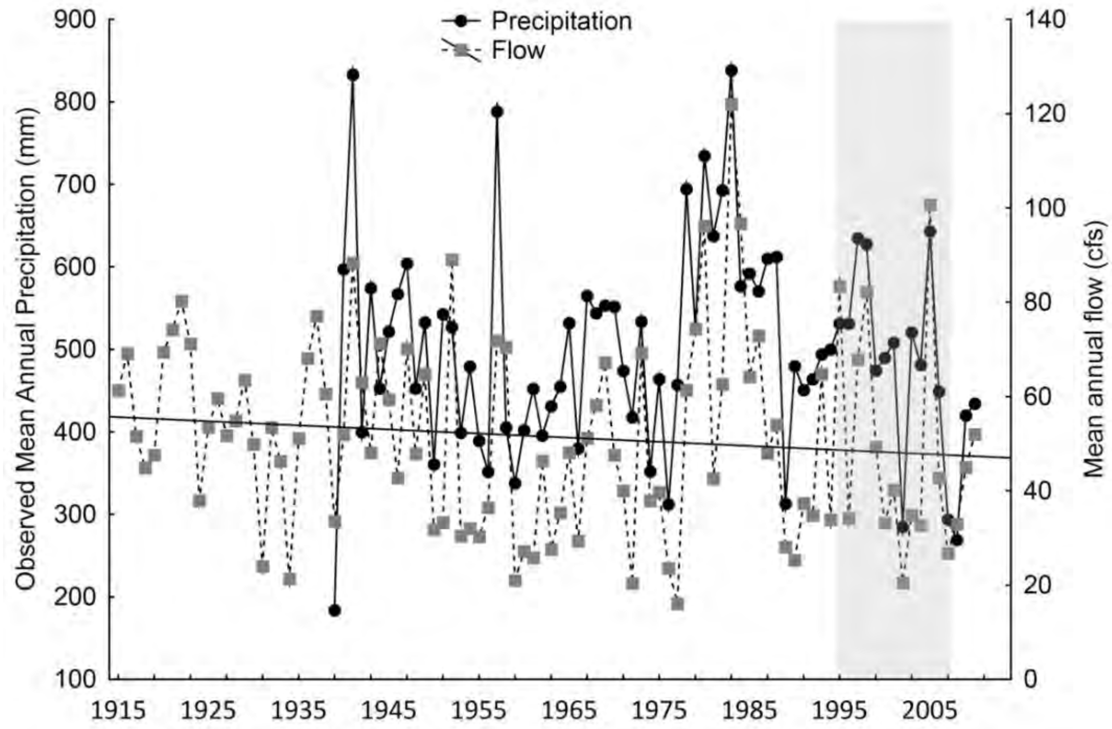

Figure 3-25. Yearly trends in mean annual flow (cfs) from 1914–2011, based on data from USGS gage 10234500. For comparative purposes, observed annual precipitation data from the Beaver Canyon PH weather station are also included from 1939–2010. The area shaded in grey corresponds to the period of biological record. When the observed data are fitted with a linear trend line, $r^2 = 0.01$, $p = 0.26$, and $y = -0.0875x + 55.707$.

Table 3-24. Range of temperature, precipitation, and flow values that occurred at the Beaver River site (UT 5940440) during the period of biological record

Parameter	Min	Max
Year	1996	2005
PRISM mean annual air temperature (°C)	7.7	9.4
Observed mean maximum July air temperature (°C)	26.5	31.1
PRISM mean annual precipitation (mm)	16.8	39.1
Mean annual flow (cfs)	189.9	438.1
Mean SON flow (cfs)	20.5	100.7

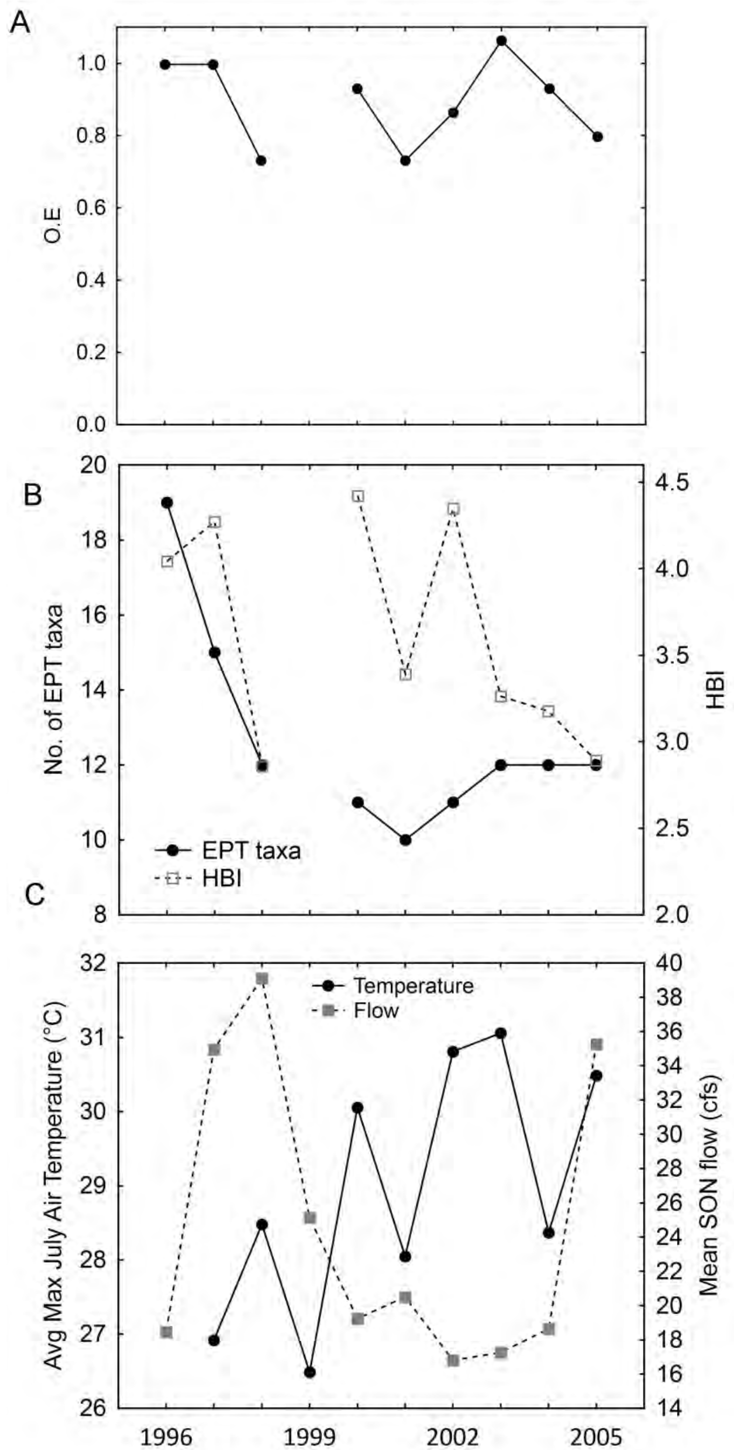

Figure 3-26. Yearly trends at the Beaver River site (UT 5940440) in (A) O/E, (B) number of EPT taxa and HBI; (C) mean maximum July temperature (°C) and mean September/October/November (SON) flow (cfs).

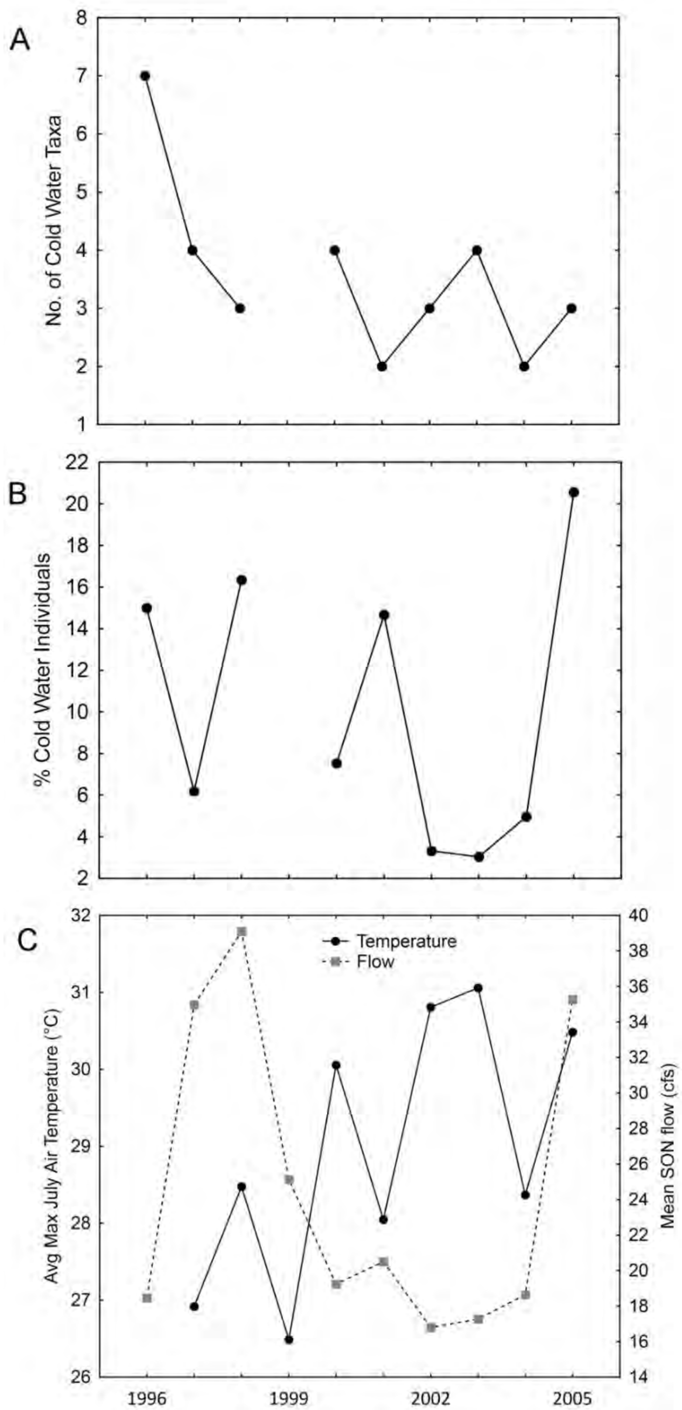

Figure 3-27. Yearly trends at the Beaver River site (UT 5940440) in (A) number of cold and warm-water taxa; (B) percentage cold and warm-water individuals; and (C) mean maximum July temperature (°C) and mean September/October/November (SON) flow (cfs).

Two potential confounding factors related to water chemistry were evident during the time period for which biological data were available. In 2004, chloride concentrations spiked to 83.3 mg/L. In years prior, on average, chloride concentrations had been approximately 5 µg/L. Aluminum concentrations also occurred in high levels during the biological sampling period. In 1999, the concentration hit a high of 500 µg/L, up from 88.5 µg/L in 1996. By 2002, aluminum concentrations had decreased back to levels ranging from 56 to 122 µg/L.

3.6.3.2. *Associations Between Biological Variables and Climatic Variables*

Kendall tau nonparametric correlations analyses were performed to examine associations between 13 commonly used biological metrics, year, temperature, flow, and precipitation variables at the Beaver River site (UT 5940440). Only two of the biological metrics showed strong associations with the environmental variables. The number of Plecoptera taxa metric had a strong negative association with PRISM mean annual air temperature ($r = -0.65$), and percentage Ephemeroptera individuals was positively correlated with mean annual flow ($r = 0.56$) (see Table 3-25). When similar analyses were performed on the cold-water taxa metrics, the percentage cold-water individuals metric showed a strong positive association with mean annual and mean fall flow ($r = 0.56$) (see Table 3-26).

The biological metrics shown in Table 3-27 have shown responsiveness to hydrologic variables in other studies (see Section 2, Table 2-2). Five of the six metrics that showed strong associations with the flow or precipitation variables at this site went against expectations. The scraper/herbivore richness metric was negatively correlated with flow and precipitation variables, and the percentage predator and swimmer composition metrics had strong positive associations with mean annual flow ($r = 0.61$ and $r = 0.50$, respectively). The one metric that showed a strong association that was in keeping with expectations was the swimmer richness metric. However, this relationship should be interpreted with caution because only one to two swimmer taxa occurred in the samples that were analyzed. Depositional taxa were not present at this site.

3.6.3.3. *Groupings Based on Climatic Variables*

Samples were partitioned into hottest/coldest/normal year groups and lowest/normal/highest flow year groups. At the Beaver River site (UT 5940440), on average, the

Table 3-25. Kendall tau nonparametric correlations analyses performed to examine associations between commonly used biological metrics, year, and climatic variables at the Beaver River site (UT 5940440). Results are based on 9 years of data. Entries are in bold text if *r* ≥ ±0.5. Ranges of biological metric values are also included. SON = September, October, November. Per reasons cited in Section 3.2, results for the HBI and Shannon-Wiener Diversity Index should be interpreted with caution because they are calculated based on abundance data (vs. relative abundance data)

	Range of metric values		*r* values (based on Kendall tau correlations)					
				Air temperature (°C)		Flow (cfs)		PRISM mean annual precipitation (mm)
Biological metric	Min	Max	Year	PRISM mean annual	Observed mean maximum July	Mean annual	Mean SON	
Total no. taxa	16.0	31.0	–0.26	–0.15	0.11	–0.20	–0.38	–0.15
No. EPT taxa	10.0	19.0	–0.28	–0.40	–0.12	0.15	0.03	0.28
No. Ephemeroptera taxa	3.0	7.0	–0.23	–0.17	0.05	–0.17	–0.30	–0.03
No. Plecoptera taxa	2.0	6.0	–0.46	**–0.65**	–0.27	0.26	0.20	0.26
No. Trichoptera taxa	4.0	6.0	–0.10	–0.03	0.05	–0.03	–0.17	0.03
No. intolerant taxa	9.0	19.0	–0.35	–0.35	–0.15	–0.06	–0.12	0.12
Percentage EPT individuals	28.9	78.2	0.28	0.00	0.14	0.56	0.33	0.11
Percentage Ephemeroptera individuals	22.1	76.0	0.28	0.00	0.07	**0.56**	0.22	0.00
Shannon-Wiener Diversity Index	1.9	3.3	–0.06	–0.33	–0.07	–0.22	–0.22	–0.11
Percentage noninsect individuals	0.6	18.1	0.11	–0.06	0.07	0.39	0.06	0.17
Percentage dominant taxon	19.4	55.1	0.28	0.22	0.14	0.33	0.22	0.00
Percentage tolerant individuals	0.0	2.1	–0.40	–0.04	0.05	–0.04	–0.25	–0.11
Hilsenhoff Biotic Index	2.9	4.4	–0.33	0.28	–0.07	–0.39	–0.39	–0.28

Table 3-26. Kendall tau nonparametric correlations analyses performed to examine associations between thermal preference metrics, year, and climatic variables at the Beaver River site (UT 5940440). No warm-water taxa were present at this site. Results are based on 9 years of data. Entries are in bold text if $r \geq \pm 0.5$. Ranges of biological metric values are also included. SON = September, October, November

Biological metric	Range of metric values		*r* values (based on Kendall tau correlations)					
				Air temperature (°C)		Flow (cfs)		PRISM mean annual precipitation (mm)
	Min	Max	Year	PRISM mean annual	Observed mean maximum July	Mean annual	Mean SON	
No. cold-water taxa	2.0	7.0	–0.46	0.03	0.29	–0.03	–0.15	0.03
Percentage cold-water individuals	3.0	20.6	–0.17	–0.33	–0.21	**0.56**	**0.56**	0.44
No. warm-water taxa	0.0	0.0	--	--	--	--	--	--
Percentage warm-water individuals	0.0	0.0	--	--	--	--	--	--

Table 3-27. Kendall tau nonparametric correlations analyses performed to examine associations between a subset of biological metrics, year, flow, and precipitation variables at the Beaver River site (UT 5940440). The subset of biological metrics were selected per the criteria outlined in Section 2 and have shown responsiveness to hydrologic variables in other studies (see Section 2, Table 2-2). Results are based on 9 years of data. Entries are in bold text if *r* ≥ ±0.5 and are highlighted in gray if they are in a direction opposite of what is expected. Ranges of biological metric values are also included. Depositional taxa were not present at this site. SON = September, October, November

Biological metric		Range of metric values		*r* values (based on Kendall Tau correlations)			
					Flow (cfs)		PRISM mean annual precipitation (mm)
		Min	Max	Year	Mean annual	Mean SON	
Richness	Collector filterer	2.0	4.0	–0.22	–0.15	–0.15	–0.07
	Collector gatherer	4.0	10.0	–0.22	–0.09	–0.34	–0.09
	Scraper/herbivore	2.0	5.0	–0.03	**–0.57**	**–0.70**	**–0.57**
	Predator	3.0	7.0	0.03	0.17	0.10	0.17
	Swimmer	1.0	2.0	–0.07	–0.45	**–0.60**	–0.37
	OCH	2.0	3.0	0.24	0.00	–0.35	–0.35
	Depositional	0.0	0.0	--	--	--	--
	Erosional	5.0	9.0	–0.15	–0.03	–0.15	0.03
Percentage individuals	Collector filterer	1.4	25.1	0.17	–0.22	–0.11	0.00
	Collector gatherer	50.7	78.5	0.00	0.17	0.17	0.06
	Scraper/herbivore	0.7	19.7	–0.39	–0.44	–0.33	–0.33
	Predator	2.5	19.2	0.00	**0.61**	0.39	0.39
	Swimmer	15.5	55.1	0.22	**0.50**	0.28	0.06
	OCH	3.1	25.9	–0.44	0.06	–0.17	–0.17
	Depositional	0.0	0.0	--	--	--	--
	Erosional	4.7	43.3	0.00	–0.17	–0.28	–0.17

hottest years were 1°C warmer than the coldest years, and highest flow years had approximately 55 more cfs of flow than lowest flow years. When samples were grouped based on temperature and flow, there were differences between mean metric values. Mean metric values for total number of taxa, number of EPT taxa, and the cold water metrics were highest in the coldest year samples (see Table 3-28), and percentage of cold-water individuals was lowest in the driest flow year samples (see Table 3-29). None of the differences across year groups were significant ($p > 0.05$). No NMDS ordinations were conducted at this site due to insufficient sample size.

3.6.4. Duchesne River (UT 4936750)

The Duchesne River site (UT 4936750) is located in the Colorado Plateaus/Semiarid Benchlands and Canyonlands ecoregion. It has a drainage area of 490 km^2 and is at an elevation of 2,124 m. Its highest maximum monthly temperatures occur during July, and its lowest average flows (≤20 cfs) occur from September through March. This station has 14 years of data, ranging from 1985−2002. When limited to fall samples only, 12 years of data are available. Temperature and precipitation data dating from 1906 to 2010 were gathered from the Duchesne weather station (SiteID 422253, Latitude: 40.1678, Longitude: 110.395), which is located approximately 50 km southeast of the biological sampling site. Three months of data were missing in 1906, so we used 1907 as the start date for our analyses. Flow data from 1990−2002 were gathered from USGS gage 927660 (W. F. Duchesne River above North Fork, near Hanna, Latitude: 40.46161, Longitude: 110.83683), which is located on a tributary approximately 0.6 km west of the biological sampling site. Figure 3-28 shows an aerial photograph of the site, along with the nearest weather station and active USGS gage.

3.6.4.1. *Temporal Trends in Climatic and Biological Variables*

Since 1907, observed mean annual air temperatures at the Duchesne River site (UT 4936750) have ranged from 4.7 to 10.6°C. There is a lot of year-to-year variability, but overall, temperatures have increased slowly over time (when fit with a linear trend line, $r^2 = 0.15$, $p < 0.01$) (see Figure 3-29). When PRISM air temperature data are compared to observed data, patterns are generally similar, but the PRISM temperatures are 1.4−4.5°C lower than the observed values, perhaps due to the differences in the locations and elevations of the weather station and biological sampling site, which are 50 km apart.

Table 3-28. Mean metric values (±1 SD) for the Beaver River site (UT 5940440) in coldest, normal, and hottest year samples. Year groups are based on PRISM mean annual air temperature values. One-way ANOVA was done to evaluate differences in mean metric values. No entries are significantly different ($p < 0.05$) across year groups

Year group	O/E	Total no. taxa	No. EPT taxa	No. cold-water taxa	No. warm-water taxa	% Cold-water individuals	% Warm-water individuals
Coldest	0.9 ± 0.1	23.0 ± 7.0	14.3 ± 4.0	4.0 ± 2.6	--	12.1 ± 6.2	--
Normal	0.9 ± 0.1	20.0 ± 2.6	12.7 ± 2.1	3.3 ± 0.6	--	10.0 ± 9.2	--
Hottest	0.9 ± 0.2	19.3 ± 3.5	11.0 ± 1.0	3.3 ± 1.2	--	8.4 ± 5.9	--

Table 3-29. Mean metric values (±1 SD) for the Beaver River site (UT 5940440) in driest, normal, and wettest flow year samples. Year groups are based on mean annual flow. One-way ANOVA was done to evaluate differences in mean metric values. No entries are significantly different ($p < 0.05$) across year groups

Year group	O/E	Total no. taxa	No. EPT taxa	No. cold-water taxa	No. warm-water taxa	% Cold-water individuals	% Warm-water individuals
Driest	0.9 ± 0.04	19.3 ± 0.6	11.3 ± 0.6	3.0 ± 1.0	--	5.3 ± 2.1	--
Normal	0.9 ± 0.2	23.3 ± 7.5	13.7 ± 4.7	4.3 ± 2.5	--	10.9 ± 6.8	--
Wettest	0.8 ± 0.1	19.7 ± 2.9	13.0 ± 1.7	3.3 ± 0.6	--	14.4 ± 7.4	--

Figure 3-28. Locations of the Duchesne River (UT 4936750) biological sampling site, W.F. Duchesne River USGS gage and Duchesne weather station. Image from Google Earth.

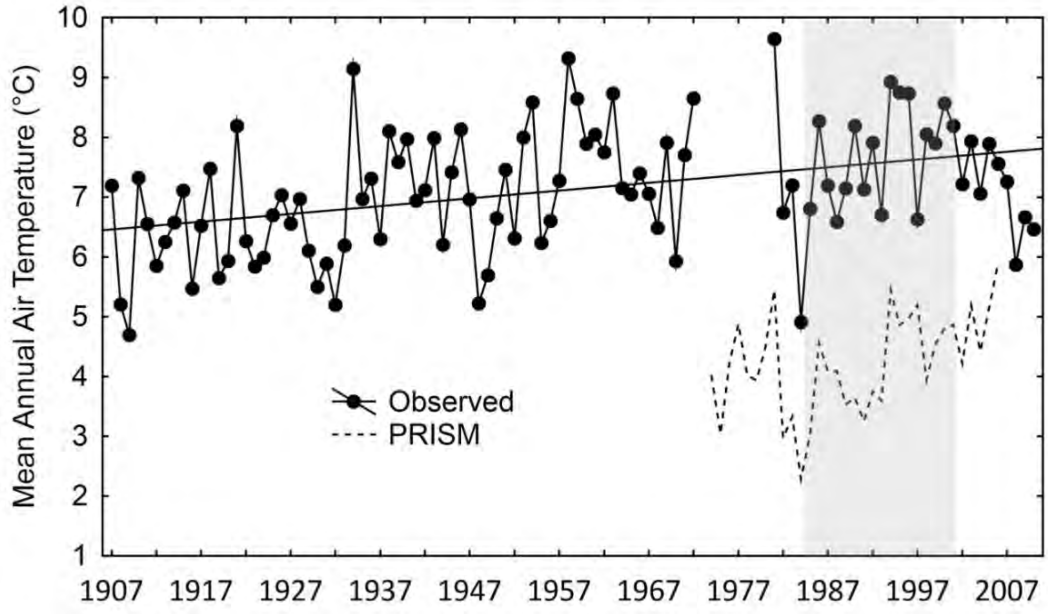

Figure 3-29. Yearly trends in annual observed air temperature (°C) from 1906–2010, based on data from the Duchesne weather station (1973–1980 were excluded due to missing data). For comparative purposes, PRISM annual air temperature data associated with the biological sampling site are also included from 1975–2005. The area shaded in grey corresponds to the period of biological record. When the observed data are fitted with a linear trend line, $r^2 = 0.15$, $p < 0.01$, and $y = 6.4434 + 0.013 \times x$.

Because flow data are not available for most of the biological sampling period, precipitation data were used as a surrogate. Since 1906, observed mean precipitation values have ranged from 120 to 462 mm. There is a great deal of year-to-year variability (when fit with a linear trend line, $r^2 = 0.00$, $p = 0.57$) (see Figure 3-30). When PRISM precipitation data are compared to observed data, patterns are generally similar, but the PRISM values are 20−175 mm higher than the observed values (see Figure 3-30).

During the period of biological record (1985−2001), mean maximum July air temperatures ranged from 28.6−32.5°C, and mean fall flow values ranged from 10.6 to 30.3 cfs (see Table 3-30). O/E scores have fluctuated over time, ranging from 0.64 to 1.07. In the late 1980s, O/E scores remained around 0.7, then increased in the early 1990s, ranging from to 0.8 to 1.0 (see Figure 3-31A). HBI scores were also variable (see Figure 3-31B); because the HBI is calculated based on abundance data (vs. relative abundance data), trends in this metric should be interpreted with caution due to reasons cited in Section 3.2. The number of EPT taxa also

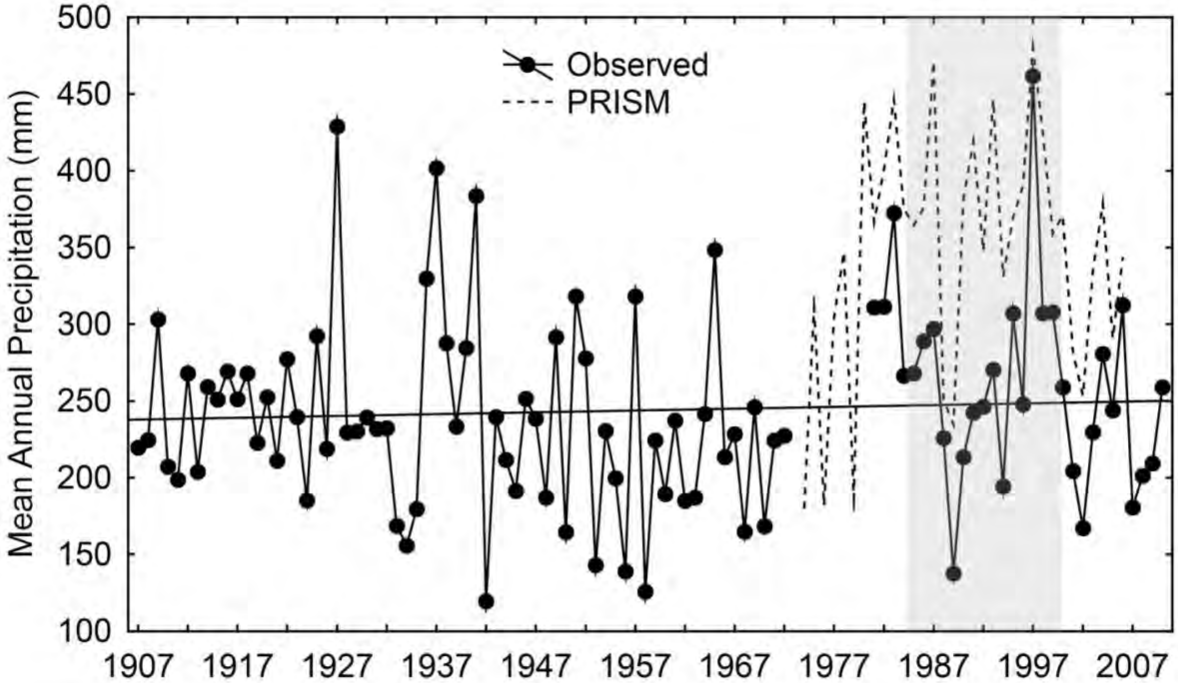

Figure 3-30. Yearly trends in mean annual precipitation (mm) from 1906−2011, based on data from the Duchesne weather station (1973–1980 were excluded due to missing data). For comparative purposes, PRISM annual precipitation data associated with the biological sampling site are also included from 1975–2005. The area shaded in grey corresponds to the period of biological record. When the observed data are fitted with a linear trend line, $r^2 = 0.00$, $p = 0.57$, and $y = 9.0483 + 0.12 \times x$.

Table 3-30. Range of temperature, precipitation, and flow values that occurred at the Duchesne River site (UT 4936750) during the period of biological record

Parameter	Min	Max
Year	1985	2001
PRISM mean annual air temperature (°C)	3.0	5.5
Observed mean maximum July air temperature (°C)	28.6	32.5
Mean annual flow (cfs)	15.3	61.7
Mean SON flow (cfs)	10.6	30.3
PRISM mean annual precipitation (mm)	234.7	480.5
Observed mean SON precipitation (mm)	7.2	42.7

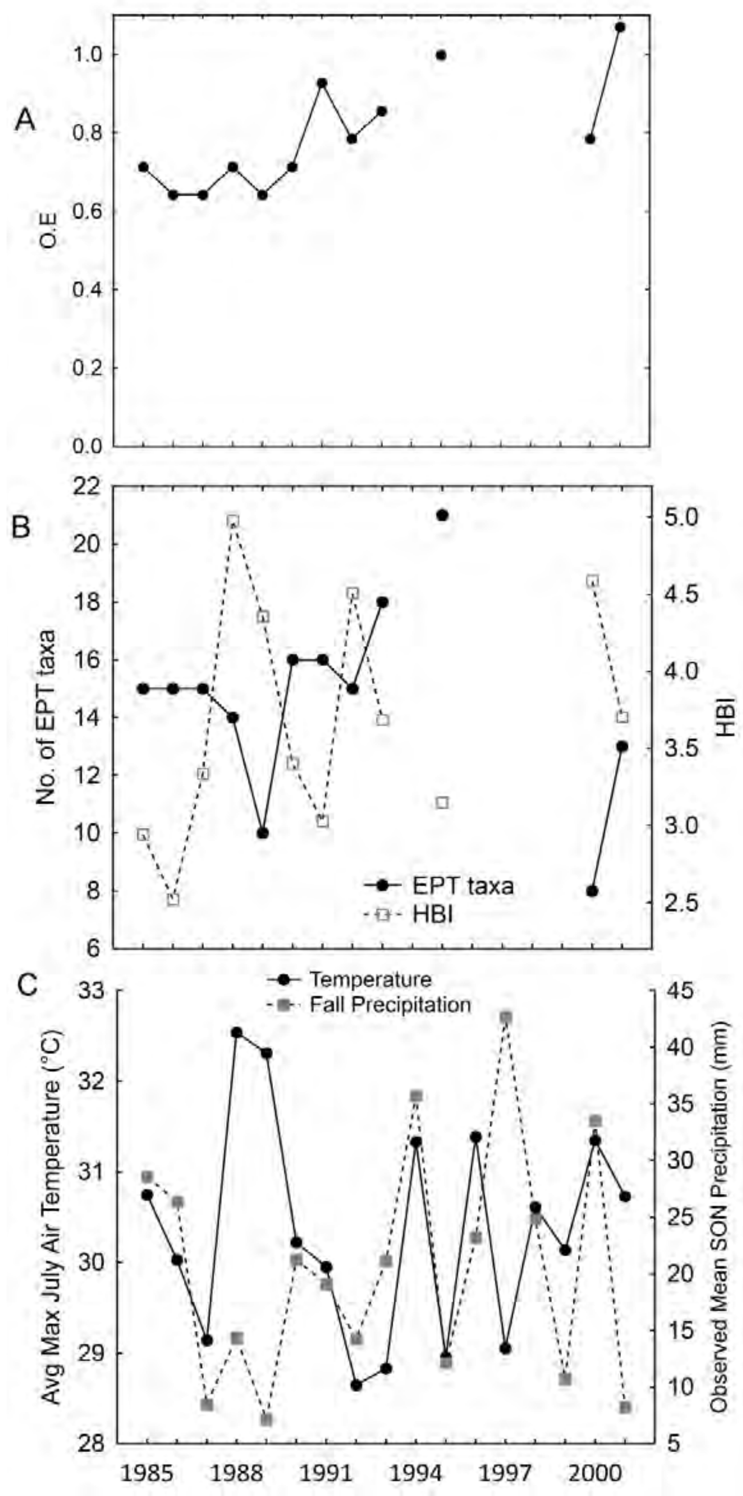

Figure 3-31. Yearly trends at the Duchesne River site (UT 4936750) in (A) O/E, (B) number of EPT taxa and HBI; (C) mean maximum July temperature (°C) and observed mean September/October/November (SON) precipitation (mm).

fluctuated over time. Numbers dropped in 1989, which was a year during which mean maximum July temperatures were higher than normal and precipitation levels were lower than normal (see Figures 3-31B and C). EPT richness values increased to a high of 21 in 1995, before dropping again in 2000. The year 1999 was drier than normal, which may have impacted the assemblage in 2000. The cold-water taxa metric values also fluctuated over time. Numbers of cold-water taxa were lowest in 2000 and 2001 (see Figure 3-32A), while percentage cold-water individuals was variable over time (see Figure 3-32B). Very few warm-water taxa occurred at this site.

From 1985−2001, water chemistry parameter values[5] were within the following ranges:

- DO: 8.6 to 11.7 mg/L
- pH: 7.1 to 8.5
- Chloride: 1.6 to 30 mg/L
- Nitrite (NO_2) + nitrate (NO_3): 0.1 to 2.44 mg/L
- Total phosphorus: 0.01 to 0.06 mg/L
- Specific conductance: 237 to 427 µmho/cm
- Turbidity: 0.4 to 6 NTU

There may have been potential confounding factors related to water chemistry in 1993 and 1994. In 1993, concentrations of nitrite + nitrate reached a high of 2.44 mg/L. In other years, nitrite + nitrate concentrations averaged 0.2 mg/L. In 1994, turbidity, total suspended solids, chloride, and sulfate concentrations were higher than normal.

3.6.4.2. *Associations Between Biological Variables and Climatic Variables*

Kendall tau nonparametric correlations analyses were performed to examine associations between 13 commonly used biological metrics, year, temperature, and precipitation variables at the Duchesne River site (UT 4936750). Five metrics (total number of taxa, number of EPT taxa, number of Trichoptera taxa, Shannon-Wiener Diversity Index, and percentage tolerant individuals) had strong negative associations with the observed mean maximum July temperature

[5] Up to four samples were collected per year; the values shown here represent an average of these samples.

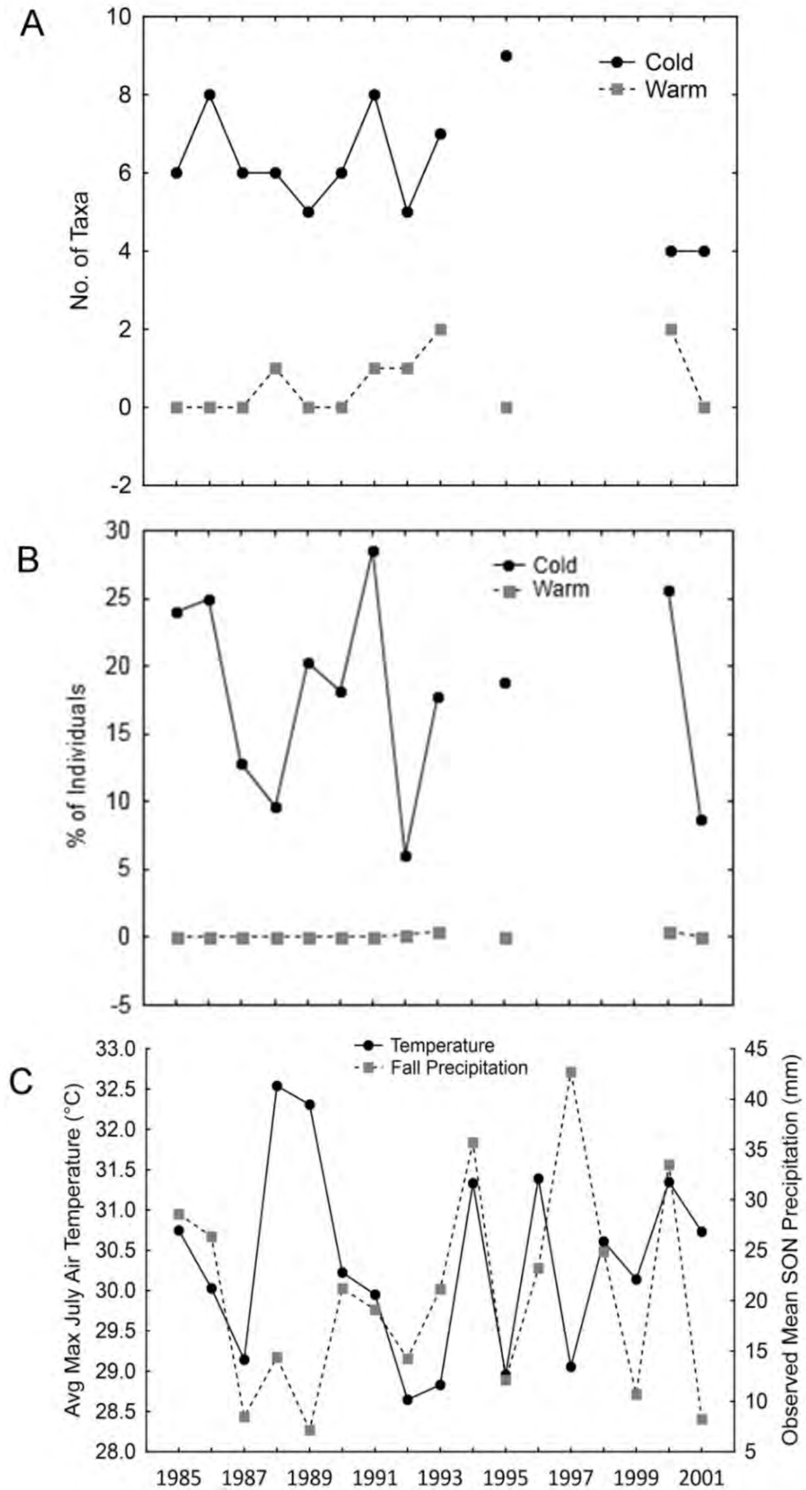

Figure 3-32. Yearly trends at the Duchesne River site (UT 4936750) in (A) number of cold and warm-water taxa; (B) percentage cold and warm-water individuals; and (C) mean maximum July temperature (°C) and observed mean September/October/November (SON) precipitation (mm).

(see Table 3-31). These relationships are as would be expected except for the abundance of tolerant taxa, which are expected to increase with increasing temperature (see Table 2-2). Though counter to expectation, the relationship between percentage tolerant individuals and temperature should be interpreted with caution because only 1 to 2 percentage of the assemblage was composed of tolerant individuals. Also, because the Shannon-Wiener Diversity Index is calculated based on abundance data (vs. relative abundance data), results for this metric should be interpreted with caution due to reasons cited in Section 3.2. There were no strong associations between the thermal preference metrics and temperature or precipitation variables (see Table 3-32).

The biological metrics shown in Table 3-33 have shown responsiveness to hydrologic variables in other studies (see Section 2, Table 2-2). Two of these metrics had strong associations with precipitation variables, and both associations were in keeping with expectations. The scraper/herbivore richness metric was positively correlated with PRISM mean annual precipitation, and the percentage swimmer individual metric was negatively correlated with mean fall precipitation. One metric, OCH richness, showed a strong positive association with year, but this relationship should be interpreted with caution because very few (0 to 2) OCH taxa occurred at this site.

3.6.4.3. *Groupings Based on Climatic Variables*

Samples were partitioned into hottest/coldest/normal year groups and driest, normal, and wettest year groups. At the Duchesne River site (UT 4936750), on average, the hottest years were 1°C warmer than the coldest years, and wettest years had approximately 150 more millimeters of precipitation than driest years. When samples were grouped based on temperature and precipitation, there were differences between mean metric values. Mean O/E values were highest in the hottest year samples, and the mean value of the percentage of cold-water individuals metric was highest in the coldest year samples (see Table 3-34). Mean values of the warm-water taxa metrics were lowest in the coldest year samples, but this relationship should be interpreted with caution because warm-water taxa occurred in very low numbers at this site (see Table 3-34). Mean numbers of total taxa and EPT taxa were highest in the wettest year samples (see Table 3-35). None of the differences across year groups were significant ($p > 0.05$). No NMDS ordination was performed at this site due to insufficient sample size.

Table 3-31. Kendall tau nonparametric correlations analyses performed to examine associations between commonly used biological metrics, year, and climatic variables at the Duchesne River site (UT 4936750). Results are based on 12 years of data. Entries are in bold text if *r* ≥ ±0.5 and are highlighted in gray if they are in a direction opposite of what is expected. Ranges of biological metric values are also included. SON = September, October, November. Per reasons cited in Section 3.2, results for the HBI and Shannon-Wiener Diversity Index should be interpreted with caution because they are calculated based on abundance data (vs. relative abundance data)

Biological metric	Range of metric values		*r* values (based on Kendall Tau correlations)				
				Air temperature (°C)		Precipitation (mm)	
	Min	Max	Year	PRISM mean annual	Observed mean maximum July	PRISM mean annual	Observed mean SON
Total no. taxa	17.0	34.0	0.34	–0.09	**–0.56**	0.28	–0.09
No. EPT taxa	8.0	21.0	0.05	–0.18	**–0.53**	0.46	0.08
No. Ephemeroptera taxa	3.0	8.0	0.13	–0.19	–0.29	0.29	–0.03
No. Plecoptera taxa	1.0	6.0	–0.29	0.19	–0.25	0.22	0.05
No. Trichoptera taxa	4.0	8.0	0.05	–0.02	**–0.73**	0.28	0.02
No. Intolerant taxa	7.0	16.0	–0.30	0.05	–0.14	0.21	0.11
Percentage EPT individuals	19.8	65.0	–0.21	–0.06	–0.06	0.21	–0.06
Percentage Ephemeroptera individuals	1.6	38.3	0.00	–0.15	–0.09	0.12	–0.27
Shannon-Wiener Diversity Index	2.0	3.7	0.12	–0.03	**–0.52**	0.30	–0.21
Percentage noninsect individuals	0.8	7.8	–0.06	–0.21	–0.21	–0.18	–0.27
Percentage dominant taxon	21.1	67.7	–0.18	–0.15	0.39	–0.24	0.33
Percentage tolerant individuals	0.0	2.0	0.22	–0.10	**–0.54**	0.35	–0.03
Hilsenhoff Biotic Index	2.5	5.0	0.30	0.15	0.21	–0.30	–0.21

Table 3-32. Kendall tau nonparametric correlations analyses performed to examine associations between thermal preference metrics, year, and climatic variables at the Duchesne River site (UT 4936750). Results are based on 12 years of data. Entries are in bold text if *r* ≥ ±0.5. Ranges of biological metric values are also included. SON = September, October, November

Biological metric	Range of metric values		*r* values (based on Kendall Tau correlations)				
				Air Temperature (°C)		Precipitation (mm)	
	Min	Max	Year	PRISM mean annual	Observed mean maximum July	PRISM mean annual	Observed mean SON
No. cold-water taxa	4.0	9.0	–0.21	–0.11	–0.31	0.31	0.11
Percentage cold-water individuals	6.1	28.5	–0.12	–0.21	0.15	0.12	0.39
No. warm-water taxa	0.0	2.0	0.37	–0.10	–0.10	0.13	0.33
Percentage warm-water individuals	0.0	0.5	0.39	–0.13	–0.17	0.17	0.28

Table 3-33. Kendall tau nonparametric correlations analyses performed to examine associations between a subset of biological metrics, year, flow, and precipitation variables at the Duchesne River site (UT 4936750). The subset of biological metrics were selected per the criteria outlined in Section 2 and have shown responsiveness to hydrologic variables in other studies (see Section 2, Table 2-2). Results are based on 12 years of data. Entries are in bold text if *r* ≥ ±0.5. Ranges of biological metric values are also included. SON = September, October, November

Biological metric		Range of metric values		*r* values		
					Precipitation (mm)	
		Min	Max	Year	PRISM mean annual	Observed mean SON
Richness	Collector filterer	1.0	5.0	0.19	0.09	–0.26
	Collector gatherer	3.0	8.0	0.34	0.08	–0.08
	Scraper/herbivore	2.0	7.0	–0.03	**0.57**	0.23
	Predator	6.0	12.0	–0.03	0.45	0.14
	Swimmer	0.0	3.0	0.06	–0.42	–0.22
	OCH	0.0	2.0	**0.77**	0.09	0.05
	Depositional	0.0	1.0	0.39	0.26	0.26
	Erosional	4.0	10.0	0.13	0.30	0.00
Percentage individuals	Collector filterer	1.9	32.1	–0.24	0.18	–0.09
	Collector gatherer	21.6	78.3	–0.06	–0.36	–0.03
	Scraper/herbivore	4.0	49.3	0.15	0.39	0.18
	Predator	2.0	9.7	–0.03	–0.27	–0.36
	Swimmer	0.0	23.3	0.12	–0.18	**–0.58**
	OCH	0.0	47.8	0.33	0.23	0.07
	Depositional	0.0	0.3	0.40	0.32	0.32
	Erosional	6.6	54.0	0.06	0.24	0.09

Table 3-34. Mean metric values (±1 SD) for the Duchesne River site (UT 4936750) in coldest, normal, and hottest year samples. Year groups are based on PRISM mean annual air temperature values. One-way ANOVA was done to evaluate differences in mean metric values. No entries are significantly different ($p < 0.05$) across year groups

Year group	O/E	Total no. taxa	No. EPT taxa	No. cold-water taxa	No. warm-water taxa	% Cold-water individuals	% Warm-water individuals
Coldest	0.8 ± 0.1	22.3 ± 6.1	13.7 ± 3.2	6.3 ± 1.5	0.3 ± 0.6	24.3 ± 4.1	0.03 ± 0.1
Normal	0.7 ± 0.1	25.7 ± 4.0	15.5 ± 1.4	6.3 ± 1.0	0.7 ± 0.8	14.9 ± 6.8	0.1 ± 0.2
Hottest	1.0 ± 0.1	24.3 ± 8.7	14.0 ± 6.6	5.7 ± 2.9	0.7 ± 1.2	17.7 ± 8.5	0.1 ± 0.2

Table 3-35. Mean metric values (±1 SD) for the Duchesne River site (UT 4936750) in driest, normal, and wettest year samples. Year groups are based on PRISM mean annual precipitation values. One-way ANOVA was done to evaluate differences in mean metric values. Groups with no superscripts are not significantly different ($p < 0.05$). Entries with superscripts have significant differences across groups; those entries with different superscripts are significantly different from each other (e.g., driest % cold-water individuals vs. normal % cold-water individuals)

Year group	O/E	Total no. taxa	No. EPT taxa	No. cold-water taxa	No. warm-water taxa	% Cold-water individuals	% Warm-water individuals
Driest	0.8 ± 0.2	20.7 ± 3.2	12.3 ± 2.1	5.0 ± 0.8	0.5 ± 0.6	11.2 ± 6.3^{A}	0.05 ± 0.1
Normal	0.8 ± 0.1	24.8 ± 6.1	15.0 ± 4.2	6.8 ± 2.2	0.5 ± 1.0	23.4 ± 3.1^{B}	0.10 ± 0.2
Wettest	0.8 ± 0.2	27.7 ± 5.1	16.3 ± 1.5	6.8 ± 0.9	0.8 ± 1.0	19.3 ± 6.6^{AB}	0.15 ± 0.3

3.7. SENSITIVITY OF BENTHIC MACROINVERTEBRATES TO TEMPERATURE, PRECIPITATION, AND STREAM FLOW

The spatial distributions of cold and warm-water taxa were examined to gain insights into which areas in Utah are likely to be most and least sensitive to projected changes in temperature and stream flow. If the assumption is made that streams with greater numbers and abundances of cold-water taxa will be most sensitive to warming temperatures and changing precipitation patterns, then streams in the higher elevation ecoregions, such as the Wasatch and Uinta Mountains, Southern Rockies, and Wyoming Basin, will be most sensitive. Table 3-36 shows differences in the distributions of thermal preference taxa between ecoregions. The prevalence and distribution of cold- and warm-water-preference taxa also vary predictably with stream order. First- and second-order streams in Utah have slightly greater relative abundance and richness of cold-water-preference taxa, and fewer warm-preference taxa, compared to third- or higher-order streams (see Figure 3-33). However, the four Utah sampling stations that had sufficient long-term data to analyze temporal trends were fourth to fifth order steams. Although the greatest number of cold-water taxa may occur in the coldest, highest elevation streams, it may be that the greatest amount of change will occur in transitional areas, where species are expected to be closer to their tolerance limits. Effects are likely to vary spatially. Poff et al. (2010) also concluded that sites will be differentially vulnerable to climate change.

3.8. IMPLICATIONS FOR UTAH DEQ'S BIOMONITORING PROGRAM

Over the last century in Utah, there has been a lot of year-to-year variability in temperature and precipitation patterns, both statewide and at the four long-term least disturbed biological monitoring sites that were closely examined. Air temperature has increased over time at all the sites, but change rates have differed depending on the location and the time period being examined. We assume that stream temperatures have followed similar patterns, although long-term continuous stream temperature data needed to test stream temperature trends is rare. Recognizing the value of such data, Utah is deploying some temperature data loggers, though only a few of these correspond to sites where repeated biological sampling occurs. Precipitation and flow patterns have been even more variable than temperature patterns over the last century. Some sites have shown a slight overall increase in mean annual flow or precipitation; at other sites, there has been a slight decrease. There is much uncertainty associated with future projections for precipitation.

Table 3-36. Summary of differences in elevation, PRISM mean annual air temperature and precipitation, and mean number and percentage of cold and warm-water-preference taxa across and within major ecoregions. Samples were not limited to a particular season

Ecoregion	No. samples	Elevation (m)	Air temperature (°C)	Richness		Relative abundance	
				Cold water	Warm water	Cold water	Warm water
Mojave basin and range	13	736.6	16.8	2.8 ± 2.4	1.3 ± 0.9	6.6 ± 8.9	5.5 ± 8.7
Central basin and range	177	1,411.7	10.0	1.4 ± 2.0	2.4 ± 1.4	2.1 ± 7.0	10.8 ± 16.5
Colorado plateaus	205	1,729.4	9.1	3.8 ± 2.8	1.2 ± 1.2	9.8 ± 11.5	6.1 ± 11.6
Northern basin and range	6	1,769.7	8.6	4.7 ± 1.0	1.2 ± 0.8	3.2 ± 2.9	12 ± 20.1
Wyoming basin	27	2,002.0	5.7	6.1 ± 4.0	1.3 ± 0.9	13.2 ± 13.2	1.1 ± 2.4
Wasatch and Uinta mountains	644	2,131.1	5.4	5.5 ± 4.0	1.0 ± 1.3	13.1 ± 15.4	3.8 ± 11.0
Southern Rockies	7	2,535.2	6.3	9.1 ± 0.7	0 ± 0	30.6 ± 14.6	0 ± 0

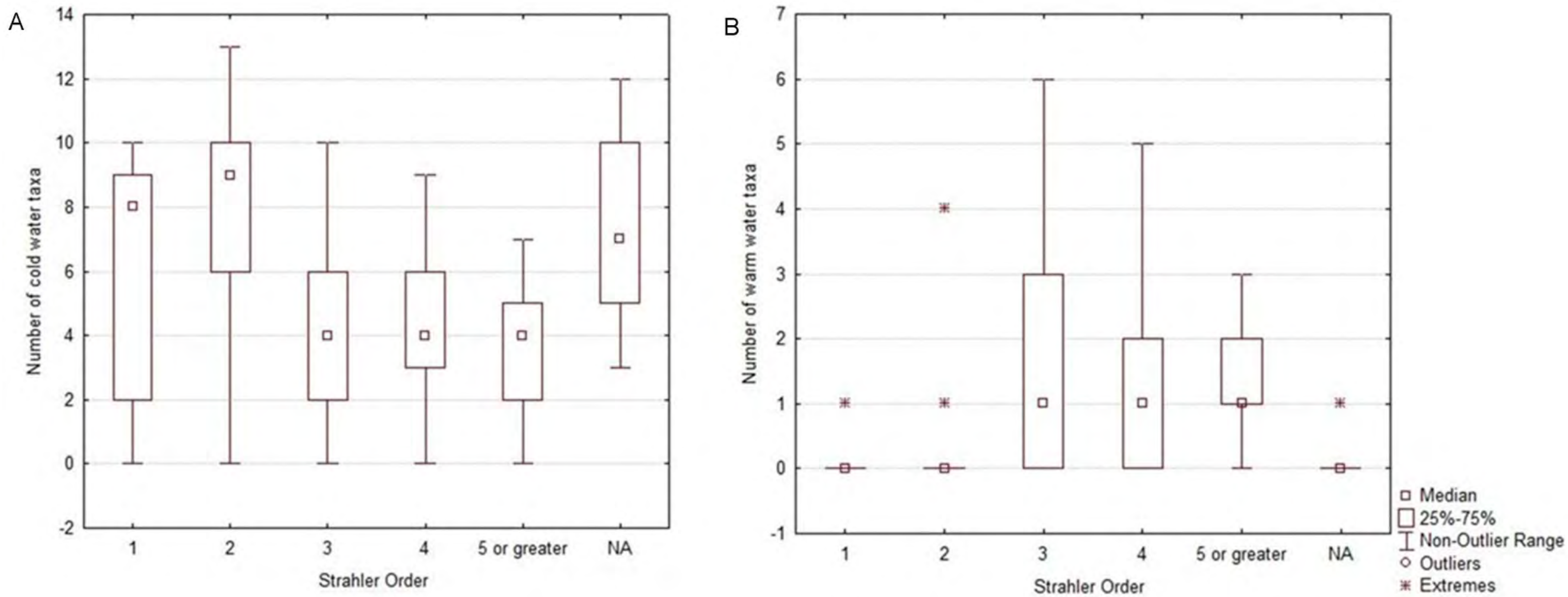

Figure 3-33. Distribution of cold- and warm-water taxa across Strahler Orders in Utah, based on fall (September–November) samples collected from 67 least-disturbed sites. (A) number of cold-water taxa; (B) number of warm-water taxa. Samples sizes are: first order = 11; second order = 29; third order = 22; fourth order = 41; fifth order or greater = 21; Strahler Order not available (NA) = 5.

At the four long-term biological sampling sites, O/E scores varied across years, but generally did not show strong associations with temperature, precipitation, or flow variables. At the Duchesne River site (UT 4936750), O/E scores were, on average, slightly higher in hottest year samples, but this difference was not significant and did not occur at the other three sites. Associations between certain biological metrics and climatic variables were more evident and suggest that variables related to temperature and stream flow have influenced community composition over time, although this cannot be proven with observational data. The Plecoptera richness metric was negatively associated with mean annual air temperature at three of the sites, while total number of taxa, number of EPT taxa, number of Ephemeroptera taxa, number of intolerant taxa, and number of cold-water taxa had strong negative associations with temperature at two sites. Other metrics showed strong associations with temperature variables as well, but these associations only occurred at single sites. Aside from the Duchesne River (UT 4936750) site, biological metrics showed stronger associations with mean annual temperature than mean maximum July temperature. Although July temperatures represent a stressful period physiologically and may impact an organism directly, these results suggest that both summer and annual temperatures should be considered, as annual temperatures encompass a number of critical time periods in an organism's life cycle and are likely to both directly and indirectly impact the organisms.

When biological samples were grouped by hottest/coldest/normal years, there were significant differences between mean metric values for total number of taxa, number of EPT taxa and number of cold-water taxa at the Weber River site (UT 4927250) and at the Virgin River site (UT 4951200). On average, at both sites, there were seven to eight fewer total taxa and EPT taxa in hottest versus coldest year samples, and four fewer cold-water taxa in the hottest year samples. Because hottest year samples were, on average, about 2°C warmer than coldest year samples, comparisons across these year groups may provide good approximations of what types of climate-induced changes we can expect by midcentury. Similar patterns (albeit nonsignificant), were also evident at the Beaver River site (UT 5940440), where mean metric values for total number of taxa, number of EPT taxa, and cold-water taxa were highest in the coldest year samples.

Fewer biological metrics had strong associations with flow or precipitation variables, and when a strong association did occur, it was only at a single site. The lack of consistency across sites may have been due in part to the large amount of year-to-year variability in flow and precipitation patterns. Metrics that showed strong positive correlations with flow or precipitation variables included number of EPT taxa (Virgin River site—UT 4951200), percentage Ephemeroptera individuals (Beaver River site—UT 5940440), and percentage cold-water individuals (Beaver River site—UT 5940440). When biological samples were grouped by driest/wettest/normal years, total number of taxa, EPT taxa, and cold-water taxa were lowest in the driest year samples at the Duchesne River site (UT 4936750).

The fact that more biological metrics had strong associations with temperature variables than with precipitation or flow variables suggests that temperature may have a stronger influence on the biological assemblage than precipitation or flow. However, it is important to consider these climatic variables in combination. At various times at each of the four sites, there were years during which temperatures were higher than normal, and flow or precipitation values were lower than normal. These hotter drier conditions sometimes occurred over consecutive years, and generally seemed to correspond with declines in biological metrics, mainly total number of taxa, number of EPT taxa, and cold water metrics. This was evident at the Weber River (UT 4927250) and Virgin River (UT 4951200) sites.

In addition to the historic trend analyses, we also performed exploratory analyses to gain insights into how future projected climatic changes might impact Utah DEQ's assessment methods. In these exploratory analyses, the climate-related predictor variables that are used in the Utah fall RIVPACS models were manipulated in a way that would simulate future projected changes. When climate-related predictor variables were altered, there was very little effect on O/E values. The amount of change that did occur was within the range of natural variability (see Appendix B). Similar results were obtained when the model was rerun in a way that allowed for inclusion of rare taxa, and when extreme changes were made to the climate-related variables (i.e., doubling temperature, halving precipitation variables).

There are a number of possible reasons that the alterations to the climate-related predictor variables resulted in small changes to O/E values. For one, the analyses were based on reference site data, and reference sites are typically more stable than test sites. In addition, elevation was disregarded in the model manipulations. It might be informative to explore how manipulations of the elevation-related predictor variables affect O/E values, especially since elevation and temperature are linked. Another consideration is the assumption that climate-related predictor variables, which are typically based on long-term (30-year) averages, are relatively invariant over ecologically-relevant time. If climate change is going to be an important factor in years to come, it would be interesting to develop a second RIVPACS model that includes predictor variables based on current climate (not just the historic benchmark climate) and to compare O/E values across these models over time. This should allow for partitioning of climate change effects over time. For more information on these exploratory analyses, see Appendix B.

Overall, these results suggest that changes in temperature and stream flow conditions have influenced community composition to varying degrees at these sites over time. Impacts were particularly evident at the Weber River site (UT 4927250) and at the Virgin River site (UT 4951200), where consecutive years of hot dry conditions occurred from 2000−2005. Although statistical inferences cannot be made on statewide trends based on data from four individual sites, these analyses further our understanding of the effects that changing temperature and stream flow conditions can have on biological assemblages, and help establish expectations for biological responses to future climate changes.

These analyses also provide insights as to which climate change indicators might be best to track over time in southwestern states. Results suggest that climate-induced trends are most likely to be detected in total taxa, EPT and EPT-related metrics, and thermal preference metrics. Some limitations of the thermal preference metrics are that they typically occur in low numbers, and most show sensitivity to organic enrichment, which confounds the associations with temperature. Individual cold preference taxa, including *Pteronarcys*, Chloroperlidae, *Ephemerella,* and *Heptagenia*, should also be considered as good indicators that could be targeted for tracking (forming a "watch list"), as could cold stenothermic community types (per Poff et al., 2010). A subset of biological metrics related to rheophily, habit, and functional feeding group that have shown responsiveness to hydrologic variables in other studies were analyzed but were generally found to be either unresponsive to precipitation or flow variables, to show patterns that were inconsistent across sites, or to show patterns that oftentimes went against expectations.

4. MAINE

4.1. EXPOSURES

4.1.1. Regional Projections for the Northeastern United States

Numerous indicators of climate change have been observed in the northeastern United States over the last century, and especially the last 3 decades, and many of the trends are projected to continue into the future. Regional average air temperatures are projected to increase by an average of 3−5^{o}C over the coming century (2070−2099 compared to 1961−1990) under low to high emission scenarios (Hayhoe et al., 2007; UCS, 2006) (see Table 4-1). While greater temperature increases have been observed in winter temperatures in recent decades, the future projections are for slightly greater temperature increases to occur in summer (Hayhoe et al., 2007).

Projections for precipitation are more variable than for temperature, and for the Northeast, result in differences in expectations for both the average amount and the seasonal distribution of precipitation changes. Hayhoe et al. (2007) project an increase in average annual precipitation over the next century, from 5 to 8% by 2064 to 7 to 14% by 2099 (see Table 4-1). However, their modeling approach results in even greater expected increases in winter precipitation, but no change to slight decreases in summer precipitation (see Table 4-1). UCS (2006) also project increases in winter precipitation, but variable projections for summer ranging from a slight increase to slight decreases (Table 4-1). In contrast, Schoof et al. (2010) project increasing precipitation for the Northeast in all seasons, due to both an increased frequency of storms and an increase in the average size of each rain event (see Table 4-1). In fact, their projected increases in warm-season precipitation are relatively large—increases of 4 to 7% in amount and 8 to 20% in frequency by mid- and end of century, respectively (see Table 4-1). For cold-season precipitation, Schoof et al. (2010) project increases in the frequency (4 to 9% by mid- to end of the century), and increases in the magnitude of precipitation of 12 to 27% for the two time periods.

A number of streamflow changes are projected in association with these temperature and precipitation changes. Total runoff is projected to increase slightly (+0.0.2 mm/day) by the end of the century, while the timing of spring peak centroid (i.e., the timing of spring runoff) is likely to occur earlier, and the magnitude of the 7-day low flow is projected to decrease by

Table 4-1. Projections for temperature and precipitation changes in the Northeast to 2100

Temperature change	Precipitation change	Change in precipitation frequency	Citation
2−3°C by 2064 3−5°C by 2099	5 to 8% by 2064 7 to 14% by 2099 (12 to 14% in winter; 0 to −2% in summer)		Hayhoe et al., 2007
Annual: 2−3°C by 2064 3−5°C by 2099 Winter: 2−3°C by 2064 3−5°C by 2099 Summer 2−4°C by 2064 3−6°C by 2099	Winter: 11 to 16% (mid-century) 20 to 30% Summer: Slight increases to slight decreases		UCS, 2006
	Warm season: 4% (midcentury) 7% (end of century) Cold season: 12% (midcentury) to 27% (end of century)	Warm season: 8% (midcentury) to 20% (end of century) Cold season: 4% (midcentury) to 9% (end of century);	Schoof et al., 2010

4−11% (Hayhoe et al., 2007). While average precipitation and runoff are both projected to increase, the frequency of droughts are also expected to increase, reflecting the minimal change to decrease in summer precipitation (as modeled by Hayhoe et al., 2007) in combination with higher temperatures and increased evaporation. Other projections are for decreases in snow water equivalent and the number of snow days (Hayhoe et al., 2007) as well as for more winter precipitation as rain instead of snow, a 25−50% decrease in length of the snow season, and an increase in the frequency of short-term summer and fall droughts (UCS, 2006).

4.1.2. Historic Climate Trends and Climate Change Projections for Maine

Maine's interior zone has a continental climate with cold winters and warm summers, while its coastal zone has more moderate summer and winter temperatures (Jacobson et al., 2009). Maine is divided into three EPA Level 3 ecoregions. The Northeastern Highlands ecoregion is located in western Maine. It is characterized by rugged hills and mountains, a mostly forested land cover, nutrient-poor soils, and numerous high-gradient streams and glacial lakes (Omernik, 1987; U.S. EPA, 2002). The Northeastern Coastal Zone ecoregion, which is located in the southwestern corner of Maine and has the highest population density of the ecoregions, has land use that consists mainly of forests, woodlands, and urban and suburban development. The Laurentian Plains and Hills ecoregion in eastern Maine is a mostly forested region with dense concentrations of continental glacial lakes. It is less rugged than the Northeastern Highlands (Omernik, 1987; U.S. EPA, 2002). Temperature and precipitation patterns vary across the state. Mean annual temperatures are highest along the coast in southern Maine (see Figure 4-1A). Precipitation patterns vary across the state, with northern Maine having the lowest amount of annual precipitation (see Figure 4-1B).

There has been a great deal of year-to-year variability in temperature patterns in Maine, but overall, temperatures have been increasing over the last century. A historic trend analysis of Maine PRISM data shows that mean annual air temperature has increased at a rate of 0.01°C/year ($p < 0.01$) from 1901−2000 (see Figure 4-2). Winter temperatures have increased at the fastest rate (0.02°C/year, $p < 0.01$), while fall temperatures have increased at the slowest rate (0.004 C/year, p-value = 0.25) (see Table 4-2, Figure 4-3). In more recent decades (1971−2000), winter temperatures increased at an even greater rate (0.05°C/year, $p = 0.13$) but none of the seasonal or annual trends from 1971−2000 are significant ($p > 0.05$) due to the high degree of year-to-year variability (see Table 4-2). Future projections for mid- and late-century for high (A2) and low (B1) emissions scenarios are summarized in Table 4-3. Based on an ensemble average across 15 models, mean annual air temperatures are projected to increase by up to 3.9°C by midcentury and up to 6.1°C by the end of the century compared to a historic time period (1961−1990). The greatest increases are projected to occur during the winter (see Table 4-3).

Precipitation patterns in Maine have been highly variable, with the direction of change varying by the time period being evaluated. From 1901−2000, mean annual precipitation increased at a rate of 1.10 mm/year ($p = 0.01$) (see Figure 4-4 and Table 4-3). Precipitation increased across all seasons, with the greatest increase occurring in the fall (0.43 mm/year, $p = 0.04$) (see Figure 4-5). In more recent decades (1971−2000), there were no significant ($p > 0.05$) annual or seasonal trends due to the high degree of year-to-year variability (see Table 4-4). From 1971−2000, winter was the only season that showed an increase

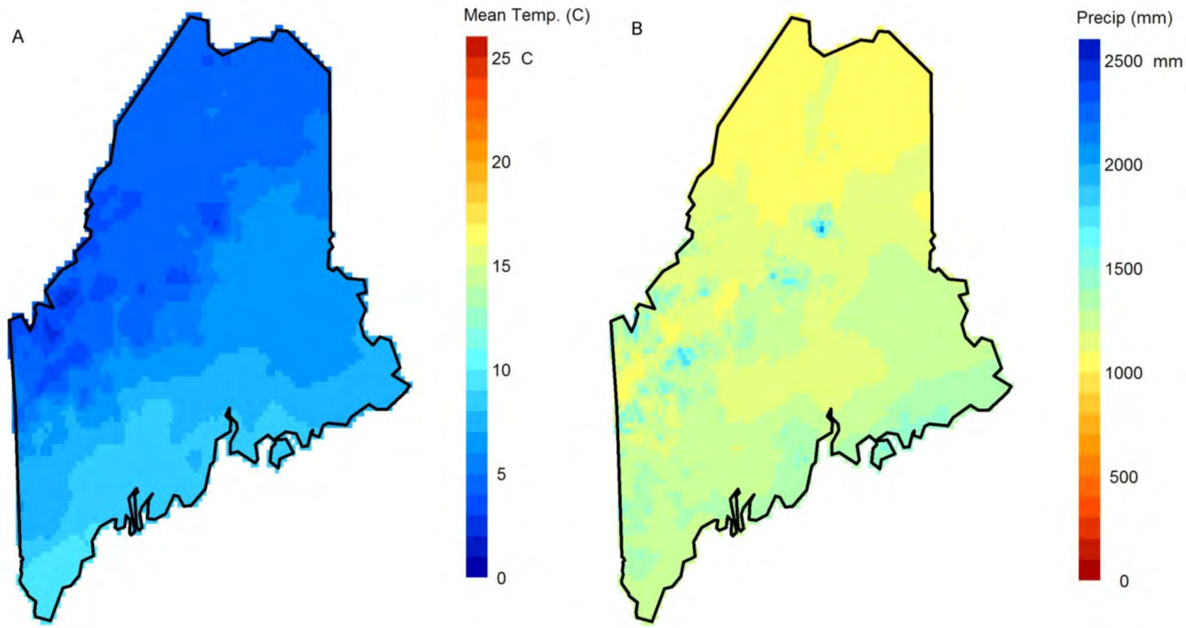

Figure 4-1. Maine's temperature and precipitation patterns. (A) Mean annual air temperature (°C) from 1971–2000; (B) Mean annual precipitation (mm) 1971−2000. Map produced using the Climate Wizard Web site (http://www.climatewizard.org/). Base climate data from the PRISM Group, Oregon State University, http://www.prismclimate.org.

Table 4-2. Change rates in Maine PRISM mean annual air temperature compared across two time periods: 1971–2000 versus 1901–2000. Entries in bold text are significant (*p* < 0.05). Data were derived from the Climate Wizard Web site (http://www.climatewizard.org/). Base climate data came from the PRISM Group, Oregon State University, http://www.prismclimate.org

	Air temperature (C/yr)				
Time period	**Annual**	**DJF**	**MAM**	**JJA**	**SON**
1901−2000	**0.01**	**0.02**	**0.01**	**0.01**	0.00
1971−2000	0.01	0.05	0.01	0.00	0.01

DJF = December, January, and February; MAM = March, April, and May; JJA = June, July, and August; SON = September, October, and November.

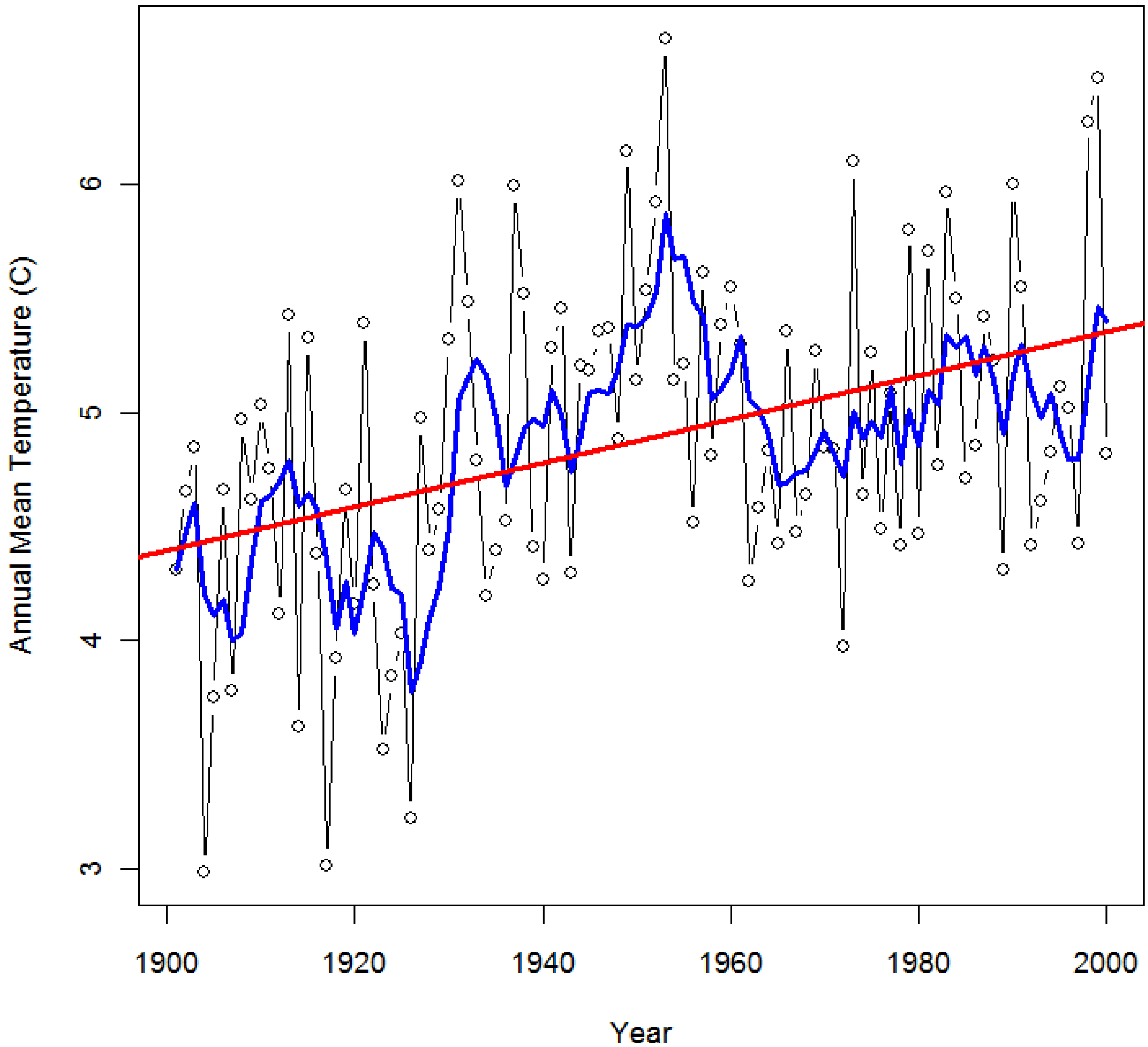

Figure 4-2. Trends in annual mean air temperature in Maine from 1901−2000. Change rate = 0.01°C/year, *p*-value < 0.01. Figure produced using Climate Wizard Web site (http://www.climatewizard.org/). Base climate data from the PRISM Group, Oregon State University, http://www.prismclimate.org.

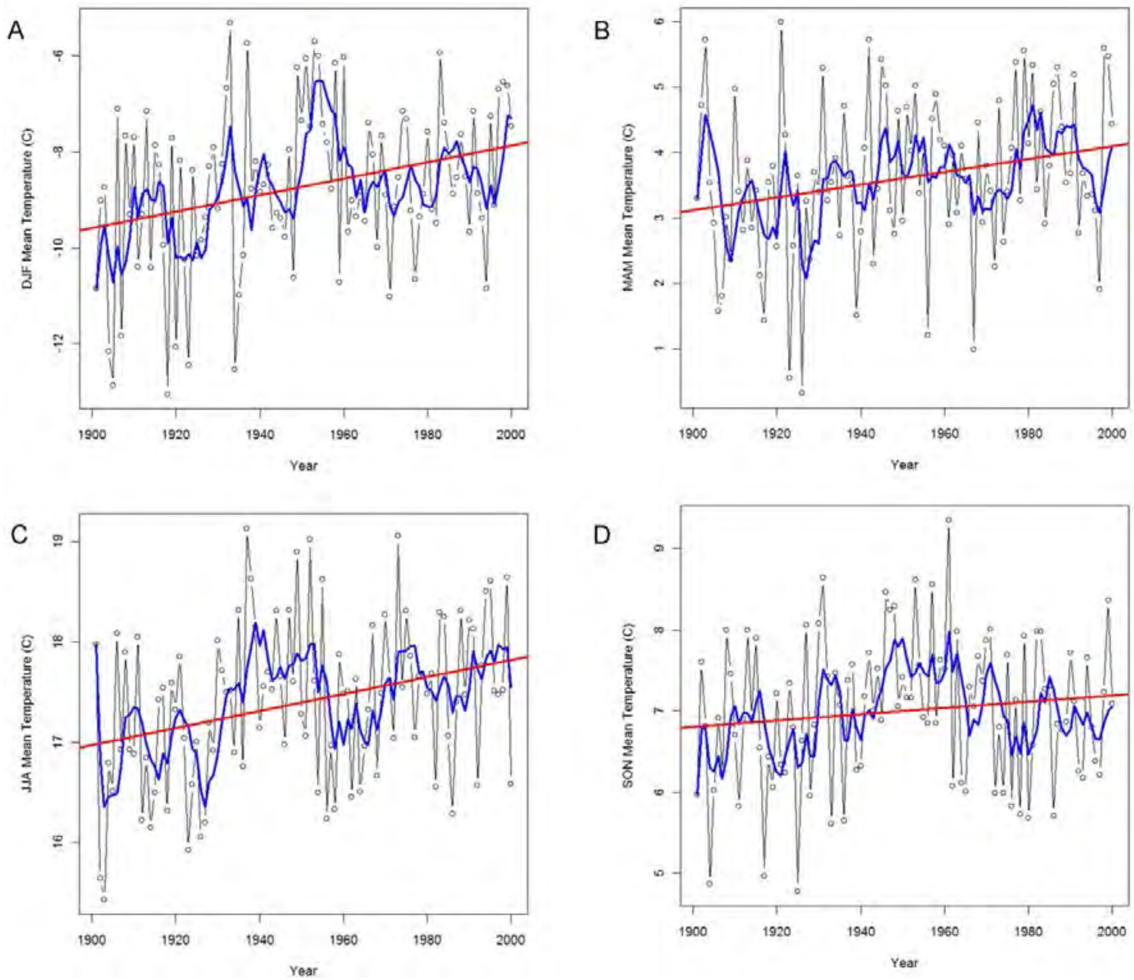

Figure 4-3. Trends in seasonal mean air temperature in Maine from 1901–2000. (A) DJF = December, January, and February, change rate = 0.017°C/year, *p*-value < 0.01; (B) MAM = March, April, and May, change rate = 0.01°C/year, *p*-value = 0.02; (C) JJA = June, July, and August, change rate = 0.008°C/year, *p*-value < 0.01; (D) SON = September, October, and November, change rate = 0.004°C/year, *p*-value = 0.25. Figure produced using Climate Wizard Web site (http://www.climatewizard.org/). Base climate data from the PRISM Group, Oregon State University, http://www.prismclimate.org.

Table 4-3. Projected departure from historic (1961–1990) trends in annual and seasonal air temperature (°C) in Maine for mid- (2040–2069) and late-century (2070–2099) for high and low emissions scenarios. Values represent the minimum, average, maximum, and standard deviations from 15 different climate models. Data were derived from the Climate Wizard Web site (http://www.climatewizard.org/)

Midcentury (2040−2069) vs. historic (1961−1990)										
	A2 (high) emissions scenario					B1 (low) emissions scenario				
Model	**Annual**	**DJF**	**MAM**	**JJA**	**SON**	**Annual**	**DJF**	**MAM**	**JJA**	**SON**
Ensemble low	1.6	1.4	1.4	1.3	1.4	1.1	0.7	1.0	1.1	1.0
Ensemble average	2.7	3.3	2.6	2.3	2.6	2.1	2.6	1.9	2.0	2.1
Ensemble high	3.9	4.4	3.9	3.4	3.7	3.1	3.5	3.0	2.7	3.2
SD	0.6	0.7	0.8	0.7	0.7	0.6	0.7	0.7	0.6	0.7
Late-century (2070−2099) vs. historic (1961−1990)										
Ensemble low	2.8	2.6	2.3	2.5	2.9	1.3	0.5	1.1	1.5	1.6
Ensemble average	3.6	4.3	3.4	3.2	3.6	2.8	3.4	2.5	2.6	2.7
Ensemble high	6.1	6.9	6.5	5.3	6.0	4.3	4.7	4.0	3.7	4.7
SD	1.0	1.2	1.3	1.0	1.0	0.8	1.0	0.9	0.8	1.0

DJF = December, January, and February; MAM = March, April and May; JJA = June, July and August and SON = September, October, and November.

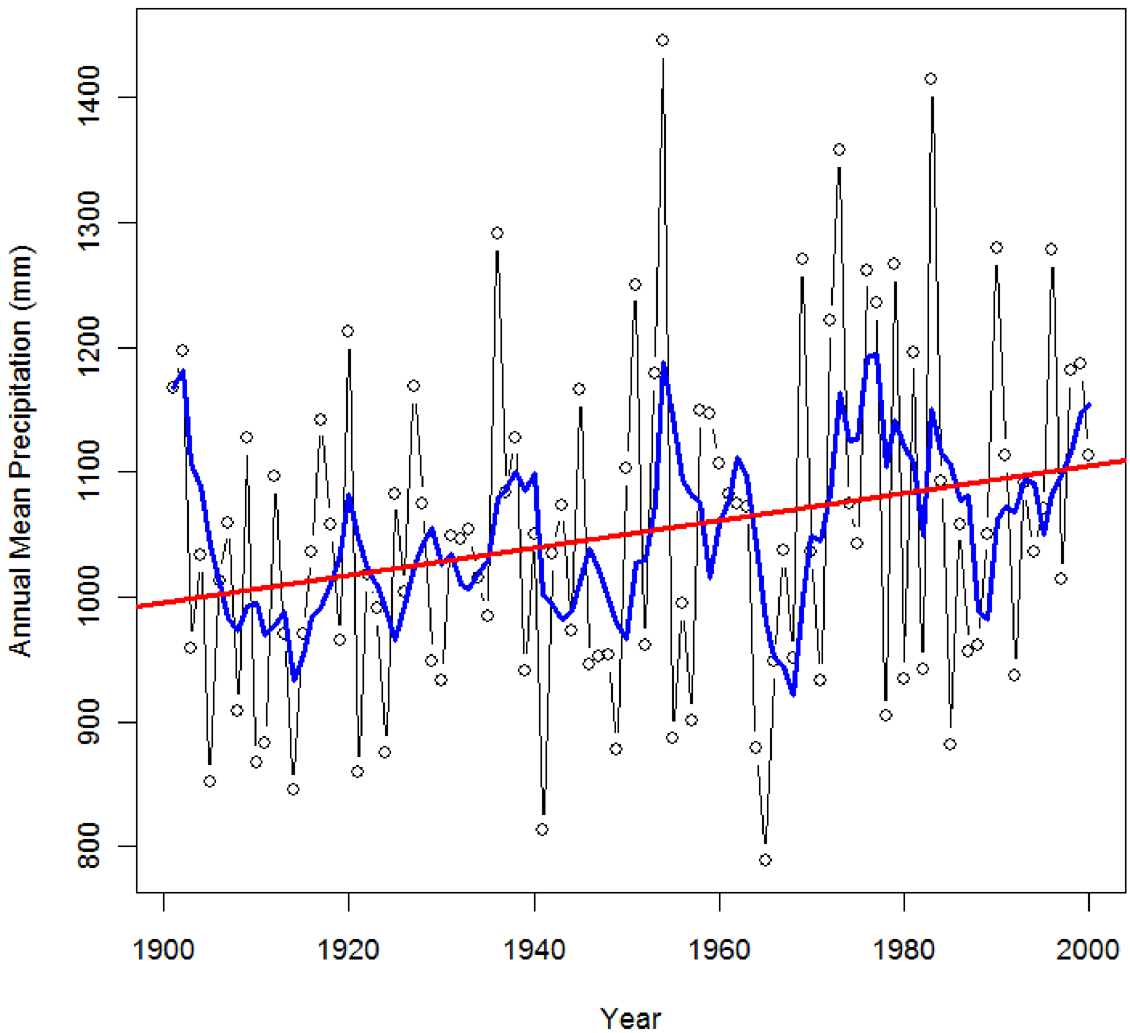

Figure 4-4. Trends in annual mean precipitation in Maine from 1901–2000. Change rate = 1.103 mm/year, *p*-value = 0.02. Figure produced using Climate Wizard Web site (http://www.climatewizard.org/). Base climate data from the PRISM Group, Oregon State University, http://www.prismclimate.org.

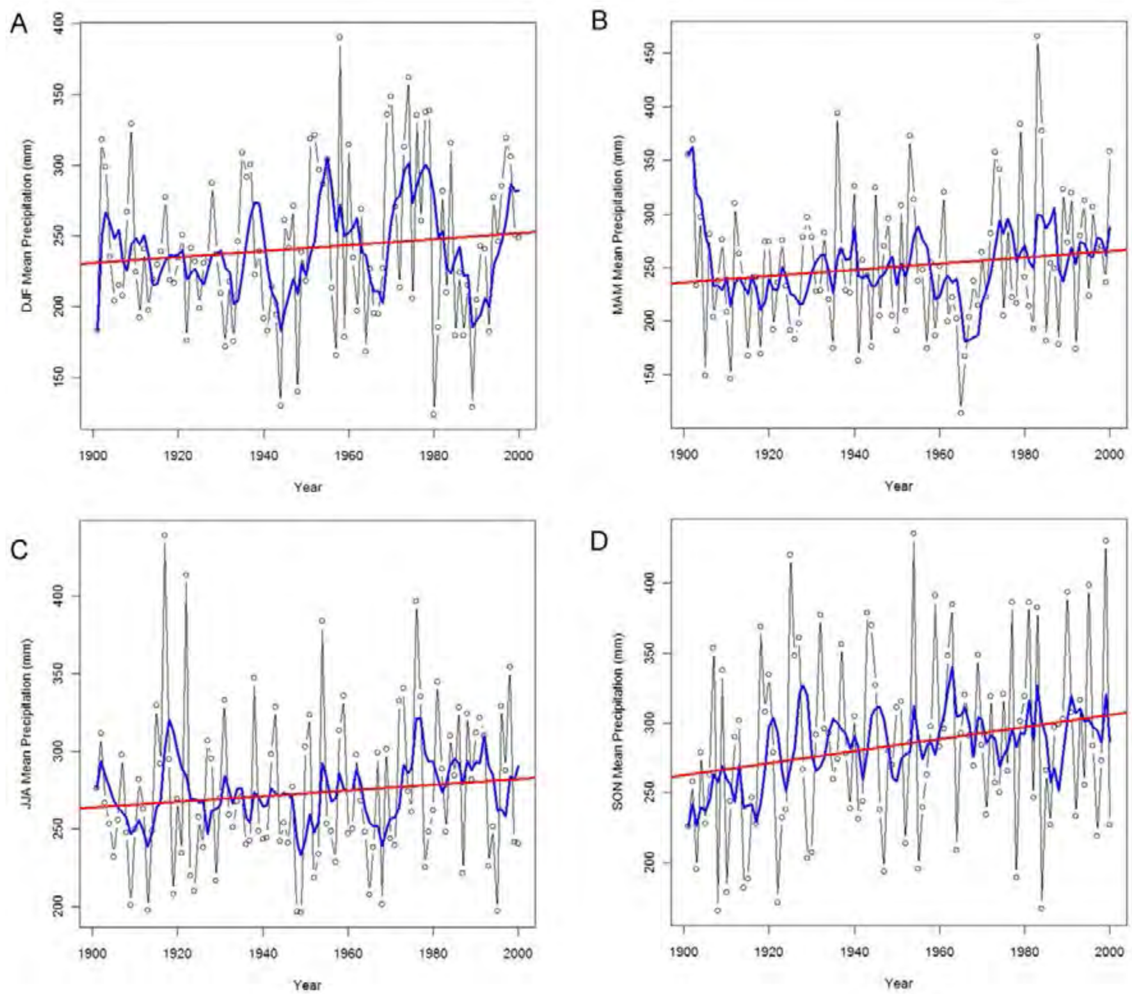

Figure 4-5. Trends in seasonal mean precipitation in Maine from 1901–2000. (A) DJF = December, January, and February, change rate = –0.207 mm/year, *p*-value = 0.35; (B) MAM = March, April, and May, change rate = 0.29 mm/year, *p*-value = 0.18; (C) JJA = June, July, and August, change rate = 0.182 mm/year, *p*-value = 0.29; (D) SON = September, October, and November, change rate = 0.432 mm/year, *p*-value = 0.04. Figure produced using Climate Wizard Web site (http://www.climatewizard.org/). Base climate data from the PRISM Group, Oregon State University, http://www.prismclimate.org.

Table 4-4. Change rates in Maine PRISM mean annual precipitation compared across two time periods: 1971–2000 versus 1901–2000. Entries in bold text are significant ($p < 0.05$). Data were derived from the Climate Wizard Web site (http://www.climatewizard.org/). Base climate data came from the PRISM Group, Oregon State University, http://www.prismclimate.org

Time period	Precipitation (mm/yr)				
	Annual	DJF	MAM	JJA	SON
1901–2000	**1.10**	0.21	0.29	0.18	**0.43**
1971–2000	–1.13	–0.90	–0.07	–0.95	0.78

DJF = December, January, and February; MAM = March, April, and May; JJA = June, July, and August; SON = September, October, and November.

(0.78 mm/year), while annual and other seasonal precipitation patterns decreased (see Table 4-4). Table 4-5 summarizes future projections for mid- and late-century for high (A2) and low (B1) emissions scenarios. The future projections are highly variable across models and emissions scenarios. Under the high emissions scenario, the ensemble average projects that mean annual precipitation will increase by 90.1 mm by midcentury and 125 mm by the end of the century compared to a historic time period (1961−1990). Under the high emissions scenario, the greatest changes are projected to occur during the winter (see Table 4-5).

4.2. DATA INVENTORY AND PREPARATION

Data for Maine were obtained from the Maine Department of Environmental Protection (DEP). Our Maine EDAS database contains data for 1,459 biological samples (which typically consist of 3 replicates) from 742 unique stations, with sampling dates ranging from 1974 to 2006. A mix of habitat, water chemistry, and in situ measurements are available for many of the sites. The parameters that were most consistently reported include instantaneous water temperature, conductivity, pH, DO, width, depth, and visual substrate estimates. Some additional water chemistry data (i.e., nitrogen, phosphorus, total suspended solids, some metals) became available after 2000. Most biological sampling sites in Maine have fewer than 5 years of data, but six sites have 10 or more years of data (see Table 4-6). Two of these sites have received Maine DEP's highest biological condition rating (Class A), which is described in more detail in Section 4.3. Figure 4-6 shows the spatial distribution of biological sampling sites.

Table 4-5. Projected departure from historic (1961–1990) trends in annual and seasonal precipitation (mm) in Maine for mid- (2040–2069) and late-century (2070–2099) for high and low emissions scenarios. Values represent the minimum, average, maximum, and standard deviations from 15 different climate models. Data were derived from the Climate Wizard Web site (http://www.climatewizard.org/)

Midcentury (2040−2069) vs. historic (1961−1990)										
	A2 (high) emissions scenario					B1 (low) emissions scenario				
Model	Annual	DJF	MAM	JJA	SON	Annual	DJF	MAM	JJA	SON
Ensemble low	34.4	0.1	–13.0	–19.8	–20.1	–80.5	3.6	–9.7	–167.7	–78.1
Ensemble average	90.1	37.3	24.6	15.1	12.0	69.0	33.5	23.7	–4.7	9.6
Ensemble high	151.3	68.8	55.2	65.7	58.8	179.4	59.4	63.2	46.1	59.8
SD	35.7	18.3	20.6	22.6	21.8	63.2	13.8	19.8	53.2	32.3
Late-century (2070–2099) vs. historic (1961–1990)										
Ensemble low	17.0	22.2	–17.9	–50.5	–32.5	–194.9	9.0	–16.6	–151.8	–130.7
Ensemble average	125.0	57.5	43.9	7.7	18.5	67.0	45.6	31.7	–8.3	–5.1
Ensemble high	204.7	113.0	93.1	116.2	61.6	182.7	70.8	61.9	55.7	52.3
SD	54.6	23.2	27.6	39.0	26.5	100.0	18.5	23.9	62.1	50.4

DJF = December, January, and February; MAM = March, April, and May; JJA = June, July, August and SON = September, October, and November.

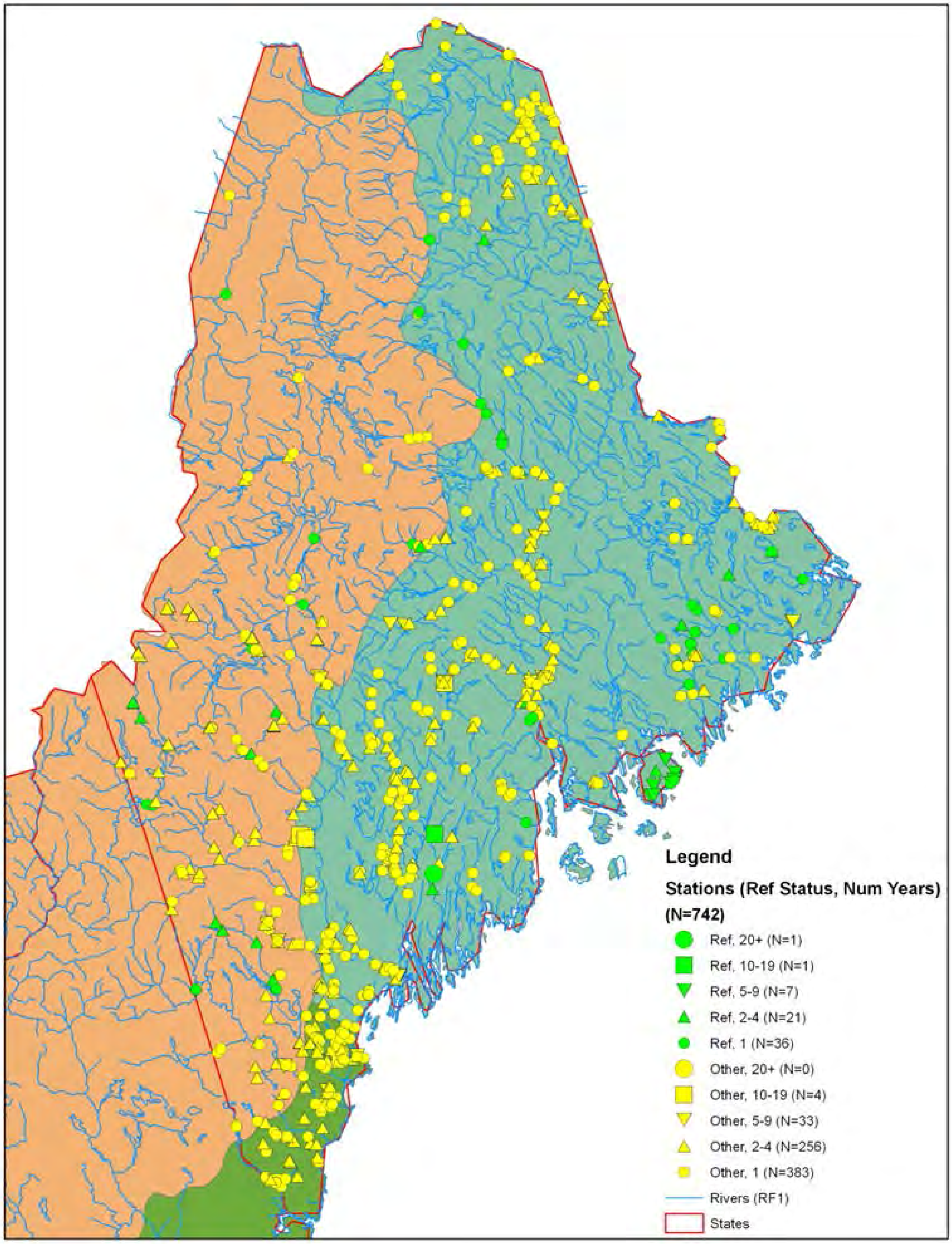

Figure 4-6. Maine biomonitoring stations, coded by reference status and duration of data.

Table 4-6. Distribution of stations that have received Class A biological condition ratings and total stations, categorized by duration of sampling

Years sampled	Maine	
	Class A	Total
1 to 4	210	696
5 to 9	10	40
≥10	2	6
Total	222	742

The original Maine data set included samples collected throughout the year using different methods. To minimize variability associated with collection method, we only analyzed samples collected using rock baskets or rock cones. Maine DEP typically deploys three rock baskets or cones per sample. Each rock basket is considered to be a replicate. When calculating metrics, we averaged values across replicates to come up with a single metric value per sample. To account for seasonal variability, we excluded samples that were collected during the winter and spring, because these are outside Maine DEP's normal sampling period. We also considered differences in subsampling efforts, as these can affect richness metrics, but our ability to do so was limited because these data were not reported consistently across samples.

We used a genus-level OTU when preparing the biological data for long-term trend analyses. Per the methods described in Section 2.1.3, we used NMDS analyses to verify the OTU. We looked for trends associated with changes in biological condition/class, EPA Level 3 ecoregion, year (in 5, 10, and 20-year increments), and taxonomy lab and found no obvious groupings (see Appendix A, Figures A-7 through A-14). There was, however, a subtle shift towards finer taxonomic resolution from the early 1980s to the present (as one would assume due to improved taxonomic keys, etc.), along with an increase in species-level identifications for certain orders in 1990−1991.

This was particularly evident for the order Trombidiformes (water mites). Water mites were identified to the suborder level (Prostigmata) prior to 1991, but from 1991 onwards, there were 28 different identifications associated with the water mites, with some to the species-level. To account for this, we grouped all taxa from the Order Trombidiformes into the suborder Prostigmata. An increase in taxonomic resolution for Chironomidae was also evident in

1990-1991. We considered grouping all Chironomidae to the family level, but decided that this would result in the loss of too much information, and that the trends associated with this taxonomic change were not consistent enough to warrant the change.

We also noticed a subtle change in the data in 1999. This was likely due to variability among the taxonomic labs, because four new labs started doing taxonomic identifications for Maine during the year. Over the 26-year period during which Maine DEP has collected biological data, they have used 16 different taxonomy labs. The number of samples processed by each lab varies; some labs have processed fewer than 10 samples, and others have processed more than 100. Although we did see some variability associated with taxonomy lab, the patterns were not clear or consistent, and the OTU "fix" resolved most of the observed differences, so no adjustments were made.

4.3. MAINE DEP METHODS

Maine DEP typically collects macroinvertebrate samples from wadeable streams using rock baskets and rock cones that are deployed in riffles or runs for 4 weeks from July−September (Davies and Tsomides, 2002). Based on Maine's water classification system, rivers and streams are divided into four classes: (1) Class A, in which aquatic life is as naturally occurs; (2) Class B, in which there are no detrimental changes in the resident biological community, and all indigenous species are maintained; (3) Class C, in which the structure and function of the resident biological community is maintained; and (4) nonattainment (NA), in which minimum aquatic life use criteria are not met.

Maine DEP uses four linear discriminant models to assign samples to classes based on biological condition. The same models are applied to all sites. Each of the four models uses different variables and provides independent estimates of class membership. The first model acts as a screen and provides four initial probabilities that a given site attains a given class. Then data are run through three subsequent models in hierarchical order (C or Better Model; B or Better Model; and A Model) before coming to a final model determination, which is then reviewed by Maine DEP. Table 4-7 shows a list of the input metrics used in each model. Appendix C provides a more detailed explanation of Maine DEP's process for determining attainment class.

4.4. INDICATORS

4.4.1. Thermal Preference

As described in Section 2.2.1, we used the guidelines of Yuan (2006) to calculate thermal optima and tolerance values. For the Maine data set, we based our calculations on a subset of 616 samples that were collected from July−September. Lists of cold and warm-water taxa for the Maine data set were developed based on these data, as well as from literature and input from the New England regional advisory group. These lists are the basis of the region-specific thermal-preference richness and relative-abundance metrics used in some analyses.

The Maine cold-water taxa list is composed of 41 taxa, and the warm-water taxa list is composed of 40 taxa. Tables 4-8 and 4-9, respectively, lists the cold and warm-water taxa, along with abundance and distribution information[6]. Sixteen of the cold-water taxa are Plecopterans, 10 are Trichopterans, 7 are Dipterans, and 4 are Ephemeropterans (see Table 4-8). Ten of the warm-water taxa are Dipterans, 9 are Ephemeropterans, and 6 are Trichopterans (see Table 4-9). The most abundant cold-water taxa are *Leuctra* (Plecopteran),*Epeorus* (Ephemeropteran), *Eurylophella* (Ephemeropteran), *Perlodidae* (Plecopteran), and *Boyeria* (Odonata). These taxa comprise only 0.3 to 0.4% of the total individuals in the Maine database. Thirty-one of the cold-water taxa have overall abundances of less than 0.1% and occur at less than 10% of the sites. *Boyeria* occurs at the largest percentage of sites (38%), followed by Perlodidae, which occurs at 25% of the sites. Two of the taxa on the cold water list, *Eurylophella* and *Glossosoma*, are on Maine DEP's Class A indicator list.

Stenonema and *Neureclipsis* are the most abundant warm-water taxa, with overall abundances of 5.2 and 2.6%, respectively. Nine of the warm-water taxa have overall abundances of less than 0.1%. *Stenonema* occurs at the highest percentage of sites (63%), followed by *Acroneuria* (39%) and *Neureclipsis* (38%). Eight of the warm-water taxa occur at less than 10% of the sites. Three of the taxa on the warm water list, *Paragnetina, Serratella,* and *Leucrocuta*, are on Maine DEP's Class A indicator list.

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[6]There are some noteworthy genera that were excluded from the Maine cold and warm water lists due to variations in thermal preferences among species within these genera. These included *Eukiefferiella* and *Rhyacophila* from the cold water list, and *Brachycentrus, Hydropsyche*, and *Ceratopsyche* from the warm water list. We also considered including *Antocha* and *Dicranota* on the cold water list based on results from the weighted average inferences but excluded them because they occurred not only at sites with cold temperatures, but also at sites which had the warmest average water temperatures.

Table 4-7. Metrics that are used in Maine DEP's four linear discriminant models

Model	Metric
First stage	Total abundance
	Generic richness
	Plecoptera abundance
	Ephemeroptera abundance
	Shannon-Wiener Generic Diversity
	Hilsenhoff Biotic Index
	Relative abundance chironomidae
	Relative richness Diptera
	Hydropsyche abundance
C or better	Probability (A + B + C) from First Stage Model
	Cheumatopsyche abundance
	EPT generic richness divided by diptera generic richness
	Relative abundance Oligochaeta
B or better	Probability A + B from First Stage Model
	Perlidae abundance
	Tanypodinae abundance
	Chironomini abundance
	Relative abundance Ephemeroptera
	EPT generic richness
	Sum of mean abundances of *Dicrotendipes*, *Micropsectra*, *Parachironomus*, and *Helobdella*
A model	Probability A from First Stage Model
	Relative generic richness Plecoptera
	Sum of mean abundances of *Cheumatopsyche*, *Cricotopus*, *Tanytarsus,* and *Ablabesmyia*
	Sum of mean abundances of *Acroneuria* and *Stenonema*
	Ratio Ephemeroptera and Plecoptera generic richness
	Ratio of Class A indicator taxa (*Brachycentrus*, *Serratella*, *Leucrocuta*, *Glossosoma*, *Paragnetina*, *Eurylophella*, and *Psilotreta*)

Table 4-8. List of Maine cold-water temperature indicator taxa, sorted by order, family, then Final ID. Distribution and abundance information is also included. Sum_Individuals = the total number of individuals from that taxon in the Utah database; Pct_Abund = percentage of total individuals in the database composed of that taxon; Num_Stations = number of stations in the database that the taxon occurred at; Pct_Stations = percentage of stations in the database at which the taxon occurred. Two of the taxa, *Malirekus* and *Taenionema*, do not occur in the Maine database, and were added based on feedback from the regional advisory group

Order	Family	Final ID	Sum_individs	Pct_abund	Num_stations	Pct_stations
Coleoptera	Elmidae	*Oulimnius*	237	0.04	37	4.36
Diptera	Chironomidae	*Heterotrissocladius*	447	0.08	73	8.6
Diptera	Chironomidae	*Larsia*	269	0.05	58	6.83
Diptera	Chironomidae	*Macropelopia*	322	0.05	43	5.06
Diptera	Chironomidae	*Natarsia*	430	0.07	65	7.66
Diptera	Chironomidae	*Pagastia*	420	0.07	96	11.31
Diptera	Chironomidae	*Prodiamesa*	392	0.07	28	3.3
Diptera	Chironomidae	*Pseudodiamesa*	139	0.02	12	1.41
Ephemeroptera	Ameletidae	*Ameletus*	63	0.01	26	3.06
Ephemeroptera	Ephemerellidae	*Eurylophella*	1,785	0.3	170	20.02
Ephemeroptera	Heptageniidae	*Epeorus*	2,132	0.36	172	20.26
Ephemeroptera	Heptageniidae	*Rhithrogena*	193	0.03	23	2.71
Megaloptera	Corydalidae	*Nigronia*	713	0.12	170	20.02
Odonata	Aeshnidae	*Boyeria*	1,761	0.3	321	37.81
Odonata	Gomphidae	*Lanthus*	36	0.01	11	1.3
Plecoptera	Capniidae	*Capnia*	71	0.01	5	0.59
Plecoptera	Capniidae	*Paracapnia*	52	0.01	17	2

Table 4-8. List of Maine cold-water temperature indicator taxa, sorted by order, family, then Final ID. Distribution and abundance information is also included. Sum_Individuals = the total number of individuals from that taxon in the Utah database; Pct_Abund = percentage of total individuals in the database composed of that taxon; Num_Stations = number of stations in the database that the taxon occurred at; Pct_Stations = percentage of stations in the database at which the taxon occurred. Two of the taxa, *Malirekus* and *Taenionema*, do not occur in the Maine database, and were added based on feedback from the regional advisory group (cont.)

Order	Family	Final ID	Sum_individs	pct_abund	Num_stations	Pct_stations
Plecoptera	Capniidae	*Utacapnia*	71	0.01	3	0.35
Plecoptera	Chloroperlidae	*Sweltsa*	640	0.11	66	7.77
Plecoptera	Chloroperlidae	*Utaperla*	2	0	2	0.24
Plecoptera	Leuctridae	*Leuctra*	2,407	0.4	142	16.73
Plecoptera	Nemouridae	*Nemoura*	17	0	4	0.47
Plecoptera	Nemouridae	*Paranemoura*	3	0	3	0.35
Plecoptera	Nemouridae	*Prostoia*	6	0	1	0.12
Plecoptera	Nemouridae	*Zapada*	2	0	1	0.12
Plecoptera	Peltoperlidae	*Peltoperla*	9	0	4	0.47
Plecoptera	Peltoperlidae	*Tallaperla*	126	0.02	12	1.41
Plecoptera	Perlodidae	*Malirekus*	0	0	0	0
Plecoptera	Perlodidae	*Perlodidae*	1,775	0.3	212	24.97
Plecoptera	Pteronarcyidae	*Pteronarcys*	248	0.04	80	9.42
Plecoptera	Taeniopterygidae	*Taenionema*	0	0	0	0
Trichoptera	Apataniidae	*Apatania*	48	0.01	23	2.71
Trichoptera	Brachycentridae	*Micrasema*	405	0.07	87	10.25
Trichoptera	Glossosomatidae	*Glossosoma*	945	0.16	119	14.02

Table 4-8. List of Maine cold-water temperature indicator taxa, sorted by order, family, then Final ID. Distribution and abundance information is also included. Sum_Individuals = the total number of individuals from that taxon in the Utah database; Pct_Abund = percentage of total individuals in the database composed of that taxon; Num_Stations = number of stations in the database that the taxon occurred at; Pct_Stations = percentage of stations in the database at which the taxon occurred. Two of the taxa, *Malirekus* and *Taenionema*, do not occur in the Maine database, and were added based on feedback from the regional advisory group (cont.)

Order	Family	Final ID	Sum_individs	pct_abund	Num_stations	Pct_stations
Trichoptera	Hydropsychidae	*Diplectrona*	1,137	0.19	47	5.54
Trichoptera	Hydropsychidae	*Parapsyche*	398	0.07	27	3.18
Trichoptera	Hydroptilidae	*Palaeagapetus*	1	0	1	0.12
Trichoptera	Limnephilidae	*Hydatophylax*	114	0.02	49	5.77
Trichoptera	Limnephilidae	*Limnephilus*	889	0.15	62	7.3
Trichoptera	Limnephilidae	*Psychoglypha*	329	0.06	37	4.36
Trichoptera	Phryganeidae	*Oligostomis*	485	0.08	87	10.25

Table 4-9. List of Maine warm-water temperature indicator taxa. Distribution and abundance information is also included Sum_Individuals = the total number of individuals from that taxon in the Utah database; Pct_Abund = percentage of total individuals in the database composed of that taxon; Num_Stations = number of stations in the database that the taxon occurred at; Pct_Stations = percentage of stations in the database at which the taxon occurred

Order	Family	Final ID	Sum_individs	Pct_abund	Num_stations	Pct_stations
Arhynchobdellida	Erpobdellidae	*Erpobdella*	265	0.04	65	7.66
Basommatophora	Ancylidae	*Ferrissia*	594	0.1	102	12.01
Basommatophora	Physidae	*Physa*	1,373	0.23	115	13.55
Basommatophora	Physidae	*Physella*	1,681	0.28	155	18.26
Basommatophora	Planorbidae	*Helisoma*	716	0.12	66	7.77
Coleoptera	Elmidae	*Stenelmis*	2,638	0.44	280	32.98
Decapoda	Cambaridae	*Orconectes*	381	0.06	99	11.66
Diptera	Chironomidae	*Cardiocladius*	200	0.03	52	6.12
Diptera	Chironomidae	*Dicrotendipes*	1,978	0.33	169	19.91
Diptera	Chironomidae	*Labrundinia*	618	0.1	137	16.14
Diptera	Chironomidae	*Nilotanypus*	413	0.07	133	15.67
Diptera	Chironomidae	*Parachironomus*	946	0.16	83	9.78
Diptera	Chironomidae	*Pentaneura*	881	0.15	139	16.37
Diptera	Chironomidae	*Psectrocladius*	1,693	0.28	161	18.96
Diptera	Chironomidae	*Rheopelopia*	729	0.12	144	16.96
Diptera	Chironomidae	*Tribelos*	1,781	0.3	78	9.19
Diptera	Empididae	*Hemerodromia*	1,764	0.3	260	30.62
Ephemeroptera	Baetidae	*Plauditus*	1,285	0.22	125	14.72
Ephemeroptera	Baetidae	*Pseudocloeon*	1,147	0.19	113	13.31
Ephemeroptera	Caenidae	*Caenis*	1,783	0.3	169	19.91

Table 4-9. List of Maine warm-water temperature indicator taxa. Distribution and abundance information is also included. Sum_Individuals = the total number of individuals from that taxon in the Utah database; Pct_Abund = percentage of total individuals in the database composed of that taxon; Num_Stations = number of stations in the database that the taxon occurred at; Pct_Stations = percentage of stations in the database at which the taxon occurred (cont.)

10	Family	Final ID	Sum_individs	Pct_abund	Num_stations	Pct_stations
Ephemeroptera	Ephemerellidae	*Serratella*	2,534	0.43	191	22.5
Ephemeroptera	Heptagenidae	*Stenonema*	30,768	5.18	536	63.13
Ephemeroptera	Heptageniidae	*Leucrocuta*	3,320	0.56	208	24.5
Ephemeroptera	Heptageniidae	*Stenacron*	6,503	1.09	196	23.09
Ephemeroptera	Isonychiidae	*Isonychia*	5,413	0.91	225	26.5
Ephemeroptera	Leptohyphidae	*Tricorythodes*	2,655	0.45	205	24.15
Haplotaxida	Naididae	*Chaetogaster*	342	0.06	70	8.24
Hoplonemertea	Tetrastemmatidae	*Prostoma*	267	0.04	61	7.18
Hydroida	Hydridae	*Hydra*	483	0.08	113	13.31
Mesogastropoda	Hydrobiidae	*Amnicola*	4,589	0.77	160	18.85
Odonata	Coenagrionidae	*Argia*	869	0.15	137	16.14
Plecoptera	Perlidae	*Acroneuria*	4,857	0.82	331	38.99
Plecoptera	Perlidae	*Attaneuria*	172	0.03	36	4.24
Plecoptera	Perlidae	*Paragnetina*	625	0.11	103	12.13
Trichoptera	Helicopsychidae	*Helicopsyche*	2,563	0.43	104	12.25
Trichoptera	Hydropsychidae	*Macrostemum*	4,557	0.77	168	19.79
Trichoptera	Hydroptilidae	*Hydroptila*	1,799	0.3	189	22.26
Trichoptera	Leptoceridae	*Ceraclea*	876	0.15	152	17.9
Trichoptera	Leptoceridae	*Oecetis*	3,390	0.57	306	36.04
Trichoptera	Polycentropodidae	*Neureclipsis*	15,523	2.61	320	37.69

Many of the taxa on the cold water list are intolerant to enrichment. There is an even distribution of warm-water taxa across enrichment tolerance categories (see Figure 4-7). Because of this overlap, it is difficult to tease out whether organisms are responding to changes associated with warming temperatures or whether they are responding to other stressors, such as enrichment.

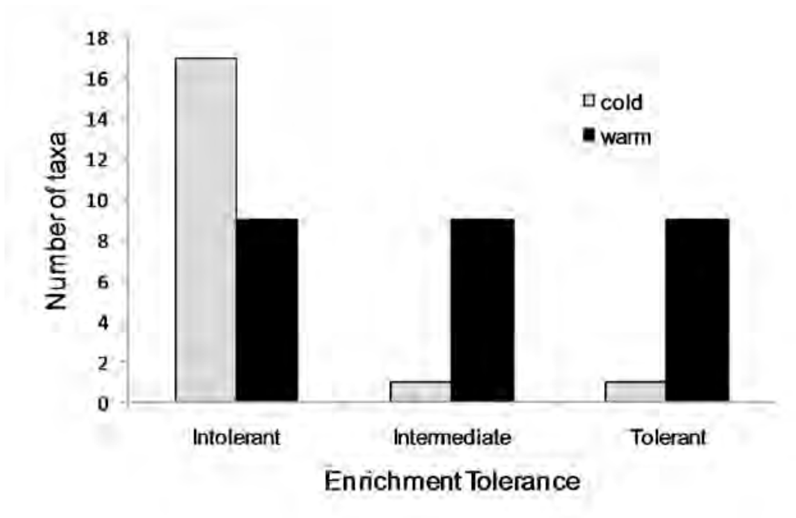

Figure 4-7. Relationship between Maine cold and warm-water-preference taxa and Maine enrichment tolerance scores. Taxa with enrichment tolerance scores of 0–3 were categorized as Intolerant; those with scores of 4–6 were Intermediate and those with scores of 7–10 were Tolerant.

4.4.2. Hydrologic Indicators

We attempted to develop a list of candidate taxa in Maine that could potentially serve as indicators of hydrologic change. We matched USGS gages with biological sampling sites per the methods described in Section 2.2.2. There were not enough USGS gages associated with biological sampling sites to run analyses that have statewide applicability. It is also worth noting that about the half of the USGS gages that did match with biological sampling sites were located in close proximity to dams and, thus, had regulated flows. We did run some analyses on matched biological-hydrological data from a biological sampling site on the Sheepscot River (Station ME 56817) that had over 20 years of continuous biological data. Based on correlation analyses from this site, *Hydropsyche* (spotted sedge caddisfly), *Promoresia* (an elmid beetle), and *Rhyacophila* (green sedge caddisfly) were significantly and positively correlated with 1- and

3-day minima flow values. There were a mix of other significant associations as well, but results were difficult to interpret and were too limited to draw statewide conclusions.

4.4.3. Traits-Based Indicators in a Warmer Drier Scenario

We developed a list of taxa that may be most and least sensitive to projected changes in temperature and streamflow based on the suite of trait modalities described in Section 2.2.3. When assessing sensitivity to future climatic changes, we focused on a generalized scenario in which temperatures are increasing and flows are decreasing during the low flow periods when state biomonitoring programs typically collect their samples. The taxa in Table 4-10 that are deemed most sensitive, or most likely to be adversely affected by these projected climatic changes, are all EPT taxa. The least sensitive taxa on our list is a Hemipteran, *Belostoma*, which has the ability to exit (as adults), has high dispersal ability, strong flying strength, strong swimming ability, and breathes through plastron-spiracles.

4.5. LEAST DISTURBED LONG-TERM BIOLOGICAL MONITORING SITES

Maine does not have a formal statewide long-term reference network. We explored grouping sites that had received Class A biological condition ratings[7] together to create a data set statewide data set to analyze for long-term trends, but site-specific differences were evident within the data set and the sample size was relatively low; therefore, we focused on individual sites. We performed trend analyses on data from three sites that had received Class A biological condition ratings and that had the longest term biological data. Figure 4-8 shows the locations of these stations. Table 4-11 summarizes site characteristics. All three sites are located in the Laurentian Plains and Hills ecoregion. Anthropogenic influences are higher than desired (>5% urban and/or >10% agricultural) at all three sites, but data were analyzed from these sites because they represented the best-available long-term data in the state database. Table 4-12 lists the time periods for which biological data are available for these sites. Data used in these analyses were limited to rock basket samples collected from July−September.

[7]It should be noted that sites that have received Class A biological condition ratings are not necessarily considered to be reference sites by Maine DEP. At the time of this report, Maine DEP was in the process of developing strict reference criteria based on considerations such as land use and land cover in the upstream catchment and proximity to NPDES discharges.

Table 4-10. List of taxa that may be most and least sensitive to a warmer and drier future scenario based on a combination of traits

Order	Family	Final ID	Sensitivity to warmer drier scenario
Trichoptera	Apataniidae	*Apatania*	most
Trichoptera	Goeridae	*Goera*	most
Trichoptera	Calamoceratidae	*Heteroplectron*	most
Trichoptera	Limnephilidae	*Onocosmoecus*	most
Trichoptera	Limnephilidae	*Pycnopsyche*	most
Trichoptera	Hydropsychidae	*Diplectrona*	most
Trichoptera	Hydropsychidae	*Parapsyche*	most
Trichoptera	Limnephilidae	*Psychoglypha*	most
Hemiptera	Belostomatidae	*Belostoma*	least

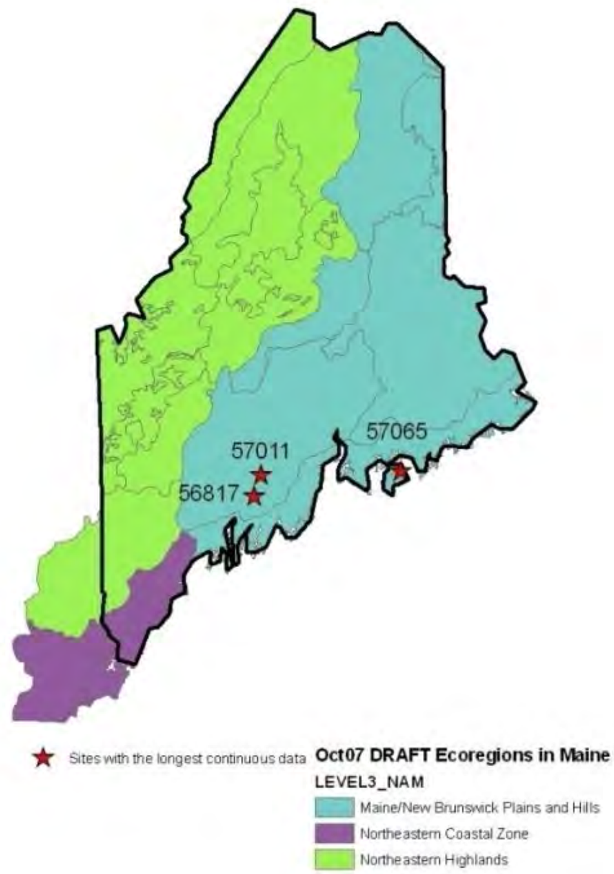

Figure 4-8. Locations of the three biological sampling sites that we performed long-term trend analyses on (56817 = Sheepscot; 57011 = West Branch Sheepscot; 57065 = Duck Brook).

Table 4-11. Site characteristics for the long-term biological monitoring stations in Maine. Percentage urban and percentage agricultural (ag) apply to a 1-km buffer zone around each site and are based on 2001 National Land Cover Data

Site ID	Water body	Longitude (°)	Latitude (°)	EPA Level 3 ecoregion	Elevation (m)	Drainage area (km^2)	% Urban	% Ag
ME 56817	Sheepscot	69.59334	44.2232	Laurentian Plains and Hills	31.6	362.8	16.4	23
ME 57011	W. Br. Sheepscot	69.53129	44.3679	Laurentian Plains and Hills	70.1	38.1	9.1	18.5
ME 57065	Duck	68.23461	44.3934	Laurentian Plains and Hills	54.6	12.8	15.9	0

Table 4-12. Time periods for which biological data were available at the long-term monitoring sites in Maine. Data used in these analyses were limited to July–September rock basket samples

Site ID	Water body	Number of years of data analyzed	Years
ME 56817	Sheepscot	23	1984–2006
ME 57011	West Branch Sheepscot	12	1995–2006
ME 57065	Duck	9	1997–2005

4.6. EVIDENCE OF TRENDS AT LEAST DISTURBED LONG-TERM MONITORING SITES

4.6.1. Sheepscot River (ME 56817)

The Sheepscot River site (ME 56817; Maine DEP Station 74) is located in southern Maine in the town of Whitefield. It is in the Laurentian Plains and Hills ecoregion and Central Interior biophysical region, has a drainage area of 362.8 km^2 and an elevation of 31.6 m. Its highest maximum monthly temperatures occur during July and August, and its lowest average flows (<85 cfs) occur from July through September. This station has 23 years of continuous biological data, spanning from 1984 to 2006, that have been collected during Maine DEP's July through September index period. We gathered daily temperature and precipitation data from 1949 to 2010 from the Augusta FAA AP weather station (SiteID 170275, Latitude: 44.3206, Longitude: 69.7972), which is located approximately 20 km northwest of the biological sampling site. Flow data from 1939−2009 were gathered from USGS gage 1038000 (Sheepscot River at North Whitefield, Latitude: 44.22278, Longitude: 69.59389), which is colocated with the biological sampling site. Figure 4-9 shows an aerial photograph of the site, along with the weather station and active USGS gage.

4.6.1.1. *Temporal Trends in Climatic and Biological Variables*

Since 1949, mean annual air temperatures at the weather station closest to the Sheepscot River (ME 56817) site have ranged from 6 to 9.8°C. There is a great deal of year-to-year variability, but overall, temperatures have been increasing over time (when fit with a linear trend line, $r^2 = 0.06$, $p = 0.05$) (see Figure 4-10). When PRISM air temperature data are compared to observed data, PRISM data are within 1°C of the observed values, and there is good correspondence between patterns. Mean annual flow and mean annual precipitation patterns have been highly variable over time (see Figure 4-11). Since 1939, mean annual flow values have ranged from 110.1 to 485.7 cfs (when fit with a linear trend line, $r^2 = 0.08$, $p = 0.02$). Precipitation patterns generally show good correspondence with flow patterns but are more variable (see Figure 4-11).

In addition to mean annual values, mean maximum July and August temperature and mean July−September flow values were also evaluated, as these are likely to be physiologically stressful time periods for the biological organisms, and also correspond with Maine DEP's index period. During the period of biological record (1984−2006), mean maximum July/August air

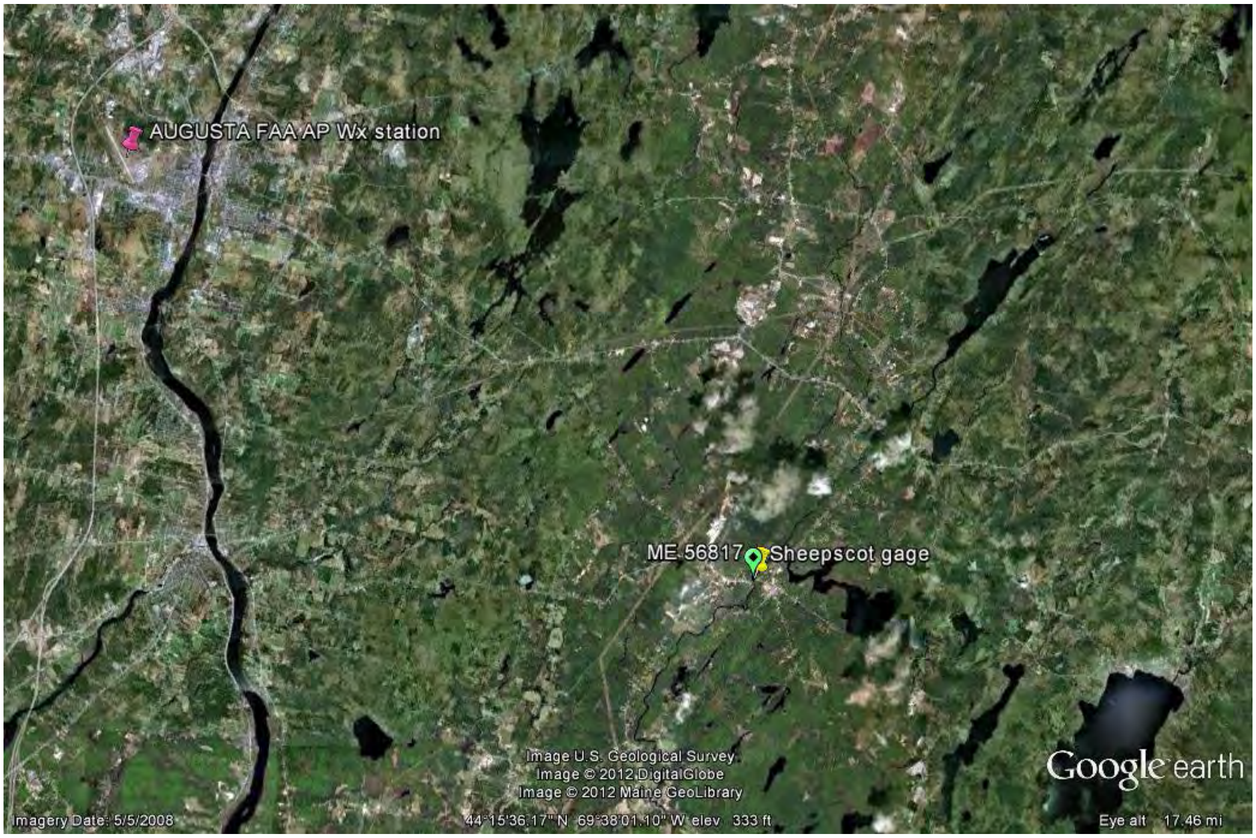

Figure 4-9. Locations of the Sheepscot River (ME 56817) biological sampling site, USGS gage 1038000 (Sheepscot River at North Whitefield) and Augusta FAA AP weather station. Image from Google Earth.

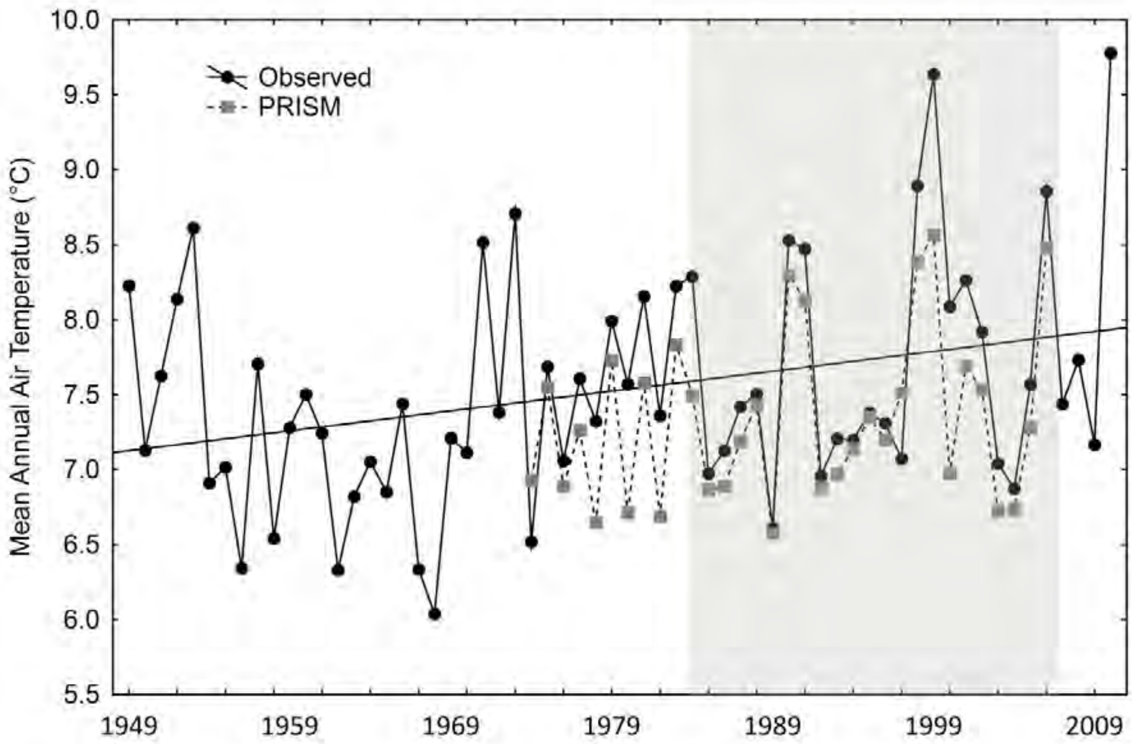

Figure 4-10. Yearly trends in annual observed air temperature (°C) at the Sheepscot River site (ME 56817) from 1949–2010, based on data from the Augusta FAA AP weather station. For comparative purposes, PRISM annual air temperature data associated with the biological sampling site are also included from 1975–2005. The area shaded in grey corresponds to the period of biological record. When the observed data are fitted with a linear trend line, $r^2 = 0.06$, $p = 0.05$, and $y = -12.718 + 0.0102 \times x$.

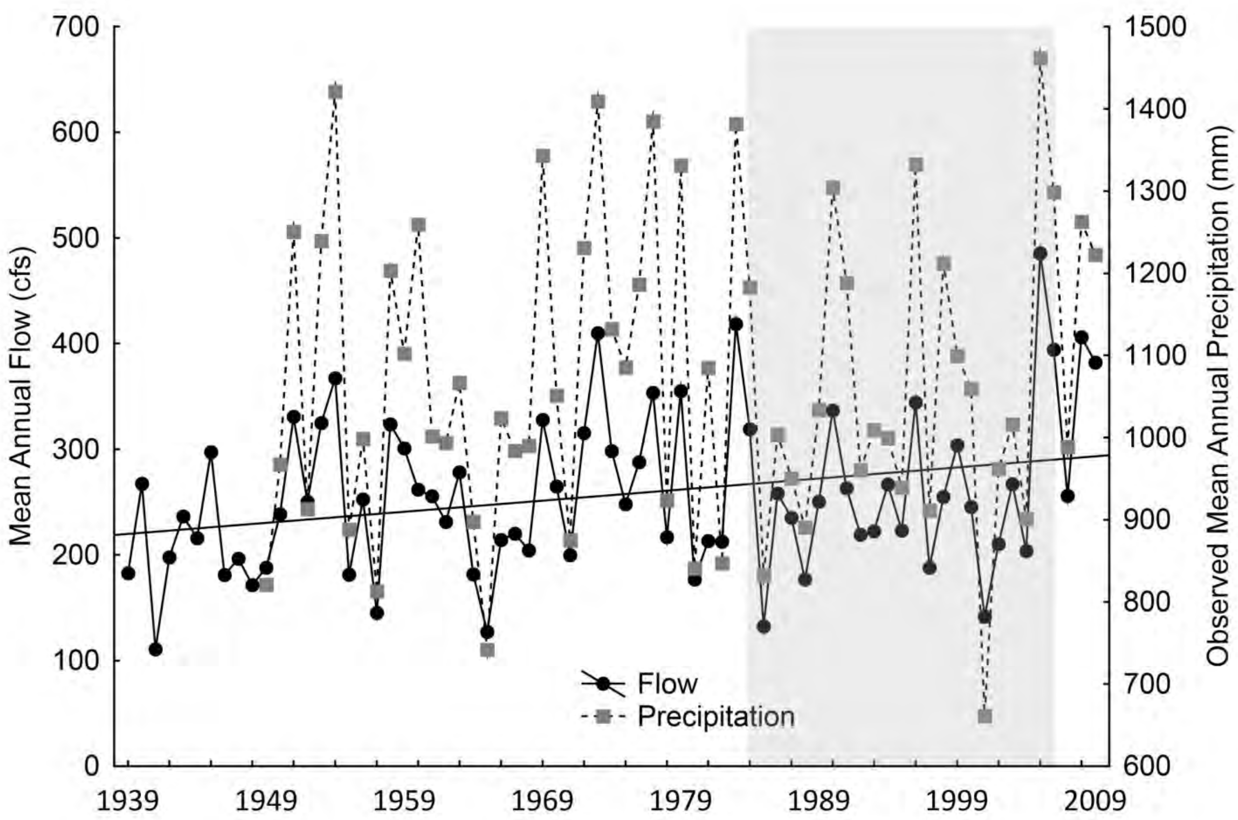

Figure 4-11. Yearly trends in mean annual flow (cfs) at the Sheepscot River site (ME 56817) from 1939–2009, based on data from USGS gage 1038000 (Sheepscot River at North Whitefield). For comparative purposes, observed annual precipitation data from the Augusta FAA AP weather station are also included from 1949–2009. The area shaded in grey corresponds to the period of biological record. When the observed data are fitted with a linear trend line, $r^2 = 0.08$, $p = 0.02$, and $y = -1{,}814.9037 + 1.0494 \times x$.

temperatures ranged from 24.2−27.8°C, and mean July−September flow values ranged from 17.0 to 156.7 cfs (see Table 4-13). Attainment classes based on biological condition have ranged from Class A to B. Since 1998, samples have attained Class A status (see Figure 4-12A). The number of EPT taxa has varied, but overall, numbers have increased over time, ranging from 5 in 1984 to 19 in 2005 (see Figure 4-12B). HBI scores have varied from year to year and did not show a clear trend, ranging from a low of 3.1 in 1995 to a high of 4.7 in 1984 (see Figure 4-12B). During the period of biological record, mean maximum July/August air temperatures and July−September flows were highly variable, with the highest maximum July/August temperature occurring in 1999, the lowest July−September flows occurring in 1994 and 2000, and the highest July−September flows occurring in 2005 (see Figure 4-12C). The number of warm-water taxa has varied, but overall, numbers have increased over time, ranging from 5 in 1984 to 12 in 1999 and 2001 (see Figure 4-13A). Warm-water taxa have comprised up to 48% of the assemblage (see Figure 4-13B). Very few cold-water taxa were present at this site, with richness values ranging from 0 to 2.

Per communications with Maine DEP, conditions at this site have been influenced by nonpoint source pollution, with potential anthropogenic influences from urban and agricultural land use (16% urban and 23% agricultural within a 1-km buffer). Some recent (post-2000) water chemistry data are available for various nutrient-related parameters. The maximum nitrogen concentration was 0.48 mg/L, the maximum ammonia concentration ammonia was 0.05 mg/L, and the maximum total phosphorus concentration was 0.02 mg/L. Confounding factors related to in situ measurements were not evident, with values in the following ranges:

- DO: 7.2 to 8.5 mg/L
- pH: 6.4 to 7.1
- Specific conductance: 37 to 84 µmho/cm

Table 4-13. Range of temperature, precipitation, and flow values that occurred at the Sheepscot River site (ME 56817) during the period of biological record

Parameter	Min	Max
Year	1984	2006
Observed mean annual air temperature (°C)	6.6	9.6
PRISM mean annual air temperature (°C)	6.6	8.6
Observed mean maximum July/August Air temperature (°C)	24.2	27.8
Mean annual flow (cfs)	132.6	485.7
Mean July−September flow (cfs)	17.0	156.7
Observed mean annual precipitation (mm)	661.3	1,461.8
PRISM mean annual precipitation (mm)	795.5	1,691.2

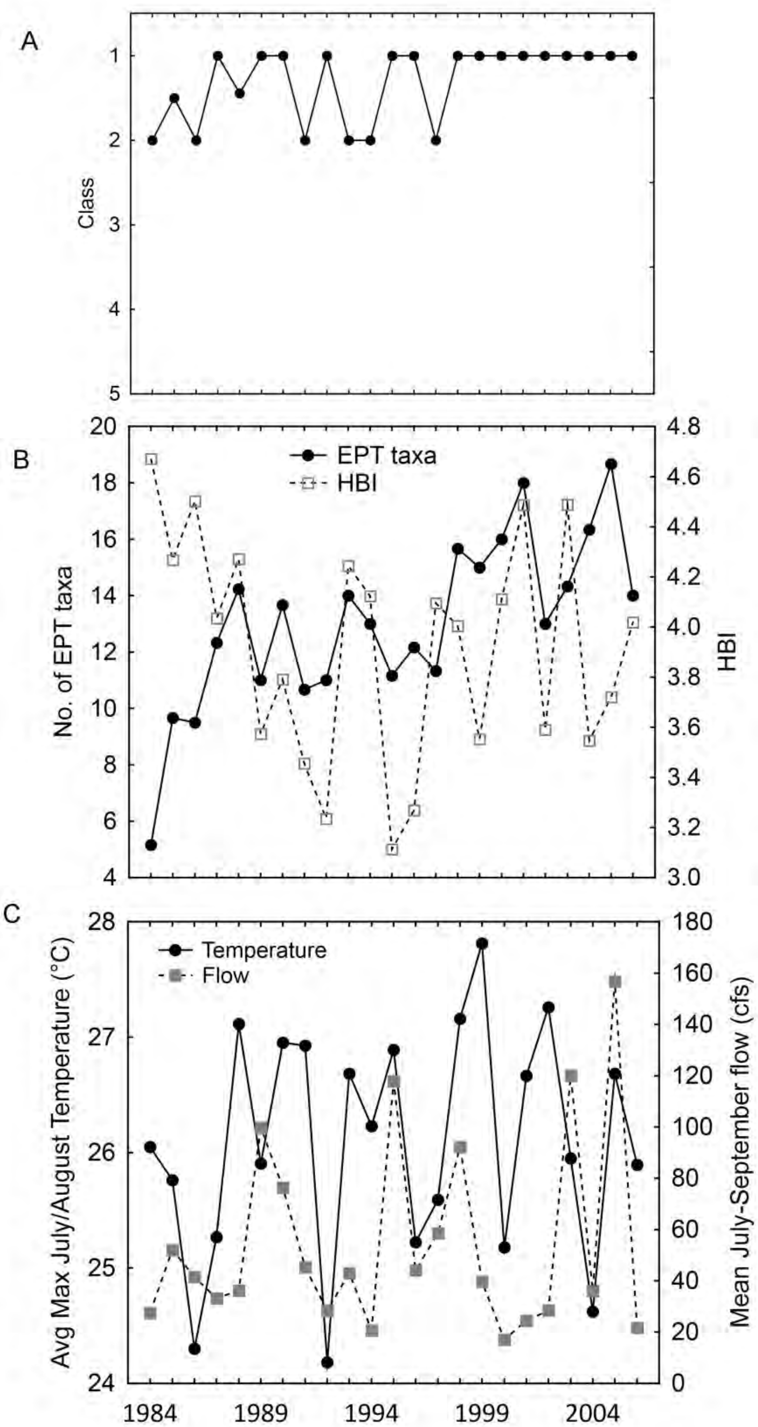

Figure 4-12. Yearly trends at the Sheepscot River site (ME 56817) in (A) biological condition class (1 = Class A; 2 = Class B; 3 = Class C; 4 = NA); (B) number of EPT taxa and HBI; and (C) mean maximum July/August temperature (°C) and mean July–September flow (cfs).

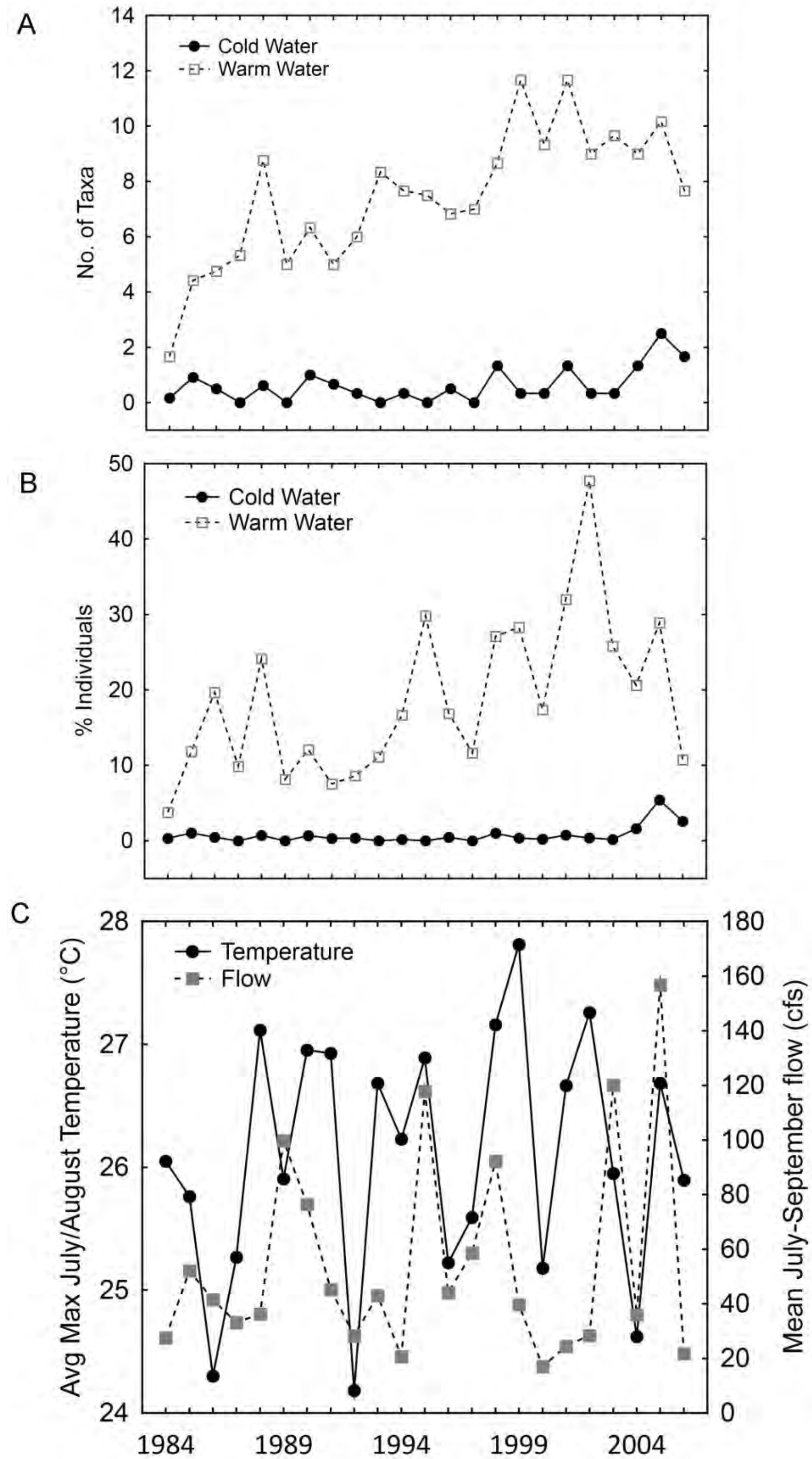

Figure 4-13. Yearly trends at the Sheepscot River site (ME 56817) in (A) number of cold and warm-water taxa; (B) percentage cold and warm-water individuals; and (C) mean maximum July/August temperature (°C) and mean July–September flow (cfs).

4.6.1.2. *Associations Between Biological and Climatic Variables*

Kendall tau nonparametric correlations analyses allow examination of associations between commonly used biological metrics, year, temperature, flow, and precipitation variables at the Sheepscot River (ME 56817) site. None of the 13 commonly used biological metrics showed strong associations ($r \geq 0.5$) with the environmental parameters (see Table 4-14). Four of the metrics (total number of taxa, number of EPT taxa, number of Trichoptera taxa, and Shannon-Wiener Diversity Index) showed strong positive associations with year. The number of warm-water taxa metric also showed a strong positive association with year (see Table 4-15), but none of the thermal preference metrics were strongly correlated with the environmental parameters. The subset of biological metrics that have shown responsiveness to hydrologic variables in other studies (see Section 2, Table 2-6) failed to show strong relationships with the flow and precipitation variables (see Table 4-16). Four of the metrics (number of collector-filterer taxa, number of scraper/herbivore taxa, number of erosional taxa, and percentage scraper/herbivore individuals) had strong positive associations with year.

4.6.1.3. *Groupings Based on Climatic Variables*

Samples were partitioned into hottest/coldest/normal year groups and lowest/normal/highest flow year groups. At the Sheepscot River site (ME 56817), on average, the hottest years were 1.4°C warmer than the coldest years, and highest flow years had 168 more cubic feet per second than lowest flow years. When samples were grouped based on temperature, there were no significant ($p > 0.05$) differences between mean metric values (see Table 4-17). Although not significant, there are some patterns worth noting. Mean numbers of total taxa, EPT taxa and warm-water taxa, and individuals were highest in hottest year samples. On average, cold water metrics were also higher in the hottest year samples, but so few cold-water taxa were present that these results should be interpreted with caution. When samples were grouped based on flow, there were also no significant ($p > 0.05$) differences between mean metric values (see Table 4-18). The mean number of warm-water taxa and individuals was highest in the driest flow year samples, and the cold-water taxa were more prevalent in the wettest flow year samples, but as mentioned, the cold-water taxa metrics should be interpreted with caution. NMDS was used to evaluate differences in taxonomic composition across the

Table 4-14. Kendall tau nonparametric correlations analyses performed to examine associations between commonly used biological metrics, year, and climatic variables at the Sheepscot River site (ME 56817). Results are based on 23 years of data. Entries are in bold text if $r \geq \pm 0.5$. Ranges of biological metric values are also included

Biological metric	Range of metric values: Min	Range of metric values: Max	*r* values (based on Kendall Tau correlations): Year	Air Temperature (°C): PRISM mean annual	Air Temperature (°C): Observed mean maximum July/August	Flow (cfs): Mean annual	Flow (cfs): Mean July−September	PRISM mean annual precipitation (mm)
Total no. taxa	9.7	29.8	**0.63**	0.18	0.24	0.07	0.02	0.13
No. EPT taxa	5.2	18.7	**0.58**	0.14	0.19	0.01	–0.03	0.10
No. Ephemeroptera taxa	1.7	7.3	0.43	0.08	0.22	0.04	0.02	0.16
No. Plecoptera taxa	0.5	1.7	0.09	0.08	0.12	0.02	0.06	0.02
No. Trichoptera taxa	3.0	11.0	**0.62**	0.15	0.11	0.04	–0.03	0.03
No. Intolerant taxa	3.0	12.8	0.48	0.14	0.11	0.20	–0.04	0.26
Percentage EPT individuals	45.6	84.3	0.04	0.11	0.16	–0.11	0.11	–0.01
Percentage Ephemeroptera individuals	3.9	35.2	0.30	0.23	0.31	0.10	0.01	0.17
Shannon-Wiener Diversity Index	1.8	4.3	**0.54**	0.13	0.20	0.07	0.01	0.12
Percentage noninsect individuals	0.0	3.6	0.32	–0.05	0.14	–0.06	–0.09	–0.04
Percentage dominant taxon	12.8	57.8	–0.36	0.00	–0.05	0.00	–0.05	0.01
Percentage tolerant individuals	0.3	15.8	–0.06	–0.01	0.13	–0.22	–0.04	–0.15
Hilsenhoff Biotic Index	3.1	4.7	–0.18	–0.11	–0.06	–0.10	–0.15	–0.14

Table 4-15. Kendall tau nonparametric correlations analyses performed to examine associations between thermal preference metrics, year, and climatic variables at the Sheepscot River site (ME 56817). Results are based on 23 years of data. Entries are in bold text if *r* ≥ ±0.50. Ranges of biological metric values are also included

Biological metric	Range of metric values		*r* values (based on Kendall Tau correlations)					
				Air temperature (°C)		Flow (cfs)		PRISM Mean annual precipitation (mm)
	Min	Max	Year	PRISM mean annual	Observed mean maximum July/August	Mean annual	Mean July−September	
No. cold-water taxa	0.0	2.5	0.27	0.23	0.07	0.14	0.03	0.24
Percentage cold-water individuals	0.0	5.4	0.21	0.18	0.05	0.08	–0.03	0.21
No. warm-water taxa	1.7	11.7	**0.63**	0.16	0.26	–0.02	–0.04	0.05
Percentage warm-water individuals	3.8	47.8	0.42	0.13	0.25	–0.11	0.11	0.01

Table 4-16. Kendall tau nonparametric correlations analyses performed to examine associations between a subset of biological metrics, year, flow, and precipitation variables at the Sheepscot River site (ME 56817). The subset of biological metrics were selected per the criteria outlined in Section 2 and have shown responsiveness to hydrologic variables in other studies (see Section 2, Table 2-6). Results are based on 23 years of data. Entries are in bold text if *r* ≥ ±0.5. Ranges of biological metric values are also included

Biological metric		Range of metric values: Min	Range of metric values: Max	*r* values (based on Kendall Tau correlations): Year	Flow (cfs): Mean annual	Flow (cfs): Mean July−September	PRISM mean annual precipitation (mm)
Richness	Collector filterer	4.0	10.7	**0.52**	0.00	−0.09	0.03
	Collector gatherer	2.3	7.3	0.27	0.14	0.14	0.16
	Scraper/herbivore	1.0	6.7	**0.54**	0.06	0.07	0.08
	Predator	1.0	4.7	0.36	0.02	0.13	0.10
	Swimmer	0.5	4.3	0.41	0.01	−0.15	0.14
	OCH	0.3	2.8	0.26	0.14	0.21	0.09
	Depositional	0.2	2.0	0.25	0.00	0.01	0.15
	Erosional	6.0	14.3	**0.55**	0.06	−0.07	0.06
Percentage individuals	Collector filterer	45.6	82.9	−0.23	−0.11	−0.13	−0.10
	Collector gatherer	9.1	40.3	−0.02	0.15	−0.04	0.18
	Scraper/herbivore	1.2	26.1	**0.53**	−0.02	0.05	0.08
	Predator	1.2	13.5	0.34	−0.11	0.19	−0.05
	Swimmer	1.2	17.6	0.26	−0.01	−0.13	0.08
	OCH	0.2	3.6	0.12	0.06	0.27	0.00
	Depositional	0.2	3.8	0.10	−0.04	0.12	0.08
	Erosional	45.7	80.3	−0.15	−0.12	−0.04	−0.11

Table 4-17. Mean metric values (±1 SD) for the Sheepscot River site (ME 56817) in coldest, normal, and hottest year samples. Year groups are based on PRISM mean annual air temperature values. One-way ANOVA was done to evaluate differences in mean metric values. There were no significant (p > 0.05) differences across year groups

Year group	Total no. taxa	No. EPT taxa	HBI	No. cold-water taxa	No. warm-water taxa	% Cold-water individuals	% Warm-water individuals
Coldest	20.9 ± 4.3	12.3 ± 2.6	4.0 ± 0.5	0.5 ± 0.5	6.7 ± 2.2	0.5 ± 0.6	15.1 ± 6.9
Normal	20.8 ± 5.4	12.7 ± 3.7	3.9 ± 0.5	0.5 ± 0.8	7.1 ± 2.5	0.8 ± 1.7	17.7 ± 8.7
Hottest	24.1 ± 3.8	14.3 ± 2.3	3.8 ± 0.4	1.0 ± 0.5	8.6 ± 2.5	0.9 ± 0.8	23.7 ± 14.4

Table 4-18. Mean metric values (±1 SD) for the Sheepscot River site (ME 56817) in driest, normal, and wettest flow year samples. Year groups are based on mean annual flow values from USGS gage 1038000. One-way ANOVA was done to evaluate differences in mean metric values. There were no significant (p > 0.05) differences across year groups

Year group	Total no. taxa	No. EPT taxa	HBI	No. cold-water taxa	No. warm-water taxa	% Cold-water individuals	% Warm-water individuals
Driest	22.2 ± 4.4	13.4 ± 3.0	3.9 ± 0.5	0.7 ± 0.5	8.0 ± 2.4	0.7 ± 0.5	22.4 ± 13.9
Normal	20.9 ± 2.8	12.6 ± 2.3	3.9 ± 0.4	0.4 ± 0.4	6.8 ± 1.8	0.2 ± 0.3	16.4 ± 8.1
Wettest	22.7 ± 6.9	13.3 ± 4.1	3.9 ± 0.5	0.9 ± 0.9	7.7 ± 3.3	1.4 ± 1.9	18.1 ± 9.8

temperature groups. The NMDS ordination showed no distinct clusters reflecting hottest, coldest, and/or normal year groups (see Figure 4-14).

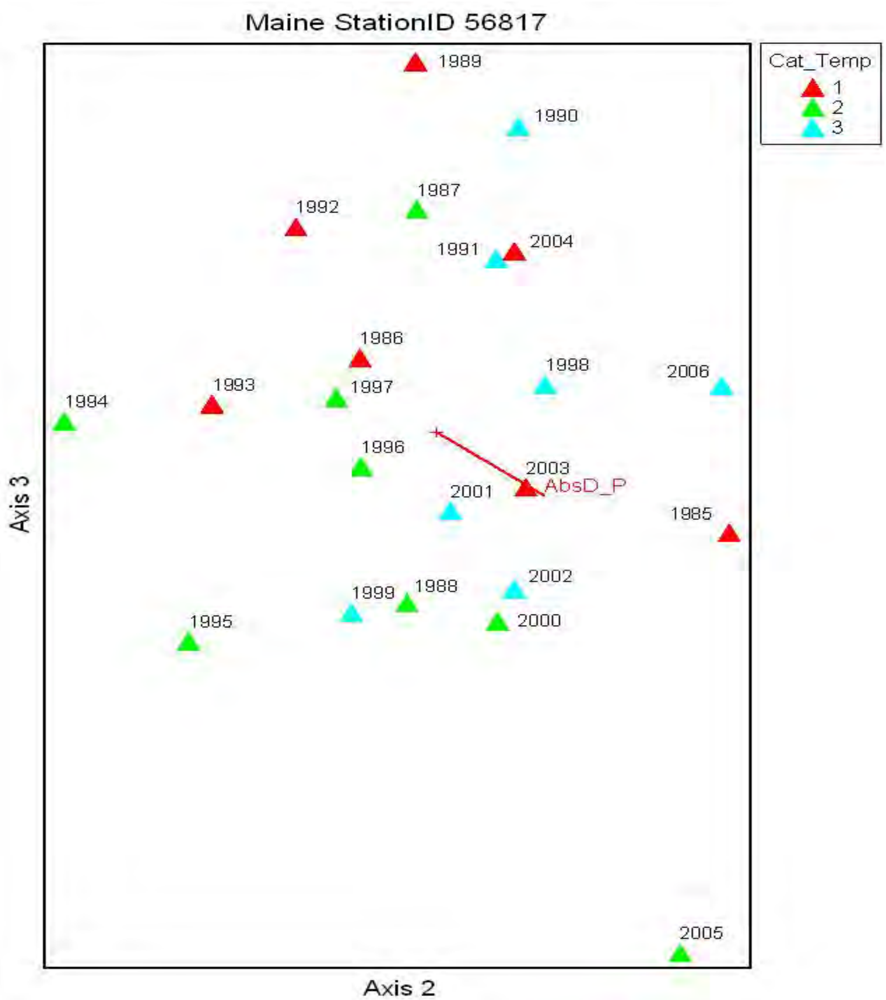

Figure 4-14. NMDS plot (Axis 1-2) for the Sheepscot River site (ME 56817). Cat_Temp refers to the temperature categories, which are 1 = coldest years; 2 = normal years; 3 = hottest years. Samples are labeled by collection year. Absolute difference between the PRISM mean annual precipitation from the sampling year and the previous year (AbsD_P) is the most strongly correlated environmental variable with Axes 2 and 3.

4.6.2. West Branch Sheepscot (ME 57011)

The West Branch Sheepscot site (ME 57011; Maine DEP Station 268) is located in southern Maine in the town of China. It is in the Laurentian Plains and Hills ecoregion and Central

Interior biophysical region, has a drainage area of 38.1 km^2, and an elevation of 70.1 m. Its highest maximum monthly temperatures occur during July and August, and its lowest average flows (<85 cfs) occur from July through September. This station has 12 years of continuous biological data, spanning from 1995 to 2006, that have been collected during Maine DEP's July through September index period. We gathered daily temperature and precipitation data from 1949 to 2010 from the Augusta FAA AP weather station (SiteID 170275, Latitude: 44.3206, Longitude: 69.7972), which is located approximately 21.8 km west/southwest of the biological sampling site. Flow data from 1939−2009 were gathered from USGS gage 1038000 (Sheepscot River at North Whitefield, Latitude: 44.22278, Longitude: 69.59389), which is located approximately 17 km south of the biological sampling site, on the mainstem of the Sheepscot. Figure 4-15 shows an aerial photograph of the site, along with the weather station and active USGS gage.

Figure 4-15. Locations of the West Branch Sheepscot site (ME 57011) biological sampling site, USGS gage 1038000 (Sheepscot River at North Whitefield) and Augusta FAA AP weather station. Image from Google Earth.

4.6.2.1. *Temporal Trends in Climatic and Biological Variables*

Since 1949, mean annual air temperatures at the weather station closest to the West Branch Sheepscot site (ME 57011) site have ranged from 6 to 9.8°C. There is a great deal of year-to-year variability, but overall, temperatures have been increasing over time (when fit with a linear trend line, $r^2 = 0.06$, $p = 0.05$) (see Figure 4-16). When PRISM air temperature data are compared to observed data, PRISM data are within 1°C of the observed values, and there is good correspondence between patterns. Based on the USGS gage located on the Sheepscot River mainstem, mean annual flow and mean annual precipitation patterns have been highly variable over time (see Figure 4-11). Since 1939, mean annual flow values have ranged from 110.1 to 485.7 cfs (when fit with a linear trend line, $r^2 = 0.08$, $p = 0.02$). Precipitation patterns generally show good correspondence with flow patterns but are more variable (see Figure 4-17).

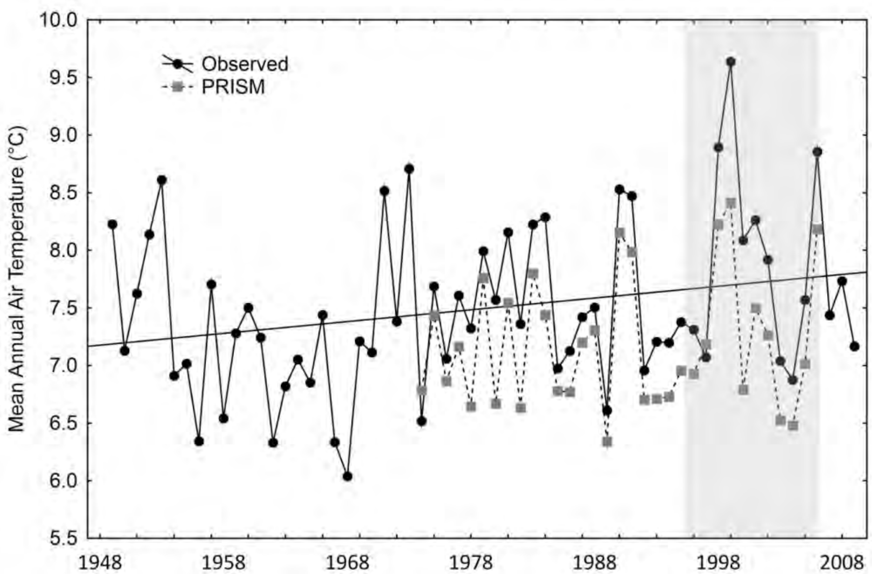

Figure 4-16. Yearly trends in annual observed air temperature (°C) at the West Branch Sheepscot site (ME 57011) from 1949–2009, based on data from the Augusta FAA AP weather station. For comparative purposes, PRISM annual air temperature data associated with the biological sampling site are also included from 1975–2005. The area shaded in grey corresponds to the period of biological record. When the observed data are fitted with a linear trend line, $r^2 = 0.06$, $p = 0.05$, and $y = -12.718 + 0.0102 \times x$.

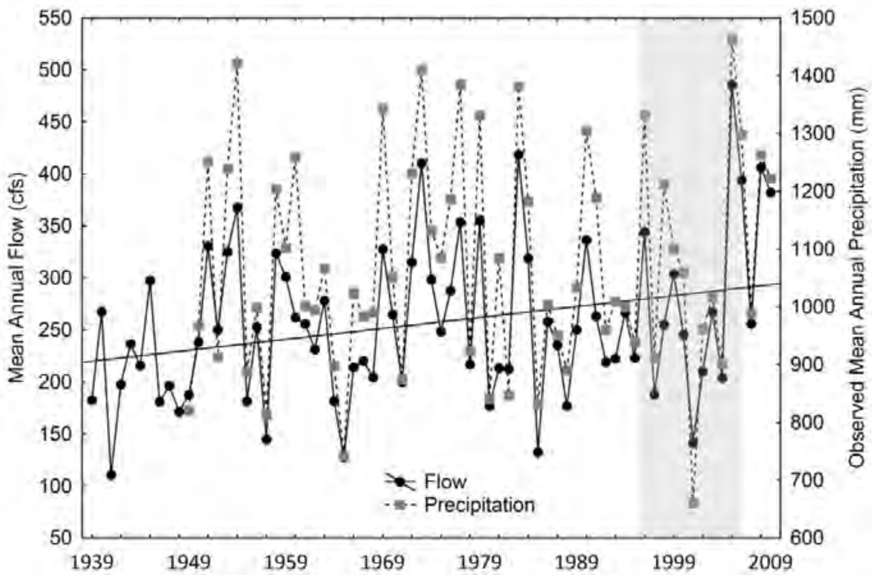

Figure 4-17. Yearly trends in mean annual flow (cfs) at the West Branch Sheepscot site (ME 57011) from 1939–2009, based on data from USGS gage 1038000 (Sheepscot River at North Whitefield). For comparative purposes, observed annual precipitation data from the Augusta FAA AP weather station are also included from 1949–2009. The area shaded in grey corresponds to the period of biological record. When the observed data are fitted with a linear trend line, $r^2 = 0.08$, $p = 0.02$, and $y = -1{,}814.9037 + 1.0494 \times x$.

In addition to mean annual values, mean maximum July and August temperature and mean July−September flow values were also evaluated. During the period of biological record (1995–2006), mean maximum July/August air temperatures ranged from 24.6−27.8°C, and mean fall flow values ranged from 17.0 to 156.7 cfs (see Table 4-19). Attainment classes based on biological condition have ranged from Class A to B. Prior to 2000, samples consistently attained Class A status, but since that time, they have fluctuated back and forth between Class A and B (see Figure 4-18A). The number of EPT taxa has increased over time, ranging from 6 in 1995 to 14 in 2005 (see Figure 4-18B). HBI scores have increased as well, from a low of 3.0 in 1995 to a high of 5.5 in 2004 (see Figure 4-18B). During the period of biological record, mean maximum July/August air temperatures and July–September flows were highly variable, with the highest maximum July/August temperature occurring in 1999, the lowest July–September flows occurring in 2000, and the highest July–September flows occurring in 2005 (see Figure 4-18C). The number of warm-water taxa has varied, but overall, numbers have increased over time, ranging from 4 in 1996 to 11 in 2001 (see Figure 4-19A). The percentage of warm water

Table 4-19. Range of temperature, precipitation, and flow values that occurred at the West Branch Sheepscot site (ME 57011) during the period of biological record

Parameter	Min	Max
Year	1995	2006
Observed mean annual air temperature (°C)	6.9	9.6
PRISM mean annual air temperature (°C)	6.5	8.4
Observed mean maximum July/August air temperature (°C)	24.6	27.8
Mean annual flow (cfs)	141.6	485.7
Mean July−September flow (cfs)	17.0	156.7
Observed mean annual precipitation (mm)	661.3	1,461.8
PRISM mean annual precipitation (mm)	756.5	1,652.4

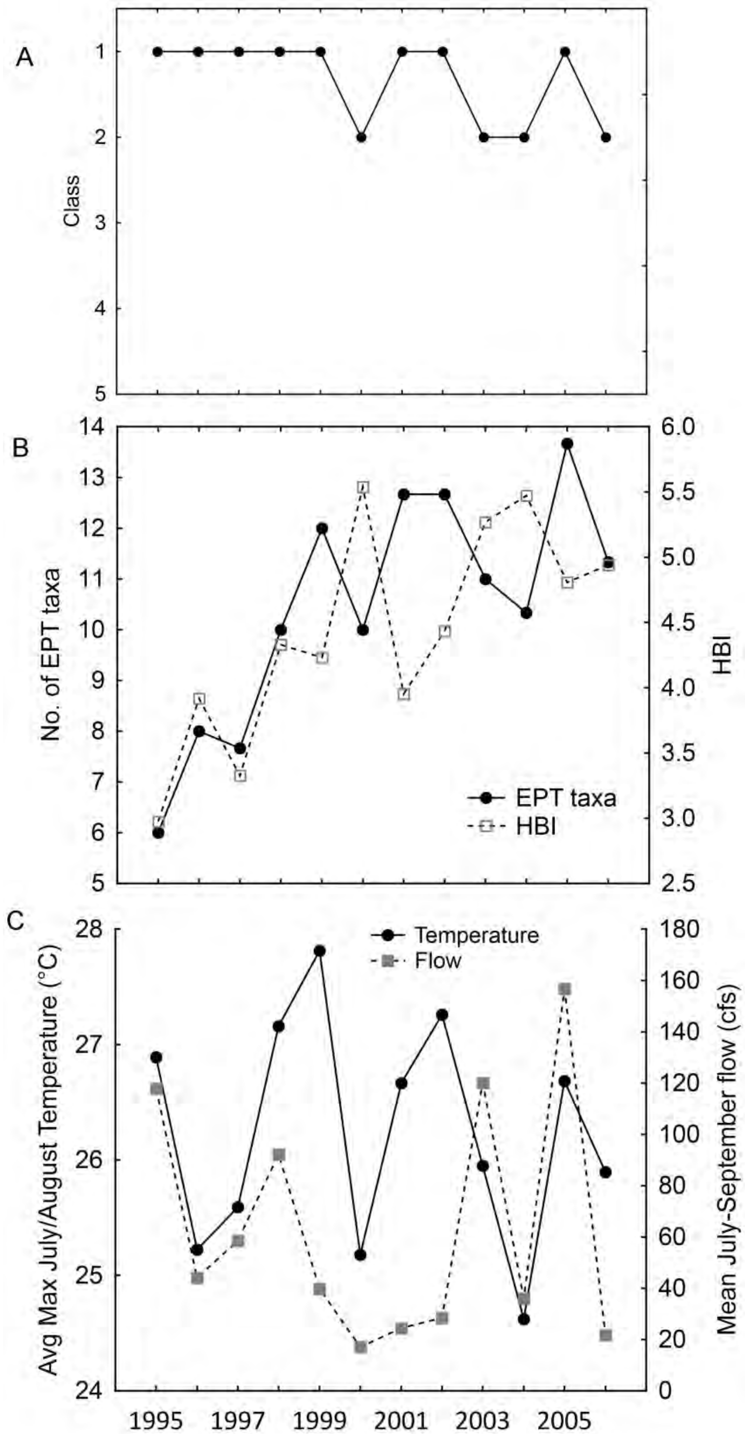

Figure 4-18. Yearly trends at the West Branch Sheepscot site (ME 57011) in (A) biological condition class (1 = Class A; 2 = Class B; 3 = Class C; 4 = NA); (B) number of EPT taxa and HBI; and (C) mean maximum July/August temperature (°C) and mean July−September flow (cfs).

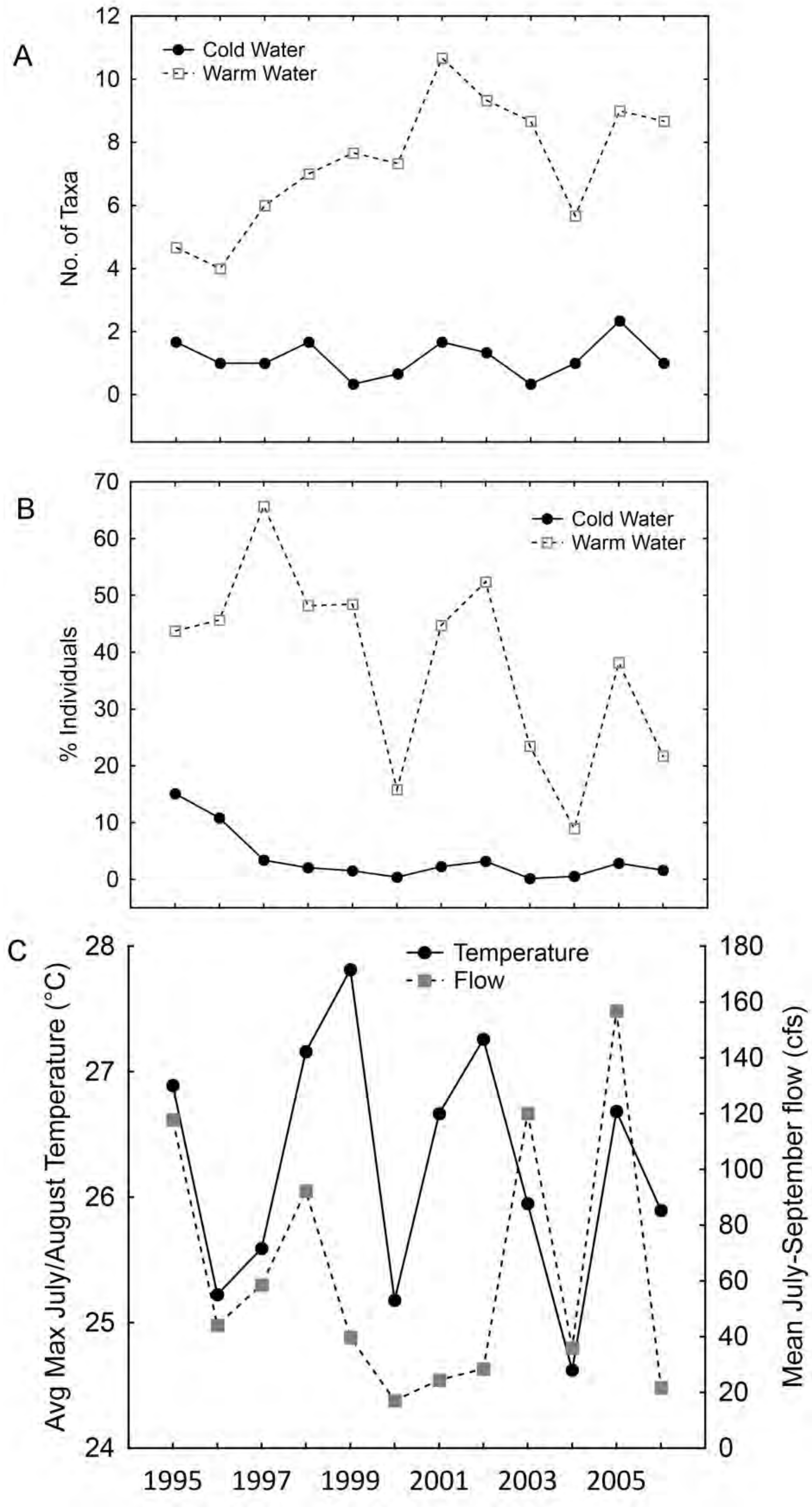

Figure 4-19. Yearly trends at the West Branch Sheepscot site (ME 57011) in (A) number of cold and warm-water taxa; (B) percentage cold and warm-water individuals; and (C) mean maximum July/August temperature (°C) and mean July–September flow (cfs).

individuals has varied over time, ranging from a high of 66% in 1997 to a low of 9% in 2004 (see Figure 4-19B). Very few cold-water taxa are present at this site, with richness values ranging from 0 to 2.

It is likely that conditions at this site have been influenced by nonpoint source pollution, with potential anthropogenic influences from urban and agricultural land use (9% urban and 18.5% agricultural within a 1-km buffer). Some recent (post-2000) water chemistry data are available for various nutrient-related parameters. The maximum nitrogen concentration was 0.56 mg/L, the maximum ammonia concentration ammonia was 0.05 mg/L, and the maximum total phosphorus concentration was 0.02 mg/L. Confounding factors related to in situ measurements were not evident, with values in the following ranges:

- DO: 7.5 to 9.5 mg/L
- pH: 6.7 to 7.4
- Specific conductance: 42 to 82 μmho/cm

4.6.2.2. *Associations Between Biological Variables and Climatic Variables*

Kendall tau nonparametric correlations analyses allow examination of associations between commonly used biological metrics, year, temperature, flow, and precipitation variables at the West Branch Sheepscot site (ME 57011) site. Three of the commonly used biological metrics (percentage EPT individuals, percentage Ephemeroptera individuals, and the Shannon-Wiener Diversity Index) showed strong positive associations ($r \geq 0.5$) with the temperature variables (see Table 4-20). The number of Ephemeroptera taxa metric also had a fairly strong ($r \geq 0.4$) positive association with temperature. If we assume that higher temperatures are associated with more stressful conditions, then the direction of these relationships is unexpected. Only one of the biological metrics had a fairly strong ($r \geq 0.4$) association with the flow and precipitation variables. The percentage noninsect individuals metric was negatively associated with mean annual flow and precipitation. Four metrics (total number of taxa, number of EPT taxa, number of Trichoptera taxa, and HBI) had strong positive associations ($r \geq 0.5$) with year (see Table 4-20). The number of intolerant taxa and number of Ephemeropteran taxa metrics also showed a fairly strong ($r \geq 0.4$) positive association with year. The positive trend in HBI

Table 4-20. Kendall tau nonparametric correlations analyses performed to examine associations between commonly used biological metrics, year, and climatic variables at the West Branch Sheepscot site (ME 57011). Results are based on 12 years of data. Entries are in bold text if $r \geq \pm 0.5$ and are highlighted in gray if they are in a direction opposite of what is expected. Ranges of biological metric values are also included

Biological metric	Range of metric values		*r* values (based on Kendall Tau correlations)					
				Air temperature (°C)		Flow (cfs)		PRISM mean annual precipitation (mm)
	Min	Max	Year	PRISM mean annual	Observed mean maximum July/August	Mean annual	Mean July−September	
Total no. taxa	12.3	33.3	**0.72**	0.05	0.20	0.14	−0.11	0.05
No. EPT taxa	6.0	13.7	**0.58**	0.12	0.25	0.18	−0.12	0.09
No. Ephemeroptera taxa	2.0	6.3	0.43	0.46	0.37	0.34	0.06	0.37
No. Plecoptera taxa	0.3	1.7	0.18	0.11	0.25	−0.25	0.04	−0.18
No. Trichoptera taxa	2.7	6.7	**0.57**	0.05	0.14	0.14	−0.29	0.08
No. Intolerant taxa	5.0	10.0	0.46	0.09	0.25	−0.03	−0.06	−0.03
Percentage EPT individuals	15.2	80.3	−0.33	**0.55**	0.45	−0.09	0.15	0.00
Percentage Ephemeroptera individuals	6.1	74.6	−0.24	**0.52**	0.48	0.18	0.18	0.27
Shannon-Wiener Diversity Index	2.1	4.2	0.12	**0.45**	0.42	0.00	0.00	−0.03
Percentage noninsect individuals	0.0	2.8	0.36	−0.14	−0.29	−0.42	−0.20	−0.45
Percentage dominant taxon	15.9	68.8	0.09	−0.30	−0.33	0.03	−0.15	0.06
Percentage tolerant individuals	2.1	7.6	0.15	−0.06	0.21	−0.03	0.21	0.00
Hilsenhoff Biotic Index	3.0	5.5	**0.58**	−0.24	−0.27	0.09	−0.27	0.06

scores suggests that the assemblage may have experienced more organic enrichment in recent years, but this is somewhat confounded by the concurrent positive trend in the number of intolerant taxa and EPT-related metrics.

We performed similar analyses on the thermal preference metrics. The percentage warm-water individuals metric had a strong ($r \geq 0.5$) positive association with the temperature variables (see Table 4-21). The number of warm-water taxa metric had a fairly strong ($r \geq 0.4$) positive association with year, and the percentage cold-water individuals metric had a fairly strong ($r \geq 0.4$) negative association with year. The subset of biological metrics that have shown responsiveness to hydrologic variables in other studies (see Section 2, Table 2-6) failed to show strong ($r \geq 0.5$) relationships with the flow and precipitation variables (see Table 4-22). The number of depositional taxa metric had a fairly strong ($r \geq 0.4$) negative association with mean annual flow, while the number of erosional taxa metric unexpectedly had a fairly strong ($r \geq 0.4$) negative association with mean July–September flows. Three of the metrics (number of collector gatherer taxa, number of swimmer taxa, and percentage predator individuals) had strong ($r \geq 0.5$) associations with year, with the percentage of predator individuals being negatively associated with year, and the others showing a positive association with year. The number of erosional taxa metric also had a fairly strong ($r \geq 0.4$) positive association with year, while the percentage of OCH individuals metric had a fairly strong ($r \geq 0.4$) negative association with year.

4.6.2.3. *Groupings Based on Climatic Variables*

Samples were partitioned into hottest/coldest/normal year groups and lowest/normal/highest flow year groups. At the West Branch Sheepscot site (ME 57011), on average, the hottest years were 1.7°C warmer than the coldest years, and highest flow years had 196 more cfs than lowest flow years. When samples were grouped based on temperature, there were no significant ($p > 0.05$) differences between mean metric values (see Table 4-23). Although not significant, there are some patterns worth noting. Mean numbers of total taxa, EPT taxa, and number of warm-water taxa were highest in hottest year samples. The percentage of warm-water individuals metric was lowest in the coldest year samples, and the HBI was highest in the coldest year samples. When samples were grouped based on flow, there were also no significant ($p > 0.05$) differences between mean metric values (see Table 4-24). Patterns worth noting are that, on average, the percentage of cold-water individuals metric was lowest in the

Table 4-21. Kendall tau nonparametric correlations analyses performed to examine associations between thermal preference metrics, year, and climatic variables at the West Branch Sheepscot site (ME 57011). Results are based on 12 years of data. Entries are in bold text if $r \geq \pm 0.5$. Ranges of biological metric values are also included

Biological metric	Range of metric values		*r* values (based on Kendall tau correlations)					
				Air temperature (°C)		Flow (cfs)		
	Min	Max	Year	PRISM mean annual	Observed mean maximum July/August	Mean annual	Mean July−September	PRISM mean annual precipitation (mm)
No. cold-water taxa	0.3	2.3	−0.03	0.20	0.20	−0.07	0.23	−0.03
Percentage cold-water individuals	0.2	15.1	−0.42	−0.03	0.12	−0.06	0.24	0.03
No. warm-water taxa	4.0	10.7	0.47	0.26	0.32	0.05	−0.11	0.02
Percentage warm-water individuals	9.0	65.8	−0.33	0.42	**0.52**	−0.15	0.09	−0.06

Table 4-22. Kendall tau nonparametric correlations analyses performed to examine associations between a subset of biological metrics, year, flow, and precipitation variables at the West Branch Sheepscot site (ME 57011). The subset of biological metrics were selected per the criteria outlined in Section 2 and have shown responsiveness to hydrologic variables in other studies (see Section 2, Table 2-2). Results are based on 15 years of data. Entries are in bold text if $r \geq \pm 0.5$. Ranges of biological metric values are also included

Biological metric		Range of metric values		*r* values (based on Kendall tau correlations)			
					Flow (cfs)		
		Min	Max	Year	Mean annual	Mean July−September	PRISM mean annual precipitation (mm)
Richness	Collector filterer	2.3	6.7	0.25	0.25	−0.34	0.13
	Collector gatherer	1.7	12.3	**0.62**	−0.06	0.00	−0.15
	Scraper/herbivore	2.3	7.0	0.36	−0.11	−0.17	−0.11
	Predator	3.3	9.3	0.34	0.09	−0.03	0.12
	Swimmer	0.0	2.7	**0.54**	0.32	0.00	0.29
	OCH	2.3	6.7	0.28	0.09	−0.12	0.15
	Depositional	1.0	4.0	0.11	−0.42	0.02	−0.39
	Erosional	4.3	9.0	0.44	0.17	−0.41	0.14
Percentage individuals	Collector filterer	6.0	78.4	0.36	0.24	−0.12	0.15
	Collector gatherer	9.5	46.2	0.06	0.06	0.24	0.09
	Scraper/herbivore	3.3	46.4	−0.30	0.00	0.06	0.09
	Predator	4.7	46.0	**−0.64**	−0.09	0.27	−0.12
	Swimmer	0.0	32.6	0.15	0.21	0.15	0.24
	OCH	1.9	25.5	−0.45	0.15	0.33	0.24
	Depositional	3.0	29.2	−0.03	−0.15	0.21	−0.12
	Erosional	6.0	45.9	−0.21	−0.03	0.03	−0.12

Table 4-23. Mean metric values (±1 SD) for the West Branch Sheepscot site (ME 57011) in coldest, normal, and hottest year samples. Year groups are based on PRISM mean annual air temperature values. One-way ANOVA was performed to evaluate differences in mean metric values. There are no significant (*p* > 0.05) differences across year groups

Year group	Total no. taxa	No. EPT taxa	HBI	No. cold-water taxa	No. warm-water taxa	% Cold-water individuals	% Warm-water individuals
Coldest	21.7 ± 4.8	9.8 ± 1.3	5.0 ± 0.8	0.8 ± 0.3	6.4 ± 2.0	3.0 ± 5.2	23.5 ± 15.9
Normal	24.1 ± 10.4	10.0 ± 3.7	3.9 ± 0.9	1.6 ± 0.6	7.3 ± 2.3	6.1 ± 6.0	50.0 ± 12.0
Hottest	25.2 ± 3.4	11.5 ± 1.1	4.4 ± 0.4	1.2 ± 0.6	8.5 ± 1.6	1.9 ± 0.4	40.8 ± 12.8

Table 4-24. Mean metric values (±1 SD) for the West Branch Sheepscot site (ME 57011) in driest, normal, and wettest flow year samples. Year groups are based on mean annual flow values from USGS gage 10128500. One-way ANOVA was performed to evaluate differences in mean metric values. There are no significant (*p* > 0.05) differences across year groups

Year group	Total no. taxa	No. EPT taxa	HBI	No. cold-water taxa	No. warm-water taxa	% Cold-water individuals	% Warm-water individuals
Driest	26.3 ± 6.2	10.8 ± 2.4	4.3 ± 0.9	1.3 ± 0.3	7.9 ± 2.5	2.3 ± 1.3	43.0 ± 24.3
Normal	20.5 ± 5.6	9.3 ± 2.2	4.5 ± 1.2	1.1 ± 0.7	6.9 ± 1.7	4.4 ± 7.2	32.8 ± 15.6
Wettest	24.2 ± 7.7	11.3 ± 2.4	4.5 ± 0.5	1.2 ± 0.8	7.3 ± 2.3	4.2 ± 4.5	38.5 ± 12.0

driest flow year samples, and the warm water metrics were highest in the driest flow year samples. There were insufficient data at this site to do NMDS ordinations.

4.6.3. Duck Brook (ME 57065)

The Duck Brook site (ME 57065; Maine DEP Station 322) is located in southeastern Maine in the town of Bar Harbor. It is in the Laurentian Plains and Hills ecoregion and East Coastal Region biophysical region, has a drainage area of 12.8 km^2, and an elevation of 54.6 m. Its highest maximum monthly temperatures and lowest average rainfall occur in July and August. This station has 9 years of continuous biological data, spanning from 1997 to 2006, that have been collected during Maine DEP's July through September index period. We gathered daily temperature and precipitation data from 1893 to 1982 from the Bar Harbor 3 NW weather station (SiteID 170371, Latitude: 44.4167, Longitude: 68.25), which is located on the coast, approximately 3 km northwest of the biological sampling site. We gathered daily temperature and precipitation data from 1982 to 2009 from the Acadia NP weather station (SiteID 170100, Latitude: 44.3739, Longitude: 68.2592), which is located approximately 3 km southwest of the biological sampling site. There were no USGS gages located in proximity to the biological sampling site. Figure 4-20 shows an aerial photograph of the site, along with the weather station and active USGS gage.

4.6.3.1. *Temporal Trends in Climatic and Biological Variables*

Since 1893, mean annual air temperatures at the weather stations closest to the Duck Brook site (ME 57065) have ranged from 5.4 to 9.3°C. There is a great deal of year-to-year variability, but overall, temperatures have been increasing over time (when fit with a linear trend line, $r^2 = 0.11$, $p < 0.01$) (see Figure 4-21). When PRISM air temperature data are compared to observed data, PRISM data are within 1°C of the observed values, and there is good correspondence between patterns. Flow data were not available for this site, so precipitation was used as a surrogate. Precipitation patterns have varied a lot from year to year, but overall, mean annual precipitation has been increasing over time (when fit with a linear trend line, $r^2 = 0.09$, $p < 0.01$) (see Figure 4-22). PRISM precipitation trends from 1975−2005 show good correspondence with the observed precipitation patterns (see Figure 4-22). In addition to

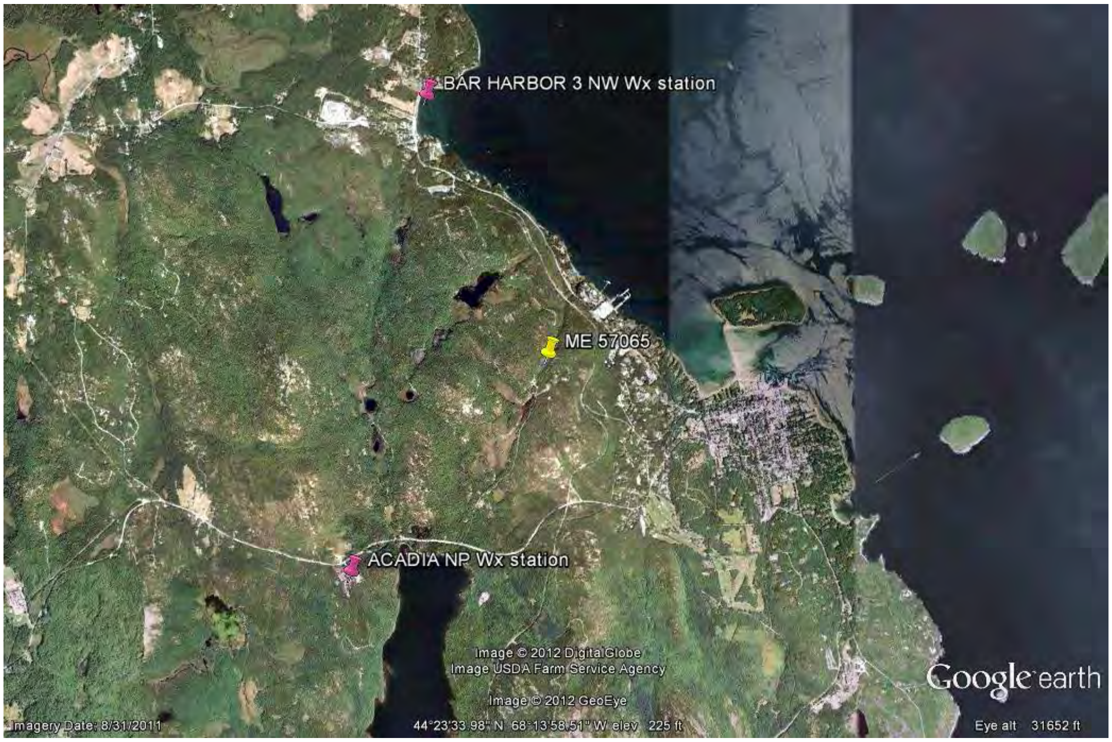

Figure 4-20. Locations of the Duck Brook site (ME 57065) biological sampling site, Bar Harbor 3 NW weather station and Acadia NP weather station. Image from Google Earth.

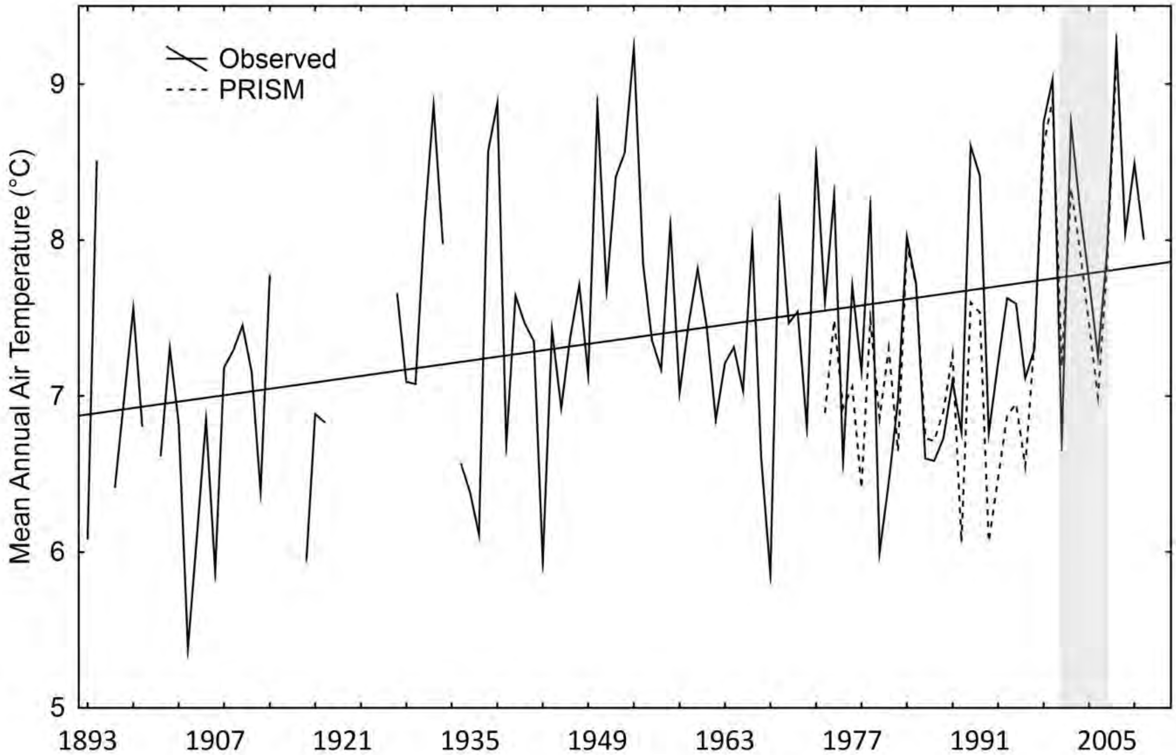

Figure 4-21. Yearly trends in annual observed air temperature (°C) at the Duck Brook site (ME 57065) from 1893–2009, based on data from the Bar Harbor 3 NW and Acadia NP weather stations. For comparative purposes, PRISM annual air temperature data associated with the biological sampling site are also included from 1975–2005. The area shaded in grey corresponds to the period of biological record. When the observed data are fitted with a linear trend line, $r^2 = 0.11$, $p < 0.01$, and $y = –8.6883 + 0.0082 \times x$.

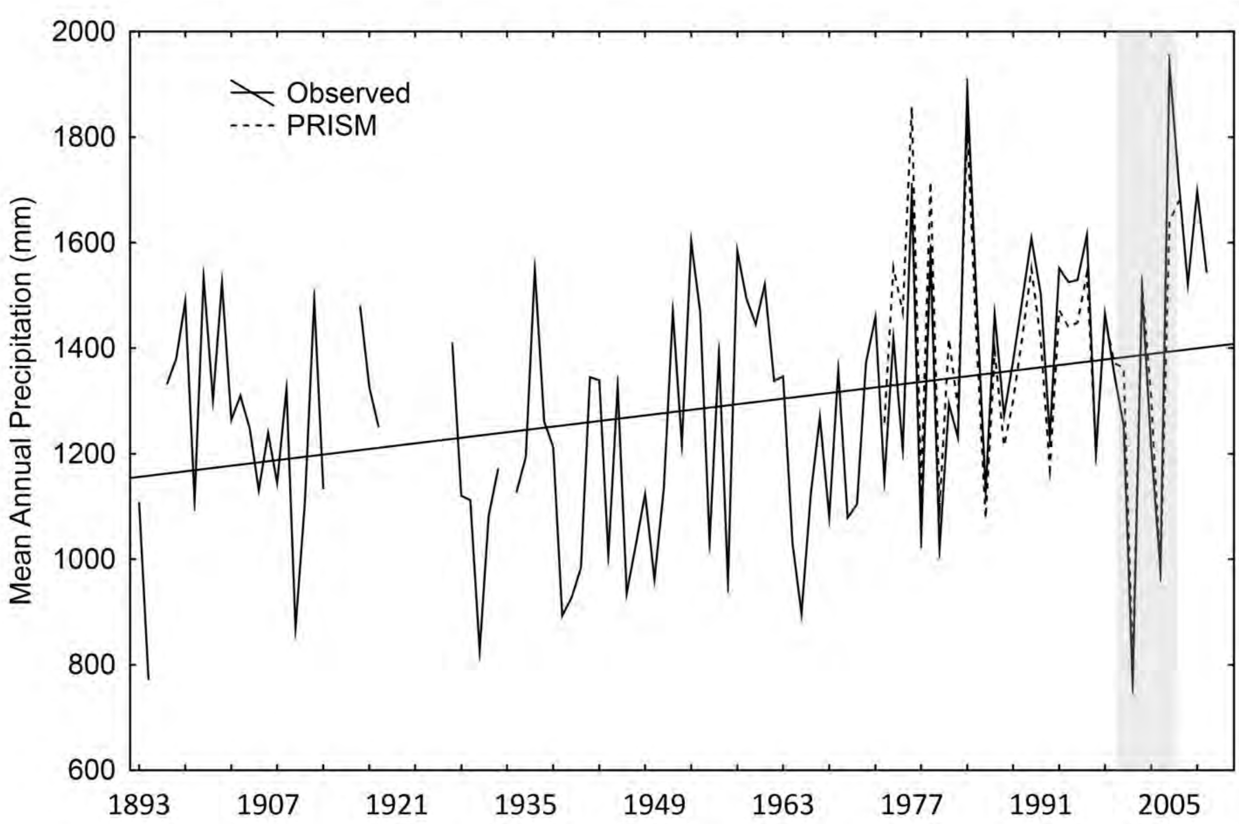

Figure 4-22. Yearly trends in annual observed precipitation (mm) at the Duck Brook site (ME 57065) from 1893–2009, based on data from the Bar Harbor 3 NW and Acadia NP weather stations. For comparative purposes, PRISM mean annual precipitation data associated with the biological sampling site are also included from 1975–2005. The area shaded in grey corresponds to the period of biological record. When the observed data are fitted with a linear trend line, $r^2 = 0.09$, $p < 0.01$, and $y = -2{,}852.2872 + 2.1174 \times x$.

mean annual values, mean maximum July and August temperature and mean July–September flow values were also evaluated. During the period of biological record (1997–2005), mean maximum July/August air temperatures ranged from 23.6−27.3°C, and mean July–September precipitation values ranged from 32.8 to 97.5 mm (see Table 4-25).

Attainment classes based on biological condition have ranged from Class A to C. From 1997 to 2000, samples met Class A status, then dropped to Class C in 2001, then improved to Class B in 2002 before returning to Class A in 2003 (see Figure 4-23A). The number of EPT taxa has been variable, but overall, numbers have increased over time, ranging from 5 in 1999 to 11 in 2004 (see Figure 4-23B). HBI scores have gone up and down over the period of record, hitting a high of 6.3 in 2001 before dropping back down to a score of 3.9 in 2004 (see Figure 4-23B). During the period of biological record, mean maximum July/August air temperatures and July–September flows were highly variable, with the highest maximum July/August temperature occurring in 1998, the lowest July–September rainfall occurring in 2001, and the highest rainfall occurring in 1999 (see Figure 4-23C). The number of warm-water taxa varied from year to year, but overall, numbers have increased over time, ranging from 3 in 1999 to 8 in 2003 (see Figure 4-24A). The percentage of warm-water individuals has been highly variable, ranging from 22 to 69% (see Figure 4-24B). Low numbers of cold-water taxa occur at this site, with richness numbers mostly ranging from one to two, except for 2004, when there were four cold-water taxa that comprised 15% of the assemblage.

It is possible that anthropogenic stressors associated with surrounding land use have influenced conditions at this site. The land use within a 1-km buffer is 16% urban due to two small roads that parallel the stream. Water chemistry data were limited to in situ measurements, which were in the following ranges:

- DO: 7.4 to 9.0 mg/L
- pH: 6.6 to 7.0
- Specific conductance: 41 to 82 µmho/cm

Table 4-25. Range of temperature, precipitation, and flow values that occurred at the Duck Brook site (ME 57065) during the period of biological record

Parameter	Min	Max
Year	1997	2005
Observed mean annual air temperature (°C)	6.7	9.0
PRISM mean annual air temperature (°C)	7.0	8.9
Observed mean maximum July/August Air temperature (°C)	23.6	27.3
Observed mean annual precipitation (mm)	763.7	1,937.8
Observed mean July−September precipitation (mm)	32.8	97.5
PRISM mean annual precipitation (mm)	794.7	1,640.4

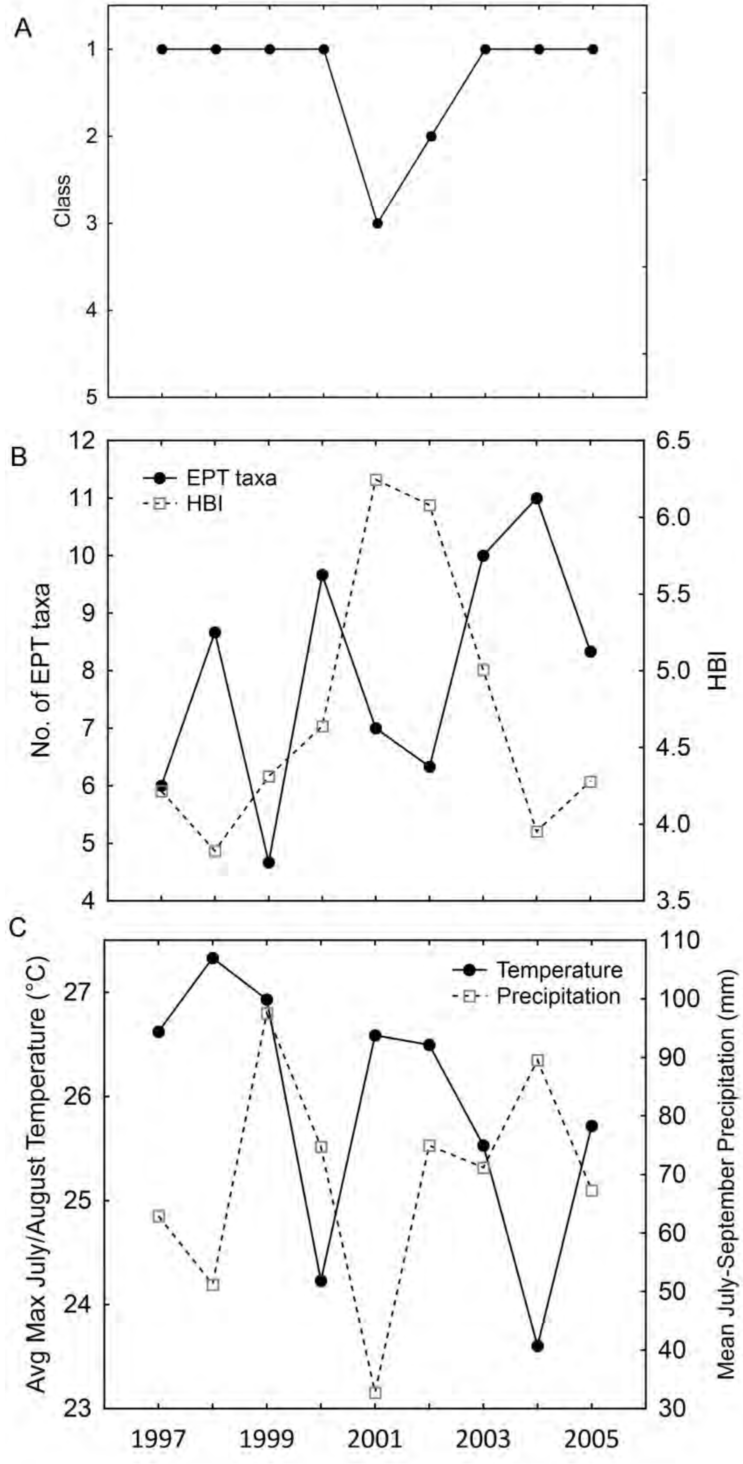

Figure 4-23. Yearly trends at the Duck Brook site (ME 57065) in (A) biological condition class (1 = Class A; 2 = Class B; 3 = Class C; 4 = NA); (B) number of EPT taxa and HBI; and (C) mean maximum July/August temperature (°C) and mean July–September precipitation (mm).

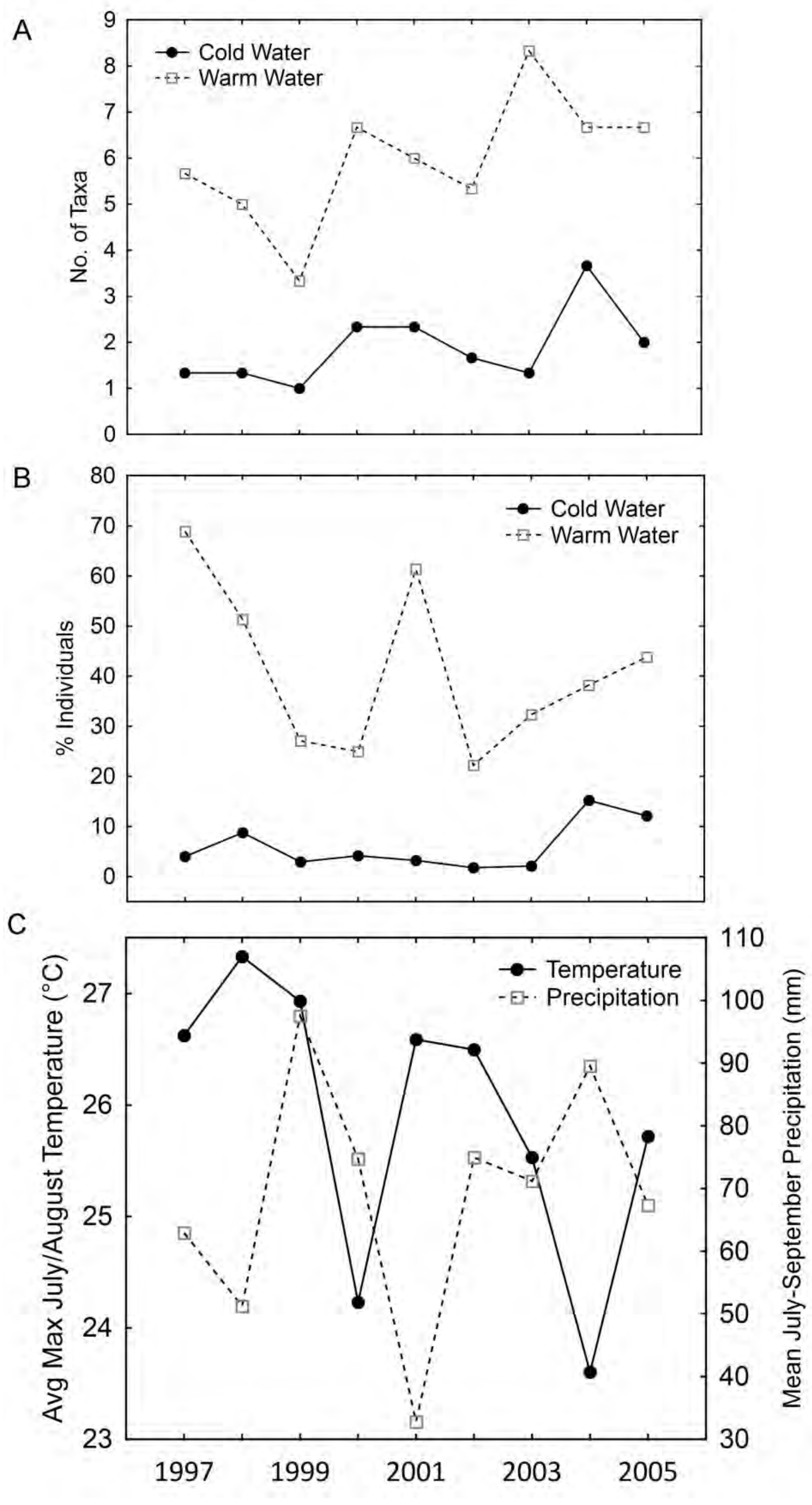

Figure 4-24. Yearly trends at the Duck Brook site (ME 57065) in (A) number of cold and warm-water taxa; (B) percentage cold and warm-water individuals; and (C) mean maximum July temperature (°C) and mean July−September precipitation (mm).

4.6.3.2. *Associations Between Biological Variables and Climatic Variables*

Kendall tau nonparametric correlations analyses allow examination of associations between commonly used biological metrics, year, temperature, and precipitation variables at the Duck Brook site (ME 57065) site. Seven of the commonly used biological metrics showed strong ($r \geq 0.5$) or fairly strong ($r \geq 0.4$) negative associations with mean annual and/or mean July/August maximum air temperature (see Table 4-26). The number of Plecoptera taxa, number of intolerant taxa, and the Shannon-Wiener Diversity Index had strong ($r \geq 0.5$) negative associations with both temperature variables, while the total number of taxa and the number of EPT taxa metrics had strong ($r \geq 0.5$) negative associations with the mean July/August maximum air temperature and fairly strong ($r \geq 0.4$) negative associations with mean annual temperature. The number of Ephemeroptera taxa metric had fairly strong ($r \geq 0.38$) negative associations with both temperature variables, and the number of Trichoptera metric had a fairly strong ($r \geq 0.4$) negative association with mean July/August maximum air temperature. Only one of the commonly used biological metrics was strongly ($r \geq 0.5$) correlated with the precipitation variables. The percentage of noninsect individuals metric was positively correlated with mean July−September precipitation. Two of the metrics, number of intolerant taxa and percentage noninsect individuals, had strong ($r \geq 0.6$) positive associations with year.

We performed similar analyses on the thermal preference metrics. The number of cold-water taxa metric showed strong ($r \geq 0.5$) negative associations with both temperature variables (see Table 4-27). The warm water metrics also had strong negative associations with both temperature variables, which was unexpected. Only one of the biological metrics that have shown responsiveness to hydrologic variables in other studies (see Section 2, Table 2-6) showed a strong ($r \geq 0.5$) relationships with the precipitation variables. The percentage collector-gatherer individuals metric had a strong ($r \geq 0.5$) negative association with mean annual precipitation (see Table 4-28). One of the metrics, number of scraper/herbivore taxa, had a strong ($r = 0.80$) positive association with year.

4.6.3.3. *Groupings Based on Climatic Variables*

Samples were partitioned into hottest/coldest/normal year groups and lowest/normal/highest flow year groups. At the Duck Brook site (ME 57065), on average, the hottest years were 1.4°C warmer than the coldest years, and wettest years had

Table 4-26. Kendall tau nonparametric correlations analyses performed to examine associations between commonly used biological metrics, year, and climatic variables at the Duck Brook site (ME 57065). Results are based on 9 years of data. Entries are in bold text if *r* ≥ ±0.5. Ranges of biological metric values are also included

	Range of metric values		*r* values (based on Kendall tau correlations)				
				Air temperature (°C)		Precipitation (mm)	
Biological metric	Min	Max	Year	PRISM mean annual	Observed mean maximum July/August	PRISM mean annual	Observed July−September
Total no. taxa	13.0	28.0	0.39	−0.33	**−0.61**	−0.11	0.17
No. EPT taxa	4.7	11.0	0.39	−0.44	**−0.61**	−0.22	0.06
No. Ephemeroptera taxa	2.3	5.3	0.26	−0.44	−0.38	−0.15	−0.03
No. Plecoptera taxa	0.3	1.7	0.30	**−0.50**	**−0.50**	−0.17	0.17
No. Trichoptera taxa	1.3	5.3	0.17	−0.23	−0.40	−0.06	0.06
No. Intolerant taxa	3.0	7.3	**0.61**	**−0.61**	**−0.84**	−0.03	0.26
Percentage EPT individuals	11.4	89.2	−0.11	−0.17	0.11	0.06	−0.33
Percentage Ephemeroptera individuals	3.6	77.4	−0.17	−0.22	0.06	−0.11	−0.39
Shannon-Wiener Diversity Index	2.8	4.1	0.22	**−0.50**	**−0.56**	−0.17	0.33
Percentage noninsect individuals	0.8	24.6	**0.61**	−0.11	−0.39	0.11	**0.50**
Percentage dominant taxon	17.9	47.6	−0.39	0.33	0.39	−0.11	−0.39
Percentage tolerant individuals	8.0	52.5	−0.06	0.11	0.06	−0.33	−0.17
Hilsenhoff Biotic Index	3.8	6.2	0.17	0.22	−0.06	−0.11	0.06

Table 4-27. Kendall tau nonparametric correlations analyses performed to examine associations between thermal preference metrics, year, and climatic variables at the Duck Brook site (ME 57065). No warm-water taxa were present at this site. Results are based on 9 years of data. Entries are in bold text if $r \geq \pm 0.5$ and are highlighted in gray if they are in a direction opposite of what is expected. Ranges of biological metric values are also included

	Range of metric values		*r* values (based on Kendall tau correlations)				
				Air temperature (°C)		Precipitation (mm)	
Biological metric	Min	Max	Year	PRISM mean annual	Observed mean maximum July/August	PRISM mean annual	Observed July−September
No. cold-water taxa	1.0	3.7	0.35	−0.47	**−0.59**	−0.18	0.00
Percentage cold-water individuals	1.8	15.2	0.06	−0.33	−0.17	0.00	−0.06
No. warm-water taxa	3.3	8.3	0.44	**−0.61**	**−0.67**	−0.15	−0.03
Percentage warm-water individuals	22.2	68.9	−0.17	0.00	0.28	−0.33	−0.61

Table 4-28. Kendall tau nonparametric correlations analyses performed to examine associations between a subset of biological metrics, year, flow, and precipitation variables at the Duck Brook site (ME 57065). The subset of biological metrics were selected per the criteria outlined in Section 2 and have shown responsiveness to hydrologic variables in other studies (see Section 2, Table 2-6). Results are based on 9 years of data. Entries are in bold text if *r* ≥ ±0.5. Ranges of biological metric values are also included

Biological metric		Range of metric values		*r* values (based on Kendall tau correlations)		
					Precipitation (mm)	
		Min	Max	Year	PRISM mean annual	Observed July−September
Richness	Collector filterer	0.7	2.0	0.15	0.27	−0.03
	Collector gatherer	4.0	9.7	0.38	−0.15	0.26
	Scraper/herbivore	3.3	5.3	**0.80**	0.23	0.00
	Predator	4.0	10.0	0.20	−0.31	0.03
	Swimmer	0.3	1.3	0.13	−0.13	0.44
	OCH	1.3	4.0	0.15	−0.39	0.15
	Depositional	0.0	1.7	0.19	−0.25	0.19
	Erosional	3.0	8.0	0.20	−0.08	−0.03
Percentage individuals	Collector filterer	1.0	27.6	0.11	0.28	0.33
	Collector gatherer	11.1	55.8	−0.22	**−0.50**	−0.33
	Scraper/herbivore	8.5	45.7	0.00	−0.06	−0.11
	Predator	12.7	34.0	0.00	0.06	0.00
	Swimmer	0.5	27.4	−0.17	0.00	−0.06
	OCH	2.9	17.8	0.17	−0.33	0.28
	Depositional	0.0	4.3	0.14	−0.14	0.25
	Erosional	9.1	36.3	0.17	0.11	0.39

547 more mm of precipitation than driest years. When samples were grouped based on temperature, there were no significant ($p > 0.05$) differences between mean metric values (see Table 4-29). Although not significant, it is worth noting that mean numbers of total taxa, EPT taxa, cold-water taxa, and warm-water taxa were lowest in the hottest year samples, as was the percentage of cold-water individuals. When samples were grouped based on precipitation, there were also no significant ($p > 0.05$) differences between mean metric values (see Table 4-30). There were insufficient data to do NMDS ordinations at this site.

4.7. SENSITIVITY OF BENTHIC MACROINVERTEBRATES TO TEMPERATURE AND STREAM FLOW

The spatial distributions of cold and warm-water taxa were examined to gain insights into which areas in Maine are likely to be most and least sensitive to projected changes in temperature and stream flow. On average, there are low numbers of cold-water taxa (<2) at all of Maine DEP's sampling locations (see Table 4-31). In all three ecoregions, on average, there are more warm-water than cold-water taxa, with the highest numbers and abundances of warm-water taxa occurring in the Laurentian Plains and Hills ecoregion. If the assumption is made that streams with the highest relative abundances of cold-water taxa will be most sensitive to warming temperatures and changing precipitation patterns, then streams in the Northeastern Highlands ecoregion will be most sensitive (see Table 4-31).

The prevalence and distribution of cold- and warm-water-preference taxa vary predictably with stream order. First- through third-order streams in Maine have slightly greater relative abundance and richness of cold-water-preference taxa (see Figure 4-25A). On average, first- and second-order streams have fewer warm-preference taxa (see Figure 4-25B). The three Maine biological sampling stations that we closely examined for long-term trends were first-, third-, and fourth-order steams. Although the coldest, highest elevation streams are likely to be sensitive to climate change effects, it may be that the greatest amount of change will occur in transitional areas, where species are expected to be closer to their tolerance limits.

Table 4-29. Mean metric values (±1 SD) for the Duck Brook site (ME 57065) in coldest, normal, and hottest year samples. Year groups are based on PRISM mean annual air temperature values. One-way ANOVA was done to evaluate differences in mean metric values. No entries are significantly different ($p < 0.05$) across year groups

Year group	Total no. taxa	No. EPT taxa	HBI	No. cold-water taxa	No. warm-water taxa	% Cold-water individuals	% Warm-water individuals
Coldest	22.1 ± 8.0	8.9 ± 2.6	4.3 ± 0.3	2.4 ± 1.2	6.3 ± 0.6	7.8 ± 6.4	44.0 ± 22.5
Normal	21.7 ± 3.5	8.2 ± 1.8	5.1 ± 0.9	1.7 ± 0.3	6.8 ± 1.5	5.3 ± 5.9	32.8 ± 10.8
Hottest	18.4 ± 3.7	6.8 ± 2.0	4.8 ± 1.3	1.6 ± 0.7	4.8 ± 1.3	5.0 ± 3.3	46.6 ± 17.6

Table 4-30. Mean metric values (±1 SD) for the Duck Brook site (ME 57065) in driest, normal, and wettest year samples. Year groups are based on mean annual flow. One-way ANOVA was done to evaluate differences in mean metric values. No entries are significantly different ($p < 0.05$) across year groups

Year group	Total no. taxa	No. EPT taxa	HBI	No. cold-water taxa	No. warm-water taxa	% Cold-water individuals	% Warm-water individuals
Driest	20.3 ± 6.5	8.0 ± 2.6	4.8 ± 1.3	2.4 ± 1.2	6.1 ± 0.5	7.5 ± 6.7	56.1 ± 16.0
Normal	23.4 ± 6.0	8.1 ± 3.0	4.7 ± 0.3	1.6 ± 0.7	6.1 ± 2.5	3.1 ± 1.0	28.1 ± 3.8
Wettest	18.4 ± 2.2	7.8 ± 1.3	4.7 ± 1.2	1.7 ± 0.3	5.7 ± 0.9	7.6 ± 5.3	39.1 ± 15.1

Table 4-31. Summary of differences in elevation, PRISM mean annual air temperature and precipitation, and mean number and percentage of cold and warm-water-preference taxa across and within major ecoregions. Samples were not limited to a particular season

Ecoregion	No. samples	Elevation (m)	Air temperature (°C)	Richness		Relative abundance	
				Cold water	Warm water	Cold water	Warm water
Northeastern Coastal Zone	576	29.3	8.3	1.7 ± 1.9	3.3 ± 2.8	5.4 ± 9.9	17.0 ± 20.6
Laurentian Plains and Hills	2,830	65.2	6.5	1.1 ± 1.4	4.7 ± 3.3	2.8 ± 6.6	22.4 ± 22.0
Northeastern Highlands	857	210.4	5.8	1.7 ± 2.0	3.2 ± 2.7	7.1 ± 11.8	15.1 ± 17.5

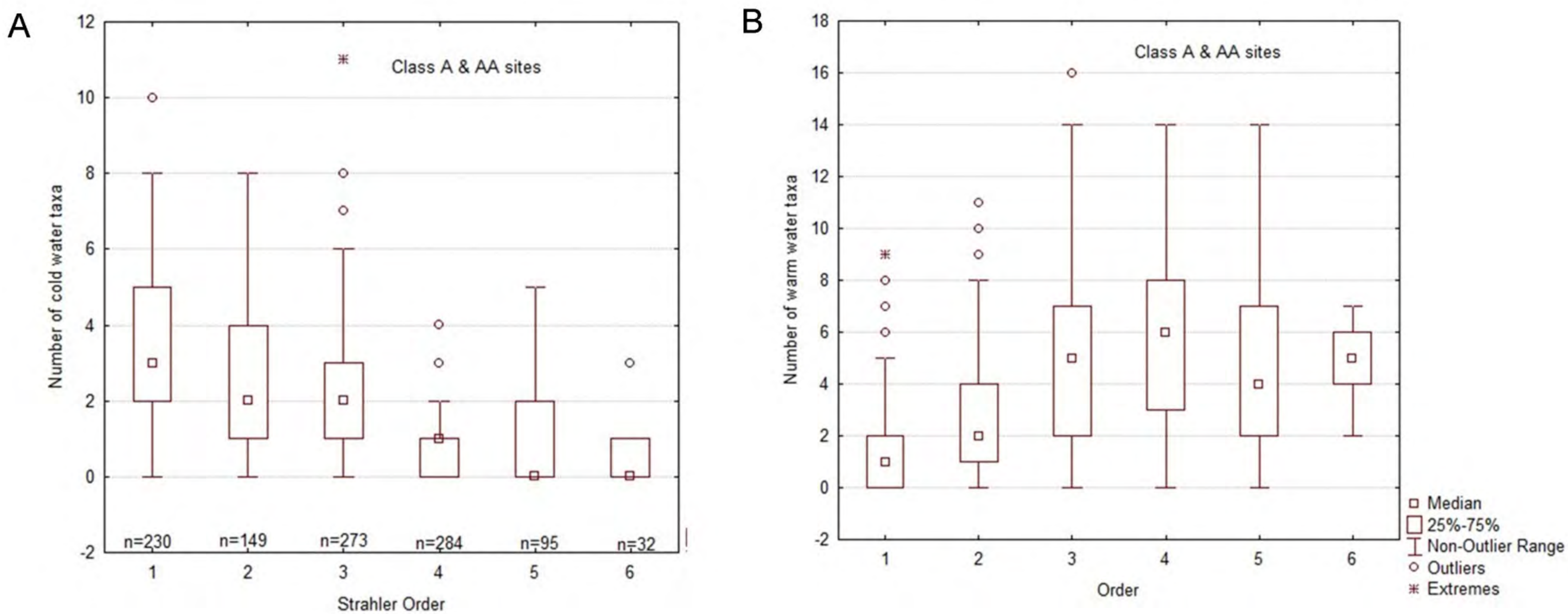

Figure 4-25. Distribution of cold and warm-water taxa across Strahler Orders in Maine, based on July−September replicates collected from sites that received Class A biological condition ratings. Replicates were analyzed separately in this analysis. (A) number of cold-water taxa; (B) number of warm-water taxa. Samples sizes are: first order = 230; second order = 149; third order = 273; fourth order = 284; fifth order = 95; and sixth order = 32.

4.8. IMPLICATIONS FOR MAINE DEP'S BIOMONITORING PROGRAM

Over the last century, there has been a lot of year-to-year variability in temperature and precipitation patterns in Maine, both statewide and at the three long-term biological monitoring sites that we closely examined for temporal trends. Overall, temperature and precipitation have increased from 1901–2000. Because there has been a high degree of year-to-year variability in more recent decades, these trends are less evident from 1971–2000. Future projections in Maine call for a continuation of warming temperatures, especially in the winter. Changes in future precipitation patterns are more difficult to project due to uncertainty associated with the climate models.

When we analyzed data from three long-term biological monitoring sites in Maine, a number of the biological variables were strongly associated with year, so temporal trends were evident. However, few of these trends were associated with temperature, flow, and precipitation variables, and when strong associations did occur with the climate variables, they were not consistent across sites, and some were not in keeping with expectations. Analyses of data grouped by hottest/normal/coldest years and lowest/normal/highest flow years also failed to reveal consistent or significant patterns in the biological data. There was one consistent but nonsignificant pattern that did occur at all three sites—the warm water metrics were highest in the lowest flow/driest year samples.

The lack of strong and consistent associations between biological and climate variables could be due in part to the large amount of year-to-year variability that occurred in the climate variables during the period of biological record. Another possible contributing factor was that anthropogenic influences were higher than desired at all three sites, so biological responses may have been driven more by nonclimate-related factors. Also, the biological assemblages that we evaluated had low numbers of cold-water taxa, which likely limits the responsiveness of the assemblage to warming temperatures. As shown in Table 4-31, on average, there are low numbers of cold-water taxa at sites sampled by Maine DEP. Assemblages composed of greater numbers of cold-water taxa likely exist in Maine, but these may be limited to higher elevation streams that are difficult to access and, thus, are sampled less frequently.

We also performed some additional analyses to try and gain more insights into how climate change may impact Maine DEP's assessment methods. We looked into the possibility of manipulating Maine DEP's linear discriminant models in ways that would simulate potential changes associated with climate change. However, due to the complexity of the models, we were unable to do so. The best alternative that we could develop was to evaluate the model input metrics individually. This type of analysis is informative but is limited by the fact that the linear discriminant models look at multiple variables simultaneously; thus, there are no firm thresholds or individual metric values at which a sample changes classification levels.

First, we evaluated differences in mean model input metric values across the different classification groups. We did this by performing one-way ANOVA analyses on a data set composed of rock basket or rock cone samples collected during Maine DEP's July–September index period. Appendix C contains box plots showing the distributions of the model input metrics across the different classification groups. Results show that Class A samples have, on average:

- High generic richness
- High richness and abundance of EPT taxa
- High Shannon-Wiener diversity index values
- Low HBI scores
- Low Chironomidae abundances
- Low relative Diptera richness
- Low relative Oligochaeta abundance
- Greater presence of Class A indicator taxa
- Greater scraper relative abundance

Based on this set of results plus results from our thermal indicator analysis, we made theoretical predictions about which model input metrics are most likely to be influenced by increasing temperatures, as well which direction the metric values are likely to change in. When making predictions, we also noted which model input metrics showed patterns associated with changing streamflow conditions at the Sheepscot River site (ME 56817) site, which has over 20 years of continuous biological and hydrologic data. These considerations were based on differences in mean metric values when samples were grouped by lowest/normal/highest flow years. Table 4-32 summarizes our predictions.

Results vary by metric, and as mentioned, are limited by the fact that Maine DEP's linear discriminant models look at multiple variables simultaneously; thus, can only theorize how changes in individual metrics might affect overall classifications. We predict that some metric scores are likely to improve, which could contribute to better overall classification ratings, while others may worsen and contribute to the lowering of overall classification ratings. A number of the model input metrics are related to EPT taxa. Because the lists of cold and warm-water taxa are composed of a mix of EPT taxa, in some cases, it is difficult to predict whether any noticeable change will occur in the EPT-related metrics, and if changes do occur, in what direction. For example, it is possible that cold-water taxa from a particular order may drop out at a site due to warming temperatures, but then warm-water taxa from the same order could replace these taxa, thus causing metric values to remain about the same. Another limitation in our ability to predict and detect changes associated with changing temperatures is the fact that the warm-water taxa in Maine are evenly distributed across enrichment tolerance categories. This makes it difficult to tease out biological responses to warming temperatures from confounding factors such as organic enrichment.

Table 4-32. List of model input metrics from Maine DEP's linear discriminant models that could be most affected by changing temperature and streamflow conditions. This table includes information on which classification is associated with high metric values (for example, on average, Class A samples have the highest EPT generic richness values), which direction we predict metric values to change in, and the reasoning behind our assessments

Metric	Classification associated with highest mean metric values	Predicted change in metric value	Reasoning
Generic richness	A and B	Increase	At ME 56817 and ME 57011, the mean total number of taxa was highest in the hottest year samples; this suggests that warming temperatures could improve scores for this metric, as well as for overall classification
EPT generic richness	A	Variable	There are more EPT taxa on the cold water list than on the warm water list, which suggests that warming temperatures are most likely to decrease scores for this metric; however, at ME 56817 and ME 57011, the mean number of EPT taxa was highest in the hottest year samples, which suggest that climate change effects on this metric will be variable
Plecoptera abundance	A	Decrease	There are 16 Plecopteran taxa on the cold water list and 3 on the warm water list; this suggests that warming temperatures are most likely to decrease scores for this metric and lower overall classification
Relative generic richness Plecoptera	A	Decrease	
Perlidae abundance	A and B	Increase	There are three Perlidae on the warm water list and none on cold water list; this suggests that warming temperatures are likely to improve scores for this metric, as well as for overall classification
Relative abundance Ephemeroptera	A	Increase	There are nine Ephemeropterans on the warm water list and four on the cold water list; this suggests that warming temperatures are likely to improve scores for this metric, as well as for overall classification
Ephemeroptera abundance	B	Increase	There are nine Ephemeropterans on the warm water list and four on the cold water list; this suggests that warming temperatures are more likely to improve scores for this metric, which could cause more samples to receive Class B ratings

Table 4-32. List of model input metrics from Maine DEP's linear discriminant models that could be most affected by changing temperature and streamflow conditions. This table includes information on which classification is associated with high metric values (for example, on average, Class A samples have the highest EPT generic richness values), which direction we predict metric values to change in, and the reasoning behind our assessments (cont.)

Metric	Classification associated with highest mean metric values	Predicted change in metric value	Reasoning
Relative abundance Chironomidae	C and NA	Variable	There are seven Chironomidae on the cold water list and nine on the warm water list; this suggests that if warming temperatures cause cold-water taxa to be replaced by warm-water taxa, metric values are likely to remain similar
Ratio of Class A indicator taxa (*Brachycentrus, Serratella, Leucrocuta, Glossosoma, Paragnetina, Eurylophella*, and *Psilotreta*)	A	Variable	Two of the seven Class A indicator taxa (*Eurylophella* and *Glossosoma*) are on the cold water list, and three (*Paragnetina, Serratella* and *Leucrocuta*) are on the warm water list; this suggests that warming temperatures will have varying effects on metric values. In an ANOVA of data from ME 56817, on average, more Class A indicator taxa were present in wettest years
Sum of mean abundances of *Dicrotendipes*, *Micropsectra*, *Parachironomus*, and *Helobdella*	NA	Increase	*Dicrotendipes* and *Parachironomus* are on the warm water list; this suggests that warming temperatures are likely to increase scores for this metric and lower overall classification
Sum of mean abundances of *Acroneuria* and *Stenonema*	B	Increase	*Acroneuria* and *Stenonema* are on the warm water list; this suggests that warming temperatures will increase scores for this metric, which could cause more samples to receive Class B ratings
Hilsenhoff Biotic Index	NA	Variable	Many of the cold-water taxa are intolerant to enrichment, and warm-water taxa are evenly distributed across tolerance groups; this suggests that warming

Table 4-32. List of model input metrics from Maine DEP's linear discriminant models that could be most affected by changing temperature and streamflow conditions. This table includes information on which classification is associated with high metric values (for example, on average, Class A samples have the highest EPT generic richness values), which direction we predict metric values to change in, and the reasoning behind our assessments (cont.)

Metric	Classification associated with highest mean metric values	Predicted change in metric value	Reasoning
			temperatures will have variable effects on HBI scores
Relative richness Diptera	C and NA	Uncertain	In an ANOVA of data from ME 56817, on average, metric values were lowest in highest flow year samples
Tanypodinae abundance	C	Uncertain	In an ANOVA of data from ME 56817, on average, metric values were lowest in highest flow year samples
EPT generic richness divided by Diptera generic richness	A	Uncertain	In an ANOVA of data from ME 56817, on average, metric values were highest in highest flow year samples
EPT generic richness relative to EPT plus Diptera	A	Uncertain	In an ANOVA of data from ME 56817, on average, metric values were highest in highest flow year samples

5. NORTH CAROLINA

5.1. EXPOSURES

5.1.1. Regional Projections for the Southeastern United States

There are a number of factors (e.g., convective precipitation, seasonal contributions from hurricanes, complex moisture sources) that make current climate in the southeast regionally variable and future climate changes challenging to model (Mearns et al., 2003). Based on a finer scale regional climate model, average temperatures in the southeastern United States are projected to increase 4−5°C with a doubling in CO_2 concentrations (Mearns et al., 2003) (see Table 5-1). Spatial variability in projected temperature increases is greatest for summer maximum temperatures, with increases of 3−4°C projected for the southwestern portion of the region and of about 7°C in the northeastern portion of the region where the biggest decreases in precipitation are also projected to occur.

Table 5-1. Projections for temperature and precipitation changes in the Southeast to 2100

Temperature change	Precipitation change	Change in precipitation frequency	Citation
4−5◦C	27−37% (spring); −31 to −17% (summer); −7 to +3% (fall); −2 –to −19% (winter)		Mearns et al., 2003
	−11% (winter); −7% (summer)	18% (winter); −37% (summer)	Schoof et al., 2010

Projected changes for precipitation are variable among seasons. Large increases in precipitation are projected for the spring, while large decreases are projected for the summer (Mearns et al., 2003) (see Table 5-1). The biggest spatial contrasts in projected precipitation changes occur in the winter and summer, grading from smaller decreases to slight increases in the northwestern corner of the region, to much larger decreases in the east to southeast (Mearns et al., 2003). Schoof et al. (2010) projects an increase in the frequency of cold season precipitation in the southeast, but decreases in the amount of precipitation. Both frequency and magnitude of warm season precipitation events are projected to decrease (Schoof et al., 2010). Despite projections for large spring increases in precipitation, runoff in the southeast is in general projected to decrease as a result of increases in evapotranspiration forced by increasing temperatures (Mulholland et al., 1997). This will be most extreme during the summer when temperature increases will be combined with projected large decreases in precipitation. In contrast, Wolock and McCabe (1999) estimated anywhere from large decreases in runoff in the southeast and Gulf using the Canadian Centre for Climate Prediction and Analysis GCM to small-to-moderate increases in runoff using the Hadley Centre for Climate Prediction and Research model, attributed mainly to projected changes in precipitation.

5.1.2. Historic Climate Trends and Climate Change Projections for North Carolina

North Carolina has a warm and wet climate, with mild winters and high humidity. Extreme weather events, such as hurricanes and droughts, are not uncommon. When assessing the biological integrity of streams, the North Carolina Department of the Environment and Natural Resources (NCDENR) divides the state into three major regions: (1) Mountain (which corresponds with the EPA Level 3 Blue Ridge ecoregion and runs along the western portion of the state); (2) Piedmont (which corresponds with the EPA Level 3 Piedmont ecoregion in central North Carolina); and (3) Coastal (which covers the eastern portion of the state and generally overlaps with the Southeastern Plains and Middle Atlantic Coastal Plain EPA Level 3 ecoregions). These regions have distinct features. Topography in the Mountain region ranges from narrow ridges to hilly plateaus to large mountainous areas with high peaks. There is a high diversity of flora and fauna with high-gradient, cool, clear streams with rocks and boulders. The Piedmont ecoregion is a transitional area between the mostly mountainous regions of the Appalachians and the relatively flat coastal plain. Major land cover transformations have occurred in this ecoregion over the past 200 years, with the landscape going from forest to farm, back to forest, and now, in many areas, spreading urban- and suburbanization (Griffith, et al., 2002). The Coastal ecoregion consists of low elevation, flat plains, with many swamps, marshes, and estuaries. Streams are relatively low-gradient and sandy-bottomed (Griffith et al., 2002; U.S. EPA, 2002). The Coastal region has the highest mean annual temperatures, while the Mountain region has the lowest mean annual air temperatures and the greatest amount of annual precipitation (see Figures 5-1A and B).

There is large year-to-year variability in historic temperature and precipitation patterns in North Carolina. A historic trend analysis of North Carolina PRISM data revealed that there is no clear trend in mean annual air temperature, either annually or seasonally, from 1901–2000 (see Table 5-2, Figures 5-2 and 5-3). In more recent decades (1971–2000), slight trends in annual and seasonal temperatures are evident, with change rates ranging from 0.01 to 0.02°C/year. From 1971–2000, only the increasing trend associated with summer temperatures is significant. Table 5-3 summarizes future projections for mid- and late-century for high (A2) and low (B1) emissions scenarios. Based on an ensemble average across 15 models, mean annual air temperatures are projected to increase by up to 2.8°C by midcentury and up to 4.9°C by the end of the century compared to a historic time period (1961–1990). On average, the greatest increases are projected to occur during the summer and fall seasons (see Table 5-3).

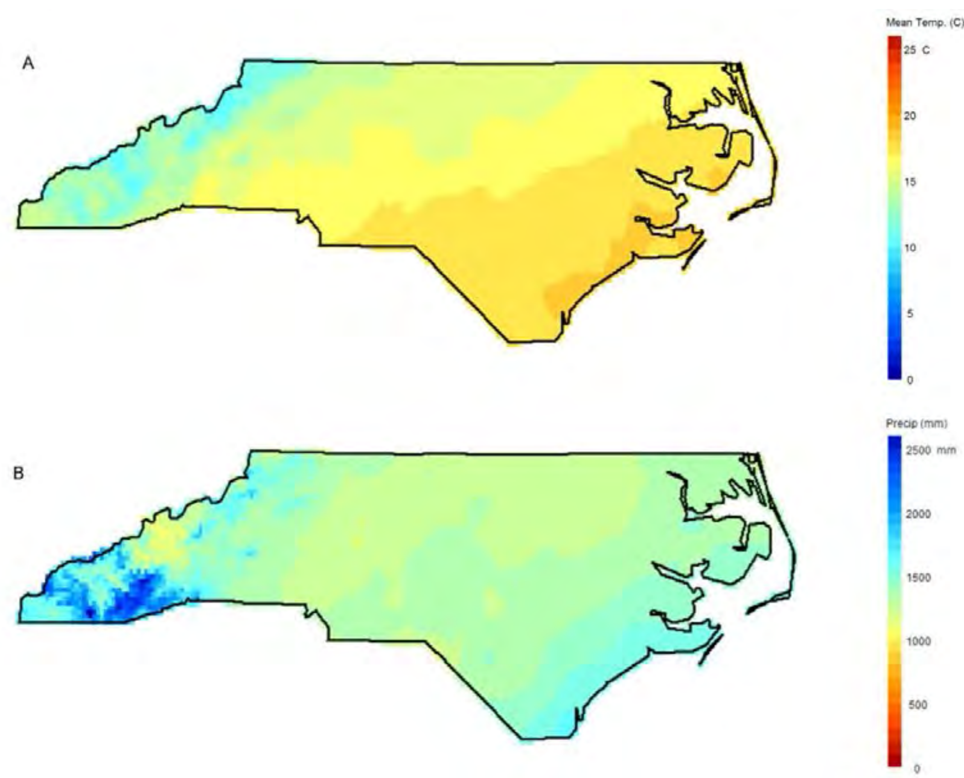

Figure 5-1. North Carolina's temperature and precipitation patterns. (A) Mean annual air temperature (°C) from 1971–2000; (B) Mean annual precipitation (mm) 1971–2000. Map produced using the Climate Wizard Web site (http://www.climatewizard.org/). Base climate data from the PRISM Group, Oregon State University, http://www.prismclimate.org.

Table 5-2. Change rates in North Carolina PRISM mean annual air temperature compared across two time periods: 1971–2000 versus 1901–2000. Entries in bold text are significant ($p < 0.05$). Data were derived from the Climate Wizard Web site (http://www.climatewizard.org/). Base climate data came from the PRISM Group, Oregon State University, http://www.prismclimate.org

Time period	Air temperature (C/yr)				
	Annual	DJF	MAM	JJA	SON
1901−2000	0.00	0.00	0.00	0.00	0.00
1971−2000	0.01	0.02	0.00	**0.02**	−0.01

DJF = December, January, and February; MAM = March, April, and May; JJA = June, July, and August; SON = September, October, and November.

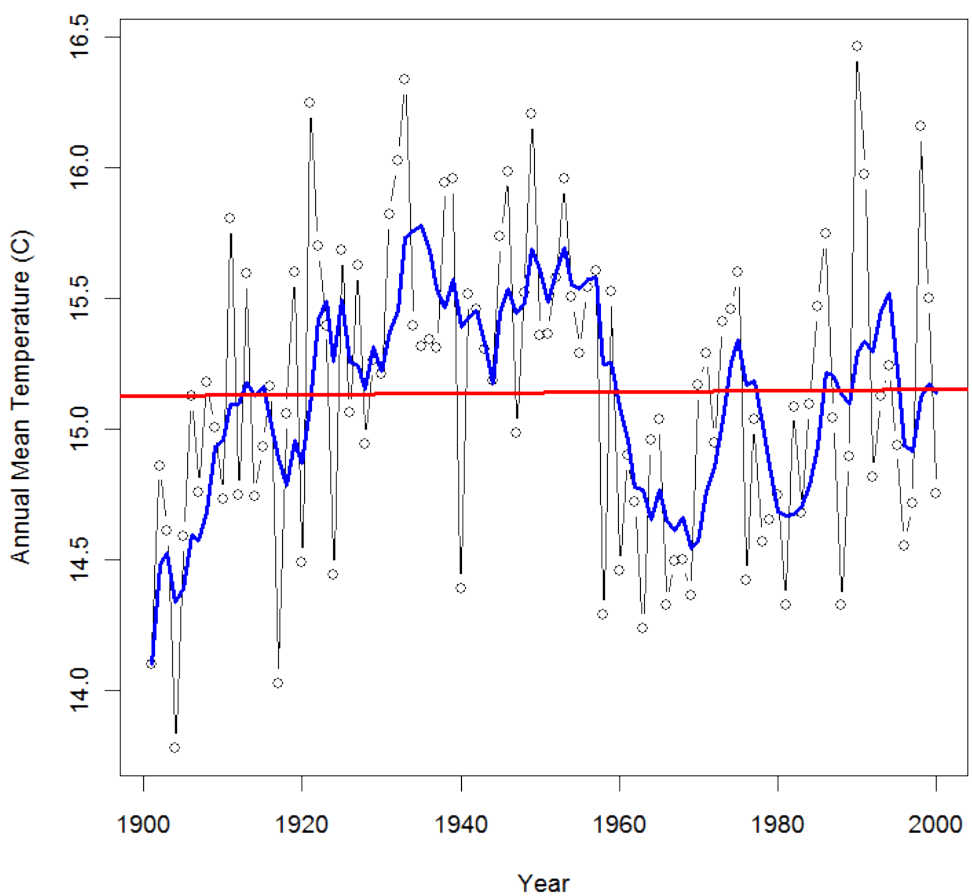

Figure 5-2. Trends in annual mean air temperature in North Carolina from 1901–2000. Change rate = 0°C/year, *p*-value = 0.93. Figure produced using Climate Wizard Web site (http://www.climatewizard.org/). Base climate data from the PRISM Group, Oregon State University, http://www.prismclimate.org.

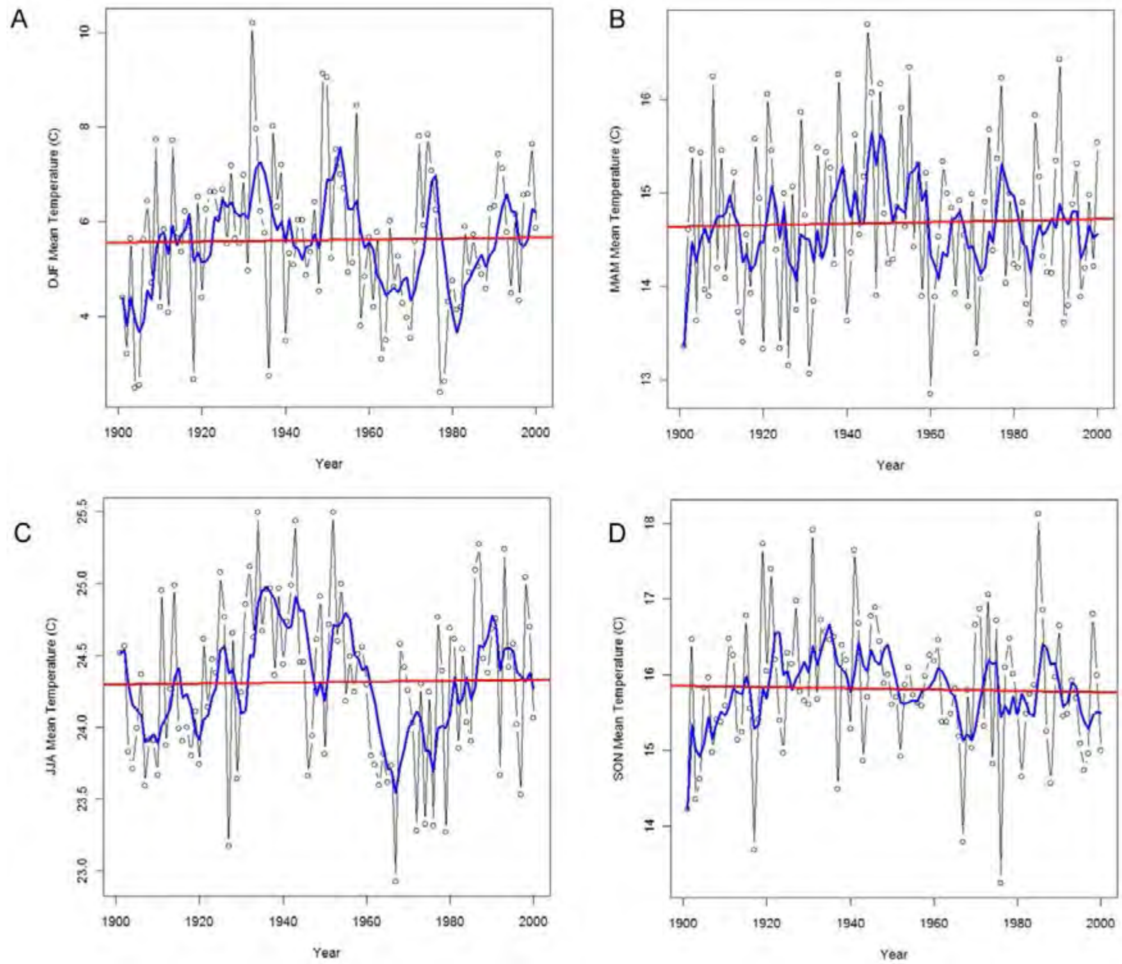

Figure 5-3. Trends in seasonal mean air temperature in North Carolina from 1901–2000. (A) DJF = December, January, and February, change rate = 0.001°C/year, *p*-value = 0.88; (B) MAM = March, April, and May, change rate = 0.001°C/year, *p*-value = 0.77; (C) JJA = June, July, and August, change rate = 0°C/year, *p*-value = 0.88; (D) SON = September, October, and November, change rate = –0.001°C/year, *p*-value = 0.80. Figure produced using Climate Wizard Web site (http://www.climatewizard.org/). Base climate data from the PRISM Group, Oregon State University, http://www.prismclimate.org.

Table 5-3. Projected departure from historic (1961–1990) trends in annual and seasonal air temperature (°C) in North Carolina for mid- (2040–2069) and late-century (2070–2099) for high and low emissions scenarios. Values represent the minimum, average, maximum, and standard deviations from 15 different climate models. Data were derived from the Climate Wizard Web site (http://www.climatewizard.org/)

Midcentury (2040−2069) vs. historic (1961−1990)										
	A2 (high) emissions scenario					B1 (low) emissions scenario				
Model	**Annual**	**DJF**	**MAM**	**JJA**	**SON**	**Annual**	**DJF**	**MAM**	**JJA**	**SON**
Ensemble low	1.4	1.3	1.2	1.3	1.5	1.1	0.6	1.0	1.1	1.0
Ensemble average	2.3	2.0	2.0	2.4	2.5	1.7	1.5	1.8	1.9	1.8
Ensemble high	2.8	3.0	3.0	3.2	3.5	2.2	2.6	2.3	3.1	2.5
SD	0.4	0.5	0.6	0.5	0.6	0.4	0.6	0.5	0.5	0.5
Late-century (2070−2099) vs. historic (1961−1990)										
Ensemble low	2.0	1.7	2.1	2.0	2.6	1.4	1.0	0.8	1.4	1.4
Ensemble average	3.7	3.1	3.3	4.1	4.2	2.2	2.0	2.2	2.4	2.3
Ensemble high	4.9	4.6	4.8	5.4	5.6	3.0	3.2	3.0	3.5	3.2
SD	0.7	0.7	0.7	0.9	0.9	0.5	0.6	0.6	0.6	0.6

DJF = December, January, and February; MAM = March, April, and May; JJA = June, July, August and SON = September, October, and November.

Precipitation patterns in North Carolina have been highly variable. From 1901–2000, mean annual precipitation increased at a rate of 0.39 mm/year ($p > 0.05$) (see Figure 5-4 and Table 5-4). There were two significant ($p < 0.05$) trends in seasonal data over this time period. Summer precipitation decreased at a rate of 0.68 mm/year, and fall precipitation increased at a rate of 0.83 mm/year (see Table 5-4 and Figure 5-5). In more recent decades (1971–2000), the trends in summer and fall precipitation were similar but not significant ($p > 0.05$). Compared to 1901–2000 trends in annual, winter, and spring precipitation changed direction, going from increasing to decreasing (see Table 5-4). Table 5-5 summarizes future projections for mid- and late-century for high (A2) and low (B1) emissions scenarios. The future projections are highly variable across models and emissions scenarios. Under the high emissions scenario, the ensemble average projects that mean annual precipitation will increase by 54 mm by midcentury and 56.9 mm by the end of the century compared to a historic time period (1961–1990). Under the high emissions scenario, the smallest changes are projected to occur during the spring (see Table 5–5).

Table 5-4. Change rates in North Carolina PRISM mean annual precipitation compared across two time periods: 1971–2000 versus 1901−2000. Entries in bold text are significant (*p* < 0.05). Data were derived from the Climate Wizard Web site (http://www.climatewizard.org/). Base climate data came from the PRISM Group, Oregon State University, http://www.prismclimate.org

	Precipitation (mm/yr)				
Time period	**Annual**	**DJF**	**MAM**	**JJA**	**SON**
1901−2000	0.39	0.04	0.19	**−0.68**	**0.83**
1971−2000	−1.47	−0.48	−2.15	0.61	1.18

DJF = December, January, and February; MAM = March, April, and May; JJA = June, July, and August; SON = September, October, and November.

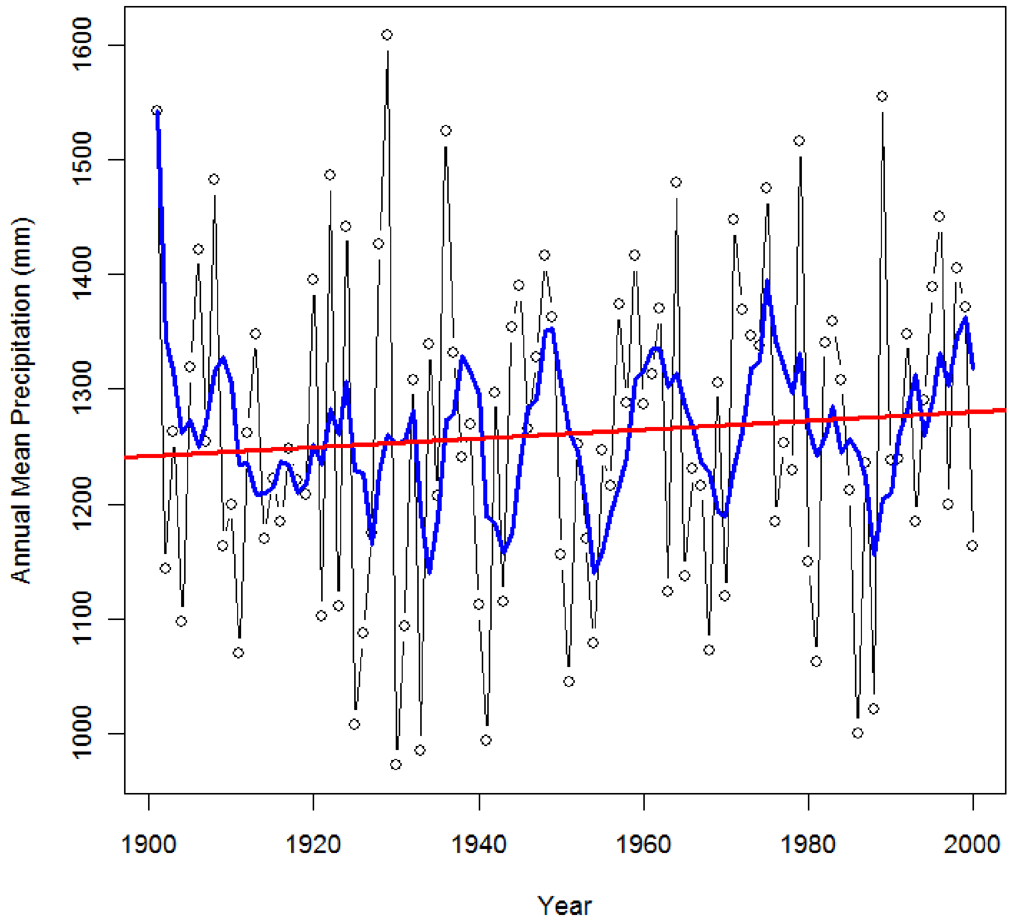

Figure 5-4. Trends in annual mean precipitation in North Carolina from 1901–2000. Change rate = 0.39 mm/year, *p*-value = 0.38. Figure produced using Climate Wizard Web site (http://www.climatewizard.org/). Base climate data from the PRISM Group, Oregon State University, http://www.prismclimate.org.

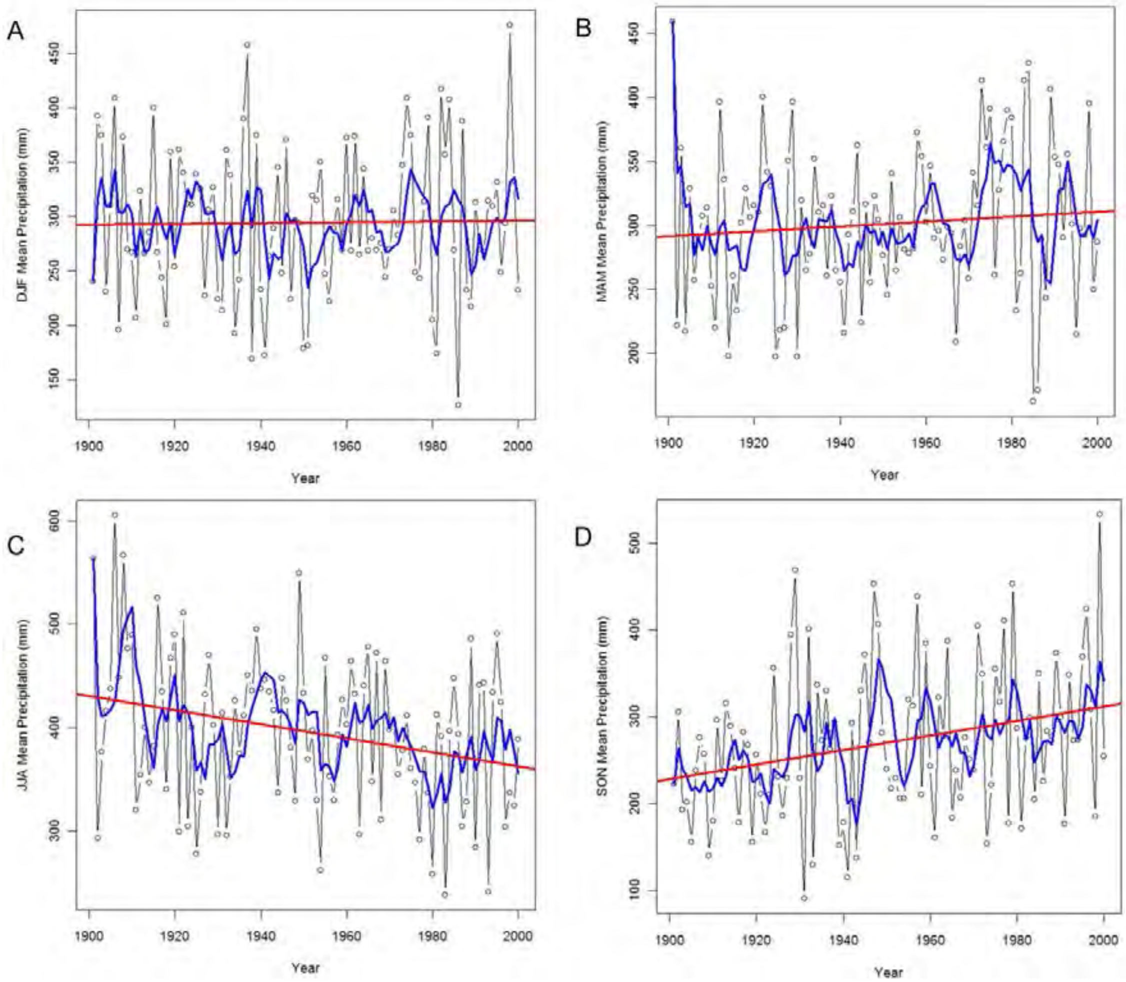

Figure 5-5. Trends in seasonal mean precipitation in North Carolina from 1901–2000. (A) DJF = December, January, and February, change rate = 0.035 mm/year, *p*-value = 0.88; (B) MAM = March, April, and May, change rate = 0.194 mm/year, *p*-value = 0.38; (C) JJA = June, July, and August, change rate = –0.677 mm/year, *p*-value = .01; (D) SON = September, October, and November, change rate = 0.83 mm/year, *p*-value < 0.01. Figure produced using Climate Wizard Web site (http://www.climatewizard.org/). Base climate data from the PRISM Group, Oregon State University, http://www.prismclimate.org.

Table 5-5. Projected departure from historic (1961–1990) trends in annual and seasonal precipitation (mm) in North Carolina for mid- (2040–2069) and late-century (2070–2099) for high and low emissions scenarios. Values represent the minimum, average, maximum, and standard deviations from 15 different climate models. Data were derived from the Climate Wizard Web site (http://www.climatewizard.org/)

Midcentury (2040−2069) vs. historic (1961−1990)										
	A2 (high) emissions scenario					B1 (low) emissions scenario				
Model	**Annual**	**DJF**	**MAM**	**JJA**	**SON**	**Annual**	**DJF**	**MAM**	**JJA**	**SON**
Ensemble low	−230.8	−61.0	−31.6	−109.2	−60.7	−400.0	−40.1	−91.2	−366.2	−185.4
Ensemble average	54.0	15.4	7.0	11.6	19.6	−1.0	16.0	−3.4	−22.5	−6.3
Ensemble high	171.7	61.5	40.9	115.1	55.9	167.4	119.0	48.5	81.5	47.7
SD	115.3	39.5	22.3	54.1	27.9	161.6	40.3	36.1	112.4	59.8
Late-Century (2070−2099) vs. historic (1961−1990)										
Ensemble low	−290.3	−63.5	−62.8	−140.9	−55.1	−554.3	−53.1	−105.5	−391.1	−205.1
Ensemble average	56.9	20.9	6.2	22.3	20.8	−16.5	24.5	−7.6	−41.5	−10.6
Ensemble high	261.2	97.0	53.4	168.5	69.0	179.2	142.0	60.3	89.3	49.7
SD	163.6	48.2	36.4	82.1	38.6	222.0	52.0	47.3	148.7	78.3

DJF = December, January, and February; MAM = March, April, and May; JJA = June, July, August and SON = September, October, and November.

5.2. DATA INVENTORY AND PREPARATION

Data for North Carolina were provided by NCDENR. Our North Carolina database contains data for 5,823 biological samples from 2,786 unique stations, with sampling dates ranging from 1978 to 2007. In situ measurements (conductivity, DO, pH, and water temperature) were provided for some of the sites, as were habitat measurements (NCDENR habitat index, width, depth, visual estimates of substrate composition, and canopy cover). The NCDENR habitat index, which has scores ranging from 1 (worst) to 100 (best), is based on assessments of channel modification, amount of instream habitat, type of bottom substrate, pool variety, bank stability, light penetration, and riparian zone width (NCDENR, 2006). The visual estimates of substrate composition were interpreted with caution due to observer bias (Trish MacPherson, NCDENR, personal communication).

NCDENR records data by waterbody name, location description, latitude and longitude, and date, but does not assign unique station IDs to its sampling sites. Sometimes we had difficulty determining whether samples were collected from the same or different sites. This occurred when samples had similar waterbody names but with slightly different spellings (for example, "Creek" might be spelled out in one sample record and abbreviated as "Cr" in another); when samples with similar waterbody names and location descriptions had slightly different latitudes and longitudes and when sites had the same water body name but slightly different location descriptions. To address this issue, we created unique identifiers for sites (station IDs) based on matching a combination of waterbody name, location, and latitude–longitude.

We used a genus-level OTU when preparing the biological data for long-term trend analyses. Per the methods described in Section 2.1.3, we used NMDS analyses to verify the OTU. Because the same taxonomists in the North Carolina biomonitoring program have done all the identifications for the last 25−30 years, we did not check for changes associated with taxonomy lab, but we did look for trends associated with changes in taxonomic identification keys, collection method, reference status, Level 3 ecoregion, and year (in 5-year increments). We found that samples that were collected using different collection methods, in particular those collected using the EPT method, tended to form distinct groups (see Appendix A, Figure A-18). Because of this, we decided to limit the data sets that we analyzed to samples collected using the standard qualitative "full-scale" method only, because the greatest number of samples were collected using this method. This correction also eliminated a spike in the total number of taxa that occurred in 1998 when a large number of estuarine sites were sampled.

By making this limitation, we lost 4 years of data (1978–1981) and reduced the number of unique stations, but this was a necessary and effective step in minimizing the chances of detecting false trends. In addition to collection method, we also found that taxonomic composition was influenced by ecoregion (see Appendix A, Figures A-22A and A-22B). We tried to account for this in our analyses, where appropriate, by limiting samples to a particular ecoregion. An exception is the maximum likelihood temperature optima and tolerance calculations that are discussed in Section 5.4.1, for which sample size was an issue, and having a wide range of temperatures was needed and appropriate.

Most of the biological sampling sites that were sampled using the full-scale collection method have fewer than 5 years of data (see Table 5-6). There are nine sites that have 10 or more years of data (see Table 5-6). NCDENR considers one of these long-term sites to be in reference (least-disturbed) condition. The NCDENR reference designations were based largely on land use/land cover in the upstream catchment area and best professional judgment.
Figure 5-6 shows the spatial distribution of all biological sampling sites (not just those sampled using the full-scale method).

Table 5-6. Distribution of reference and unclassified stations, categorized by duration of sampling. These numbers apply only to stations that were sampled using the standard qualitative (full-scale) collection method

# Years sampled	Reference stations	Unclassified stations
10+	1	8
5 to 9	2	146
3 to 4	4	182
2	8	237
1	12	933

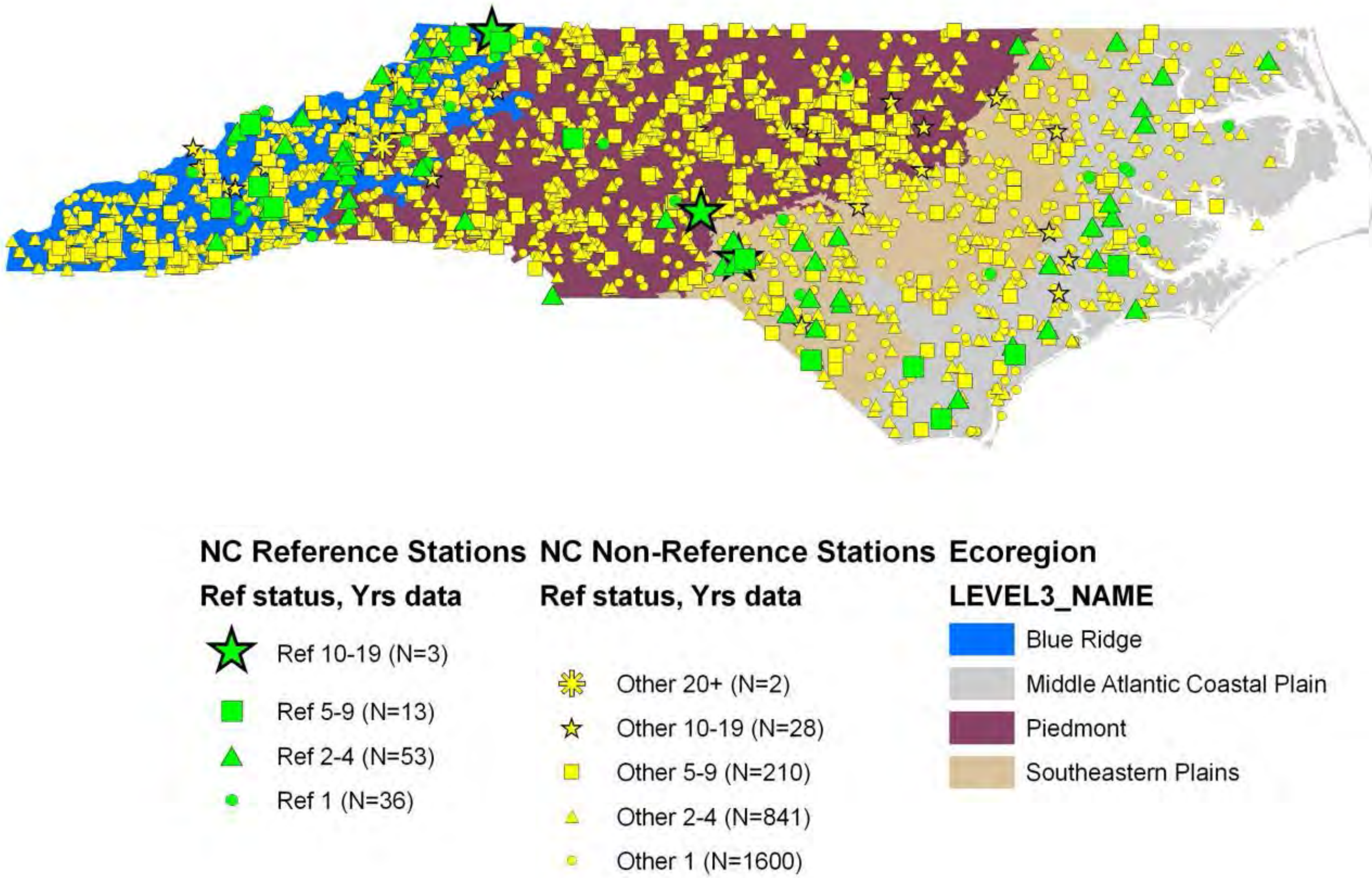

Figure 5-6. NCDENR biomonitoring stations, coded by reference status and duration of data (this includes all sites, not just those sampled using the standard qualitative [full-scale] collection method).

5.3. NORTH CAROLINA DEPARTMENT OF THE ENVIRONMENT AND NATURAL RESOURCE (NCDENR) METHODS

NCDENR uses several different methods to collect its samples, but for reasons described in Section 5.2, we focused our analyses on the standard qualitative "full-scale" method samples only. The full-scale collection method is composed of two kicks, three sweeps, one leaf pack sample, two fine mesh rock and/or log wash samples, and one sand sample. In addition, crew members do visual collections during which they walk the stream reach, and sample habitats and substrate types that might be missed or undersampled by the other collection techniques (NCDENR, 2006). Abundance data were recorded as rare = 1 (1−2 specimens), common = 3 (3−9 specimens), or abundant (≥10 specimens).

NCDENR assigns bioclassification scores of excellent, good, good/fair, fair or poor to samples collected using the standard qualitative "full-scale" method, per the scoring system outlined in Table 5-7. Different scoring criteria are applied to the Mountain, Piedmont, and Coastal Plain regions. Two metrics, the NCBI and number of EPT taxa, are typically considered when assigning bioclassification scores. The NCBI is calculated like the HBI, except it uses tolerance values that are derived from the North Carolina database (see NC Standard Operating Procedures [SOP; NCDENR, 2006] for more details). It documents the contribution of pollution tolerant taxa to the composition of the community (Hillsenhoff, 1987). The higher the HBI, the more strongly the community is dominated by taxa tolerant of organic pollution, and the more impaired the site is considered. The scoring criteria for the EPT richness metric are based on species- (or lowest) level identifications.

For most sites, when calculating the bioclassification scores, NCDENR gives equal weight to both the NCBI value and EPT taxa richness. Exceptions are outlined in the NC SOP (NCDENR, 2006), and include such things as pristine high altitude mountain streams, swamp streams, and Coastal B streams. If averaging the NCBI and EPT taxa richness results in a final score midway between two ratings, EPT abundance is taken into account when deciding whether to round up or round down. As described in Table 5-7, due to seasonal variations in EPT taxa (i.e., changes in winter/spring Plecoptera), corrections for nonsummer collections are also taken into account.

Table 5-7. These tables are used to determine the scores for EPT taxa richness values and NCBI values for all standard qualitative samples after seasonal corrections are made. EPT N refers to EPT abundance (from NCDENR, 2006)

	NCBI values			EPT values		
Score	MT	P	CP	MT	P	CP
5	<4.00	<5.14	<5.42	>43	>33	>29
4.6	4.00−4.04	5.14−5.18	5.42−5.46	42−43	32−33	28
4.4	4.05−4.09	5.19−5.23	5.47−5.51	40−41	30−31	27
4	4.10−4.83	5.24−5.73	5.52−6.00	34−39	26−29	22−26
3.6	4.84−4.88	5.74−5.78	6.01−6.05	32−33	24−25	21
3.4	4.89−4.93	5.79−5.83	6.06−6.10	30−31	22−23	20
3	4.94−5.69	5.84−6.43	6.11−6.67	24−29	18−21	15−19
2.6	5.70−5.74	6.44−6.48	6.68−6.72	22−23	16−17	14
2.4	5.75−5.79	6.49−6.53	6.73−6.77	20−21	14−15	13
2	5.80−6.95	6.54−7.43	6.78−7.68	14−19	10−13	8−12
1.6	6.96−7.00	7.44−7.48	7.69−7.73	12−13	8−9	7
1.4	7.01−7.05	7.49−7.53	7.74−7.79	10−11	6−7	6
1	>7.05	>7.53	>7.79	0−9	0−5	0−5

Biotic index corrections for nonsummer data:
summer = Jun−Sep; fall = Oct−Nov; winter = Dec−Feb; spring = Mar−May

	Fall	Winter	Spring
Mountain correction	+0.4	+0.5	+0.5
Piedmont correction	+0.1	+0.1	+0.2
Coastal Plain correction	+0.2	+0.2	+0.3

Rounding criteria: round down if EPT N < criterion, otherwise round up.

Bioclassification (Score)	MT	P	CA
Excellent (5) vs. good (4)	191	135	108
Good (4) vs. good−fair (3)	125	103	91
Good−fair (3) vs. fair (2)	85	71	46
Fair (2) vs. poor (1)	45	38	18

MT = Mountain, P = Piedmont, CP = Coastal Plain.

5.4. INDICATORS

5.4.1. Thermal Preference

As described in Section 2.2.1, we used the guidelines of Yuan (2006) to calculate thermal optima and tolerance values. Because the North Carolina data set is composed of categorical abundance data, it was more appropriate to derive values using maximum likelihood calculations instead of weighted averaging. We based our calculations on a subset of the North Carolina biomonitoring database composed of standard qualitative "full-scale" collection method samples. These, along with literature, primarily the traits matrix in Poff et al. (2006b) and the USGS traits database (Vieira et al., 2006), were used as a basis for making some additional initial designations. We refined the lists based on case studies and best professional judgment from a regional advisory group. These lists were used to define cold and warm-water taxa for the North Carolina data set, and are the basis of the region-specific thermal-preference richness and relative-abundance metrics used in some analyses.

The North Carolina cold-water taxa list is composed of 32 taxa, and the warm-water taxa list is composed of 27 taxa. Tables 5-8 and 5-9, respectively, list the cold and warm-water taxa, along with abundance and distribution information. Ten of the cold-water taxa are Dipterans, eight are Plecopterans, six are Ephemeropterans, and six are Trichopterans. The rest are Coleopterans and Odonates (see Table 5-8). Seven of the warm-water taxa are Odonates, five are Dipterans, and four are Trichopterans (see Table 5-9).

The most abundant cold-water taxa are *Epeorus* (Ephemeroptera), *Antocha* (Diptera), *Isoperla* (Plecoptera), and *Tallaperla* (Plecoptera). These taxa comprise only 0.4 to 0.6% of the total individuals in the North Carolina database. Seventeen of the cold-water taxa have overall abundances of less than 0.1%. *Physella* (Basommatophora), *Chimarra* (Trichopteran), and *Macromia* (Odonata) are the most abundant warm-water taxa, with overall abundances ranging from 0.6 to 0.8%. Twelve of the warm-water taxa have overall abundances of less than 0.1%. Of the cold-water taxa, *Antocha* occurs at the largest percentage of sites (25%), followed by a Chironomidae, *Eukiefferiella*, and a Plecopteran, *Isoperla*, which occur at 18–19% of the sites. Eighteen of the cold-water taxa occur at less than 10% of the sites. Among the warm-water taxa, *Physella* occurs at the highest percentage of sites (30%), followed by *Macromia* (29%) and *Stenochironomus* (27%). Nineteen of the warm-water taxa occur at less than 10% of the sites.

Table 5-8. List of North Carolina cold-water temperature indicator taxa. Distribution and abundance information is also included. Sum_Individuals = the total number of individuals from that taxon in the North Carolina database; Pct_Abund = percentage of total individuals in the database composed of that taxon; Num_Stations = number of stations in the database that the taxon occurred at; Pct_Stations = percentage of stations in the database at which the taxon occurred

Order	Family	Final ID	Sum_individs	Pct_abund	Num_stations	Pct_stations
Coleoptera	Elmidae	*Promoresia*	3,020	0.36	332	11.81
Diptera	Athericidae	*Atherix*	1,236	0.15	240	8.54
Diptera	Chironomidae	*Cardiocladius*	2,300	0.27	376	13.38
Diptera	Chironomidae	*Diamesa*	734	0.09	185	6.58
Diptera	Chironomidae	*Eukiefferiella*	2,974	0.35	533	18.96
Diptera	Chironomidae	*Heleniella*	95	0.01	50	1.78
Diptera	Chironomidae	*Pagastia*	751	0.09	157	5.59
Diptera	Chironomidae	*Potthastia*	757	0.09	292	10.39
Diptera	Chironomidae	*Rheopelopia*	135	0.02	64	2.28
Diptera	Tipulidae	*Antocha*	5,103	0.61	711	25.29
Diptera	Tipulidae	*Dicranota*	1,384	0.16	284	10.1
Ephemeroptera	Baetidae	*Acentrella*	2,745	0.33	427	15.19
Ephemeroptera	Ephemerellidae	*Drunella*	2,846	0.34	218	7.76
Ephemeroptera	Heptagenidae	*Cinygmula*	247	0.03	40	1.42
Ephemeroptera	Heptageniidae	*Epeorus*	5,226	0.62	403	14.34
Ephemeroptera	Heptageniidae	*Nixe*	64	0.01	16	0.57
Ephemeroptera	Heptageniidae	*Rhithrogena*	725	0.09	152	5.41
Odonata	Gomphidae	*Lanthus*	1,174	0.14	300	10.67

Table 5-8. List of North Carolina cold-water temperature indicator taxa. Distribution and abundance information is also included. Sum_Individuals = the total number of individuals from that taxon in the North Carolina database; Pct_Abund = percentage of total individuals in the database composed of that taxon; Num_Stations = number of stations in the database that the taxon occurred at; Pct_Stations = percentage of stations in the database at which the taxon occurred (cont.)

Order	Family	Final ID	Sum_individs	Pct_abund	Num_stations	Pct_stations
Plecoptera	Nemouridae	*Amphinemura*	1,210	0.14	281	10
Plecoptera	Nemouridae	*Zapada*	3	0	3	0.11
Plecoptera	Peltoperlidae	*Tallaperla*	3,337	0.4	377	13.41
Plecoptera	Perlodidae	*Clioperla*	574	0.07	155	5.51
Plecoptera	Perlodidae	*Cultus*	296	0.04	70	2.49
Plecoptera	Perlodidae	*Diploperla*	393	0.05	122	4.34
Plecoptera	Perlodidae	*Isoperla*	4,556	0.54	498	17.72
Plecoptera	Perlodidae	*Malirekus*	753	0.09	132	4.7
Trichoptera	Apataniidae	*Apatania*	339	0.04	47	1.67
Trichoptera	Glossosomatidae	*Agapetus*	247	0.03	53	1.89
Trichoptera	Glossosomatidae	*Glossosoma*	1,755	0.21	309	10.99
Trichoptera	Hydropsychidae	*Arctopsyche*	222	0.03	40	1.42
Trichoptera	Hydropsychidae	*Parapsyche*	280	0.03	52	1.85
Trichoptera	Philopotamidae	*Dolophilodes*	2,905	0.35	316	11.24

Table 5-9. List of North Carolina warm-water temperature indicator taxa. Distribution and abundance information is also included. Sum_Individuals = the total number of individuals from that taxon in the North Carolina database; Pct_Abund = percentage of total individuals in the database composed of that taxon; Num_Stations = number of stations in the database that the taxon occurred at; Pct_Stations = percentage of stations in the database at which the taxon occurred

Order	Family	Final ID	Sum_individs	Pct_abund	Num_stations	Pct_stations
Arhynchobdellida	Erpobdellidae	*Erpobdella/Mooreobdella*	760	0.09	210	7.47
Basommatophora	Physidae	*Physella*	6,677	0.79	853	30.35
Coleoptera	Dytiscidae	*Lioporeus*	182	0.02	83	2.95
Coleoptera	Hydrophilidae	*Berosus*	1,843	0.22	277	9.85
Decapoda	Palaemonidae	*Palaemonetes*	2,262	0.27	271	9.64
Diptera	Chironomidae	*Nilothauma*	180	0.02	124	4.41
Diptera	Chironomidae	*Parachironomus*	395	0.05	128	4.55
Diptera	Chironomidae	*Pentaneura*	771	0.09	154	5.48
Diptera	Chironomidae	*Procladius*	3,460	0.41	706	25.12
Diptera	Chironomidae	*Stenochironomus*	3,419	0.41	750	26.68
Ephemeroptera	Leptohyphidae	*Tricorythodes*	4,939	0.59	363	12.91
Hemiptera	Belostomatidae	*Belostoma*	173	0.02	99	3.52
Isopoda	Asellidae	*Caecidotea*	3,203	0.38	544	19.35
Odonata	Calopterygidae	*Hetaerina*	854	0.1	153	5.44
Odonata	Coenagrionidae	*Ischnura*	318	0.04	101	3.59
Odonata	Corduliidae	*Epicordulia*	178	0.02	78	2.77
Odonata	Corduliidae	*Helocordulia*	188	0.02	95	3.38
Odonata	Corduliidae	*Macromia*	5,064	0.6	813	28.92

Table 5-9. List of North Carolina warm-water temperature indicator taxa. Distribution and abundance information is also included. Sum_Individuals = the total number of individuals from that taxon in the North Carolina database; Pct_Abund = percentage of total individuals in the database composed of that taxon; Num_Stations = number of stations in the database that the taxon occurred at; Pct_Stations = percentage of stations in the database at which the taxon occurred (cont.)

Order	Family	Final ID	Sum_individs	Pct_abund	Num_stations	Pct_stations
Odonata	Corduliidae	*Neurocordulia*	1,511	0.18	278	9.89
Odonata	Corduliidae	*Tetragoneuria*	687	0.08	202	7.19
Rhynchobdellida	Glossiphoniidae	*Helobdella*	835	0.1	225	8
Rhynchobdellida	Glossiphoniidae	*Placobdella*	677	0.08	339	12.06
Trichoptera	Dipseudopsidae	*Phylocentropus*	576	0.07	201	7.15
Trichoptera	Hydropsychidae	*Macrostemum*	1,753	0.21	134	4.77
Trichoptera	Philopotamidae	*Chimarra*	5,178	0.62	554	19.71
Trichoptera	Polycentropodidae	*Neureclipsis*	2,092	0.25	241	8.57
Unionoida	Unionidae	*Elliptio*	1,556	0.18	189	6.72

Most of the taxa on the cold water list are intolerant to enrichment, while most of the warm-water taxa are tolerant or have intermediate tolerance to enrichment (see Figure 5-7). Because of this, it may be difficult to tease out whether organisms are responding to changes associated with warming temperatures or whether they are responding to other stressors, such as enrichment.

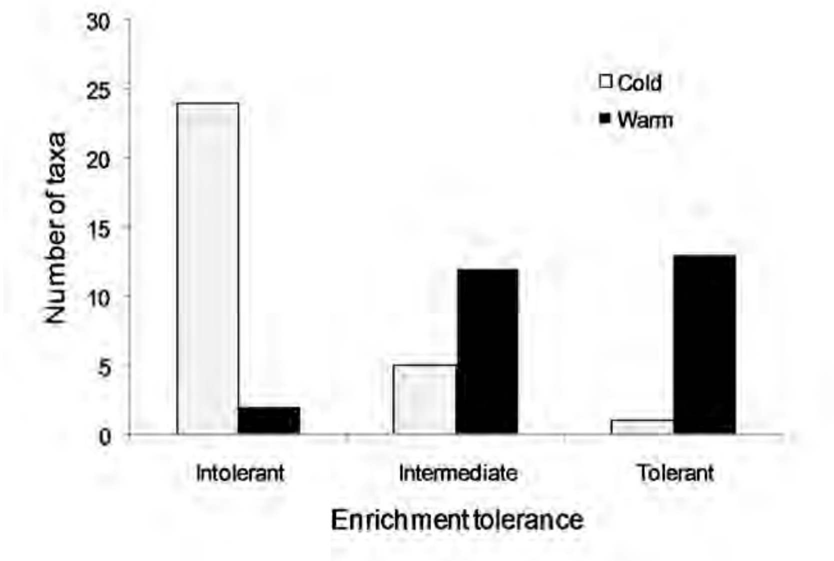

Figure 5-7. Relationship between North Carolina cold- and warm-water-preference taxa and North Carolina enrichment tolerance scores. Taxa with enrichment tolerance scores of 0–3 were categorized as Intolerant, those with scores of 4–6 were Intermediate, and those with scores of 7–10 were Tolerant.

5.4.2. Hydrologic Indicators

We attempted to develop a list of candidate taxa in North Carolina that could serve as indicators of hydrologic change. We were able to match USGS gage data with data for 440 biological samples. We calculated IHA parameters and the RBI per the methods described in Section 2.2.2, and then performed NMDS ordinations on the data set. Results showed two hydrologic parameters, baseflow index and number of reversals, to have fairly strong associations with taxonomic composition, but when samples were grouped by ecoregion, it became apparent that the relationships are most likely driven by the ecoregional distribution of taxa (see Figure 5-8). Additional results from our analyses on the paired hydrologic/biological data set are available upon request.

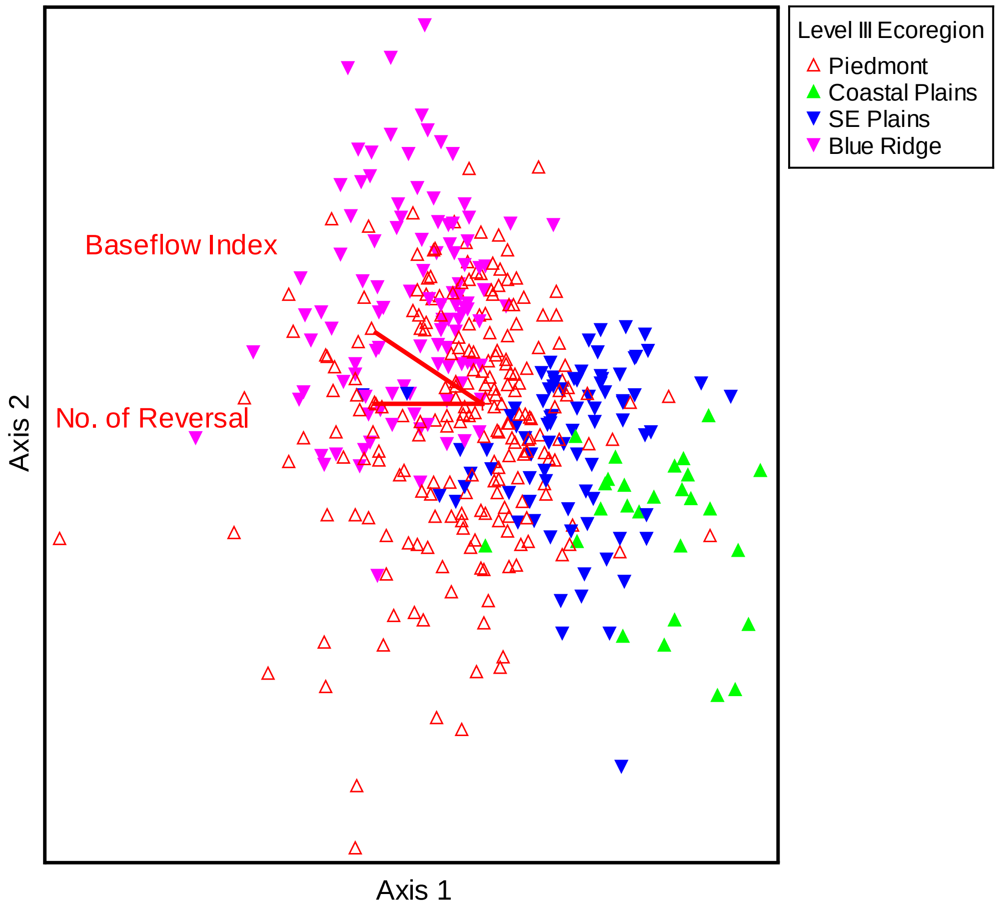

Figure 5-8. NMDS plot of macroinvertebrate taxonomic composition and its relationship with hydrologic parameters for a subset of North Carolina data. Baseflow index and number of reversals were associated with Axis 2.

We also considered results from studies conducted by NCDENR on flow permanence, flooding, and drought. NCDENR has developed lists of indicator taxa for intermittent and perennial streams (NCDWQ, 2005). They consider streams to be intermittent if they have water for a significant part of an average year, but are dry for part of the year, while perennial streams are defined as those that have water for the entire year. Based on NCDENR's findings, amphipods, isopods, worms, small elongate Dipteran larvae, winter stoneflies, Dytiscid beetles, and Hemipterans tend to be more dominant in intermittent conditions (many of these taxa are also found in perennial streams). Taxa that require perennial conditions (i.e., water for their entire life cycle) include mayflies, caddisflies, nonwinter stoneflies, Megalopterans, riffle beetles, some Dipterans, clams, fish, crayfish, salamanders, and large tadpoles (NCDWQ, 2005).

When NCDENR conducted research on responses of macroinvertebrates to hurricane flooding that occurred in September 2004, they documented an overall decline in bioclassification scores (NCDENR, 2005). Mayflies were reduced at all sites, and net-spinning caddisflies declined at some sites, but the impacts were less severe than expected. Winter stoneflies and ephemerellid mayflies, which likely hatched after the flooding, were the dominant taxa at all the sites. In samples collected using the standard qualitative full-scale method, beetles and odonates declined dramatically. This likely occurred because the woody debris that they inhabit was swept away in the floods (NCDENR, 2005).

NCDENR also conducted research on responses of macroinvertebrates to drought conditions that occurred from 1999 to 2002 (NCDENR, 2004). They documented an overall decline in the macroinvertebrate communities. The degree of impact and speed of recovery appeared to be influenced by baseflow, drainage area, underlying geology, and type and size of tributary streams. Baetids and stoneflies recovered quickly, flow-dependent taxa such as Hydropsychids, *Heterocloeon*, heptageniids, and *Hydroptila* were slower to recover, and edge species such as *Triaenodes* and *Nectopsyche* were not present when sites were sampled in 2002.

5.4.3. Traits-Based Indicators in a Warmer Drier Scenario

We developed a list of taxa that may be most and least sensitive to projected changes in temperature and streamflow based on the suite of trait modalities considered in Section 2.2.3. When assessing sensitivity to future climatic changes, we focused on a generalized scenario in which temperatures are increasing, and flows are decreasing during the low flow periods when state biomonitoring programs typically collect their samples. The taxa in Table 5-10 that are deemed most sensitive, or most likely to be adversely affected by these projected climatic changes, are mostly EPT taxa. A Hemipteran, *Belostoma*, was included on the least sensitive list. This taxon has the ability to exit (as adults), has high dispersal ability, strong flying strength, strong swimming ability, and breathes through plastron-spiracles.

Table 5-10. List of taxa that may be most and least sensitive to a warmer and drier future scenario based on the combination of traits described in Section 2.2.3

Order	Family	Final ID	Sensitivity to warmer drier scenario
Diptera	Athericidae	*Atherix*	most
Ephemeroptera	Heptageniidae	*Rhithrogena*	most
Plecoptera	Perlodidae	*Cultus*	most
Plecoptera	Perlodidae	*Diploperla*	most
Trichoptera	Hydropsychidae	*Arctopsyche*	most
Trichoptera	Hydropsychidae	*Parapsyche*	most
Trichoptera	Philopotamidae	*Dolophilodes*	most
Hemiptera	Belostomatidae	*Belostoma*	least

5.5. LEAST-DISTURBED LONG-TERM BIOLOGICAL MONITORING SITES

North Carolina does not have a formal statewide long-term reference monitoring network. We explored grouping least-disturbed sites together to create ecoregion-specific data sets that could be analyzed for long-term trends, but site-specific differences were evident within the data sets, and sample sizes were relatively low; therefore, we focused on data from individual sites. Five least-disturbed stations (as designated by NCDENR) from the Blue Ridge and Piedmont ecoregions with long-term biological data were identified and analyzed for temporal trends. We focused on the Blue Ridge and Piedmont ecoregions because these ecoregions contain the greatest number of biological sampling sites. Figure 5-9 shows locations of these five stations. Table 5-11 summarizes site characteristics. Table 5-12 lists the time periods for which biological data are available for these sites. Biological data were limited to samples collected during the summer (June−September) index period using the standard qualitative (full-scale) method.

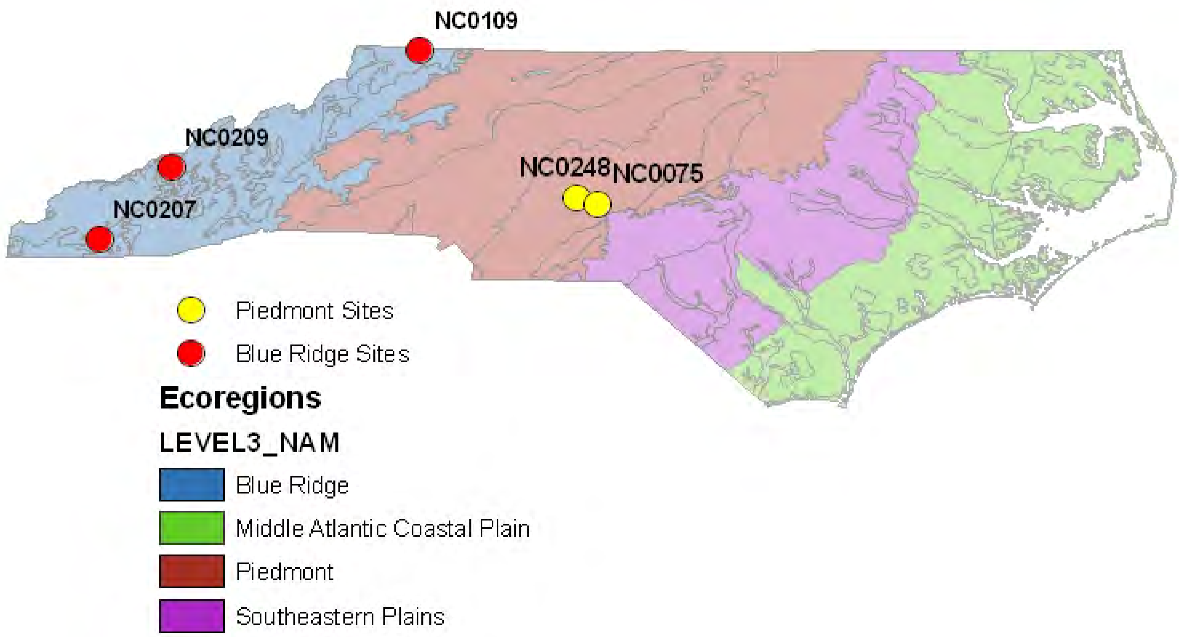

Figure 5-9. Locations of the five least disturbed long-term biological monitoring sites that were examined for long-term trends (NC0109 = New River; NC0209 = Cataloochee Creek; NC0207 = Nantahala River; NC0248 = Barnes Creek; NC0075 = Little River).

Table 5-11. Site characteristics for the long-term biological monitoring stations in North Carolina. Percentage urban and percentage agricultural (ag) apply to a 1-km buffer zone around each site and are based on 2001 National Land Cover Data. Reference status was designated by NCDENR

Station ID	Water body—location	Longitude (DD)	Latitude (DD)	EPA Level 3 ecoregion	Elevation (m)	Drainage area (km^2)	% Urban	% Ag
NC0109	New River—SR 1345	−81.18330	36.55220	Blue Ridge	713.6	2,121.6	3.3	44[a]
NC0207	Nantahala River—FS RD 437	−83.61916	35.12694	Blue Ridge	1,878.3	134.4	2.6	0.4
NC0209	Cataloochee Creek—SR 1395	−83.07277	35.66722	Blue Ridge	756.9	127.4	3	0
NC0248	Barnes Creek—SR 1303	−80.00055	35.43861	Piedmont	106.7	60.3	0.6	5.4
NC0075	Little River—SR 1340	−79.83220	35.38638	Piedmont	149.3	223.8	1.4	0.1

[a]99.6% pasture/hay.

Table 5-12. Time periods for which biological data were available at the long-term monitoring sites in North Carolina. Data used in these analyses were limited to samples collected during the summer (June–September) index period using the standard qualitative (full-scale) method

Station ID	Water body	Number of years of data analyzed	Years
NC0109	New River	11	1983–1990, 1993, 1998, 2003
NC0207	Nantahala River	8	1984, 1986, 1988, 1990, 1991, 1994, 1999 and 2004
NC0209	Cataloochee Creek	7	1984, 1986, 1989, 1990, 1991, 1992 and 1997
NC0075	Little River	6	1983, 1985, 1988, 1996, 2001 and 2006
NC0248	Barnes Creek	5	1985, 1987, 1989, 1996 and 2001

5.6. EVIDENCE OF TRENDS AT LEAST-DISTURBED LONG-TERM MONITORING SITES

5.6.1. New River (NC0109)

The New River (NC0109) site is located in northwestern North Carolina, along State Route 1345 in Alleghany County. It is in the Blue Ridge ecoregion, has a drainage area of 2,121.6 km^2, and an elevation of 713.6 m. Its highest maximum monthly temperatures occur during August, and lowest average flows (<1,500 cfs) occur from July through October. This station has 11 years of biological data collected during the summer (June−September) index period using the standard qualitative (full-scale) method. The period of biological record ranges from 1983 to 2003. We gathered flow data from 1930−2010 from USGS gage 03164000 (New River near Galax, VA, Latitude: 36.6473497, Longitude: 80.978969). The gage is located 21 km northeast of the biological sampling site (as the crow flies). We also gathered daily temperature and precipitation data from the Sparta 2SE weather station (SiteID 318158, Latitude: 36.4819, Longitude: 81.0931), which is located approximately 11 km southeast of the biological sampling site.

Daily precipitation data were available from 1942−2010, while air temperature data were limited to July 2006−2010. Figure 5-10 shows an aerial photograph of the site, along with the nearest weather station and active USGS gage.

5.6.1.1. *Temporal Trends in Climatic and Biological Variables*

Since 1974, mean annual air temperatures at the New River (NC0109) site have ranged from 9.8 to 12.1°C. Overall, temperatures have shown a slight increase, but there has been a great deal of year-to-year variability, and this trend is not significant (when fit with a linear trend line, $r^2 = 0.01$, $p = 0.62$) (see Figure 5-11). Mean annual flow and mean annual precipitation patterns have also been highly variable over time, with flows ranging from 927 to 3,007 cfs (see Figure 5-12). Overall, mean annual flows have increased slightly over time, but this trend is not significant (when fit with a linear trend line, $r^2 = 0.01$, $p = 0.50$). Precipitation patterns generally show good correspondence with flow patterns (see Figure 5-12).

Figure 5-10. Locations of the New River (NC0109) biological sampling site, USGS gage 03164000 (New River near Galax, VA) and Sparta 2 SE weather station. Image from Google Earth.

In addition to mean annual values, mean summer flow values were also evaluated, as this generally corresponds with low flow and potentially physiologically stressful conditions for the biological organisms. We would have evaluated July/August maximum temperatures from the nearest weather station as well, but these data were not available for the biological period of record. From 1983−2003, mean summer flows ranged from 588.7 to 3,073.3 cfs (see Table 5-13). Bioclassification scores ranged from good (4) (1985−1990) to excellent (5) (1983−1984, post-1990) (see Figure 5-13A). The number of EPT taxa and HBI metrics[8], which are used to calculate the bioclassification scores, were variable, with the highest HBI scores

[8]Because the bioclassification scoring scheme is based on species-level data, bioclassification scores were calculated based on the original species-level data, while the EPT taxa and HBI metrics shown in Figure 5-14 were calculated based on the genus-level OTU that we developed for the long-term data set.

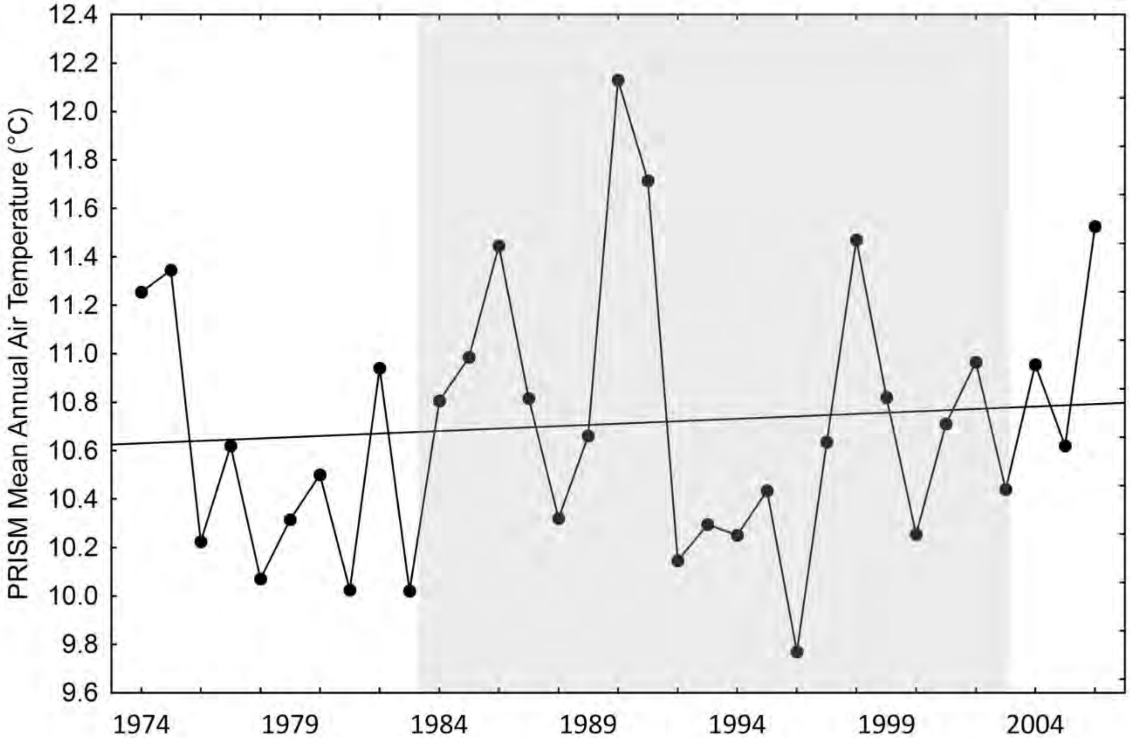

Figure 5-11. Yearly trends in PRISM mean annual air temperature (°C) at the New River (NC0109) site from 1974–2006. Observed temperature data from the Sparta 2 SE weather station are not shown because they are not available for the period of biological record. The area shaded in grey corresponds to the period of biological record. When the observed data are fitted with a linear trend line, $r^2 = 0.01$, $p = 0.62$, and $y = 0.6917 + 0.005 \times x$.

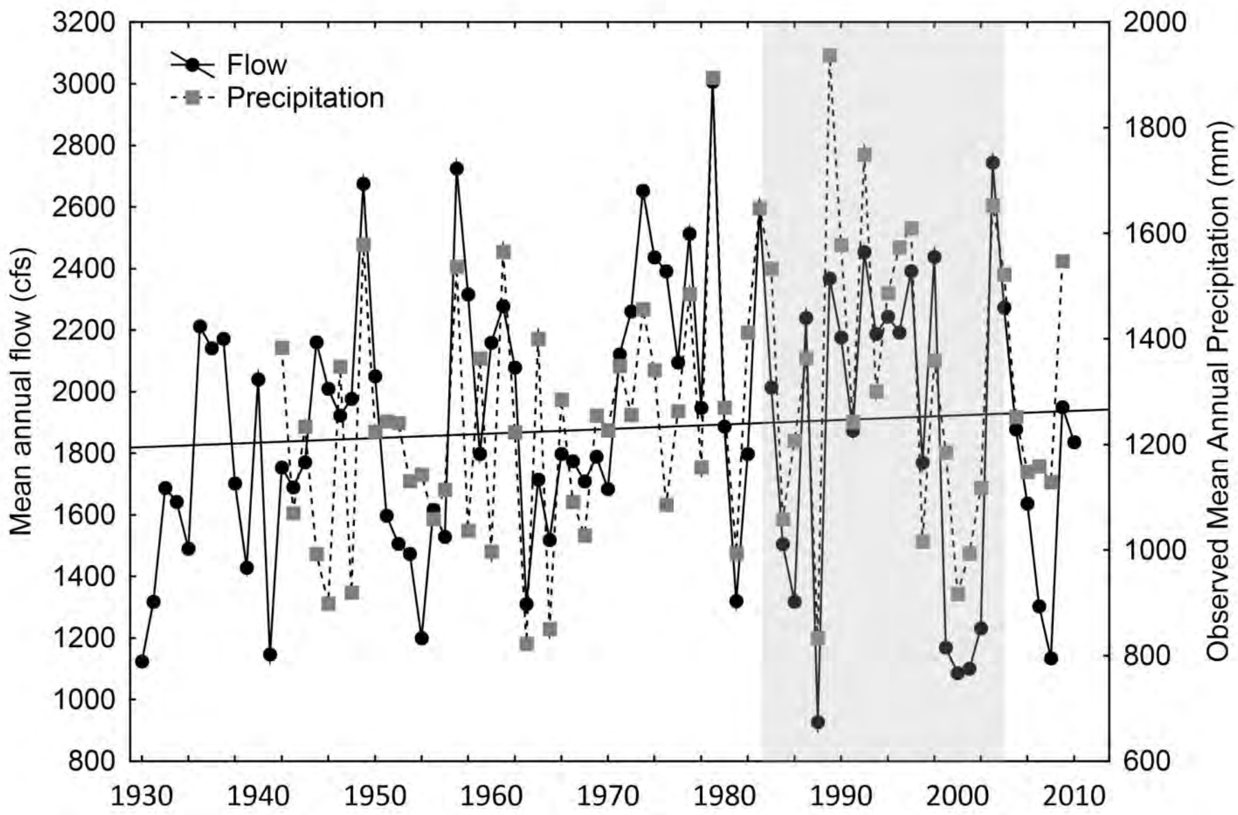

Figure 5-12. Yearly trends in mean annual flow (cfs) at the New River (NC0109) site from 1930–2010, based on data from USGS gage 03164000 (New River near Galax, VA). For comparative purposes, observed annual precipitation data from the Sparta 2 SE weather station are also included from 1942–2009. The area shaded in grey corresponds to the period of biological record. When the observed data are fitted with a linear trend line, $r^2 = 01$, $p = 0.50$, and $y = -1{,}012.0647 + 1.4674 \times x$.

Table 5-13. Range of temperature, precipitation, and flow values that occurred at the New River (NC0109) during the period of biological record. Summer = June−September

Parameter	Min	Max
Year	1983	2003
PRISM mean annual air temperature (°C)	10.0	12.1
Mean annual flow (cfs)	927.4	2,744
Mean summer flow (cfs)	588.7	3,073.3
PRISM mean annual precipitation (mm)	707.7	1,581.3

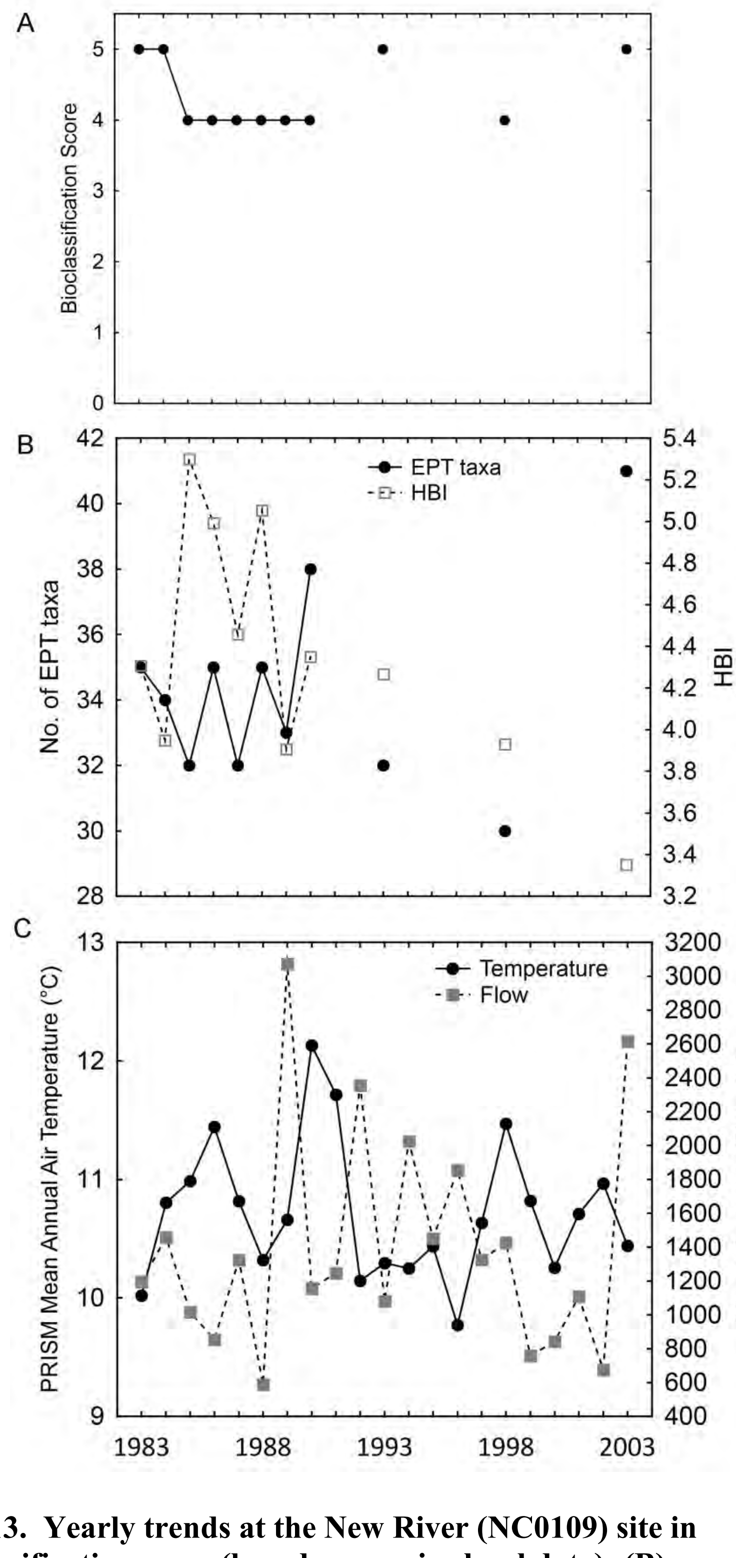

Figure 5-13. Yearly trends at the New River (NC0109) site in (A) bioclassification score (based on species-level data); (B) number of EPT taxa and HBI (based on genus-level OTU); and (C) PRISM mean annual air temperature (°C) and mean summer (June–September) flow (cfs).

occurring in the late 1980s and improving since the early 1990s (see Figure 5-14B). During the period of biological record, mean annual air temperatures and summer flows were highly variable, with the highest annual temperature occurring in 1990, the lowest summer flow occurring in 1988, and the highest summer flow occurring in 1989 (see Figure 5-14C). More warm-water than cold-water taxa are present at this site. The number of cold-water taxa has increased since the early 1990s (see Figures 5-14A and B).

Anthropogenic influence is higher than desired at this site (44% agricultural, 99.6% of this is pasture hay). Based on HBI scores, organic enrichment may have influenced the biological assemblage at this site in the mid- to late-1980s. Habitat index scores were not available for this site, and confounding factors related to in situ measurements in 1998 and 2003 were not evident. In situ parameter values were within the following ranges:

- DO: 8 to 8.3 mg/L
- pH: 7.5 to 7.7
- Specific conductance: 55 to 70 µmho/cm
- Water temperature: 24.2 to 25 °C

5.6.1.2. *Associations Between Biological and Climatic Variables*

Kendall tau nonparametric correlations analyses allow examination of associations between commonly used biological metrics, year, temperature, flow, and precipitation variables at the New River (NC0109) site. None of the commonly used biological metrics were strongly associated with PRISM mean annual air temperature, but eight showed strong associations with flow and/or precipitation variables (see Table 5-14). The directions of the relationships were in keeping with expectations for five of the metrics. The number of Plecoptera taxa, percentage EPT individuals, and percentage of Ephemeroptera individuals metrics had strong positive associations with flow and precipitation variables, while the percentage of noninsect individuals and HBI metrics were negatively associated with flow and precipitation. If we assume that low flows are more stressful to organisms, the total number of taxa metric and the Shannon-Wiener Diversity Index showed unexpected negative relationships with precipitation and flow, while the percentage of dominant taxon metric had an unexpected strong positive association with mean summer flow. Three of the metrics showed fairly strong ($r > |0.4|$) relationships with year. The

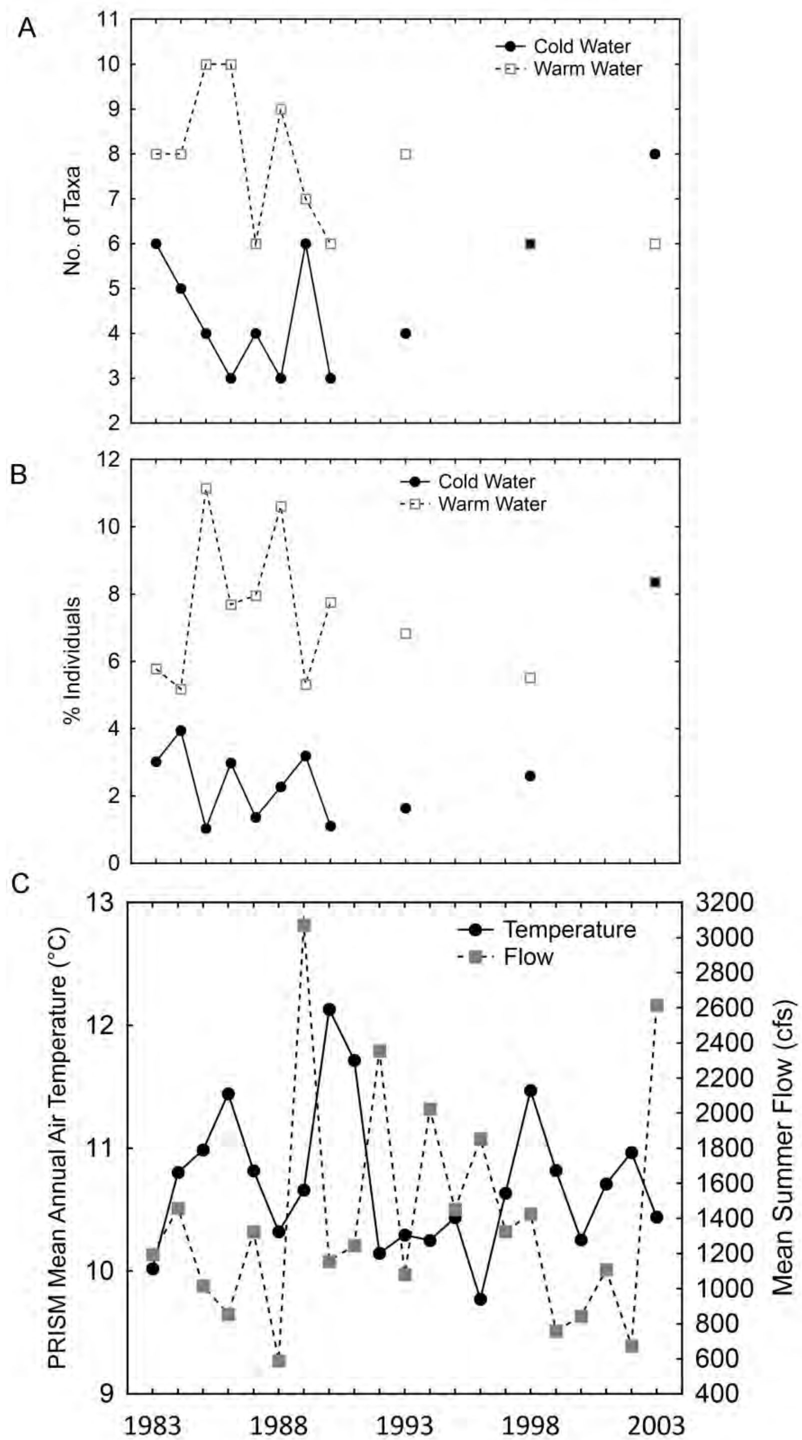

Figure 5-14. Yearly trends at the New River (NC0109) site in (A) number of cold and warm-water taxa; (B) percentage cold and warm-water individuals; and (C) PRISM mean annual air temperature (°C) and mean summer (June−September) flow (cfs).

Table 5-14. Kendall tau nonparametric correlations analyses performed to examine associations between commonly used biological metrics, year, and climatic variables at the New River (NC0109) site. Results are based on 11 years of data. Entries are in bold text if $r \geq \pm 0.5$ and are highlighted in gray if they are in a direction opposite of what is expected. Ranges of biological metric values are also included. Summer = June-September

Biological metric	Range of metric values		r values (based on Kendall Tau correlations)				
	Min	Max	Year	PRISM mean annual air temperature (°C)	Flow (cfs) Mean annual	Flow (cfs) Mean summer	PRISM mean annual precipitation (mm)
Total no. taxa	64	107	−0.49	0.15	**−0.67**	−0.45	**−0.60**
No. EPT taxa	30	41	−0.02	−0.13	−0.02	−0.06	0.17
No. Ephemeroptera taxa	13	18	−0.06	−0.15	0.02	0.02	0.11
No. Plecoptera taxa	1	6	0.43	0.04	0.23	**0.51**	**0.51**
No. Trichoptera taxa	12	19	−0.06	−0.02	−0.06	−0.26	−0.06
No. Intolerant taxa	1	4	0.23	0.23	0.08	−0.08	0.08
Percentage EPT individuals	42.7	74.6	0.49	−0.05	**0.56**	**0.60**	**0.67**
Percentage Ephemeroptera individuals	25.6	42.4	0.38	−0.16	**0.53**	**0.56**	**0.64**
Shannon-Wiener Diversity Index	5.3	6.1	−0.27	0.13	**−0.71**	**−0.75**	**−0.67**
Percentage noninsect individuals	5.1	18.6	−0.13	0.20	**−0.71**	−0.45	**−0.60**
Percentage dominant taxon	5.5	9.0	0.09	−0.24	0.31	**0.56**	0.35
Percentage tolerant individuals	0.3	3.5	0.13	0.09	−0.16	−0.05	−0.20
Hilsenhoff Biotic Index	3.4	5.3	−0.42	0.13	**−0.56**	**−0.67**	**−0.75**

total number of taxa metric and the HBI were negatively associated with year, while percentage of EPT individuals was positively associated with year.

Similar analyses were performed on the thermal preference metrics. None were strongly associated with PRISM mean annual air temperature (see Table 5-15). The cold water metrics were positively associated with the flow and precipitation variables, and the warm water metrics were negatively associated with flow and precipitation. The richness metrics showed stronger ($r > |0.5|$) associations with the flow and precipitation variables than the percentage composition metrics. The number of warm-water taxa metric showed a fairly strong ($r > |0.4|$) negative relationship with year.

A subset of biological metrics that have shown responsiveness to hydrologic variables in other studies (see Section 2, Table 2-5c) was also examined (see Table 5-16). Three of the metrics—number of collector-filterer taxa, number of collector-gatherer taxa, and percentage scraper/herbivore individuals—showed strong ($r > |0.5|$) associations with year. Five metrics showed strong associations with the precipitation and flow variables. One of these, number of scraper/herbivore taxa, went against expectations (see Table 2-5c), showing a negative correlation with flow precipitation. The percentage of erosional individuals metric had a strong positive association with the flow variables, and the predator metrics were negatively correlated with flow and precipitation.

5.6.1.3. *Groupings Based on Climatic Variables*

Samples were partitioned into hottest/coldest/normal year groups and lowest/normal/highest flow year groups. At the New River (NC0109) site, on average, the hottest years were 1.5°C warmer than the coldest years, and highest flow years had 477 more cfs than lowest flow years. When samples were grouped based on temperature, there were no significant ($p > 0.05$) differences between any of the mean metric values, but the number of warm-water taxa metric was unexpectedly highest in the coldest year samples, and the number of cold-water taxa was highest in the normal year samples (see Table 5-17). When samples were grouped based on mean annual flow, the number of warm-water taxa metric was significantly higher ($p < 0.05$) in the driest flow years versus the normal flow years (see Table 5-18).

Table 5-15. Kendall tau nonparametric correlations analyses performed to examine associations between thermal preference metrics, year, and climatic variables at the New River (NC0109) site. Results are based on 11 years of data. Entries are in bold text if *r* ≥ ±0.50. Ranges of biological metric values are also included. Summer = June–September

	Range of metric values		*r* values (based on Kendall Tau correlations)				
					Flow (cfs)		
Biological metric	**Min**	**Max**	**Year**	**PRISM mean annual air temperature (°C)**	**Mean annual**	**Mean summer**	**PRISM mean annual precipitation (mm)**
No. cold-water taxa	3	8	0.12	−0.32	**0.76**	**0.68**	**0.72**
Percentage cold-water individuals	1.0	8.4	0.05	−0.27	0.35	0.45	0.45
No. warm-water taxa	6	10	−0.46	−0.14	**−0.54**	**−0.50**	**−0.54**
Percentage warm-water individuals	5.2	11.1	0.05	0.02	−0.16	−0.42	−0.35

Table 5-16. Kendall tau nonparametric correlations analyses performed to examine associations between a subset of biological metrics, year, flow, and precipitation variables at the New River (NC0109) site. The subset of biological metrics were selected per the criteria outlined in Section 2 and have shown responsiveness to hydrologic variables in other studies (see Section 2, Table 2-5c). Results are based on 11 years of data. Entries are in bold text if $r \geq \pm 0.5$ and are highlighted in gray if they are in a direction opposite of what is expected. Ranges of biological metric values are also included. Summer = June–September

Biological metric		Range of metric values		*r* values (based on Kendall Tau correlations)			
					Flow (cfs)		
		Min	Max	Year	Mean annual	Mean summer	PRISM mean annual precipitation (mm)
Richness	Collector filterer	9	13	**−0.58**	−0.26	−0.18	−0.22
	Collector gatherer	19	31	**−0.58**	−0.43	−0.31	−0.31
	Scraper/herbivore	12	20	−0.14	**−0.65**	**−0.65**	**−0.61**
	Predator	15	34	−0.19	**−0.72**	**−0.65**	**−0.69**
	Swimmer	6	11	0.12	0.00	−0.16	−0.16
	OCH	11	20	0.09	−0.17	0.17	−0.02
	Depositional	5	10	−0.33	−0.25	−0.25	−0.06
	Erosional	21	29	0.12	−0.04	−0.04	0.08
Percentage individuals	Collector filterer	10.2	21.3	0.35	0.27	**0.53**	0.45
	Collector gatherer	25.0	36.2	−0.42	−0.05	0.05	0.13
	Scraper/herbivore	14.4	22.7	**0.60**	0.24	0.20	0.05
	Predator	14.9	30.8	−0.02	−0.45	**−0.71**	**−0.56**
	Swimmer	9.3	22.4	0.38	0.38	0.27	0.42
	OCH	10.1	26.6	0.27	−0.16	−0.13	−0.13
	Depositional	4.1	10.6	−0.24	−0.02	−0.05	0.09
	Erosional	22.2	42.5	0.45	**0.53**	**0.56**	0.35

Table 5-17. Mean metric values (±1 SD) for the New River (NC0109) site in coldest, normal, and hottest year samples. Year groups are based on PRISM mean annual air temperature values. One-way ANOVA was done to evaluate differences in mean metric values. There were no significant differences across year groups ($p > 0.05$)

Year group	No. total taxa	No. EPT taxa	HBI	No. cold-water taxa	No. warm-water taxa	% Cold-water individuals	% Warm-water individuals
Coldest	86.0 ± 7.0	34.0 ± 1.7	4.5 ± 0.4	4.3 ± 1.5	8.3 ± 0.6	2.3 ± 0.7	7.7 ± 2.5
Normal	84.2 ± 6.8	34.4 ± 3.8	4.2 ± 0.7	5.4 ± 1.7	7.4 ± 1.7	3.6 ± 2.9	7.6 ± 2.5
Hottest	84.7 ± 21.5	34.3 ± 4.0	4.4 ± 0.5	4.0 ± 1.7	7.3 ± 2.3	2.2 ± 1.0	7.0 ± 1.3

Table 5-18. Mean metric values (±1 SD) for the New River (NC0109) site in driest, normal, and wettest flow year samples. Year groups are based on mean annual flow values from USGS gage 03164000. One-way ANOVA was done to evaluate differences in mean metric values. Groups with no superscripts are not significantly different ($p < 0.05$). Entries with superscripts have significant differences across groups; those entries with different superscripts are significantly different from each other (e.g., driest no. warm-water taxa vs. normal and wettest no. warm-water taxa)

Year group	No. total taxa	No. EPT Taxa	HBI	No. cold-water taxa	No. warm-water taxa	% Cold-water individuals	% Warm-water individuals
Driest	95.0 ± 11.1	33.7 ± 1.5	4.7 ± 0.7	4.0 ± 1.0	9.3 ± 1.2^{A}	2.7 ± 1.5	8.0 ± 3.0
Normal	79.4 ± 8.8	33.0 ± 3.0	4.2 ± 0.3	4.6 ± 1.3	6.6 ± 0.9^{B}	2.0 ± 0.9	6.7 ± 1.2
Wettest	83.7 ± 10.0	37.0 ± 3.5	4.2 ± 0.9	5.7 ± 2.5	7.7 ± 1.5^{AB}	4.5 ± 3.3	8.2 ± 2.4

The number of EPT taxa metric and the cold-water taxa metrics were highest in the highest flow year samples ($p > 0.05$).

5.6.2. Nantahala River (NC0207)

The Nantahala River (NC0207) site is located in southwestern North Carolina, along Forest Service Road 437 in Macon County. It is in the Blue Ridge ecoregion, has a drainage area of 134.4 km^2, and an elevation of 1,878.3 m. Most of the upstream catchment is in the Nantahala National Forest. The highest maximum monthly temperatures at this site occur during July and August, and the lowest average flows (<120 cfs) occur from August through October. This station has 8 years of biological data collected during the summer (June−September) index period using the standard qualitative (full-scale) method. The period of biological record ranges from 1984 to 2004.

We gathered flow data from 1941−2010 from USGS gage 03504000 (Nantahala River near Rainbow Springs) Latitude: 35.1275, Longitude: 83.61861), which is colocated at the biological sampling site. We also gathered daily temperature and precipitation data from 1946−2010 from the Franklin weather station (SiteID 313228, Latitude: 35.1803, Longitude: 83.61861), which is located approximately 21 km east/northeast of the biological sampling site. Figure 5-15 shows an aerial photograph of the site, along with the nearest weather station and active USGS gage.

5.6.2.1. *Temporal Trends in Climatic and Biological Variables*

Since 1946, mean annual air temperatures at the Franklin weather station have ranged from 12.2 to 15.0°C. There has been a lot of year-to-year variability, but overall, observed temperatures at the weather station have decreased over time (when fit with a linear trend line, $r^2 = 0.11$ and $p = 0.01$) (see Figure 5-16). When PRISM air temperature data are compared to observed data from 1974−2006, the PRISM data are 0.1−3°C lower than observed values, and the PRISM data show an increasing trend. Because the weather station is located more than 20 km from the biological sampling site and is at a lower elevation (648 m vs. 1,878 m), the PRISM data are likely more representative of conditions at the biological sampling. Mean annual flow and mean annual precipitation patterns have been highly variable over time (see Figure 5-17). Since 1941, mean annual flow values have ranged from 119.5 to 302.4 cfs (when fit with a linear trend line, $r^2 = 0.00$, and $p = 0.99$). Precipitation patterns show good correspondence with flow patterns (see Figure 5-17). In addition to mean annual values, mean maximum July/August temperature and mean summer flow values were also evaluated, as these are likely to be physiologically stressful time periods for the biological organisms. During the period of biological record (1984−2004), mean maximum July/August air temperatures ranged from 27.0−31.4°C, and mean summer flow values ranged from 54.4 to 299.8 cfs (see Table 5-19).

Figure 5-15. Locations of the Nantahala River (NC0207) biological sampling site, USGS gage 03504000 (Nantahala River near Rainbow Springs) and Franklin weather station. Image from Google Earth.

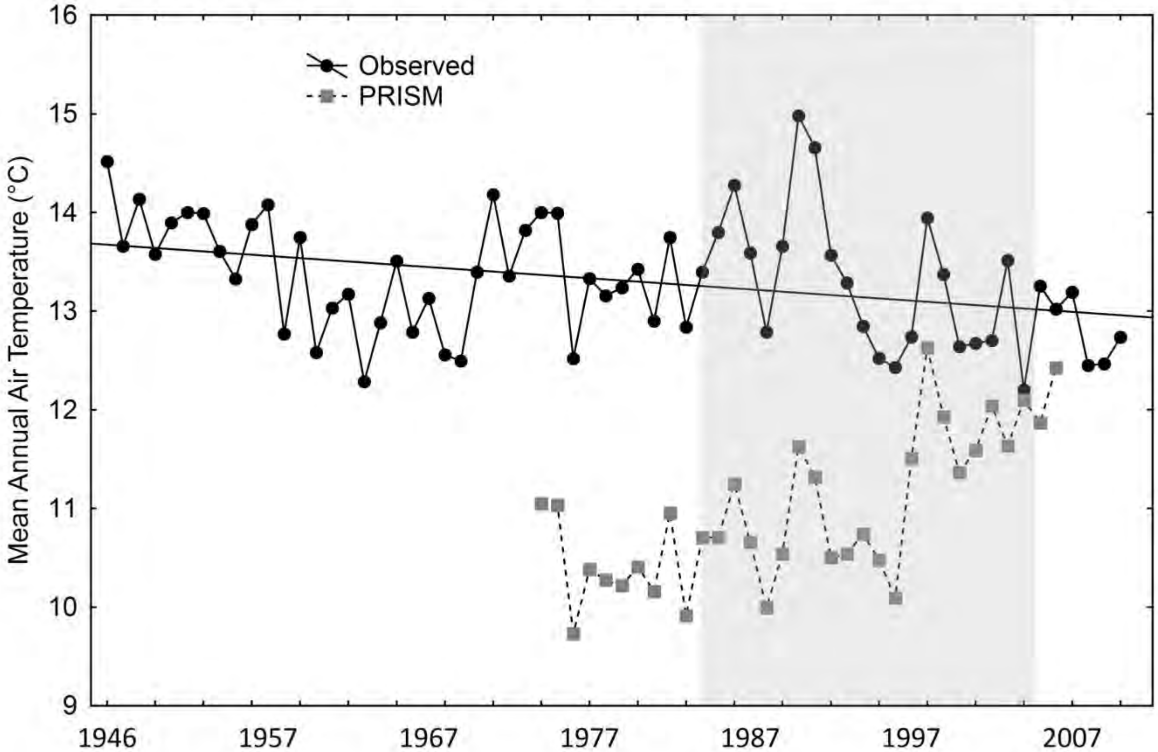

Figure 5-16. Yearly trends in observed mean annual air temperature (°C) at the Franklin weather station from 1946–2010. For comparative purposes, PRISM mean annual air temperature data are also included from 1974–2006. The area shaded in grey corresponds to the period of biological record. When the observed data are fitted with a linear trend line, $r^2 = 0.11$, $p = 0.01$, and $y = 5.7408 - 0.0113 \times x$.

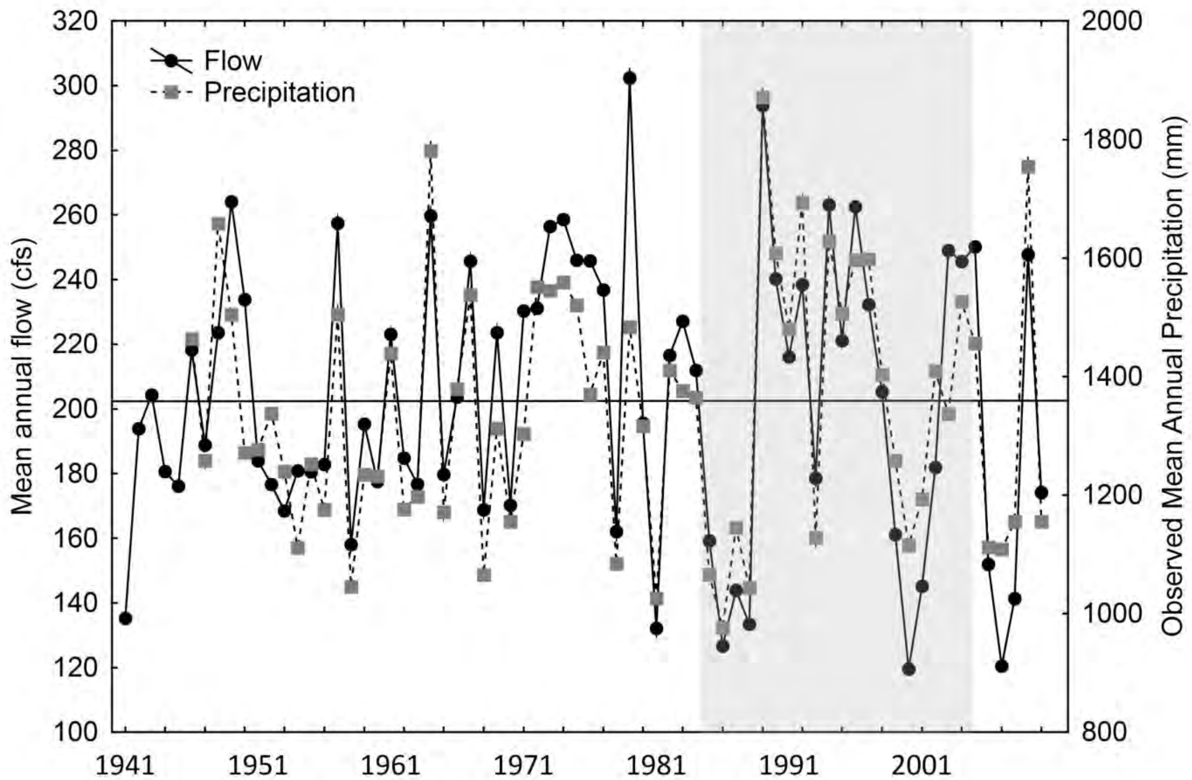

Figure 5-17. Yearly trends in mean annual flow (cfs) at the Nantahala River (NC0207) site from 1941–2010, based on data from USGS gage 03504000 (Nantahala River near Rainbow Springs). For comparative purposes, observed annual precipitation data from the Franklin weather station are also included from 1946–2010. The area shaded in grey corresponds to the period of biological record. When the observed data are fitted with a linear trend line, $r^2 = 0.00$, $p = 0.99$, and $y = 198.1436 + 0.0022 \times x$.

Table 5-19. Range of temperature, precipitation, and flow values that occurred at the Nantahala River (NC0207) site during the period of biological record. Summer = June–September

Parameter	Min	Max
Year	1984	2004
PRISM mean annual air temperature (°C)	10	12.6
Observed mean maximum July air temperature (°C)	27.0	31.4
Mean annual flow (cfs)	119.5	302.4
Mean summer flow (cfs)	54.4	299.8
PRISM mean annual precipitation (mm)	1,337.9	2,351.9

This site has received bioclassification scores of excellent (5) over the period of record (see Figure 5-18A), with consistently low HBI scores (the highest HBI score was a 3.65, which occurred in 1984), and high numbers of EPT taxa (34 or more [calculated using a genus-level OUT]) (see Figure 5-18B). During the period of biological record, mean maximum July/August air temperatures and summer flows were highly variable, with the highest maximum July/August temperature occurring in 1993, the lowest summer flows occurring in 1985 and 1999, and the highest summer flows occurring in 1988 and 2004 (see Figure 5-18C). The cold-water taxa metrics have been consistently high over time (13 or more taxa, comprising 17% or more of the assemblage) (see Figures 5-19A and B). Very few warm-water taxa are present at this site, with richness values ranging from 0 to 2.

Confounding factors related to land use appear to be minimal at this site (<3% urban and <0.5% agricultural within a 1-km buffer). Habitat index scores from 1999 and 2004 are in the range of "natural" condition (scores range from 83 to 87, with a maximum possible score of 100).

Confounding factors related to in situ measurements were not evident, with values in the following ranges:

- DO: 7.8 to 9.0 mg/L
- pH: 6.9 to 7.0
- Specific conductance: 16 to 17 μmho/cm
- Water temperature: 16.0 to 16.9 °C

5.6.2.2. *Associations Between Biological Variables and Climatic Variables*

This site did not have an appropriate data set for performing Kendall tau nonparametric correlations analyses (less than 9 years of data, gaps between data collection years).

5.6.2.3. *Groupings Based on Climatic Variables*

This site did not have an appropriate data set for performing analyses on biological data grouped by extremes in temperature, flow, and/or precipitation variables (less than 9 years of data, gaps between data collection years).

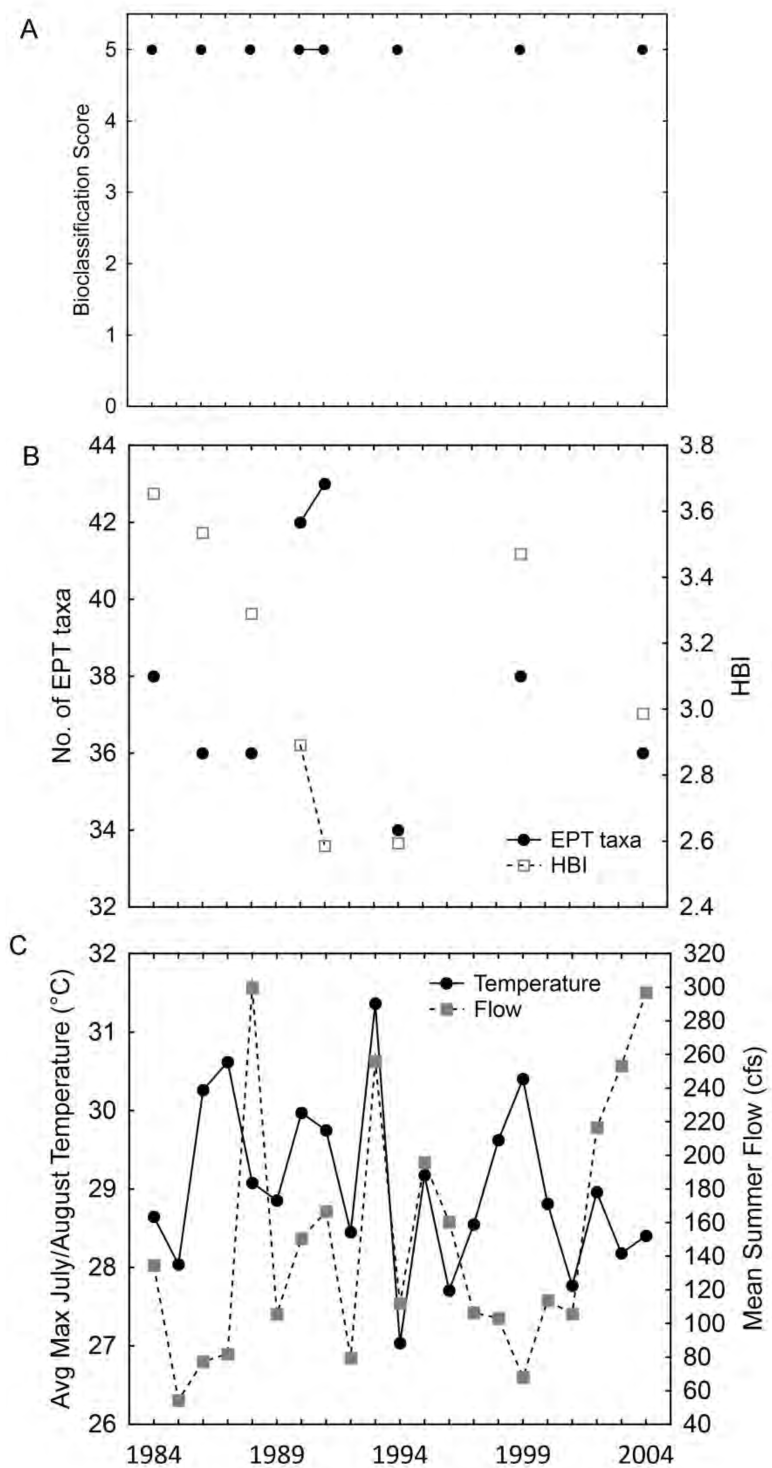

Figure 5-18. Yearly trends at the Nantahala River (NC0207) site in (A) bioclassification score (based on species-level data); (B) number of EPT taxa and HBI (based on genus-level OTU); and (C) observed mean July/August maximum air temperature (°C) and mean summer (June-September) flow (cfs).

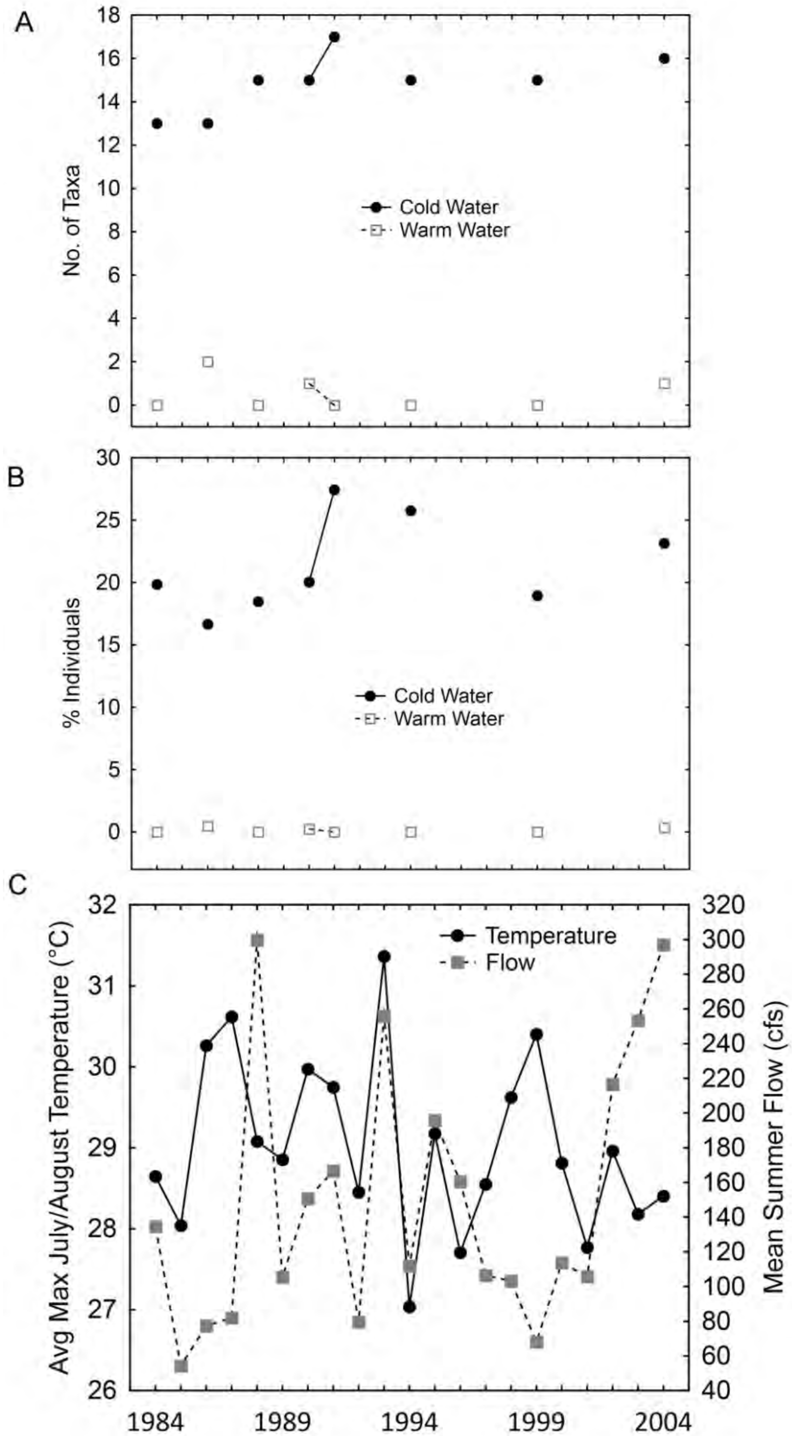

Figure 5-19. Yearly trends at the Nantahala River (NC0207) site in (A) number of cold and warm-water taxa; (B) percentage cold and warm-water individuals; and (C) observed mean July/August maximum air temperature (°C) and mean summer (June–September) flow (cfs).

5.6.3. Cataloochee Creek (NC0209)

The Cataloochee Creek (NC0209) site is located in the Great Smokey Mountains National Park in western North Carolina, along State Route 1395 in Haywood County. It is in the Blue Ridge ecoregion, has a drainage area of 127.4 km^2, and an elevation of 756.9 m. The highest maximum monthly temperatures at this site occur during July and August, and lowest average flows (<200 cfs) occur from September through November. This station has 7 years of biological data collected during the summer (June−September) index period using the standard qualitative (full-scale) method. The period of biological record ranges from 1984 to 1997.

We gathered flow data from 1935−2010 from USGS gage 03460000 (Cataloochee Creek near Cataloochee; Latitude: 35.6675, Longitude: 83.07361), which is colocated with the biological sampling site. We also gathered daily temperature and precipitation data from the Cataloochee weather station (SiteID 311564, Latitude: 35.6375, Longitude: 83.0958), which is located approximately 4 km south/southwest of the biological sampling site. Precipitation data were available from 1949−2009, while temperature data were available starting in 1966. Figure 5-20 shows an aerial photograph of the site, along with the nearest weather station and active USGS gage.

5.6.3.1. *Temporal Trends in Climatic and Biological Variables*

Since 1966, mean annual air temperatures at the Cataloochee weather station have ranged from 9.1 to 13.1°C. There has been a lot of year-to-year variability, but overall, observed temperatures at the weather station have increased over time (when fit with a linear trend line, $r^2 = 0.06$, and $p = 0.12$) (see Figure 5-21). When PRISM air temperature data are compared to observed data from 1974−2006, the PRISM data are within 2°C of the observed values, and the patterns in the PRISM data show good correspondence with patterns in the observed data. Mean annual flow and mean annual precipitation patterns have been highly variable over time (see Figure 5-22). Since 1935, mean annual flow values have ranged from 54.2 to 168.3 cfs (when fit with a linear trend line, $r^2 = 0.00$, $p = 0.90$). Precipitation patterns show good correspondence with flow patterns (see Figure 5-22). During the period of biological record (1984−1997), mean maximum air temperatures during the hottest months (July and August) ranged from 19.5−21.2°C, and mean summer flows ranged from 30.8 to 135.8 cfs (see Table 5-20).

Figure 5-20. Locations of the Cataloochee Creek (NC0209) biological sampling site, USGS gage 03460000 (Cataloochee Creek near Cataloochee) and Cataloochee weather station. Image from Google Earth.

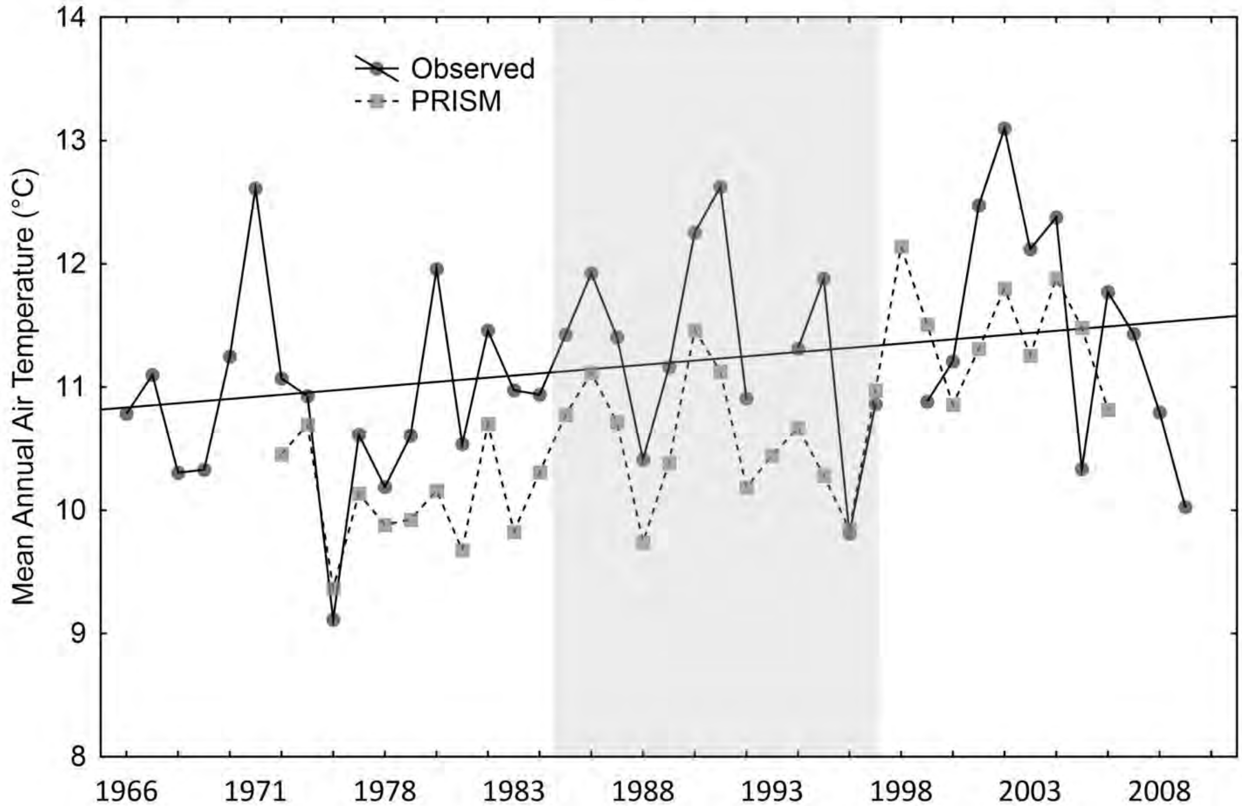

Figure 5-21. Yearly trends in observed mean annual air temperature (°C) at the Cataloochee weather station from 1966−2009. For comparative purposes, PRISM mean annual air temperature data are also included from 1974−2006. The area shaded in grey corresponds to the period of biological record. When the observed data are fitted with a linear trend line, $r^2 = 0.06$, $p = 0.12$, and $-21.26 + 0.0163 \times x$.

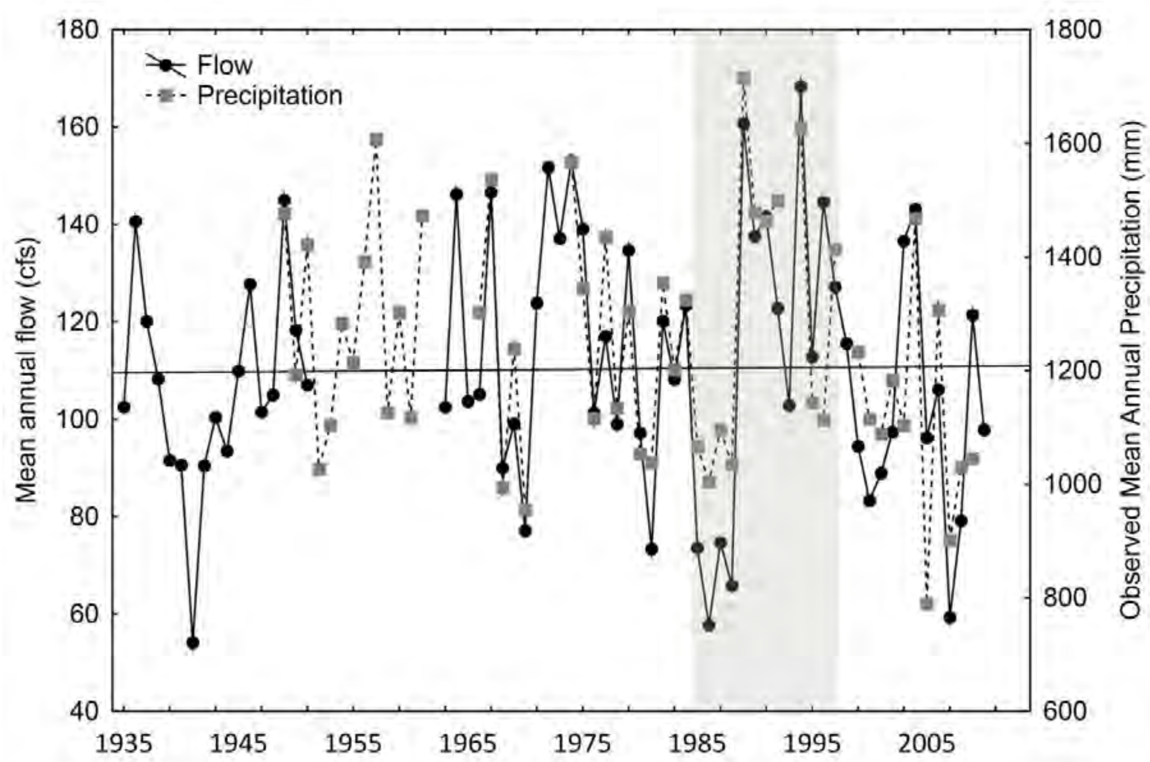

Figure 5-22. Yearly trends in mean annual flow (cfs) at the Cataloochee Creek (NC0209) site from 1935−2010, based on data from USGS gage 03460000 (Cataloochee Creek near Cataloochee). For comparative purposes, observed annual precipitation data from the Cataloochee weather station are also included from 1949−2009. The area shaded in grey corresponds to the period of biological record. When the observed data are fitted with a linear trend line, $r^2 = 0.00$, $p = 0.90$, and $y = 73.7837 + 0.0185 \times x$.

Table 5-20. Range of temperature, precipitation, and flow values that occurred at the Beaver River site (UT 5940440) during the period of biological record

Parameter	Min	Max
Year	1984	1997
Observed annual air temperature (°C)	9.8	12.6
PRISM mean annual air temperature (°C)	9.7	11.5
Observed mean maximum July/August air temperature (°C)	19.5	21.2
Mean annual flow (cfs)	57.7	168.3
Observed annual precipitation (mm)	1,003.7	1,715.3
PRISM mean annual precipitation (mm)	1,014.4	1,664.7
Mean summer flow (cfs)	30.8	135.8

This site has received bioclassification scores of excellent (5) over the period of record (see Figure 5-23A). HBI scores have been low (less than 3.3) and variable. The number of EPT taxa metric, which ranged from 34 to 42 (based on a genus-level OTU), also varied from year to year, increasing from 1984 to 1989 and then decreasing from 1989 to 1992 (see Figure 5-23B).

During the period of biological record, there was a fair amount of year of year variability in the mean maximum July/August air temperatures and summer flows (see Figure 5-23C). From 1986−1988, conditions for the biological organisms may have been particularly stressful, with high temperatures and very low summer flows. Biological responses to these conditions were not evident, but this may have been due in part to gaps in the biological data. The cold-water taxa metrics have been consistently high over time (16 or more taxa, comprising 25% or more of the assemblage) (see Figures 5-24A and B). Very few warm-water taxa are present at this site (richness values range from 0 to 2).

Confounding factors related to land use appear to be minimal at this site (≤3% urban and 0% agricultural within a 1-km buffer). This site received a habitat index score of 93 in 1997 (out of a possible score of 100), which is in the range of "natural" condition. Confounding factors related to in situ measurements were not evident, with values in the following ranges:

- DO: 9.0 mg/L
- pH: 6.9
- Specific conductance: 10 to 16 µmho/cm
- Water temperature: 17.6 to 18.0 °C

5.6.3.2. *Associations Between Biological Variables and Climatic Variables*

This site did not have an appropriate data set for performing Kendall tau nonparametric correlations analyses (less than 9 years of data, gaps between data collection years).

5.6.3.3. *Groupings Based on Climatic Variables*

This site did not have an appropriate data set for performing analyses on biological data grouped by extremes in temperature, flow, and/or precipitation variables (less than 9 years of data, gaps between data collection years).

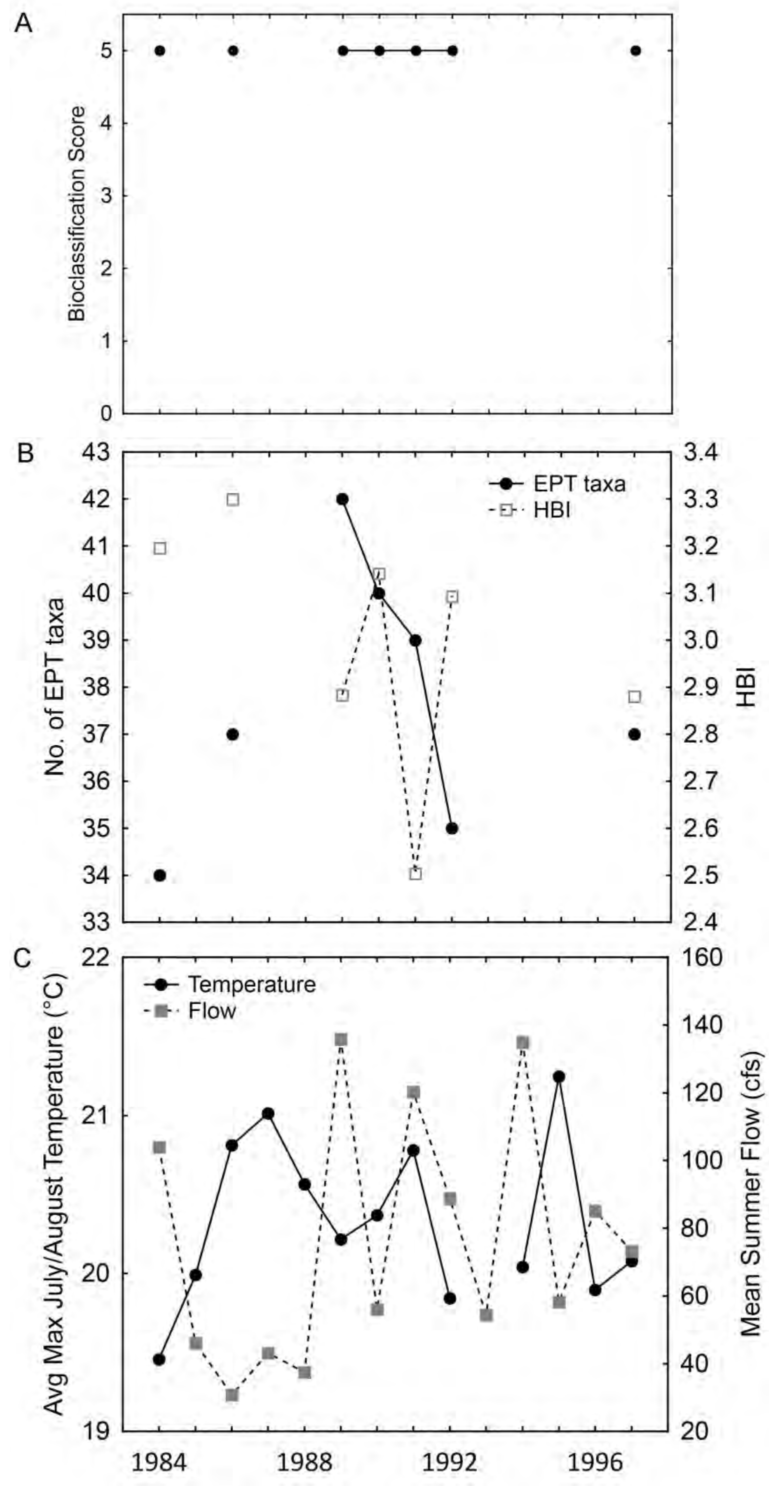

Figure 5-23. Yearly trends at the Cataloochee Creek (NC0209) site in (A) bioclassification score (based on species-level data); (B) number of EPT taxa and HBI (based on genus-level OTU); and (C) observed mean July/August maximum air temperature (°C) and mean summer (June–September) flow (cfs).

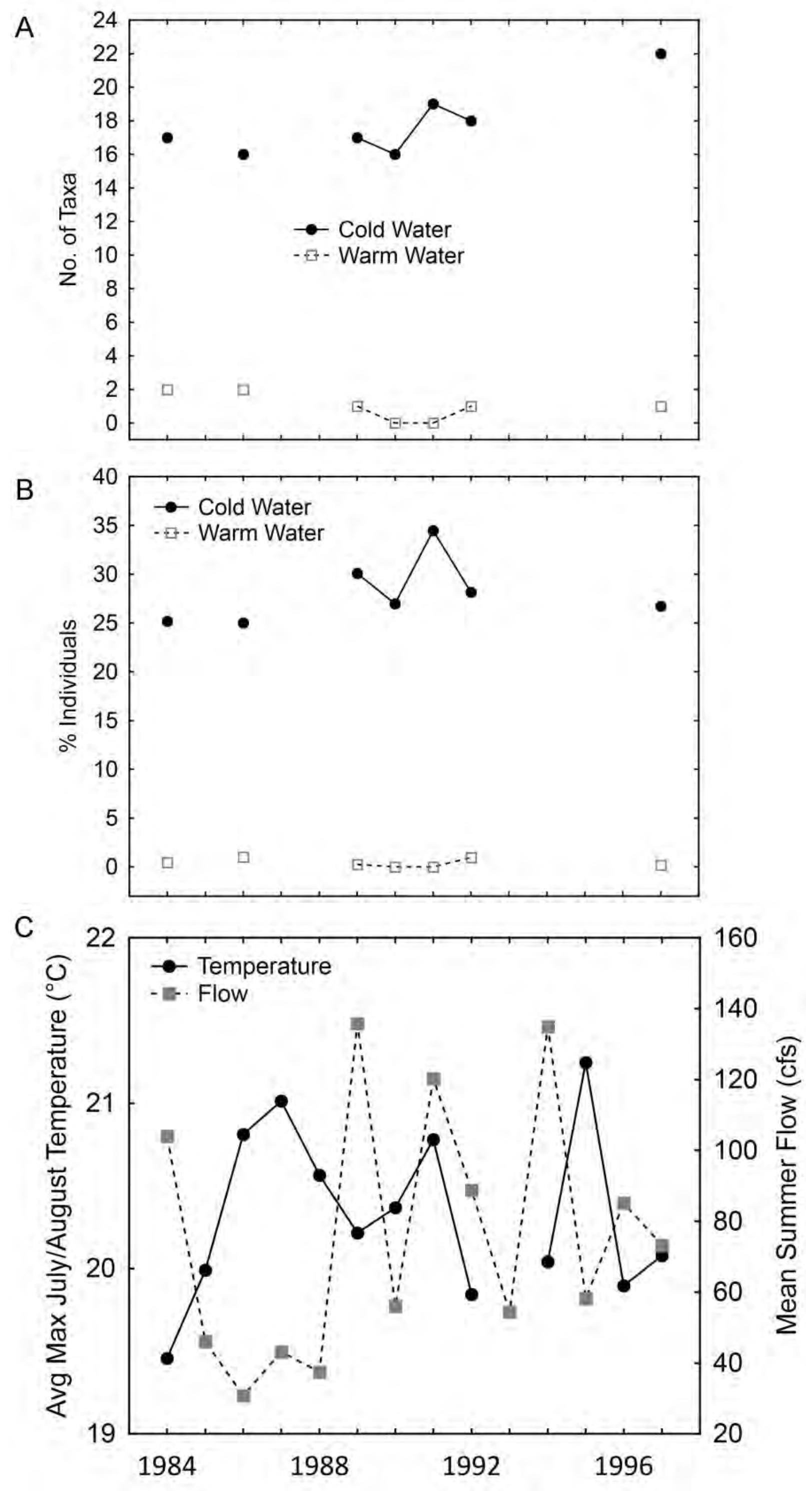

Figure 5-24. Yearly trends at the Cataloochee Creek (NC0209) site in (A) number of cold and warm-water taxa; (B) percentage cold and warm-water individuals; and (C) observed mean July/August maximum air temperature (°C) and mean summer (June–September) flow (cfs).

5.6.4. Barnes Creek (NC0248)

The Barnes Creek (NC0248) site is located in central North Carolina, along State Route 1303 in Montgomery County. It is in the Piedmont ecoregion, has a drainage area of 60.3 km^2 and an elevation of 106.7 m. The highest maximum monthly temperatures at this site occur during July and August, and lowest rainfall occurs from October through December. This station has 5 years of biological data collected during the summer (June−September) index period using the standard qualitative (full-scale) method. The period of biological record ranges from 1985 to 2001.

We gathered daily temperature and precipitation data from the Albemarle weather station (SiteID 310090, Latitude: 35.3992, Longitude: 80.1994), which is located approximately 19 km southwest of the biological sampling site. Data were available from 1912−2010 (with some gaps). There were no USGS gages located in proximity to the biological sampling site. Figure 5-25 shows an aerial photograph of the biological sampling site and the Albemarle weather station.

5.6.4.1. *Temporal Trends in Climatic and Biological Variables*

Since 1912, mean annual air temperatures at the Albemarle weather station have ranged from 14.3 to 17.4°C. There has been a lot of year-to-year variability, but overall, observed temperatures at the weather station have decreased over time (when fit with a linear trend line, $r^2 = 0.03$ and $p = 0.09$) (see Figure 5-26). When PRISM air temperature data are compared to observed data from 1974−2006, the PRISM data are within 1.1°C of the observed values and correspond closely with the patterns seen in the observed data. Mean annual precipitation patterns have been highly variable over time (see Figure 5-27). Since 1912, mean annual precipitation values have ranged from 743.8 to 1,626.1 mm (when fit with a linear trend line, $r^2 = 0.00$ and $p = 0.72$). The PRISM precipitation data correspond closely with the observed data. During the period of biological record (1985 to 2001), mean maximum air temperatures during the hottest months (July and August) ranged from 29.8−33.7°C, and mean summer precipitation ranged from 162.4 to 688.6 mm (see Table 5-21).

Figure 5-25. Locations of the Barnes Creek (NC0248) biological sampling site and the Albemarle weather station. Image from Google Earth.

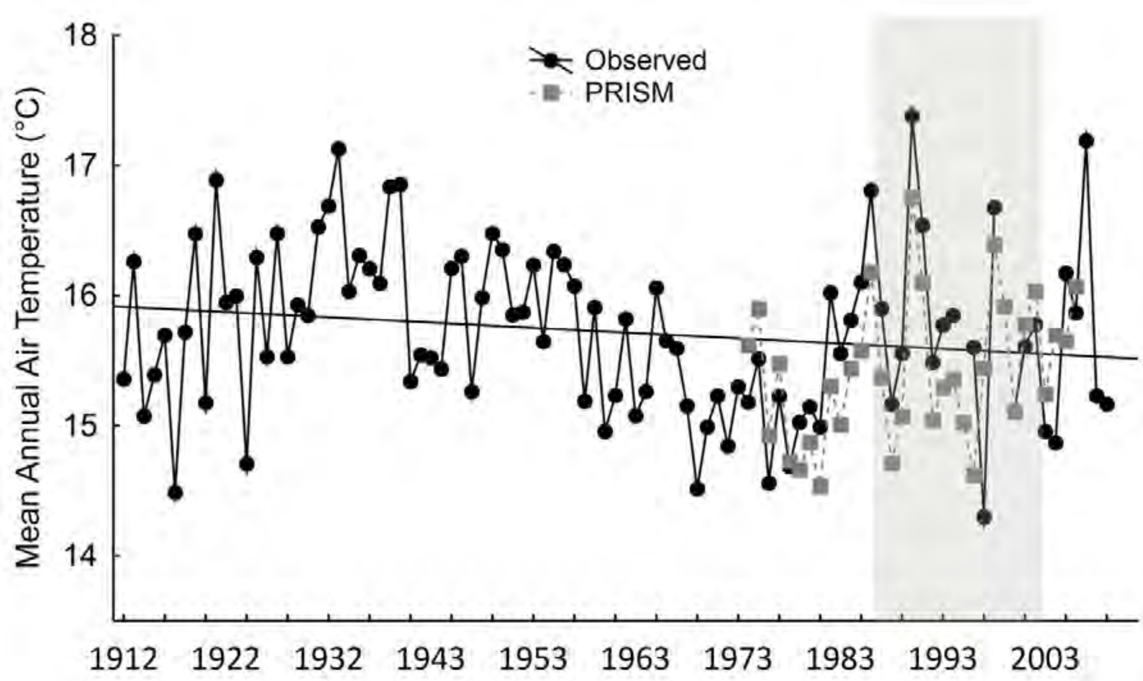

Figure 5-26. Yearly trends in observed mean annual air temperature (°C) at the Albemarle weather station from 1912–2009. For comparative purposes, PRISM mean annual air temperature data are also included from 1974–2006. The area shaded in grey corresponds to the period of biological record. When the observed data are fitted with a linear trend line, $r^2 = 0.03$, $p = 0.09$, and $y = 23.6125 - 0.004 \times x$.

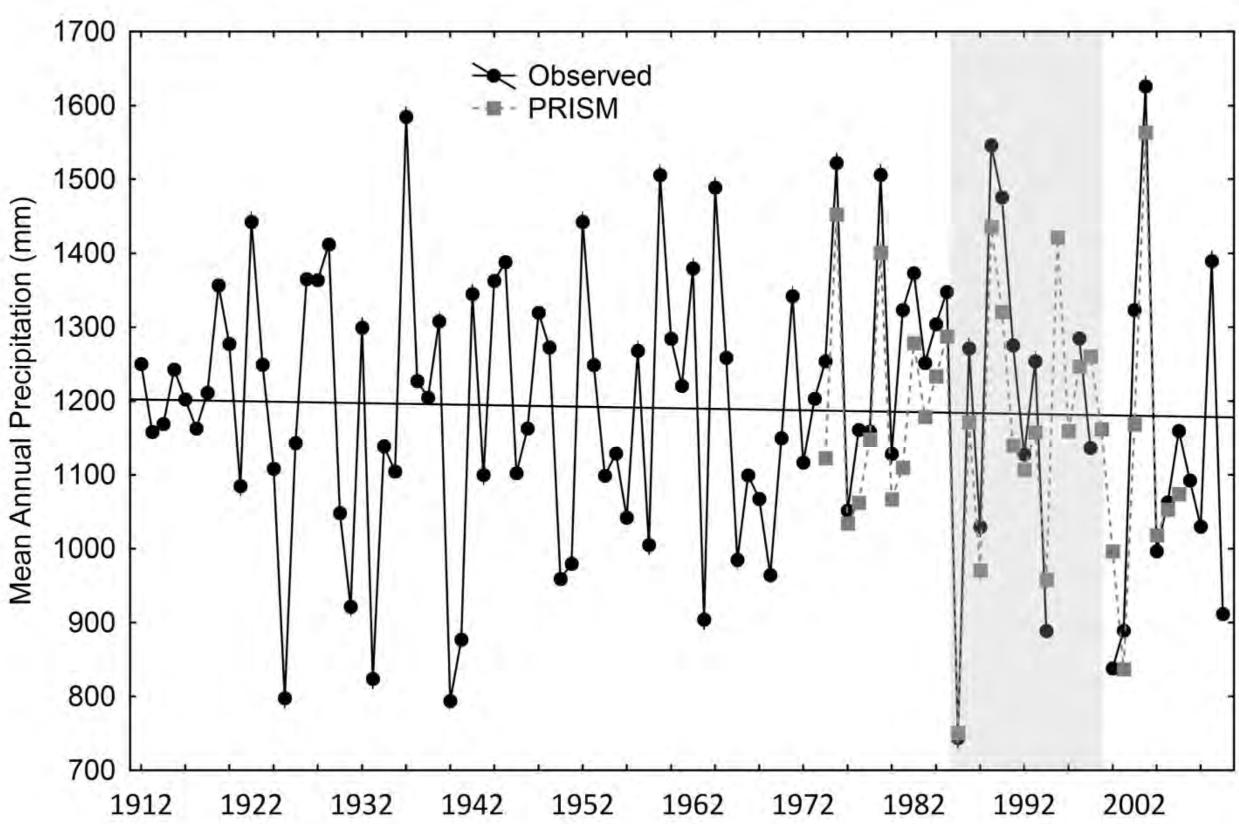

Figure 5-27. Yearly trends in mean annual precipitation (mm) at the Albemarle weather station from 1912–2010. For comparative purposes, PRISM mean annual precipitation data are also included from 1974–2006. The area shaded in grey corresponds to the period of biological record. When the observed data are fitted with a linear trend line, $r^2 = 0.00$, $p = 0.72$, and $y = 1668.9664 - 0.2443 \times x$.

Table 5-21. Range of temperature and precipitation values that occurred at the Barnes Creek (NC0248) site during the period of biological record

Parameter	Min	Max
Year	1985	2001
Observed annual air temperature (°C)	14.3	17.4
PRISM mean annual air temperature (°C)	14.6	16.8
Observed mean maximum July/August air temperature (°C)	29.8	33.7
Observed annual precipitation (mm)	743.8	1,546.2
PRISM mean annual precipitation (mm)	750.8	1,435.4
Observed mean summer precipitation (mm)	162.4	688.6

Bioclassification scores at this site have ranged from good (4) in 1987 and 1989 to excellent (5) (see Figure 5-28A). Since 1989, the number of EPT taxa has increased from 22 to 33 (based on a genus-level OTU), and HBI scores have decreased from a high of 4.6 in 1987 to a low of 3.9 in 2001 (see Figure 5-28B). During the period of biological record, there was a lot of year of year variability in the mean maximum July/August air temperatures and summer precipitation patterns. The highest maximum temperatures occurred in 1993 and 1987, the lowest summer rainfall occurred in 1990, and the highest summer rainfall occurred in 1989 (see Figure 5-28C). There are similar numbers of cold and warm-water taxa at this site, with richness numbers ranging from 3 to 6, and each comprising less than 10% of the assemblage (see Figures 5-29A and B). No clear patterns in the cold and warm water metrics are evident over time.

There may be some confounding factors related to agricultural land use in the surrounding area (5.4% agricultural within a 1-km buffer). Since 1996, this site has received habitat index scores ranging from 87 to 90, which are in the range of "natural" condition. Confounding factors related to in situ measurements were not evident, with values in the following ranges:

- DO: 7.3 to 11.7 mg/L
- pH: 7.2 to 7.6
- Specific conductance: 40 to 61 µmho/cm
- Water temperature: 16 to 25 °C

5.6.4.2. *Associations Between Biological Variables and Climatic Variables*

This site did not have an appropriate data set for performing Kendall tau nonparametric correlations analyses (less than 9 years of data, gaps between data collection years).

5.6.4.3. *Groupings Based on Climatic Variables*

This site did not have an appropriate data set for performing analyses on biological data grouped by extremes in temperature, flow, and/or precipitation variables (less than 9 years of data, gaps between data collection years).

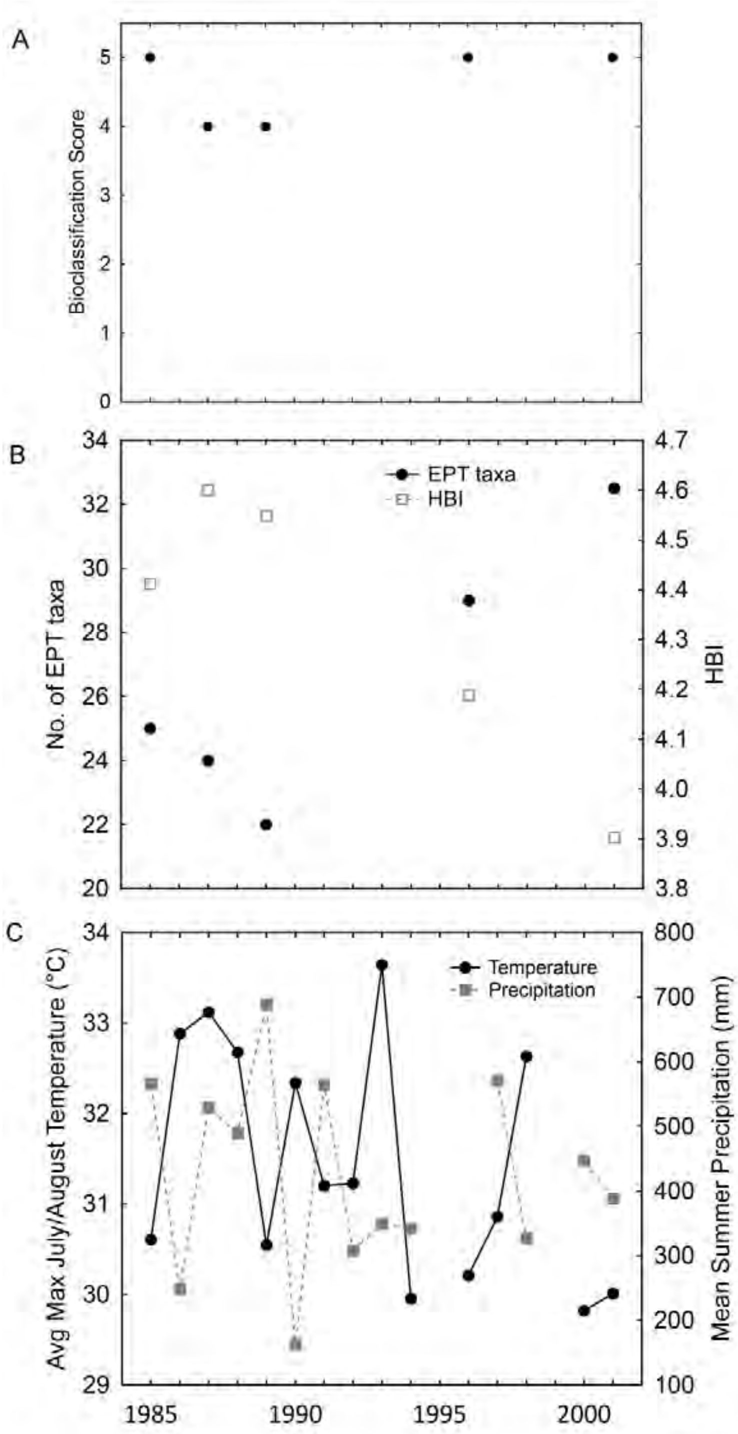

Figure 5-28. Yearly trends at the Barnes Creek (NC0248) site in (A) bioclassification score (based on species-level data); (B) number of EPT taxa and HBI (based on genus-level OTU); and (C) observed mean July/August maximum air temperature (°C) and mean summer (June-September) precipitation (mm).

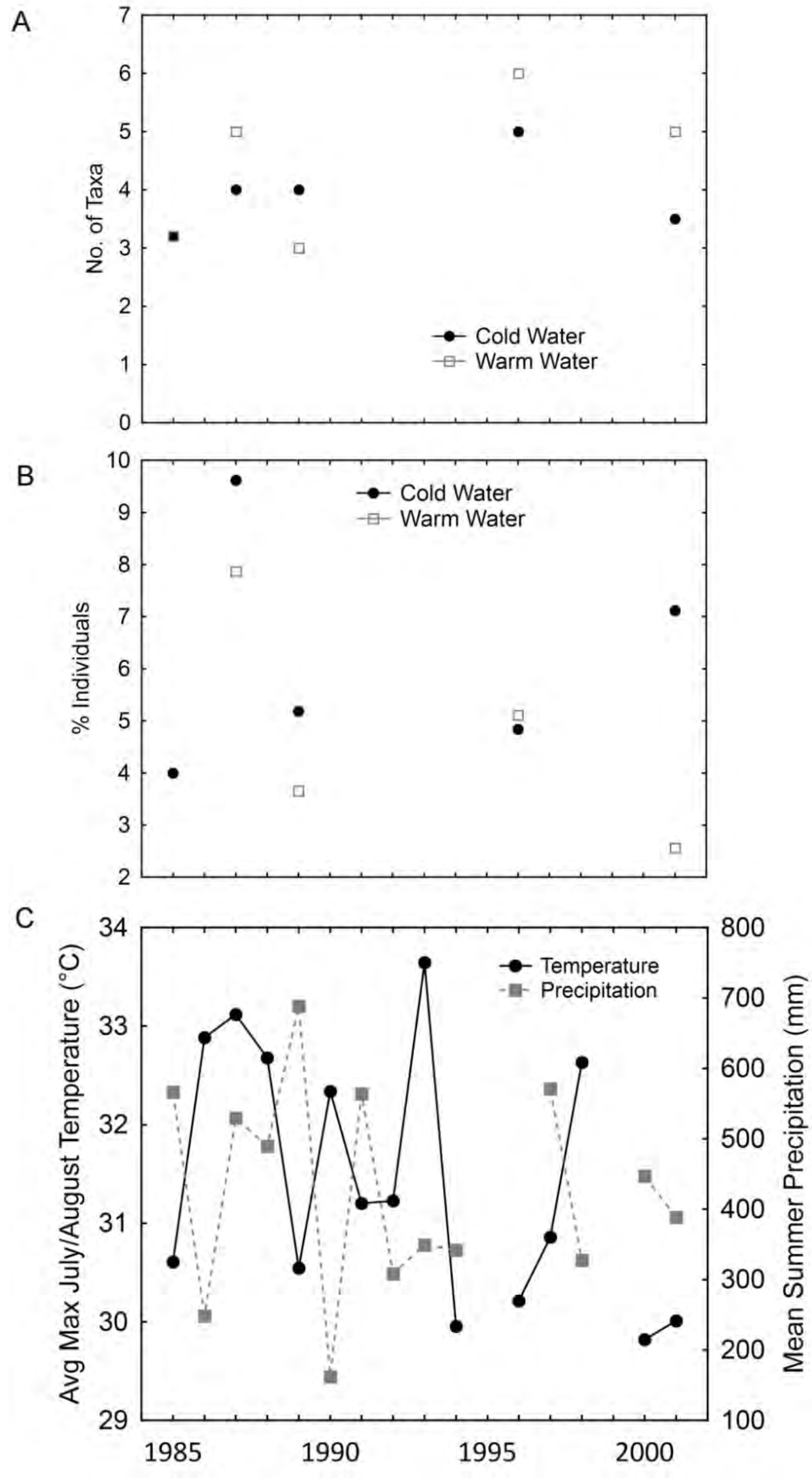

Figure 5-29. Yearly trends at the Barnes Creek (NC0248) site in (A) number of cold and warm-water taxa; (B) percentage cold and warm-water individuals; and (C) observed mean July/August maximum air temperature (°C) and mean summer (June–September) precipitation (mm).

5.6.5. Little River (NC0075)

The Little River (NC0075) site is located in central North Carolina, along State Route 1340 in Montgomery County. It is in the Piedmont ecoregion, has a drainage area of 223.8 km^2, and an elevation of 149.3 m. The highest maximum monthly temperatures at this site occur during July and August, and the lowest average flows (≤60 cfs) occur from July through September. This station has 6 years of biological data collected during the summer (June−September) index period using the standard qualitative (full-scale) method. The period of biological record ranges from 1983 to 2006.

We gathered flow data from 1955−2010 from USGS gage 02128000 (Little River near Star, NC Latitude: 35.38722, Longitude: 79.83139), which is colocated with the biological sampling site. We also gathered daily temperature and precipitation data from the Jackson Springs 5 WNW weather station (SiteID 314464, Latitude: 35.1858, Longitude: 79.6772), which is located approximately 27 km southeast of the biological sampling site. Data were available from 1953−2010. Figure 5-30 shows an aerial photograph of the site, along with the nearest weather station and active USGS gage.

5.6.5.1. *Temporal Trends in Climatic and Biological Variables*

Since 1953, mean annual air temperatures at the Jackson Springs 5 WNW weather station have ranged from 14.7 to 17.3°C. There has been a lot of year-to-year variability, but overall, observed temperatures at the weather station have increased over time (when fit with a linear trend line, $r^2 = 0.02$ and $p = 0.31$) (see Figure 5-31). When PRISM air temperature data are compared to observed data from 1974−2006, the PRISM data are within 1°C of the observed values, and the patterns in the PRISM data show very close correspondence with patterns in the observed data.

Mean annual flow and mean annual precipitation patterns have been highly variable over time (see Figure 5-32). Since 1955, mean annual flow values have ranged from 30.7 to 216.2 cfs (when fit with a linear trend line, $r^2 = 0.01$ and $p = 0.42$). Precipitation patterns show fairly close correspondence with flow patterns (see Figure 5-32). During the period of biological record (1983−2006), mean maximum air temperatures during the hottest months (July and August) ranged from 24.4−26.9°C, and mean summer flows ranged from 10.2 to 241.2 cfs (see Table 5-22).

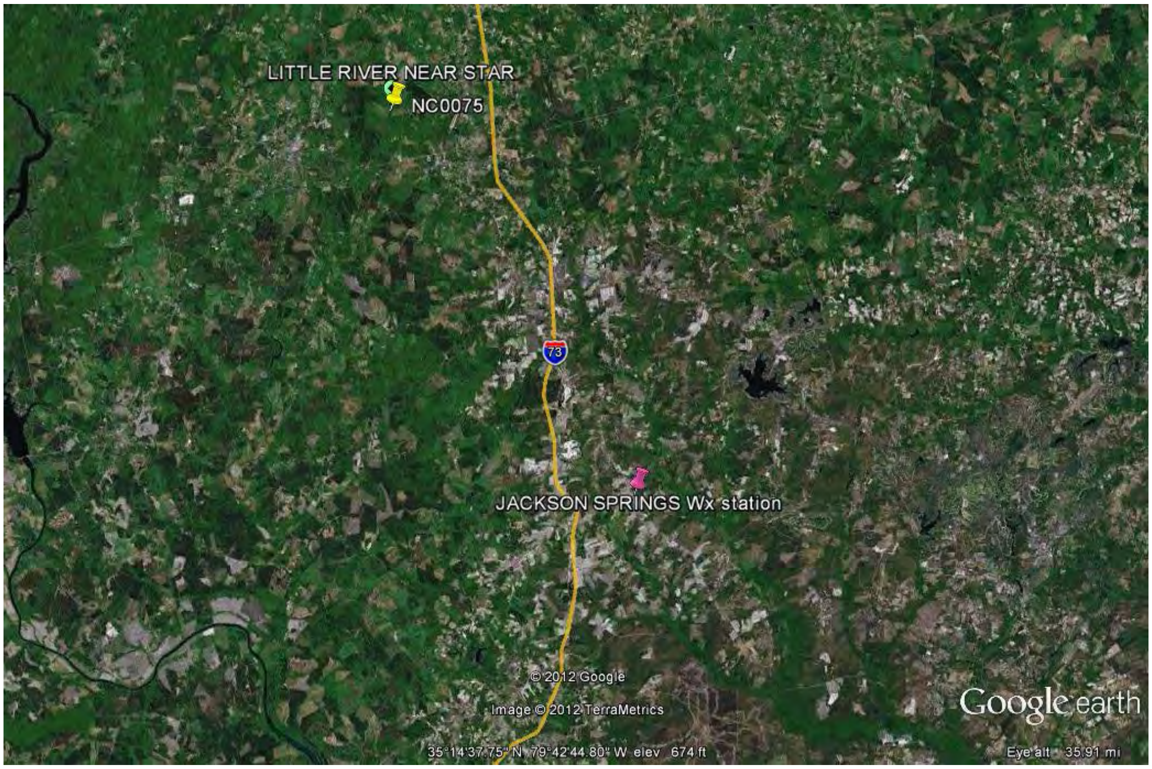

Figure 5-30. Locations of the Little River (NC0075) biological sampling site, USGS gage 02128000 (Little River near Star, NC) and the Jackson Springs 5 WNW weather station. Image from Google Earth.

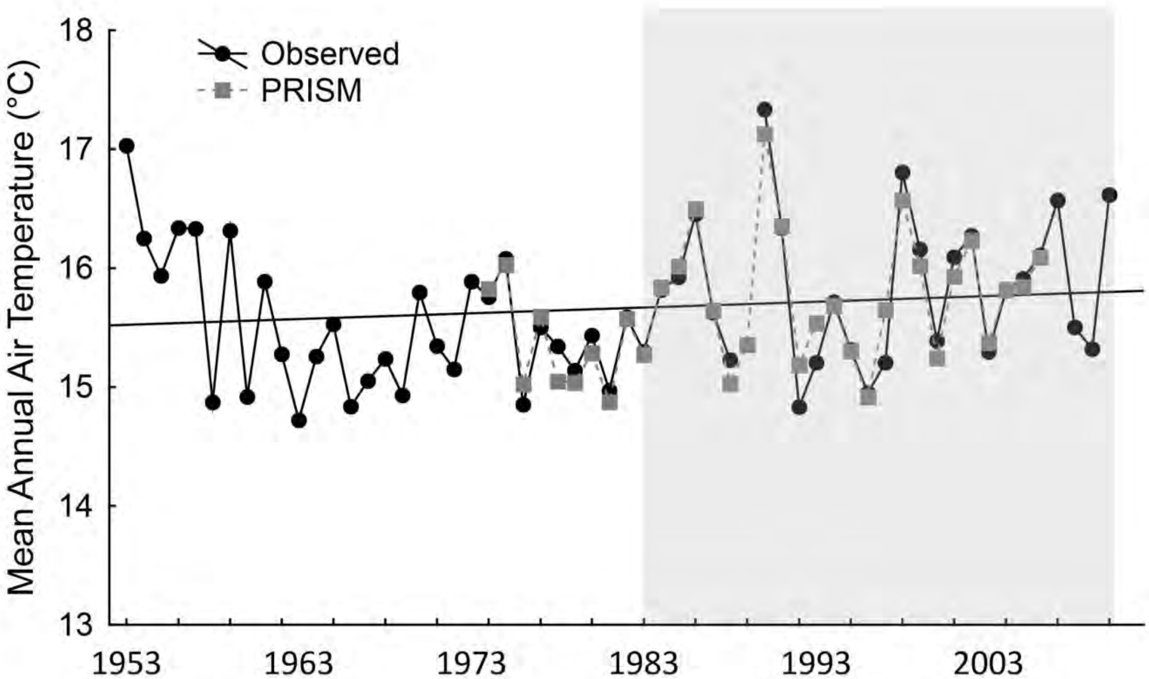

Figure 5-31. Yearly trends in observed mean annual air temperature (°C) at the Jackson Springs 5 WNW weather station from 1953–2010. For comparative purposes, PRISM mean annual air temperature data are also included from 1974–2006. The area shaded in grey corresponds to the period of biological record. When the observed data are fitted with a linear trend line, $r^2 = 0.02$, $p = 0.31$, and $y = 6.0624 + 0.0048 \times x$.

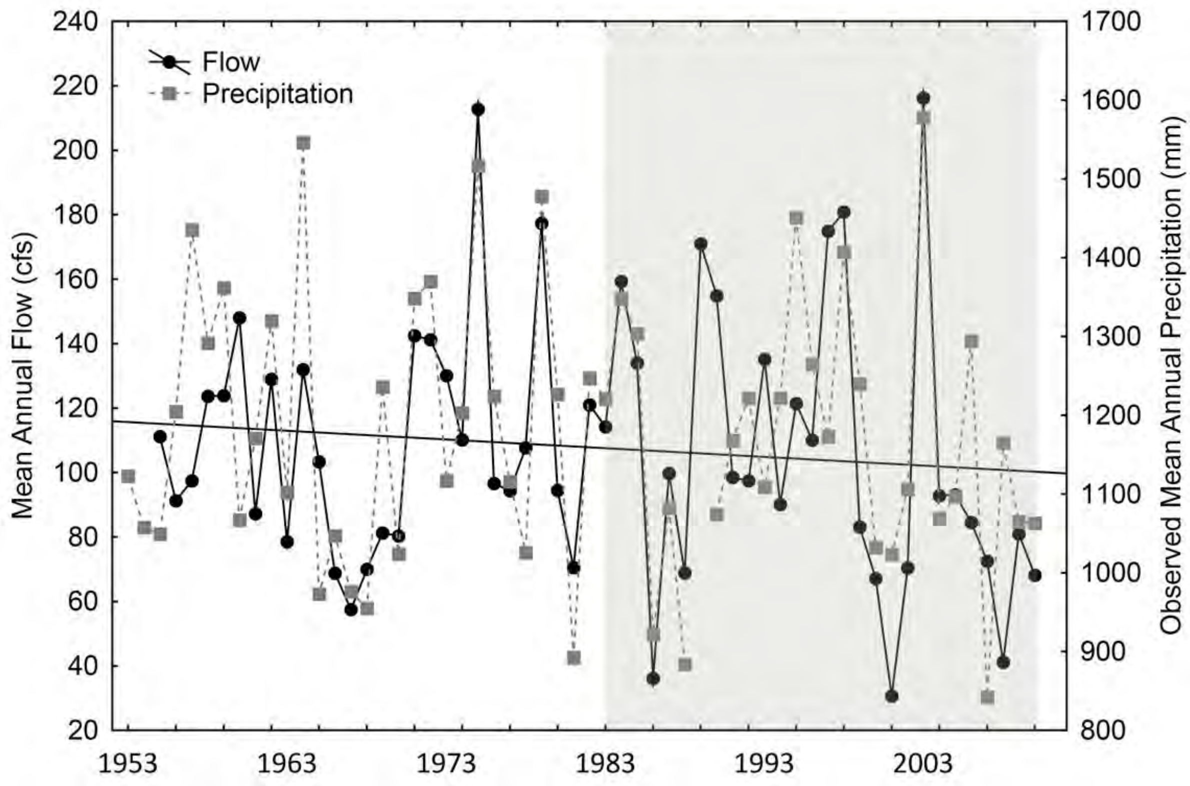

Figure 5-32. Yearly trends in mean annual flow (cfs) at the Little River (NC0075) site from 1955–2010, based on data from USGS gage 02128000 (Little River near Star, NC). For comparative purposes, observed annual precipitation data from the Jackson Springs 5 WNW are also included from 1953−2010. The area shaded in grey corresponds to the period of biological record. When the observed data are fitted with a linear trend line, $r^2 = 0.01$, $p = 0.42$, and $y = 644.3522 - 0.2707 \times x$.

Table 5-22. Range of temperature, precipitation, and flow values that occurred at the Little River (NC0075) during the period of biological record

Parameter	Min	Max
Year	1983	2006
Observed annual air temperature (°C)	14.8	17.3
PRISM mean annual air temperature (°C)	14.9	17.1
Observed mean maximum July/August air temperature (°C)	24.4	26.9
Mean Annual flow (cfs)	30.7	216.2
Observed annual precipitation (mm)	884.2	1,578.4
PRISM mean annual precipitation (mm)	846.8	1,541.9
Mean summer flow (cfs)	10.2	241.2

This site has received bioclassification scores ranging from good (4) in 1983 to excellent (5) (see Figure 5-33A). HBI scores have been variable over time, ranging from 4.0 to 4.7. The number of EPT taxa also varied from year to year, ranging from a low of 22 in 1983 to a high of 32 in 1988 (based on a genus-level OTU) (see Figure 5-33B). During the period of biological record, there was a lot of year of year variability in the mean maximum July/August air temperatures, and mean summer flows were much higher than normal in 2003 and 1997 (see Figure 5-33C). There are more warm-water taxa than cold-water taxa at this site (4 to 7 warm-water taxa vs. 1 to 2 cold-water taxa), but warm-water taxa only comprise a small proportion of the assemblage (less than 6%) (see Figures 5-34A and B). The cold and warm water metrics did not show clear trends over time.

Confounding factors related to land use appear to be minimal at this site (<1.5% urban and 0.1% agricultural within a 1-km buffer). Habitat index scores at this site have ranged from 71 (moderate) in 2001 to 80 (natural) in 1996. Confounding factors related to in situ measurements were not evident, with values in the following ranges:

- DO: 6.7 to 8.1 mg/L
- pH: 6.8 to 7.3
- Specific conductance: 60 to 80 μmho/cm
- Water temperature: 24.2 to 27 °C

5.6.5.2. *Associations Between Biological Variables and Climatic Variables*

This site did not have an appropriate data set for performing Kendall tau nonparametric correlations analyses (less than 9 years of data, gaps between data collection years).

5.6.5.3. *Groupings Based on Climatic Variables*

This site did not have an appropriate data set for performing analyses on biological data grouped by extremes in temperature, flow, and/or precipitation variables (less than 9 years of data, gaps between data collection years).

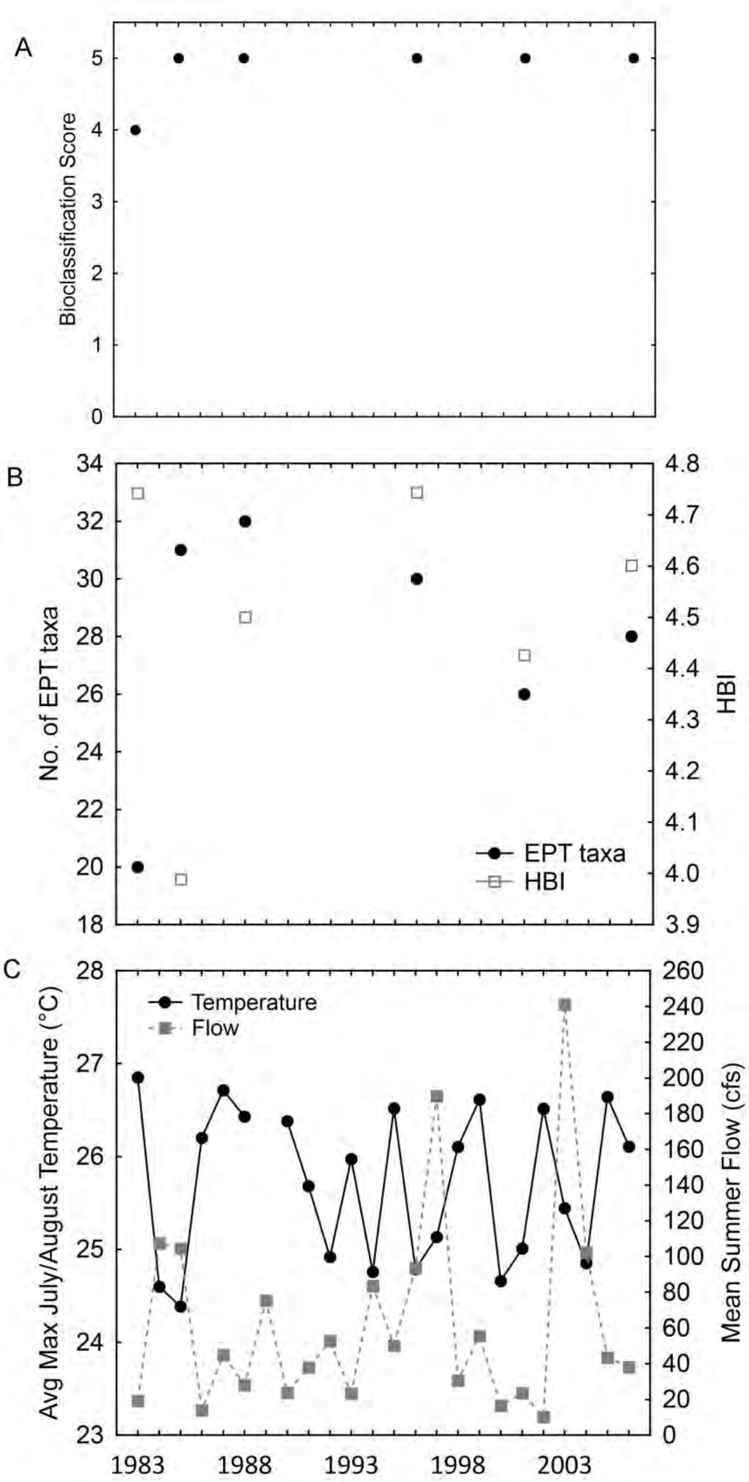

Figure 5-33. Yearly trends at the Little River (NC0075) site in (A) bioclassification score (based on species-level data); (B) number of EPT taxa and HBI (based on genus-level OTU); and (C) observed mean July/August maximum air temperature (°C) and mean summer (June−September) flow (cfs).

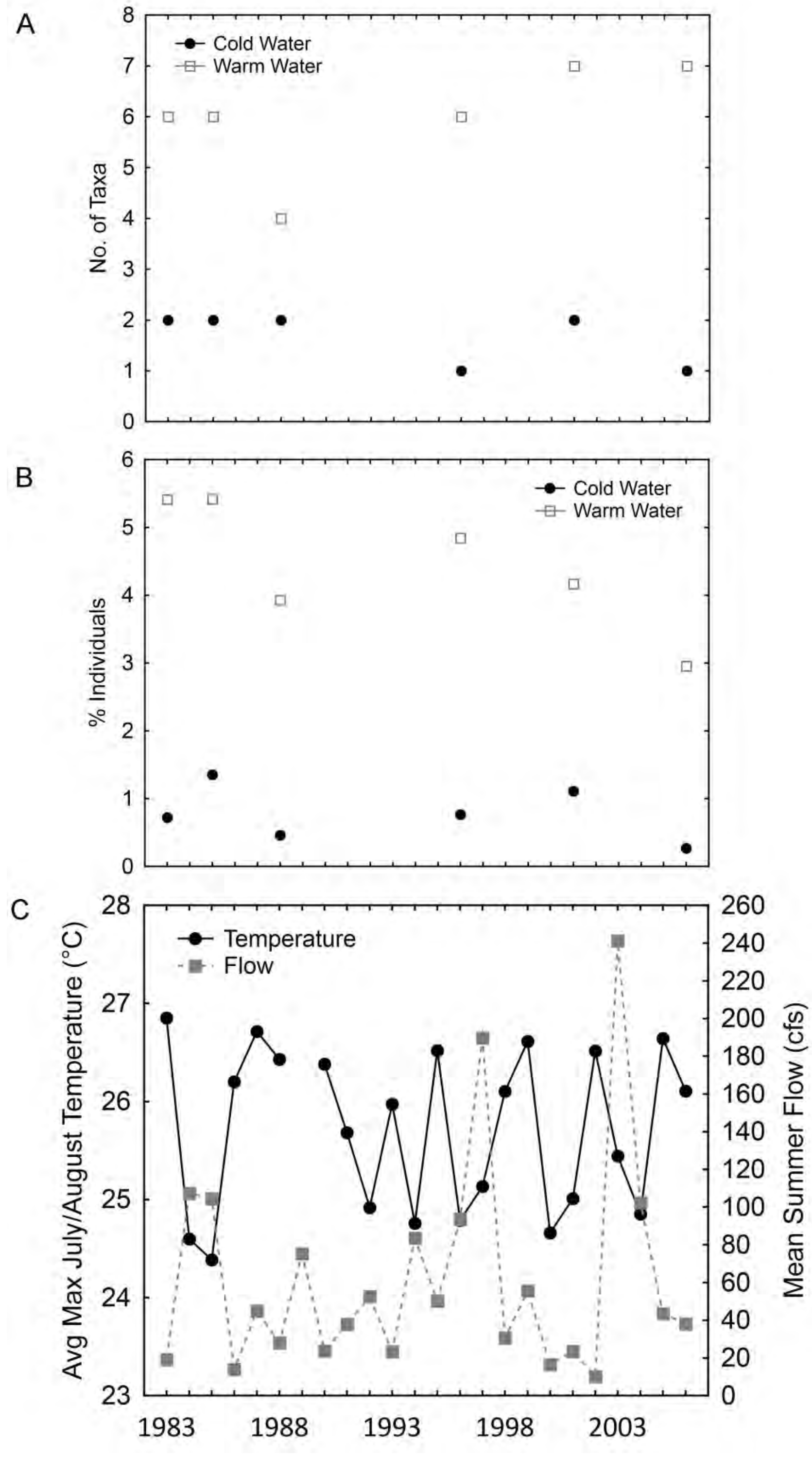

Figure 5-34. Yearly trends at the Little River (NC0075) site in (A) number of cold and warm-water taxa; (B) percentage cold and warm-water individuals; and (C) observed mean July/August maximum air temperature (°C) and mean summer (June–September) flow (cfs).

5.7. SENSITIVITY OF BENTHIC MACROINVERTEBRATES TO TEMPERATURE AND STREAM FLOW

The spatial distributions of cold and warm-water taxa were examined to gain insights into which areas in North Carolina are likely to be most and least sensitive to projected changes in temperature and stream flow. Table 5-23 shows differences in the distributions of thermal preference taxa between ecoregions. If the assumption is made that streams with greater numbers and abundances of cold-water taxa will be most sensitive to warming temperatures and changing precipitation patterns, then streams in the Blue Ridge ecoregion will be most sensitive, and those in the Coastal region will be least sensitive. The prevalence and distribution of cold- and warm-water- taxa also vary predictably with stream size. The median number of cold-water taxa is highest in small and medium-sized streams (see Figure 5-35A) while the greatest numbers of warm-water taxa occur in the largest streams (see Figure 5-35B). Of the 5 least-disturbed sites that we closely examined for long-term trends, the New River (NC0109) site is largest (>2,000 km^2), Barnes Creek (NC0248) is the smallest (<65 km^2), and the three remaining sites are medium-sized (125−225 km^2). Although the greatest number of cold-water taxa may occur in the coldest, highest elevation streams, it may be that the greatest amount of change will occur in transitional areas, where species are expected to be closer to their tolerance limits. If this is the case, then the greatest changes may occur in the Piedmont ecoregion.

5.8. IMPLICATIONS FOR NORTH CAROLINA DEPARTMENT OF THE ENVIRONMENT AND NATURAL RESOURCES (NCDENRS) BIOMONITORING PROGRAM

Over the last century, there has been a lot of year-to-year variability in temperature and precipitation patterns in North Carolina, both statewide and at the five least disturbed biological monitoring sites that we closely examined for temporal trends. During some years, there have been extreme weather events, such as hurricane flooding that occurred in 2004 and drought conditions from 1999−2002. In the future, extreme weather events are projected to occur with greater frequency, and air temperatures are projected to increase. There is much uncertainty associated with future projections for precipitation.

We were limited in the types of analyses that we were able to perform at four of the five sites. This was due primarily to small sample sizes and to gaps and associated lack of

Table 5-23. Summary of differences in elevation, PRISM mean annual air temperature, and mean number and percentage of cold and warm-water taxa (based on full-scale samples only) in the North Carolina EPA Level 3 ecoregions. Relative abundances were calculated based on categorical abundance data

State	Ecoregion	No samples	Elevation (m)	Air temperature (°C)	Richness		Relative abundance	
					Cold water	Warm water	Cold water	Warm water
North Carolina	Middle Atlantic Coastal Plain	173	4.7	16.7	0.1 ± 0.2	4.7 ± 5.1	0.1 ± 0.4	12.3 ± 6.4
	Southeastern Plains	317	34.1	16.3	0.1 ± 0.4	8.8 ± 3.4	0.1 ± 0.4	12.1 ± 5.1
	Piedmont	1,106	183.5	15.0	1.5 ± 2.0	5.2 ± 3.1	1.8 ± 2.7	6.7 ± 4.7
	Blue Ridge	631	714.5	12.1	8.0 ± 4.5	2.8 ± 2.4	11.4 ± 7.9	3.1 ± 3.7

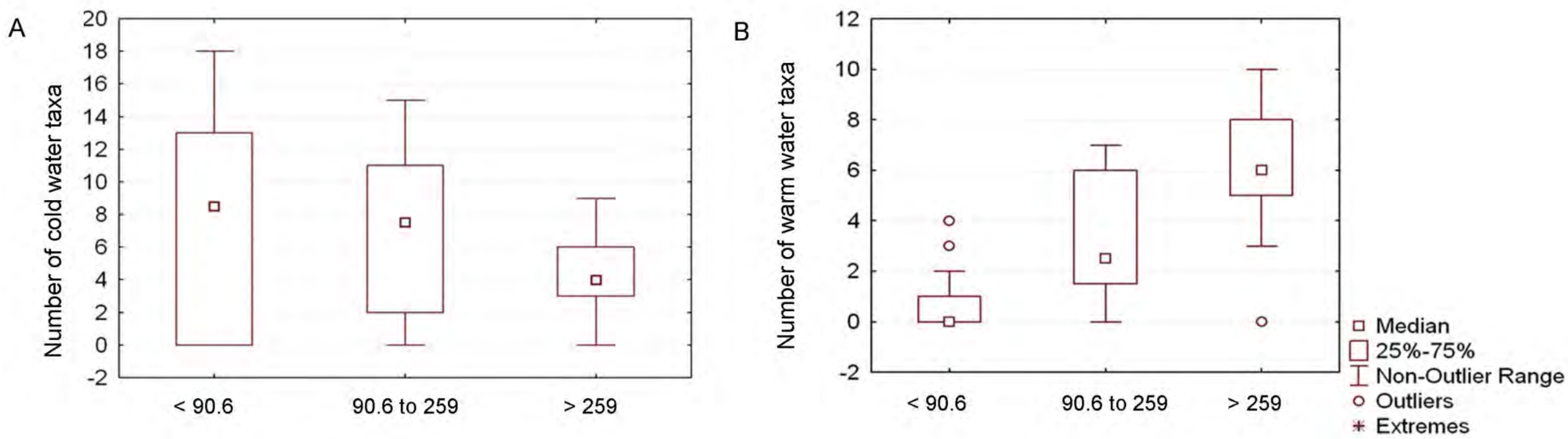

Figure 5-35. Distribution of cold and warm-water taxa across different stream size categories at North Carolina reference sites (as designated by NCDENR). (A) number of cold-water taxa; (B) number of warm-water taxa. Stream sizes categories are based on watershed areas (km^2); thresholds are based on distributions of watershed areas within the reference data set (tertiles).

continuity in the biological data. At the New River site (NC0109), where we had sufficient long-term data to run correlation and ANOVA, the biological metrics were more strongly associated with precipitation than temperature variables. Several of the EPT-related metrics had strong positive associations with flow and precipitation, and the HBI was negatively associated with the flow and precipitation variables. When we grouped samples based on mean annual flow, on average, there were about three more warm-water taxa in the lowest flow year samples compared to the normal year samples, and there were several more EPT and cold-water taxa in the highest versus lowest flow year samples. Although one cannot make causal inferences based on observational data from this site, it seems evident that flow has an important influence on the biological assemblage, and in this case, more of an influence than temperature.

At the other four sites, we did not see clear associations between the biological and environmental variables in the temporal trend plots, but this was not unexpected due to the small sample sizes, gaps in the biological data, and the large amount of year-to-year variability in the climatic variables. We paid particular attention to a period during which hotter and drier than normal conditions occurred at Cataloochee Creek (NC0209) for several consecutive years, but a biological response to these conditions was not evident.

Because of the limitations associated with our individual site analyses, we also performed exploratory analyses to gain insights into how future projected climatic changes might impact NCDENR's assessment methods. We tried two techniques. In the first, we manipulated the existing data at the three Blue Ridge sites (New River [NC0109], Nantahala River [NC0207], and Cataloochee Creek [NC0209]) such that 50 and 100% of the cold-water EPT taxa were removed from the assemblage. Then we recalculated the bioclassification scores based on these two scenarios, with the intent of simulating the loss of cold-water taxa due to warming temperatures associated with climate change. Results show that the loss of cold-water taxa has the greatest effect on samples in the excellent and good site condition categories, with samples generally dropping one bioclassification level (e.g., from excellent to good) (see Figure 5-36). Sites in the "excellent" category are more likely to drop a level because this category has the most stringent scoring criteria (i.e., it takes less of a change for a sample to drop from Excellent to Good vs. from Good to Good-Fair).

We acknowledge that a scenario in which there is complete community replacement is highly unlikely, especially in the near term. Nevertheless, we felt this scenario was worth

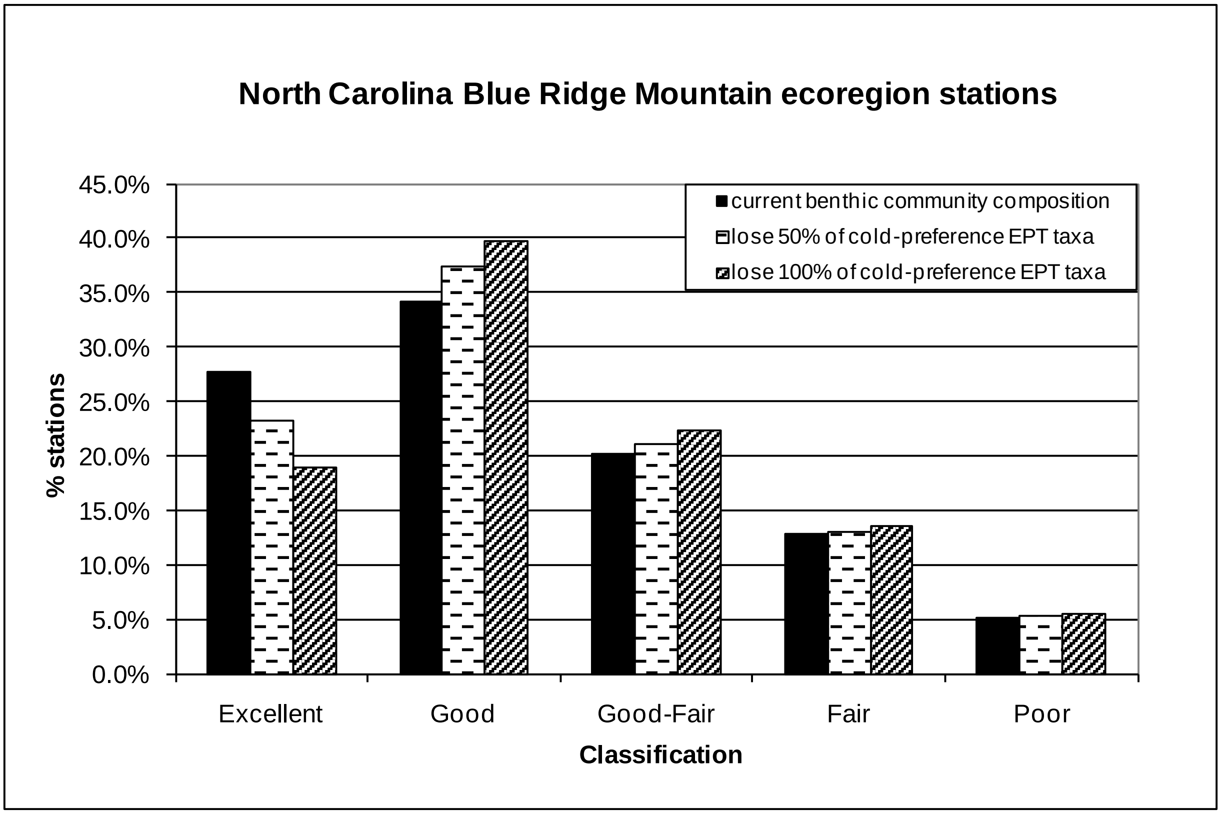

Figure 5-36. Exploratory exercise on reference station drift (degradation of assessed site condition) over time at the three Blue Ridge stations, simulating the loss of cold-preference EPT taxa over time due to climate change effects.

exploring, especially because the two metrics (EPT richness and HBI) that go into the calculation of bioclassification scores are linked to thermal tolerance. As discussed earlier, there is a strong association between thermal preference taxa and enrichment tolerance values, such that many of the cold-water taxa are intolerant to enrichment, and many of the warm-water taxa are tolerant or moderately tolerant. An increase in warm-water taxa and decrease in cold-water taxa could result in an increase in HBI scores, which could cause a sample to drop to a lower bioclassification level. A similar effect may be evident in future EPT richness values, because many of the cold-water taxa are EPT taxa.

In our second exploratory analysis, we examined how bioclassification scores would change if Mountain biocriteria were applied to biological data from the two Piedmont reference sites (Barnes Creek [NC0248] and Little River [NC0075]). The premise of this analysis is that biological assemblages in the Mountain region, which on average have the highest numbers of cold-water taxa, may become increasingly like Piedmont assemblages in the future. Results show that if Mountain assemblages do indeed become like Piedmont assemblages, such as those found at Barnes Creek (NC0248) and Little River (NC0075), and Mountain scoring criteria remain the same, then bioclassification scores will decrease one level (from Excellent [5] to Good [4]) (see Figure 5-37).

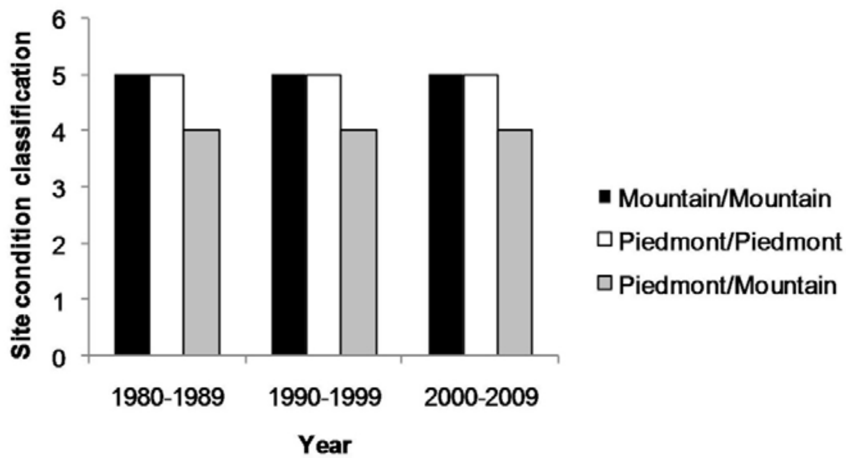

Figure 5-37. Site-condition classification scores at three reference Mountain sites (Station NC0109 [New], Station NC0207 [Nantahala], and Station NC0209 [Cataloochee]) and two reference Piedmont sites (Station NC0075 [Little River] and Station NC0248 [Barnes Creek]) averaged across three 10-year periods. The black bars represent average scores at Mountain sites when Mountain criteria are applied; the white bars represent average scores at Piedmont sites when Piedmont criteria are applied; the gray bars represent average scores at Piedmont sites when Mountain criteria are applied.

Although there were limitations with the long-term trend analyses that we were able to perform on the North Carolina data, the analyses that we were able to perform further our understanding of the effects that changing temperature and stream flow conditions can have on biological assemblages, and help establish expectations for biological responses to future climate changes. Through these analyses, we were also able to provide insights as to which climate change indicators might be best to track over time in southeastern states. Results suggest that climate-induced trends are most likely to be detected in EPT-related metrics and thermal preference metrics. Some limitations of the thermal preference metrics are that they typically occur in low numbers, and most show sensitivity to organic enrichment, which confounds the associations with temperature.

6. OHIO

6.1. EXPOSURES

6.1.1. Regional Projections for the Midwestern United States

Climate conditions in the Midwest are affected by its location in the middle of the continent, removed from the moderating effects of the oceans, and by the Great Lakes (Karl et al., 2009), and both existing conditions and future projections reflect this. Projected temperature changes range from 1−11^{o}C by the end of the century (Wuebbles and Hayhoe, 2004), though several studies project changes within the lower to mid-portion of this range (Easterling and Karl, 2001; Hayhoe et al., 2010) (see Table 6-1).

Table 6-1. Projections for temperature and precipitation changes in the Midwest to 2100

Temperature change	Precipitation change	Change in precipitation frequency	Citation
3−6°C by end of century	Increase	Increase	Easterling and Karl, 2001
2−3°C by midcentury; 3–5°C by end of century	20–30% (winter, spring)		Hayhoe et al., 2010
1–9°C (winter); 1−11°C (summer)	−10 to +40%		Wuebbles and Hayhoe, 2004
	10% (midcentury) to 20% (end of century, winter); 7% (midcentury) to 10% (end of century, summer)	−5% (midcentury) to −9% (end of century, winter); −3% (midcentury) to −6% (end of century, summer)	Schoof et al., 2010

Projections for precipitation changes are more variable and range from small decreases to moderate increases (Easterling and Karl, 2001; Wuebbles and Hayhoe, 2004; Hayhoe et al., 2010; Schoof et al., 2010) (see Table 6-1). Precipitation increases are expected largely from increased occurrence of more intense storms (Easterling and Karl, 2001). This is supported by the work of Schoof et al. (2010), showing that net increases in precipitation should occur with decreases in the frequency of storms along with increases in the amount of precipitation.

Estimates of the combined effects of changing temperatures and precipitation on streamflow also are variable. Easterling and Karl (2001) project net decreases in stream runoff for the midwest despite projected increases in average annual and winter precipitation amounts, due largely to the combination of increased temperatures leading to increased evapotranspiration, while summer precipitation is more variable and may decrease. Wuebbles and Hayhoe (2004) project winter and spring runoff to increase but summer stream runoff to decrease. More recent work projects variable streamflow over the near term, with net increases by the end of the century (Hayhoe et al., 2010; Cherkauer and Sinha, 2010). End-of-the-century projections include big increases in winter and spring flows, but variable summer flows with decreases in low flows, increases in peak flows, decreases in the number of days with flows above the annual mean flow, and increases in flashiness (Cherkauer and Sinha, 2010).

Several multidecadal climate changes have already been observed in the Midwest, including increases in average annual temperature, with the largest temperature increases in winter, along with earlier dates for last frost, reduced lake ice cover, extension of the growing season by approximately 1 week, more severe and more frequent heat waves, above average winter and summer precipitation, doubling of the frequency of heavy rain events, increased frequency of large floods, and lower lake water levels resulting mainly from increased evapotranspiration (Karl et al., 2009).

6.1.2. Historic Climate Trends and Climate Change Projections for Ohio

Ohio has a temperate climate characterized by hot, humid summers and cold winters. In some parts of the state, the weather is influenced by the Great Lakes; these areas have increased growing seasons, more winter cloudiness, and greater snowfall. Glaciation has played an important role in shaping Ohio’s landscape. The unglaciated areas in the southern and eastern portions of the state are more rugged, hilly, and wooded than the glaciated areas to the north and west. The glaciated areas consist of flat or rolling plains, low rounded hills, scattered end moraines, kettles, wetland areas, and, in some places, relic sand dunes and beach ridges. Some of the glaciated areas have been cleared, artificially drained, and converted to agricultural lands (U.S. EPA, 2002). With relatively flat topography, there is not a great deal of variation in temperature and precipitation patterns across Ohio (see Figure 6-1). The southern part of the state has the warmest mean annual temperatures (see Figure 6-1A), and northwestern Ohio receives the least amount of annual precipitation (see Figure 6-1B).

Over the last century, there has been a great deal of year-to-year variability in temperature patterns in Ohio, with no clear or significant trend (see Figure 6-2). Annual temperatures have, however, shown a more noticeable, albeit slight, increase in recent decades (1971−2000), with the greatest increase occurring in the winter (see Table 6-2). However, even this winter increase is not statistically significant, along with the other seasonal trends (see Figure 6-3). Table 6-2 summarizes future temperature projections for mid- and late-century for high (A2) and low (B1) emissions scenarios. Based on an ensemble average across 15 models, mean annual air temperatures are projected to increase by up to 3.6°C by midcentury and up to 5.8°C by the end of the century compared to a historic time period (1961−1990). Under the high (A2) emissions scenario, the greatest increases are projected to occur during the fall (see Table 6-3).

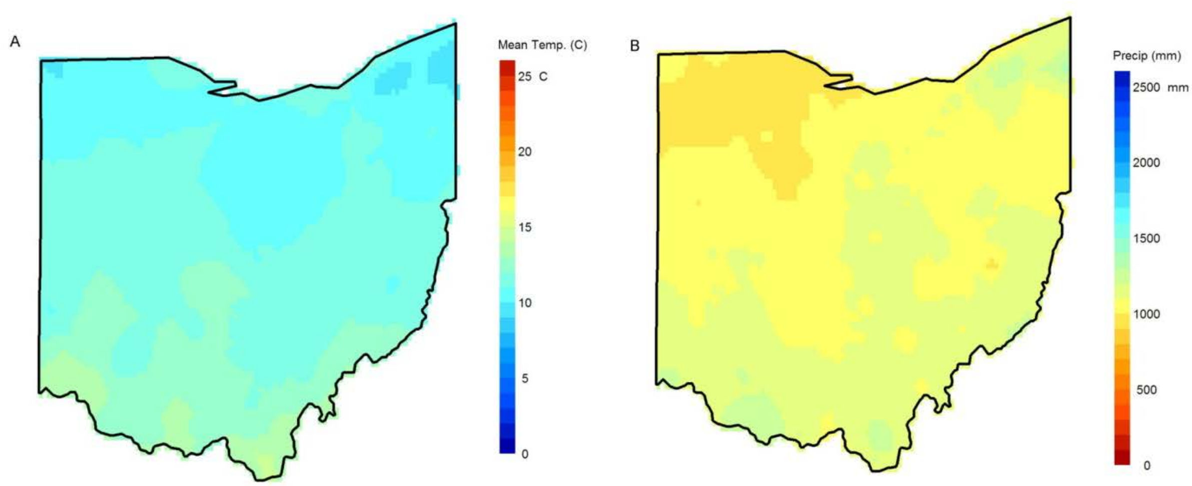

Figure 6-1. Ohio's temperature and precipitation patterns. (A) Mean annual air temperature (°C) from 1971–2000; (B) Mean annual precipitation (mm) 1971−2000. Map produced using the Climate Wizard Web site (http://www.climatewizard.org/). Base climate data from the PRISM Group, Oregon State University, http://www.prismclimate.org.

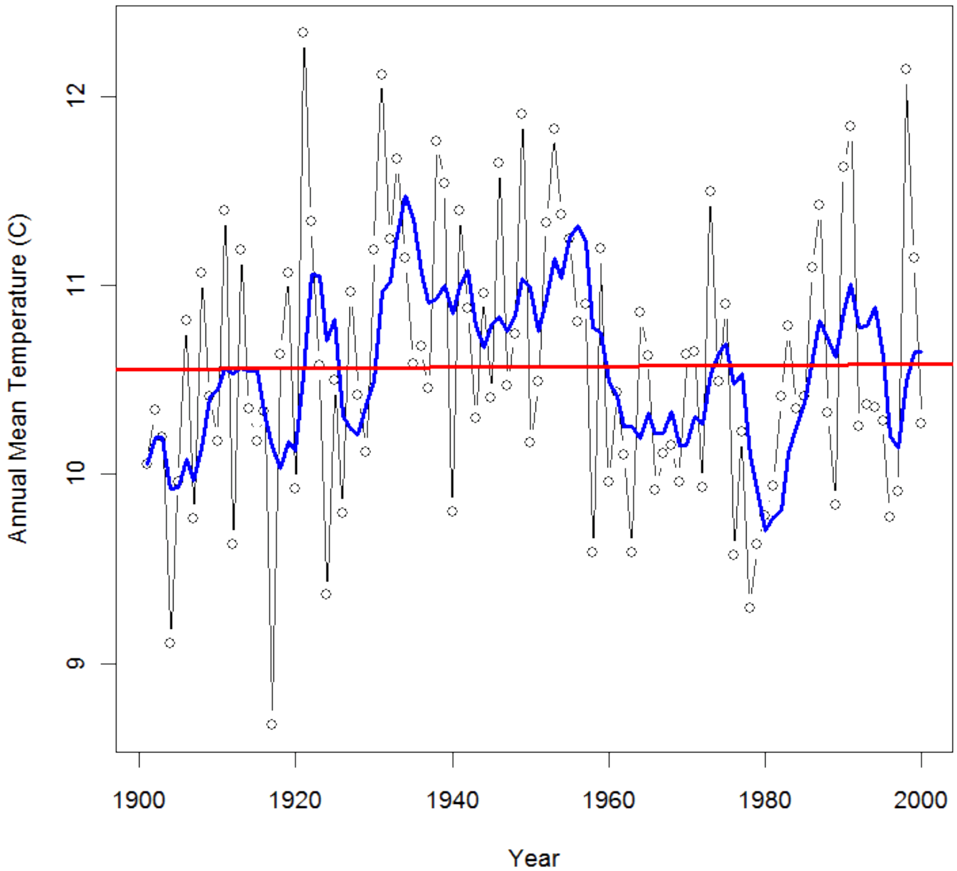

Figure 6-2. Trends in annual mean air temperature in Ohio from 1901–2000. Change rate = 0°C/year, *p*-value = 0.93. Figure produced using Climate Wizard Web site (http://www.climatewizard.org/). Base climate data from the PRISM Group, Oregon State University, http://www.prismclimate.org.

Table 6-2. Change rates in Ohio PRISM mean annual and seasonal air temperatures compared across two time periods: 1971–2000 versus 1901−2000. No trends are significant (*p* > 0.05). Data were derived from the Climate Wizard Web site (http://www.climatewizard.org/). Base climate data came from the PRISM Group, Oregon State University, http://www.prismclimate.org

Time period	Air temperature (C/yr)				
	Annual	DJF	MAM	JJA	SON
1901−2000	0.00	0.00	0.00	0.00	0.00
1971−2000	0.02	0.06	0.01	0.02	−0.01

DJF = December, January, and February; MAM = March, April, and May; JJA = June, July, and August; SON = September, October, and November.

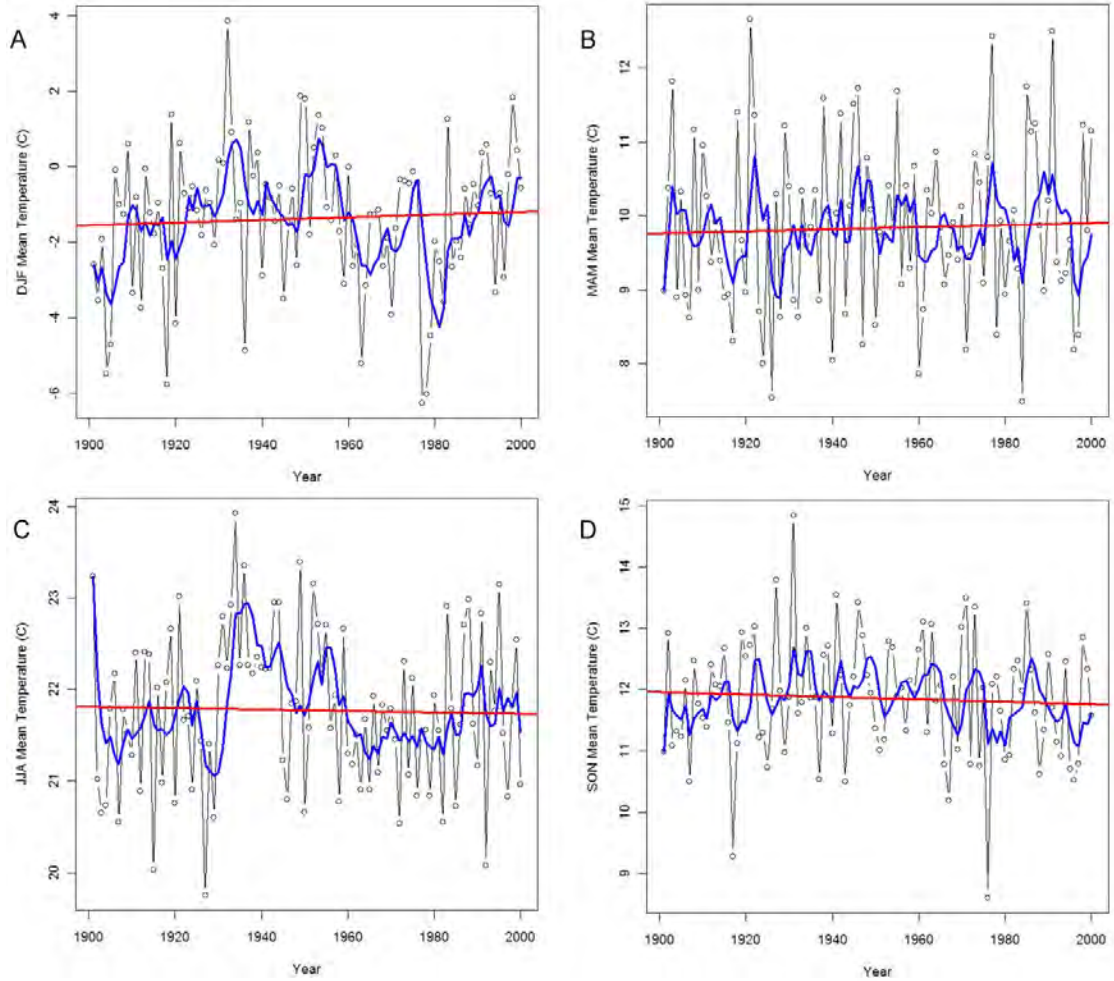

Figure 6-3. Trends in seasonal mean air temperature in Ohio from 1901–2000. (A) DJF = December, January, and February, change rate = 0.004°C/year, *p*-value = 0.66; (B) MAM = March, April, and May, change rate = 0.001°C/year, *p*-value = 0.70; (C) JJA = June, July, and August, change rate = –0.001°C/year, *p*-value = 0.81; (D) SON = September, October, and November, change rate = –0.002°C/year, *p*-value = 0.58. Figure produced using Climate Wizard Web site (http://www.climatewizard.org/). Base climate data from the PRISM Group, Oregon State University, http://www.prismclimate.org.

Table 6-3. Projected departure from historic (1961–1990) trends in annual and seasonal air temperature (°C) in Ohio for mid- (2040–2069) and late-century (2070–2099) for high and low emissions scenarios. Values represent the minimum, average, maximum and standard deviations from 15 different climate models. Data were derived from the Climate Wizard Web site (http://www.climatewizard.org/)

Midcentury (2040−2069) vs. historic (1961−1990)										
	A2 (high) emissions scenario					B1 (low) emissions scenario				
Model	Annual	DJF	MAM	JJA	SON	Annual	DJF	MAM	JJA	SON
Ensemble low	1.5	1.8	1.2	1.3	1.7	1.2	1.0	0.9	1.2	0.9
Ensemble average	2.7	2.7	2.6	2.7	3.0	2.2	2.2	2.1	2.3	2.2
Ensemble High	3.6	4.2	4.0	3.4	4.7	2.9	3.5	3.3	3.3	3.2
SD	0.6	0.7	0.9	0.6	0.8	0.5	0.6	0.7	0.7	0.7
Late-Century (2070−2099) vs. historic (1961−1990)										
Ensemble low	2.5	2.6	2.6	2.4	3.1	1.7	1.4	1.2	1.7	1.5
Ensemble average	4.5	4.2	4.2	4.6	5.0	2.7	2.8	2.6	2.9	2.7
Ensemble high	5.8	6.7	6.2	6.0	7.8	3.8	4.2	4.0	3.9	3.6
SD	0.9	1.1	1.1	1.0	1.2	0.7	0.8	0.8	0.8	0.7

DJF = December, January, and February; MAM = March, April, and May; JJA = June, July August, and SON = September, October, and November.

Precipitation patterns in Ohio have been highly variable. Trend direction varies depending on the time period being evaluated. From 1901−2000, mean annual precipitation increased at a rate of 0.22 mm/year (see Figure 6-4 and Table 6-4), while from 1971−2000, mean annual precipitation decreased by 0.33 mm/year (see Table 6-4). Due to the high degree of year-to year variability, none of the historic trends in precipitation are significant ($p > 0.05$). The same holds true with seasonal change rates; the amount and direction of change vary depending on season and time period, and no trends are significant (see Table 6-4 and Figure 6-5).
Table 6-5 summarizes future projections for mid- and late-century for high (A2) and low (B1) emissions scenarios. The future projections are highly variable across models and emissions scenarios. Under the high emissions scenario, the ensemble average projects that mean annual precipitation will increase by 56.7 mm by midcentury and 82 mm by the end of the century compared to a historic time period (1961−1990) with the greatest changes during the spring (see Table 6-5).

Table 6-4. Change rates in Ohio PRISM mean annual and seasonal precipitation compared across two time periods: 1971–2000 versus 1901–2000. No trends are significant (*p* > 0.05). Data were derived from the Climate Wizard Web site (http://www.climatewizard.org/). Base climate data came from the PRISM Group, Oregon State University, http://www.prismclimate.org

Time period	Precipitation (mm/yr)				
	Annual	DJF	MAM	JJA	SON
1901−2000	0.22	−0.17	0.03	0.15	0.25
1971−2000	−0.33	0.63	1.06	−0.40	−1.30

DJF = December, January, and February; MAM = March, April, and May; JJA = June, July, and August; SON = September, October, and November.

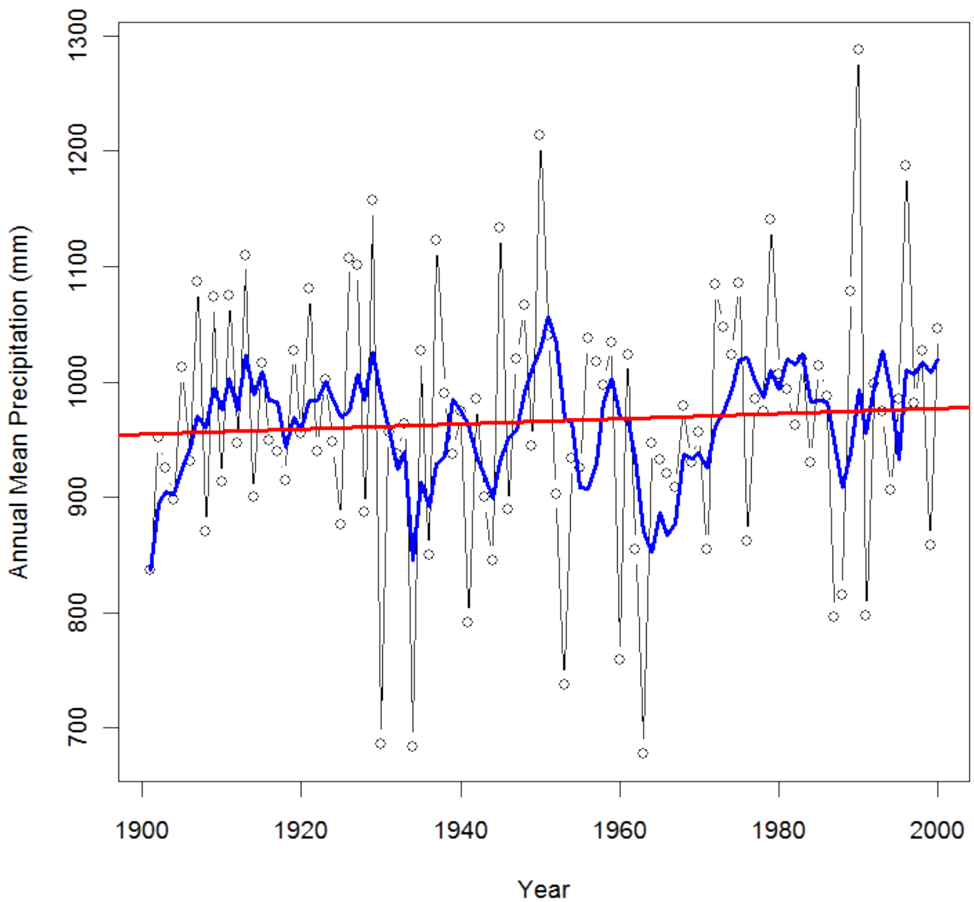

Figure 6-4. Trends in annual mean precipitation in Ohio from 1901–2000. Change rate = 0.218 mm/year, *p*-value = 0.51. Figure produced using Climate Wizard Web site (http://www.climatewizard.org/). Base climate data from the PRISM Group, Oregon State University, http://www.prismclimate.org.

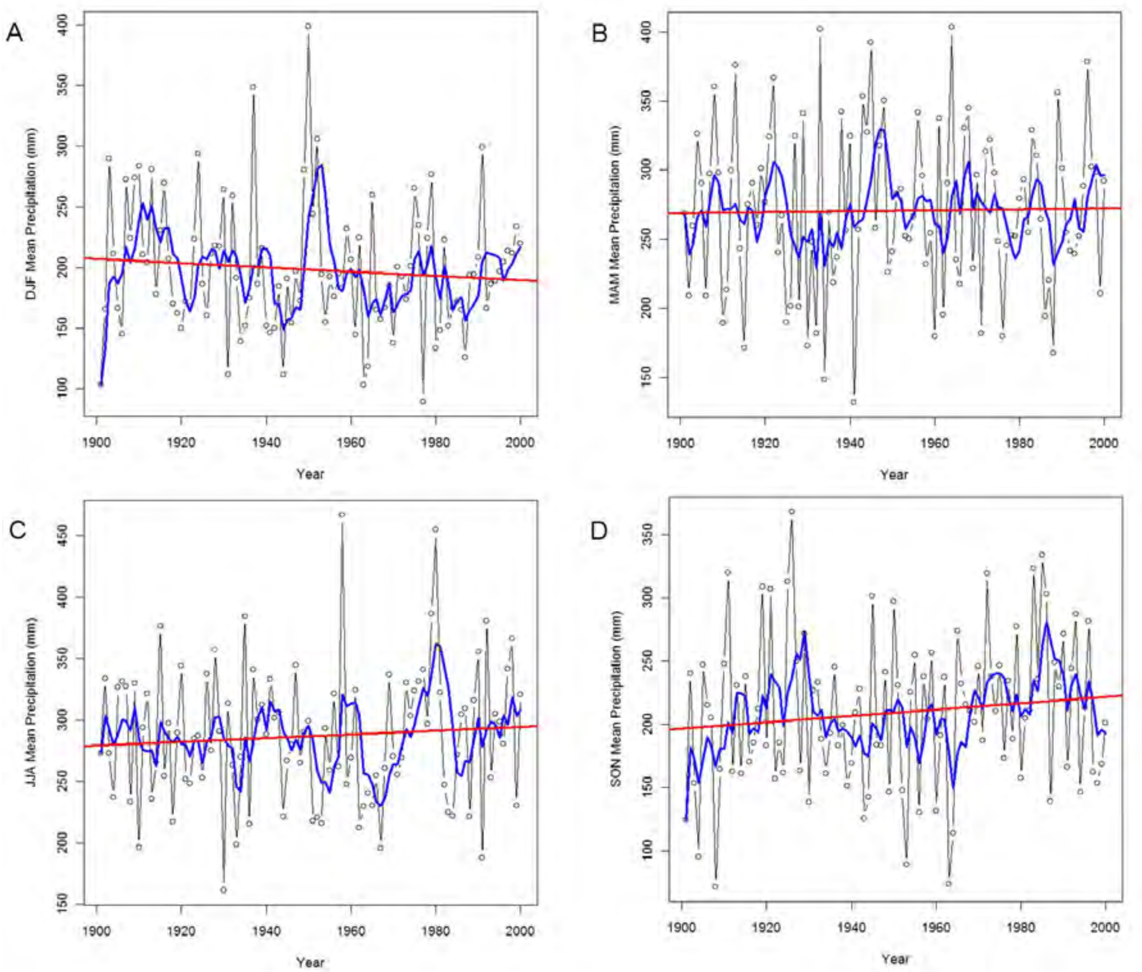

Figure 6-5. Trends in seasonal mean precipitation in Ohio from 1901–2000. (A) DJF = December, January, and February, change rate = –0.171 mm/year, *p*-value = 0.43; (B) MAM = March, April, and May, change rate = 0.034 mm/year, *p*-value = 0.86; (C) JJA = June, July, and August, change rate = 0.149 mm/year, *p*-value = 0.42; (D) SON = September, October, and November, change rate = 0.248 mm/year, *p*-value = 0.23. Figure produced using Climate Wizard Web site (http://www.climatewizard.org/). Base climate data from the PRISM Group, Oregon State University, http://www.prismclimate.org.

Table 6-5. Projected departure from historic (1961–1990) trends in annual and seasonal precipitation (mm) in Ohio for mid- (2040–2069) and late-century (2070–2099) for high and low emissions scenarios. Values represent the minimum, average, maximum and standard deviations from 15 different climate models. Data were derived from the Climate Wizard Web site (http://www.climatewizard.org/)

Midcentury (2040−2069) vs. historic (1961−1990)										
	A2 (high) emissions scenario					B1 (low) emissions scenario				
Model	Annual	DJF	MAM	JJA	SON	Annual	DJF	MAM	JJA	SON
Ensemble low	−83.6	−15.6	−5.5	−49.0	−37.5	−66.6	−22.8	−15.5	−38.3	−40.3
Ensemble average	56.7	23.0	29.5	−5.4	9.0	73.0	28.0	33.7	7.6	11.1
Ensemble high	154.4	50.6	64.9	46.7	56.3	425.0	141.8	112.2	98.1	116.2
SD	68.2	20.8	23.0	30.4	23.8	120.1	39.9	28.8	35.6	38.4
Late-Century (2070−2099) vs. historic (1961−1990)										
Ensemble low	−146.3	−4.3	−24.7	−98.7	−50.7	−52.3	−4.2	−13.2	−52.4	−25.4
Ensemble average	82.0	33.4	51.3	−5.5	11.1	99.7	45.1	43.0	6.2	15.0
Ensemble high	297.0	95.9	152.3	54.5	72.3	443.8	179.3	101.1	90.2	114.8
SD	122.6	26.4	45.6	50.5	34.9	140.3	58.0	32.3	39.1	42.0

DJF = December, January, and February; MAM = March, April, and May; JJA = June, July, August and SON = September, October, and November.

6.2. DATA INVENTORY AND PREPARATION

Ohio was one of the first states to systematically use biological assemblage data to determine aquatic life use designations and assess the condition of those uses. Dating back to the late 1970s, the Ohio data set represents a nearly 30-year span of standardized biological data for fish and macroinvertebrates, and is the only state from which we looked at fish (see Section 2). The Ohio fish assemblage database contains data from more than 10,000 unique sites and more than 24,000 unique sampling events. Macroinvertebrate assemblage data were also collected at most of these sites, as were habitat QHEI data (Ohio EPA, 2006; Rankin, 1995, 1989).

In the 1980s, with assistance from EPA-ORD, Ohio EPA began a focused sampling of least-impacted reference sites in order to determine the efficacy of level III ecoregions (Omernik, 1987) as a way to account for and stratify natural variations in biological assemblages (Yoder, 1989; Ohio EPA, 1987; Whittier et al., 1987). Ohio EPA used this and other sampling data to establish a network of "least-impacted" regional reference sites that eventually supported the derivation of numerical biocriteria for Ohio streams and rivers. This was also accomplished across practically all wadeable and nonwadeable streams and rivers from >1 mi^2 up to the largest inland rivers (~6,000−8,000 mi^2) that could be sampled.

The initial reference data set was developed from a statewide network of about 300 reference sites that was sampled over a 10-year period (1980−1989; Table 6-6). That reference site network was maintained and expanded with the initial resampling during 1990−1999 and a second resampling from 2000−2009 (at the time of this project, we only had access to data through 2006). Data on habitat quality (QHEI), water quality, and other physical data such as temperature were also collected and were based on multiple grab samples collected during "normal" seasonal flows within a summer-fall seasonal index period (mid-June through mid-October).

Data gathering, preparation, and analyses were conducted by MBI. Prior to running analyses, MBI screened the data to identify any methodological differences in data collection (environmental and biological) that could either confound or mask apparent trends. MBI also assessed the relative contribution of taxonomic changes to trends in ICI and IBI scores at reference sites. While fish data can be influenced by factors such as sampling efficiency, MBI found the fish taxonomy to be comparatively stable during the period over which the Ohio reference database was developed. Using the methods described in Section 2.1.3, MBI did,

Table 6-6. Summary of Ohio EPA regional reference site network including original sites (1980–1989) and updates via first (1990–1999) and second round resampling (2000–2006) that were used in data analyses

Reference network	Size type	Fish: latest (all data)	Macroinvertebrates
Original reference sites: 1980−1989 (sites/samples)	Headwaters	112/225	242
	Wadeable	166/399	
	Boatable	97/254	
New reference sites: 1990−2006 (sites/samples)	Headwaters	115(149)/150(296)	309 (525)
	Wadeable	184(231)/281(539)	
	Boatable	68(84)/127(278)	

however, find significant changes in macroinvertebrate taxonomy over time, mostly in the form of improved discrimination within certain genera (e.g., Baetid mayflies).

To determine how much of an impact these taxonomic changes had on ICI scores, MBI calculated the ICI, total taxa metric, mayfly metric, and qualitative EPT metric with the original taxon designations and then compared these values to metric and ICI scores that were calculated using the newly "refined" taxonomy. MBI performed these calculations on data from the earliest and most recent time periods. The recalculation of ICIs from all sites showed a 5.9 point increase in the mean ICI score between the two time periods (see Table 6-7). MBI also evaluated how taxonomic refinements affected ICI scores in samples from different ecoregions in WWH and EWH. In two instances, there was a change in the biocriteria: the Huron/Erie Lake Plain WWH biocriterion (38.5 compared to 42) and the Erie Ontario Lake Plain WWH biocriterion (42 compared to 44) (see Table 6-8).

MBI also performed exploratory analyses to look for obvious trends related to stream-size bias. Going into the analyses, they knew that some stream-size bias did exist in the Ohio data set because headwater streams were less frequently sampled in the 1980s than in the 1990s and 2000s. Recognizing that the distribution of sites was different between these periods, they tested whether bias was evident in low percentiles (1st, 5th, and 25th) for species distributions across all sites in Ohio. Results showed that some bias between time periods existed for species distributions. Nearly all selected sensitive species had distributions that extended further into small streams during the later (1998−2008) compared to the earliest (1978−1989) sampling periods. MBI performed some additional exploratory analyses. Because these analyses may

Table 6-7. Changes in ICI and mayfly influence ICI metrics related to increasing taxonomic resolution over time in the Ohio EPA least impacted reference data set

Metric	Original reference sites		New reference sites (latest data)	
	Standard taxonomy mean taxa (mean score)	Lumped taxonomy mean taxa (mean score)	Standard taxonomy mean taxa (mean score)	Lumped taxonomy mean taxa (mean score)
Total taxa	35.97 (4.89)	35.93 (4.89)	38.36 (5.18)	37.65 (5.04)
Number of Mayfly taxa	6.95 (4.20)	6.90 (4.17)	7.42 (4.59)	6.59 (4.16)
QUAL EPT taxa	11.29 (3.63)	11.24 (3.60)	15.16 (5.16)	14.23 (4.91)
ICI score	39.59	39.53	45.35	44.56

Table 6-8. Table of original and recalibrated Ohio biocriteria with adjustments made to equilibrate taxonomic advances made in the later time period. Highlighted cells indicate where standardizing taxonomic resolution would have resulted in altered criteria

Ecoregion	Warmwater habitat			Exceptional warmwater habitat		
	Original reference	Latest reference	Latest reference w/refined taxonomy	Original reference	Latest reference	Latest reference w/refined taxonomy
Huron/Erie Lake Plain (HELP)	34	42	38.5	46	50	50
Interior Plateau (IP)	30	38	38			
Erie Ontario Lake Plain (EOLP)	34	44	42			
Western Allegheny Plateau (WAP)	36	40	40			
Eastern Corn Belt Plain (ECBP)	36	42	42			

have been confounded by year-to-year variability in flow or temperature within each time period being evaluated, they encourage that a more sensitive approach be used in future analyses (i.e., one that controls for or considers annual variation and regional variation in flows, which can be extracted from USGS flow data using IHA flow indicators).

6.3. OHIO EPA METHODS

Ohio implemented standardized sampling methods for biological assessments in the late 1970s. Collection methods used by Ohio EPA for both fish and macroinvertebrates have been stable over the period of the Ohio reference database. When collecting macroinvertebrate samples, Ohio EPA uses a modified Hester-Dendy multiplate artificial substrate sampler that is placed in-stream to colonize for 6 weeks between mid-June and late September (DeShon, 1995). Fish sampling is conducted during the same index period and includes two or three passes. Fish sampling gear varies depending on stream size (Ohio EPA, 1989).

Ohio calculates an ICI to evaluate biological condition based on the benthic macroinvertebrate assemblage (DeShon, 1995) and an IBI used to evaluate fish assemblages at wading sites, boat sites, and headwaters stream sites. Tables 6-9 and 6-10 (Ohio EPA, 1989) show the metrics that go into the ICI and IBI.

6.4. INDICATORS

6.4.1. Thermal Preference

To evaluate which taxa could potentially serve as indicators of temperature change, MBI used weighted-average modeling to calculate thermal optima and tolerance values (which they termed WSVs) for fish and macroinvertebrate taxa. For more details on this methodology, see Section 2.2.1. Separate calculations were done for headwater (drainage area $\leq$20 mi^2) and wadeable streams (drainage area >20 to 300 mi^2).

MBI ordered the data by temperature optima to provide a sequential listing of sensitive species/taxa that could potentially be used to detect temperature trends. These data are available upon request. To visualize the distribution of the macroinvertebrate data with taxa sensitivities, MBI plotted the means of these values versus the weighted means (WSVs) color coded by the existing taxa tolerance rankings of Ohio EPA (see Figure 6-6). The WSVs generally track with the "general" tolerance categories assigned by Ohio EPA for each taxon for both headwater (see

Table 6-9. Macroinvertebrate community metrics used in the ICI for evaluating biological condition in Ohio. Scoring of each metric ranges from 0 to 6 in increments of 2, and is based on drainage area (as defined in Figures 5-1 to 5-10 in Ohio EPA, 1989)

Metric
Total number of taxa
Total number of Mayfly taxa
Total number of Caddisfly taxa
Total number of Dipteran taxa
Percentage Mayfly composition
Percentage Caddisfly composition
Percentage Tribe Tanytarsini Midge composition
Percentage Other Dipteran and noninsect composition
Percentage tolerant organisms (from Table 5-2)
Total number of qualitative EPT taxa

Table 6-10. Index of Biotic Integrity metrics used to evaluate wading sites, boat sites, and headwaters stream sites in Ohio. Original metrics from Karr (1981) are given first with substitute metrics following. Taken from Table 4-1 in Ohio EPA's "Standardized Biological Field Sampling and Laboratory Methods for Assessing Fish and Macroinvertebrate Communities" (1989)

IBI metric	Headwaters sites[a,b]	Wading sites[b]	Boat sites[c]
1. Total number of species[d]	X	X	X
2. Number of Darter species	X[e]	X	
Percentage round-bodied suckers[f]			X
3. Number of Sunfish species		X	X
Number of headwater species	X		
4. Number of Sucker species		X	X
Number of Minnow species	X		
5. Number of intolerant species		X	X
Number of sensitive species	X		
6. Percentage green Sunfish			
Percentage tolerant species	X	X	X
7. Percentage omnivores	X	X	X
8. Percentage insectivorous Cyprinids			
Percentage insectivorous species	X	X	X
9. Percentage top carnivores		X	X
Percentage pioneering species	X		
10. Number of individuals[g]			
11. Percentage hybrids			
Percentage simple Lithophils		X	X
number of simple Lithophilic species	X		
12. Percentage diseased individuals			
Percentage DELT anomalies[h]	X	X	X

[a]Applies to sites with drainage areas less than 20 sq. mi.
[b]These sites are sampled with wading methods.
[c]These sites are sampled with boat methods.
[d]Excludes exotic species.
[e]Includes sculpins.
[f]Includes suckers in the genera *Hypentelium*, *Moxostoma*, *Minytrema*, and *Erimyzon*; excludes white sucker (*Catostomus commersoni*).
[g]Excludes species designated as tolerant, hybrids, and exotics.
[h]Includes deformities, eroded fins, lesions, and external tumors (DELT).

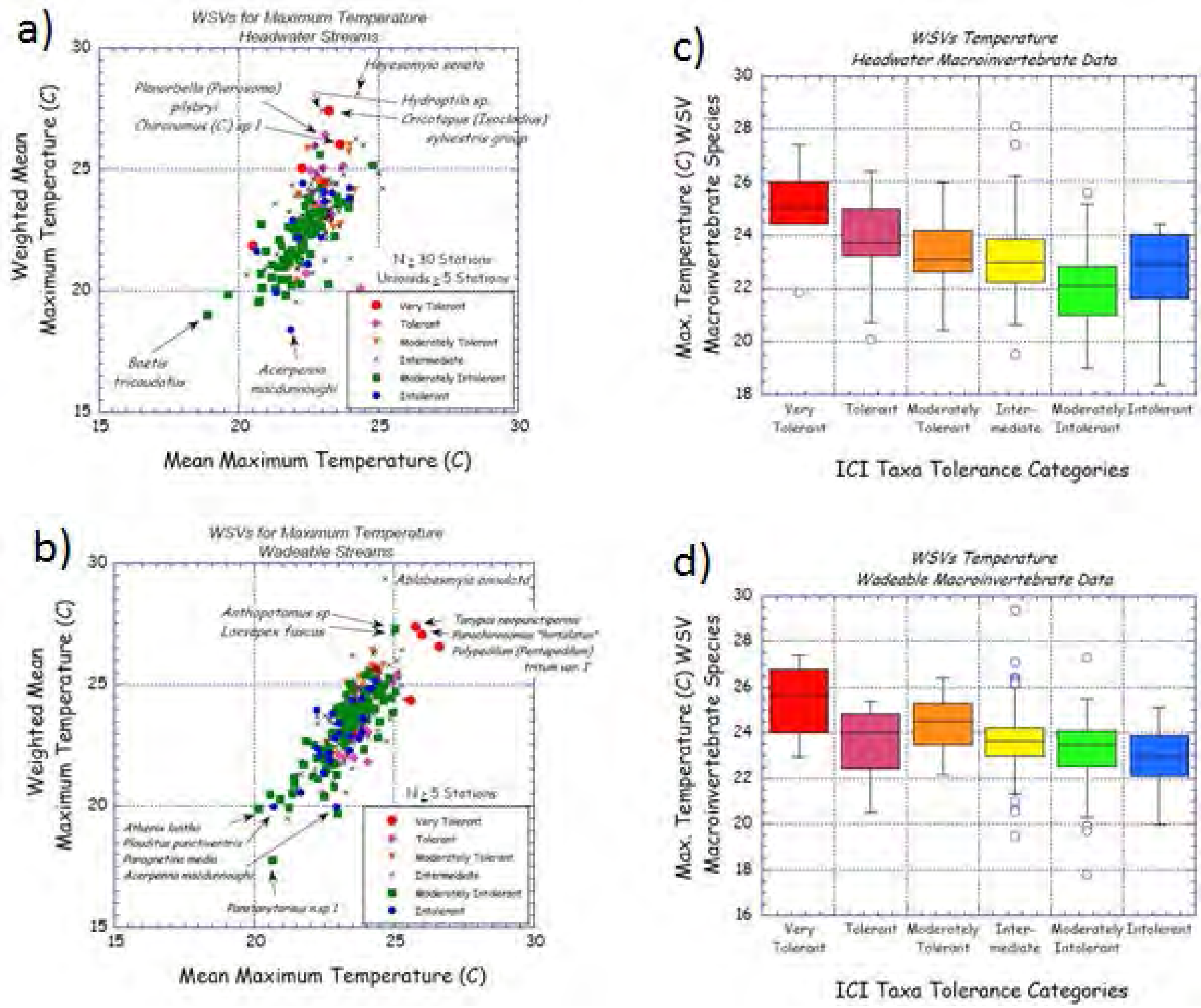

Figure 6-6. Plots of macroinvertebrate taxa maximum temperature WSV values versus mean maximum values for taxa for headwater streams (a) and wadeable streams (b) and box and whisker plots of WSVs for maximum temperatures by Ohio EPA macroinvertebrate tolerance values (derived for the ICI) for headwater streams (c) and wadeable streams (d). Data for taxa represents data collected from artificial substrates where at least five samples were represented for each stream size category.

Figure 6-6C) and wadeable streams (see Figure 6-6D). A similar pattern was observed for fish species. WSVs for temperature can be confounded with WSVs for other stressors, particularly habitat. However, the extremes of these distributions can be useful for identifying possible indicator taxa for future applications. For example, it was interesting to note that selected Chironomidae taxa occurred at both extremes of the WSV for temperature. *Paratanytarsus n.sp. 1* had the lowest WSV for temperature at wadeable sites, and *Parachironomus "hirtalatus"* and *Tanypus neopunctipennis* had among the highest WSVs (see Figure 6-6B). Additional traits-based analyses could help in identifying rare taxa that exhibit some sensitive traits, but that may be too rare by themselves to serve as useful indicators.

6.4.2. Hydrologic Indicators

To evaluate which taxa could potentially serve as indicators of hydrologic change, MBI used weighted-average modeling to calculate WSVs for flow-related habitat variables for fish and macroinvertebrate taxa. Calculations were made using the methodology described in Section 2.2.2. Separate analyses were done for headwater (drainage area ≤20 mi^2) and wadeable streams (drainage area >20 to 300 mi^2).

MBI made these calculations based on a subindex of the QHEI, which they termed the Hydro-QHEI. The Hydro-QHEI is composed of the two QHEI subcomponents most related to hydrology—current and depth. Table 6-11 details scoring calculations for the Hydro-QHEI. The presence of fast current or the presence of eddies is a characteristic of permanent summer base flows (QHEI assessments are generally conducted during summer−fall low flow periods). Attributes related to depth (i.e., deep pool and deep runs) are also regarded as good indicators of base flow influence. Thus, the Hydro-QHEI is expected to reflect a gradient of baseflow stability, one of the attributes that would be expected to change with alterations in precipitation patterns as a result of climate change.

MBI ordered the data by optima values to provide a sequential listing of sensitive species/taxa that could potentially be used to detect changes in hydrology. These data are available upon request. MBI plotted several examples of the WSVs for these variables versus the simple means for these same variables (see Figure 6-7) in order to reveal the distributions of tolerant and sensitive species along this gradient, as they did for temperature. Fish and

Table 6-11. Subcomponents of the Ohio QHEI, which were used to score a Hydro-QHEI, and current and depth subscores

Current metric		Depth metric	
QHEI current attribute	**Score**	**QHEI depth attribute**	**Score**
Very fast current	+5	Deep pools (cover metric)	+4
Fast current	+3	Pool depths > 1m	+4
Moderate current	+2	Pool depths 0.7−1.0 m	+3
Slow current	+1	Pool depths 0.4−0.7 m	+2
Eddies	+2	Pool depths 0.2−0.4 m	+1
Very deep riffles	+3	Pool depths < 0.20	−1
Moderate depth riffles	+1	Deep riffles	+3
Interstitial flow	−1	Moderate riffles	+2
Intermittent flow	−3	Shallow riffles	+1
		Riffles absent or nonfunctional	−1

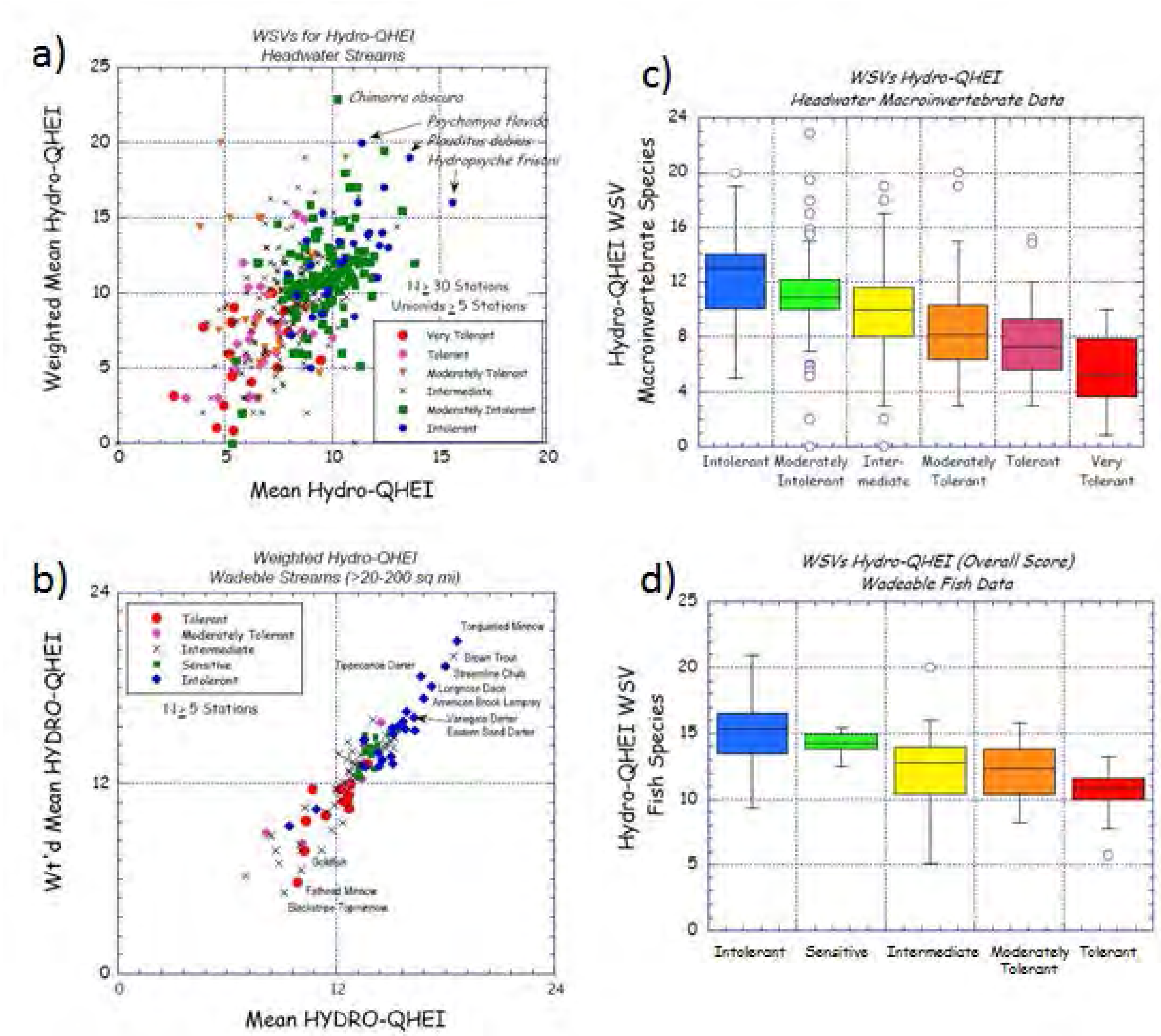

Figure 6-7. Scatter plots of taxa/species Hydro-QHEI WSV values versus mean Hydro-QHEI values for macroinvertebrates taxa for headwater streams (a) and for species in wadeable streams (b) and box and whisker plots of macroinvertebrate (c) and fish (d) WSVs for Hydro-QHEI for these waters. Data from Ohio EPA.

macroinvertebrate WSVs for Hydro-QHEI and its subcomponents tracked relatively closely to the Ohio EPA tolerance designations for macroinvertebrate taxa and fish species (see Figure 6-7). Outlier points and variability are often associated with small sample sizes for a given species at a given stream size. Intolerant species are frequently rarer than "sensitive" species, especially for fish, and as such, may exhibit more variation than "sensitive" species where sample sizes are typically larger. As expected, tolerant species generally have wider sensitivity ranges.

The identification of certain intolerant fish species in headwater streams at the "sensitive" end of the Hydro-QHEI gradient suggests that the distribution of these species at the tails of their preferred stream size range may reflect the degree of base flow. Fish species such as streamline chub, variegate darter, river chub, and stonecat madtom (all with high Hydro-QHEI WSVs) are generally found in larger wadeable streams, and their presence in headwater streams is associated with high Hydro-QHEI scores that indicate more stable flow regimes. Year-to-year or long-term trends of these species in headwater streams could represent a response to climate-induced hydrologic changes. Thus, we suggest that this could be an opportunity to explore whether the stream size "tails" of sensitivity distributions shift with hydrological change.

6.4.3. Traits-Based Indicators in a Warmer Drier Scenario

In the Maine, North Carolina, and Utah data sets, we performed exploratory exercises to develop lists of taxa that may be most and least sensitive to projected changes in temperature and streamflow based on combinations of traits. MBI did not perform these types of analyses on the Ohio data set.

6.5. LEAST DISTURBED LONG-TERM BIOLOGICAL MONITORING SITES

As discussed in Section 6.2, Ohio EPA began a focused sampling of least-impacted reference sites in the 1980s. This network of "least-impacted" regional reference sites eventually supported the derivation of numerical biocriteria for Ohio streams and rivers. Most stations are sampled on a regionally rotating basis, at 10-year intervals. If placed on a BCG scale (Davies and Jackson, 2006), the Ohio reference sites generally span BCG Level 3−Level 4, with an occasional 2 and 5. Few undisturbed sites remain in Ohio, with widespread agricultural and development changes occurring across the landscape. Although anthropogenic influences are higher than desired at some of the sites, the data were analyzed because they represent the best-available long-term data in the state database. When MBI performed analyses on this reference data set, they evaluated trends in reference condition across the entire network (stratified by size and sometimes habitat categories) and did not perform analyses on data from individual sites.

6.6. EVIDENCE OF TRENDS AT LEAST-DISTURBED LONG-TERM MONITORING SITES

6.6.1. Reference Sites

6.6.1.1. *Temporal Trends in Climatic and Biological Variables*

MBI looked at the amount and direction of change in state bioassessment scores over the last 30 years at Ohio's network of "least-impacted" regional reference sites. Table 6-12 summarizes the ranges of years that represent the original and resampled reference sites. On average, the latest data period was 13−16 years after the mean of the original reference sample dates (see Table 6-12). Before making the calculations, MBI stratified the fish assemblage indices by three stream and river size strata: headwater streams (<20 mi^2), "wadeable" streams (20−~300 mi^2), and "boatable" (i.e., nonwadeable) rivers (>~150−200 mi^2) (Yoder and Rankin, 1995). Macroinvertebrate assemblage indices were calibrated continuously across the entire range of stream and river sizes. Samples were also divided into three habitat groups: MWH, WWH, and EWH.

Table 6-12. Average and range of years represented by original reference site data and resampled (latest) data by index and stream size category

Index/stream size	Mean year sampled (range)	
	Original reference sites	Resampled sites
ICI—all sites	1984 (1980−1988)	2000 (1989−2007)
IBI—headwaters	1984 (1978−1988)	2000 (1989−2006)
IBI—wading	1984 (1979−1988)	2000 (1990−2006)
IBI—boat	1984 (1979−1988)	1997 (1990−2005)

Table 6-13 reports the original biocriteria values and statistics, a recalculation of those statistics using refined variables, and "new" biocriteria values based on the latest resampled reference sites. The reason the original biocriteria statistics were recalculated was because there are a few minor discrepancies related to uncertainties about the exact membership of the original reference sites and gradual changes made to the database since 1990 due to changing taxonomy and a more precise calculation of drainage area (Rankin, 2009). The direction of change in bioassessment scores between the original and latest reference site data was either positive (an increase) or neutral (no change), with three exceptions: (1) the ICI biocriterion for the nonacidic mine drainage modified use was four points lower (possible small sample size); (2) the IBI for WWH headwater site type in the Erie Ontario Lake Plain ecoregion was two points lower; and, (3) the IBI for WWH headwater site type in the Western Allegheny Plateau ecoregion was two points lower (see Table 6-13). None of these changes are considered to be outside the range of natural variability for each index. The largest positive changes in the biocriteria were in the WWH boatable fish sites (IBI and the Modified Index of Well-Being (MIwb), a measure of the health of the fish assemblage that is used in conjunction with the IBI), and in the WWH ICI.

6.6.1.2. *Associations Between Biological and Climatic Variables*

In the Maine, North Carolina, and Utah data sets, we performed correlation analyses on individual sites to look for associations between state bioassessment scores, selected biological metrics, year, temperature, flow, and precipitation variables. MBI did not perform these types of analyses on the Ohio data set.

6.6.1.3. *Groupings Based on Climatic Variables*

In the Maine, North Carolina, and Utah data sets, we grouped biological data based on extremes in temperature, flow, and/or precipitation variables, using these groupings as proxies for future climate conditions. MBI did not perform these types of analyses on the Ohio data set.

6.7. SENSITIVITY OF BENTHIC MACROINVERTEBRATES TO TEMPERATURE AND STREAM FLOW

Sensitivities in Ohio may best be monitored by tracking changes in the distributions of the candidate thermal and hydrologic indicator taxa that MBI identified through weighted-averaging analyses, and by carefully monitoring the habitats that those taxa occur in. Changes in baseflow stability could be particularly important in Ohio. The identification of certain intolerant fish species in headwater streams at the “sensitive” end of the Hydro-QHEI gradient suggests that the distribution of these species at the tails of their preferred stream size range may reflect the degree of baseflow. Year-to-year or long-term trends of these species in headwater streams could represent a response to climate-induced hydrologic changes.

Table 6-13. Original Ohio biocriteria (O), recalculated biocriteria (R) using similar sites, and new biocriteria (N) using the latest data from resampling of original reference sites. Because IBI or ICI scores based on single samples are always even values, calculated percentage values were rounded upwards (e.g., 41 to a 42). Sites with discrepancies between original and recalculated criteria are shaded. MIwb refers to the Modified Index of Well-Being, a measure of the health of the fish assemblage that is used in conjunction with the IBI

Ecoregion	MWH Channelized			MWH Nonacidic mine drainage			MWH Impounded			WWH			EWH		
IBI—headwater site type															
	O	**R**	**N**	**O**	**R**	**N**	**O**	**R**	**N**	**O**	**R**	**N**	**O**	**R**	**N**
HELP	**20**	**20**	**26**							**28**	**-**	**-**	**50**	**50**	**52**
IP	**24**	**24**	**26**							**40**	**40**	**40**			
EOLP										**40**	**38**	36			
WAP				24	24	[a]				**44**	**44**	**42**			
ECBP										**40**	**40**	**44**			
IBI—wadeable site type															
HELP	**22**	**22**	**22**							**32**	**-**	**-**	**50**	**50**	**52**
IP	**24**	**24**	**30**							**40**	**40**	**44**			
EOLP	**24**	**24**	**30**							**38**	**38**	**42**			
WAP	**24**	**24**	**30**	**24**	**24**	**32**				**44**	**44**	**46**			
ECBP	**24**	**24**	**30**							**40**	**40**	**40**			
IBI—boatable site type															
HELP	**20**	**20**	**20**				**22**	**22**	**26**	**34**	**30** **34**	**30** **34**	**48**	**48**	**52**
IP	**24**	**24**	**24**				**30**	**28**	**34**	**38**	**38**	**47**			
EOLP	**24**	**24**	**24**				**30**	**28**	**34**	**40**	**40**	**46**			
WAP	**24**	**24**	**24**	**24**	**24**	**26**	**30**	**28**	**34**	**40**	**40**	**40**			
ECBP	**24**	**24**	**24**				**30**	**28**	**34**	**42**	**42**	**42**			
MIwb—wadeable site type															
HELP	**5.6**	**5.9**	**6.4**							**7.3**	**-**	**-**	**9.4**	**9.4**	**9.5**
IP	**6.2**	**6.4**								**8.1**	**8.1**	**8.1**			
EOLP	**6.2**	**6.4**								**7.9**	**7.9**	**8.2**			
WAP	**6.2**	**6.4**		**5.5**	**4.7**	**6.1**				**8.4**	**8.3**	**8.8**			
ECBP	**6.2**	**6.4**								**8.3**	**8.3**	**7.8**			

Table 6-13. Original Ohio biocriteria (O), recalculated biocriteria (R) using similar sites, and new biocriteria (N) using the latest data from resampling of original reference sites. Because IBI or ICI scores based on single samples are always even values, calculated percentage values were rounded upwards (e.g., 41 to a 42). Sites with discrepancies between original and recalculated criteria are highlighted in yellow. MIwb refers to the Modified Index of Well-Being, a measure of the health of the fish assemblage that is used in conjunction with the IBI (cont.)

Ecoregion	MWH									WWH			EWH		
	Channelized			Nonacidic mine drainage			Impounded								
MIwb—boatable site type															
HELP	5.7	5.7	7.5[a]				5.7	5.7	7.4	8.6	-	-			
IP	5.8	5.7	6.1[a]				6.6	7.0	7.5	8.7	8.7	9.6			
EOLP	5.8	5.7	6.1[a]				6.6	7.0	7.5	8.7	8.8	8.9	9.6	9.6	10.2
WAP	5.8	5.7	6.1[a]	5.4	5.4	6.4	6.6	7.0	7.5	8.6	8.6	9.2			
ECBP	5.8	5.7	6.1[a]				6.6	7.0	7.5	8.5	8.5	9.7			
ICI—all site types combined															
HELP	22	22	24							34	34	42			
IP	22	22	24							30	30	38			
EOLP	22	22	24							34	34	44	46	46	50
WAP	22	22	24	30	30	26				36	36	40			
ECBP	22	22	24							36	36	42			

[a]Nonacidic mining influenced modified sites for headwaters combined with wading sites due to small sample size. HELP = Huron/Erie Lake Plain, IP = Interior Plateau, EOLP = Erie Ontario Lake Plain, WAP = Western Allegheny Plateau , ECBP = Eastern Corn Belt Plain.

Assemblages in small headwater streams (currently undersampled), streams already near the “edge” of temperature and hydrologic thresholds, and cold water systems, exceptional systems and areas that are “islands” of the above categories may be particularly sensitive, as they would have difficulty recovering from episodic stressors due to lack of refugia or recolonization areas.

6.8. IMPLICATIONS FOR OHIO EPA’S BIOMONITORING PROGRAM

In Ohio and other midwestern states, climate change projections are for warmer temperatures and slight increases in precipitation. The expectation for changes in flow are less certain, being affected by both increasing precipitation, which may increase flows, and increasing temperatures, which can also increase evapotranspiration and contribute to decreasing flows at least seasonally.

When MBI analyzed data from the Ohio reference data set to search for a signal or lack of signal related to the effects of global climate change, they found that, in general, the biological condition at Ohio's reference sites has improved over the last 30 years. Climate change effects may be a contributing component to these observed trends, or may be decreasing the magnitude of the positive response. However, there is evidence that the trends have been driven largely by other environmental factors. Main contributors include reductions in point source loadings, changes in land uses (e.g., increased urbanization), altered pollutant loadings from agricultural lands (e.g., reductions in sediments and nutrients in response to increased conservation tillage), and localized improvement in habitat quality due to stream restoration. There may also be changes that are still contributing to degradation, such as loss of habitat quality due to agricultural drainage practices and suburbanization.

The improvements in fish assemblages in large rivers are most attributable to reduced pollution from point sources, mostly due to municipal wastewater treatment plant upgrades after 1988 (Yoder et al., 2005). While it was necessary in the derivation of the original Ohio IBI for boatable sites to include reference sites located in effluent dominated rivers, the sites were positioned below known recovery points. Nevertheless, the lessening of secondary impacts from nutrient enrichment by the aforementioned controls had positive effects on fish assemblages at these reference sites. Large river pollution reductions have also facilitated the movement of intolerant species between watersheds (i.e., have become highways for recolonization). In headwater and small streams, biological conditions have generally improved over time due to better agricultural practices (e.g., conservation tillage).

In the future, it will continue to be challenging to tease out climate-related impacts from other confounding factors in the Ohio data set, especially because a number of the "least-impacted" regional reference sites are affected to some degree by pollution or land alterations. If biological responses to climate change effects do become more evident, the direction of these changes could be in a positive or negative direction. The most plausible expectation would be for a decline in bioassessment scores due to the loss of highly intolerant species and taxa (i.e., temperature and flow sensitive taxa/species), and an increase in intermediate, moderately, and/or highly tolerant taxa/species. Such expectations are supported by MBI's analyses that identify a general concordance between intolerant and sensitive species as categorized for the IBI and ICI and species sensitive to temperature and habitat features indicative of altered flow conditions. These changes could be tracked by monitoring the distributions of taxa that MBI identified as being sensitive to changing temperature and hydrology.

7. SYNTHESIS

7.1. EVIDENCE FOR EXISTING CLIMATE CHANGE RESPONSES

7.1.1. Existing Climate Trends Support Expectations for Biological Responses

The direction and magnitude of historic trends in air temperature, precipitation, water temperature, and flow records define whether climate-related biological responses might be expected during the period of record in the different regions. Long-term air temperature increases are evident from PRISM data for most states, though there is variability in the magnitude of increases among the regions examined (see also Karl et al., 2009. North Carolina and Ohio showed no trend in temperature over the past century, but there were modest though nonsignificant (1−2 °C) increasing trends in temperature for these states over that past 3 decades (see Table 7-1). Maine had similar long- and shorter-term historic net temperature increases of about 1°C (only the long-term rate was statistically significant). Greater temperature increases are documented in Utah, where a gradual (1 °C) but significant increase was found over that past century, and a steeper (4 °C) and significant rate of increase occurred since 1970; this is the largest historic temperature rise among the 4 states studied (see Table 7-1). The projected rates of future temperature increases are generally consistent with the current documented rates of increase in magnitudes and regional patterns. They are highest for Utah and lowest for North Caroline, but the differences are small.

It is also reasonable to expect long-term water temperature trends to follow air temperature trends. Previous studies (e.g., Pilgrim et al., 1998; Wehrly et al., 2009; Stephan and Preudhomme, 1993) have established a relationship of water temperature to air temperature of from 0.86 to 1. From this, it can be expected that an increasing trend in air temperature of 2°C will, on the average, result in an increase in water temperature of 1.7−2 °C. Support for this also comes from analysis of USGS gaging station records from around the United States. Stations analyzed were screened to include gages with long-term water temperature records (30 years), and to minimize the likelihood of confounding effects (e.g., sewage treatment plant discharges, heavy urban/suburban development, effects of dam releases) or temporal discontinuities from methods or data quality issues. The rate of water temperature increases averaged 0.76°C per 10-year period (see Table 7-2), but varied around the country, partly in relation to stream size. This suggests that estimates for water temperatures increases of 1−2°C over the approximately

2 decades of biological sampling are reasonable. The screening process eliminated gage data from two (Ohio and Maine) of the four states evaluated in this study. However, the North Carolina stream analyzed had a larger water temperature increase than the Utah stream, even though climate change-related temperature projections are slightly greater for Utah (see Table 7-2), suggesting that differences in stream size also are an important influence.

Table 7-1. Observed and modeled future rates of change for air temperature and precipitation for the four states analyzed in this study. Estimated changes based on significant increasing or decreasing trends are shown in bold. See Tables 3-1 to 3-4, 4-1 to 4-4, 5-1 to 5-4, and 6-1 to 6-4 for sources of data

Existing and projected rates per century	Utah	Maine	North Carolina	Ohio
Air temperature (°C)				
Existing (1901−2000)	**1**	**1**	0	0
Existing short term rate (1970−2000) projected to century	**4**	1	1	2
Projected midcentury (low to high emissions scenarios)	2.3−2.9	2.1−2.7	1.7−2.3	2.2−2.7
Projected end of century (low to high emissions scenarios)	3.0−4.8	2.8−3.6	2.2−3.7	2.7−4.5
Precipitation—average annual (mm)				
Existing (1901−2000)	+35	**+110**	+39	+22
Existing short term rate (1970−2000) projected to century	+128	−113	−147	−33
Projected midcentury (low to high emissions scenarios)	+22.3 to −2.7	+69.0 to +90.1	−1.0 to +54.0	+73.0 to +56.7
Projected end of century (low to high emissions scenarios)	+50.7 to −5.8	+67.0 to +125.0	−16.5 to +56.9	+99.7 to +82.0
Precipitation—summer (mm)				
Existing (1901−2000)	+11	+18	**−68**	+15
Existing short term rate (1970−2000) projected to century	+69	−95	+61	−40
Projected midcentury (low to high emissions scenarios)	+16.8 to −6.9	−4.7 to +15.1	−22.5 to +11.6	+7.6 to −5.4
Projected end of century (low to high emissions scenarios)	+32.8 to −4.4	−8.3 to +7.7	−41.5 to +22.3	+6.2 to −5.5

Table 7-2. Summary of results from water temperature trend analyses at 23 USGS stations that met the screening criteria. Rates of temperature (°C) change per 10-year period were evaluated at 23 of the stations. Stations in states analyzed in this study are highlighted in grey

Site #	Stream name	Stream order	NPDES	Land use	State	TempΔ/10year	R^2
2423130	Cahaba River	3	no	FOR/AG (URB)	AL	0.73	0.024
10339400	Martis Creek	3	no	FOR	CA	0.28	0.02
7086000	Cache Creek	2	no	FOR	CO	1.48	0.151
9169500	Dolores River	5	no		CO	0.93	0.05
2266300	Reedy Creek	3	no	URB	FL	0.3	0.081
5474000	Skunk River	6	no	FOR	IA	0.25	0.006
13340600	Beaver Creek	4	no		ID	0.4	0.032
3354000	White River	5	no	AG	IN	0.32	0.017
1600000	North Branch Potomac River	5	no		MD	0.5	0.013
1021050	Saint Croix River	6	no	URB/FOR	ME	0.39	0.02
12363000	Flathead River	6	no	AG (URB)	MT	1.36	0.17
2077200	Hyco Creek	3	no	FOR	NC	0.7	0.192
6338490	Missouri River	1	no	GRASSLAND	ND	5.09	0.508
5056000	Sheyenne River	4	no	GRASSLAND	ND	0.41	0.013
5058700	Sheyenne River	1	no	GRASSLAND	ND	0.43	0.018
1466500	McDonalds Branch	1	no	FOR	NJ	0.33	0.03
1428500	Delaware River	6	no	FOR	NY	0.42	0.019
14138870	Fir Creek	2	no		OR	0.38	0.059
14372300	Rogue River	6	no	FOR	OR	0.16	0.011
2160700	Enoree River	5	no	FOR (urb)	SC	0.5	0.04
8123800	Beals Creek	5	no	Shrub	TX	0.46	0.018
8181500	Medina River	5	no	AG	TX	0.7	0.095
408000000	Middle Branch Embarrass River	3	no	AG	WI	0.96	0.03

NPDES = National Pollutant Discharge Elimination System.

As discussed in Sections 3.1, 4.1, 5.1, and 6.1, interannual variation in precipitation is much greater than for temperature, making historic trends more difficult to characterize and future projections more uncertain. This variability is reflected in the comparison among states summarized in Table 7-1. All four states had increasing trends in precipitation from 1901−2000, with the greatest increases in Maine and the lowest in Ohio. Only the long-term trend in average annual precipitation in Maine was significant. But for the more recent historic period covering the period of biological sampling, Maine, North Carolina, and Ohio had decreasing trends in precipitation, with the largest decrease in North Carolina. Future projections for average annual precipitation among states were variable. For Maine and Ohio, the projections are fairly consistently for increases in average annual precipitation. This would lead to an expected scenario of modest temperature increases and wetter conditions for these two states. But seasonal variability must also be considered. In particular, historic trends and future projections for summer precipitation give a somewhat different expectation. For example, in North Carolina, average annual precipitation increased over the past century, but average summer precipitation declined at an even higher rate (see Table 7-1). This suggests that the scenario during the summer biological sampling period is one of warmer and drier (not wetter) conditions (Karl et al., 2009).

Based on the relatively large historic rate of temperature increases in Utah, expectations are that biological responses would be most readily observed for this state. However, there are often observed interactions between temperature and flow (e.g., Yarnell et al., 2010), and though flow data were not available from most of the long-term sites examined for biological responses, the increasing historic trend in precipitation suggests that wetter conditions over the period of biological sampling may have ameliorated higher temperatures to some extent. This scenario may continue in the future, but there is a lot of uncertainty around the projections for summer precipitation changes in Utah (Christensen and Lettenmeier, 2006; Schoof et al., 2010; Gutzler and Robbins, 2011), which range from moderate increases to small decreases (see Table 7-1). While Maine and Ohio both have seen declines in average summer precipitation over the previous 3 decades, model projections are for increases in summer precipitation for the future (Hayhoe et al., 2007; UCS, 2006; Easterling and Karl, 2001; Wuebbles and Hayhoe, 2004; Hayhoe et al., 2010; Schoof et al., 2010). From this, expectations for Maine and Ohio should be for warmer and wetter conditions during the summer, the season typically considered stressful to aquatic biota, and during which biological sampling usually takes place. Even with more precipitation, increasing evapotranspiration associated with higher temperatures could still result in lower stream flows.

7.2. COMPARISON OF REGIONAL TRENDS AND INDICATORS—HOW TO INTERPRET OBSERVED RESPONSES

7.2.1. Comparison of Indicator Responses Among States and Regions

Biological responses were found in this study in both trend analyses with time and climate variables, and in contrasts between years partitioned into hot and cold or wet and dry groupings representing surrogates of future climate conditions. Such findings are reasonable, in particular for ecological or life history trait groups that have been documented in other studies (e.g., Gallardo et al., 2009; Beche and Resh, 2007; Bonada et al., 2007b). However, analyses testing for relevant biological responses to climate patterns often lacked spatial consistency both within and across states. This can be seen in the comparative results summarized in Tables 7-3 to 7-8 (original and more detailed results are presented by state in Sections 3 to 6). Temperature preference trait groups responded to temperature and precipitation or flow changes, albeit with regional variation (see Tables 7-5, 7-6, and 7-8). The number of warm-water taxa increased significantly over time at lower elevation locations in both Maine (site 56187—Sheepscot, site 57011—W. Br. Sheepscot) and Utah (site 4951200—Virgin), but not at all stations, and not in North Carolina (see Table 7-3). The response of warm-water taxa at the Maine stations appears consistent with climate change expectations, given the predominance of warm-water taxa coupled with the observed increasing temperatures over time. However, neither abundance nor richness of warm-water taxa was directly correlated with temperature at this station. The increasing temporal trend in warm-water taxa was corroborated by correlation with temperature in Utah, but not in Maine (see Table 7-4).

Cold-water taxa decreased over time at one of the higher elevation sites in Utah (site 4927250—Weber), and were also negatively correlated with temperature, as would be expected for a trait group responding to increases in temperature. Comparable associations with temperature were not found in Maine or North Carolina. The longest-term station in Maine (56817) occurred at a relatively low elevation, such that the number of cold-water taxa was very small. Therefore, even though the long data record and low variation made trends in this trait group significant, they are largely meaningless.

Table 7-3. Kendall tau nonparametric correlations analyses performed to examine associations between commonly used biological metrics and year at long-term reference sites from three states. Entries are in bold text if $r \geq \pm 0.5$ and are highlighted in gray if they are in a direction opposite of what is expected. SON = September, October, November

Biological metric	Utah				Maine			North Carolina
	4927250	4951200	4936750	5940440	56817	57011	57065	NC0109
No. cold-water taxa	**–0.50**	–0.33	–0.21	–0.46	0.27	–0.03	0.35	0.12
Percentage cold-water individuals	**–0.71**	–0.45	–0.12	–0.17	0.21	–0.42	0.06	0.05
No. warm-water taxa	–0.03	**0.67**	0.37	--	**0.63**	0.47	0.44	–0.46
Percentage warm-water individuals	–0.14	0.16	0.39	--	0.42	–0.33	–0.17	0.05
Total no. taxa	–0.10	–0.09	0.34	–0.26	**0.63**	**0.72**	0.39	–0.49
No. EPT taxa	–0.35	–0.32	0.05	–0.28	**0.58**	**0.58**	0.39	–0.02
No. Ephemeroptera taxa	–0.41	**–0.53**	0.13	–0.23	0.43	0.43	0.26	–0.06
No. Plecoptera taxa	**–0.62**	–0.44	–0.29	–0.46	0.09	0.18	0.30	0.43
No. Trichoptera taxa	–0.02	0.17	0.05	–0.10	**0.62**	**0.57**	0.17	–0.06
No. intolerant taxa	–0.37	–0.46	–0.30	–0.35	0.48	0.46	**0.61**	0.23
Percentage EPT individuals	0.00	0.01	–0.21	0.28	0.04	–0.33	–0.11	0.49
Percentage Ephemeroptera individuals	–0.37	0.27	0.00	0.28	0.30	–0.24	–0.17	0.38
Shannon-Wiener Diversity Index	0.13	–0.16	0.12	–0.06	**0.54**	0.12	0.22	–0.27
Percentage noninsect individuals	–0.06	–0.14	–0.06	0.11	0.32	0.36	**0.61**	–0.13
Percentage dominant taxon	–0.10	0.16	–0.18	0.28	–0.36	0.09	–0.39	0.09
Percentage tolerant individuals	0.19	0.20	0.22	–0.40	–0.06	0.15	–0.06	0.13
Hilsenhoff Biotic Index	–0.09	0.16	0.30	–0.33	–0.18	**0.58**	0.17	–0.42

Table 7-3. Kendall tau nonparametric correlations analyses performed to examine associations between commonly used biological metrics and year at long-term reference sites from three states. Entries are in bold text if $r \geq \pm 0.5$ and are highlighted in gray if they are in a direction opposite of what is expected. SON = September, October, November (cont.)

		Utah				Maine			North Carolina
	Biological metric	**4927250**	**4951200**	**4936750**	**5940440**	**56817**	**57011**	**57065**	**NC0109**
Richness	Collector filterer	–0.08	0.13	0.19	–0.22	**0.52**	0.25	0.15	**–0.58**
	Collector gatherer	–0.20	0.14	0.34	–0.22	0.27	**0.62**	0.38	**–0.58**
	Scraper/herbivore	0.00	–0.35	–0.03	–0.03	**0.54**	0.36	**0.80**	–0.14
	Predator	–0.18	–0.02	–0.03	0.03	0.36	0.34	0.20	–0.19
	Swimmer	–0.12	0.06	0.06	–0.07	0.41	**0.54**	0.13	0.12
	OCH	**0.56**	0.44	**0.77**	0.24	0.26	0.28	0.15	0.09
	Depositional	**–0.51**	–0.05	0.39	--	0.25	0.11	0.19	–0.33
	Erosional	–0.03	0.06	0.13	–0.15	**0.55**	0.44	0.20	0.12
Percentage individuals	Collector filterer	0.32	–0.25	–0.24	0.17	–0.23	0.36	0.11	0.35
	Collector gatherer	–0.35	0.05	–0.06	0.00	–0.02	0.06	–0.22	–0.42
	Scraper/herbivore	0.43	0.03	0.15	–0.39	**0.53**	–0.30	0.00	**0.60**
	Predator	–0.15	–0.45	–0.03	0.00	0.34	**–0.64**	0.00	–0.02
	Swimmer	–0.04	0.49	0.12	0.22	0.26	0.15	–0.17	0.38
	OCH	**0.53**	**0.50**	0.33	–0.44	0.12	–0.45	0.17	0.27
	Depositional	–0.36	0.16	0.40	--	0.10	–0.03	0.14	–0.24
	Erosional	0.34	0.08	0.06	0.00	–0.15	–0.21	0.17	0.45

Table 7-4. Kendall tau nonparametric correlations analyses performed to examine associations between commonly used biological metrics and temperature at long-term reference sites from three states. Entries are in bold text if $r \geq \pm 0.5$ and are highlighted in gray if they are in a direction opposite of what is expected. SON = September, October, November

Biological metric	Utah								Maine						North Carolina	
	4927250		4951200		4936750		5940440		56817		57011		57065		NC0109	
	PRISM mean annual	Obs mean max Jul	PRISM mean annual	Obs mean max Jul	PRISM mean annual	Obs mean max Jul	PRISM mean annual	Obs mean max Jul	PRISM mean annual	Obs mean max Jul	PRISM mean annual	Obs mean max Jul	PRISM mean annual	Obs mean max Jul	PRISM mean annual	Obs mean max Jul
No. cold-water taxa	**–0.57**	–0.36	–0.31	–0.29	–0.11	–0.31	0.03	0.29	0.23	0.07	0.20	0.20	–0.47	**–0.59**	–0.32	--
Percentage cold-water individuals	–0.46	–0.28	–0.36	–0.12	–0.21	0.15	–0.33	–0.21	0.18	0.05	–0.03	0.12	–0.33	–0.17	–0.27	--
No. warm-water taxa	-0.38	–0.22	0.42	0.19	–0.10	–0.10	--	--	0.16	0.26	0.26	0.32	**–0.61**	**–0.67**	–0.14	--
Percentage warm-water individuals	–0.15	–0.13	**0.56**	0.23	–0.13	–0.17	--	--	0.13	0.25	0.42	**0.52**	0.00	0.28	0.02	--
Total no. taxa	–0.32	–0.25	**–0.72**	–0.20	–0.09	**–0.56**	–0.15	0.11	0.18	0.24	0.05	0.20	–0.33	**–0.61**	0.15	--
No. EPT taxa	–0.45	–0.38	**–0.72**	–0.34	–0.18	**–0.53**	–0.40	–0.12	0.14	0.19	0.12	0.25	–0.44	**–0.61**	–0.13	--
No. Ephemeroptera taxa	**–0.55**	–0.38	**–0.79**	–0.44	–0.19	–0.29	–0.17	0.05	0.08	0.22	0.46	0.37	–0.44	–0.38	–0.15	--
No. Plecoptera taxa	**–0.51**	–0.44	**–0.56**	–0.09	0.19	–0.25	**–0.65**	–0.27	0.08	0.12	0.11	0.25	**–0.50**	**–0.50**	0.04	--
No. Trichoptera taxa	–0.23	–0.24	–0.24	–0.19	–0.02	**–0.73**	–0.03	0.05	0.15	0.11	0.05	0.14	–0.23	–0.40	–0.02	--
No. intolerant taxa	**–0.51**	–0.29	**–0.66**	–0.32	0.05	–0.14	–0.35	–0.15	0.14	0.11	0.09	0.25	**–0.61**	**–0.84**	0.23	--
Percentage EPT individuals	0.07	0.10	0.27	0.08	–0.06	–0.06	0.00	0.14	0.11	0.16	**0.55**	0.45	–0.17	0.11	–0.05	--

Table 7-4. Kendall tau nonparametric correlations analyses performed to examine associations between commonly used biological metrics and temperature at long-term reference sites from three states. Entries are in bold text if *r* ≥ ±0.5 and are highlighted in gray if they are in a direction opposite of what is expected. SON = September, October, November (cont.)

Biological metric	Utah								Maine						North Carolina	
	4927250		4951200		4936750		5940440		56817		57011		57065		NC0109	
	PRISM mean annual	Obs mean max Jul	PRISM mean annual	Obs mean max Jul	PRISM mean annual	Obs mean max Jul	PRISM mean annual	Obs mean max Jul	PRISM mean annual	Obs mean max Jul	PRISM mean annual	Obs mean max Jul	PRISM mean annual	Obs mean max Jul	PRISM mean annual	Obs mean max Jul
Percentage Ephemeroptera individuals	–0.36	–0.35	0.41	0.12	–0.15	–0.09	0.00	0.07	0.23	0.31	**0.52**	0.48	–0.22	0.06	–0.16	--
Shannon-Wiener Diversity Index	–0.04	0.03	–0.43	0.03	–0.03	**–0.52**	–0.33	–0.07	0.13	0.20	**0.45**	0.42	**–0.50**	**–0.56**	0.13	--
Percentage noninsect individuals	–0.02	0.04	–0.49	0.05	–0.21	–0.21	–0.06	0.07	–0.05	0.14	–0.14	–0.29	–0.11	–0.39	0.20	--
Percentage dominant taxon	–0.04	–0.06	0.34	–0.03	–0.15	0.39	0.22	0.14	0.00	–0.05	–0.30	–0.33	0.33	0.39	–0.24	--
Percentage tolerant individuals	0.00	–0.17	–0.20	0.04	–0.10	**–0.54**	–0.04	0.05	–0.01	0.13	–0.06	0.21	0.11	0.06	0.09	--
Hilsenhoff Biotic Index	–0.14	–0.16	–0.10	–0.12	0.15	0.21	0.28	–0.07	–0.11	–0.06	–0.24	–0.27	0.22	–0.06	0.13	--

Table 7-5. Kendall tau nonparametric correlations analyses performed to examine associations between commonly used biological metrics and precipitation at long-term reference sites from three states. Entries are in bold text if $r \geq \pm 0.5$ and are highlighted in gray if they are in a direction opposite of what is expected. SON = September, October, November

Biological metric	Utah						Maine				North Carolina
	4927250	4951200		4936750		5940440	56817	57011	57065		NC0109
	PRISM mean annual	PRISM mean annual	Observed SON	PRISM mean annual	Observed SON	PRISM mean annual	PRISM Mean annual	PRISM mean annual	PRISM mean annual	Observed SON	PRISM mean annual
No. cold-water taxa	–0.05	0.33	–0.17	0.31	0.11	0.03	0.24	–0.03	–0.18	0.00	**0.72**
Percentage cold-water individuals	–0.06	0.25	–0.16	0.12	0.39	0.44	0.21	0.03	0.00	–0.06	0.45
No. warm-water taxa	–0.02	–0.11	0.29	0.13	0.33	--	0.05	0.02	–0.15	–0.03	**–0.54**
Percentage warm-water individuals	–0.08	–0.32	–0.08	0.17	0.28	--	0.01	–0.06	–0.33	–0.61	–0.35
Total no. taxa	–0.16	0.32	–0.05	0.28	–0.09	–0.15	0.13	0.05	–0.11	0.17	**–0.60**
No. EPT taxa	–0.18	**0.57**	0.05	0.46	0.08	0.28	0.10	0.09	–0.22	0.06	0.17
No. Ephemeroptera taxa	–0.10	0.32	0.01	0.29	–0.03	–0.03	0.16	0.37	–0.15	–0.03	0.11
No. Plecoptera taxa	–0.15	0.36	–0.19	0.22	0.05	0.26	0.02	–0.18	–0.17	0.17	**0.51**
No. Trichoptera taxa	–0.02	0.38	0.40	0.28	0.02	0.03	0.03	0.08	–0.06	0.06	–0.06
No. intolerant taxa	–0.17	0.48	–0.11	0.21	0.11	0.12	0.26	–0.03	–0.03	0.26	0.08
Percentage EPT individuals	–0.21	0.10	–0.10	0.21	–0.06	0.11	–0.01	0.00	0.06	–0.33	**0.67**
Percentage Ephemeroptera individuals	0.07	0.05	–0.05	0.12	–0.27	0.00	0.17	0.27	–0.11	–0.39	**0.64**
Shannon-Wiener Diversity Index	–0.40	0.10	–0.36	0.30	–0.21	–0.11	0.12	–0.03	–0.17	0.33	**–0.67**
Percentage noninsect individuals	–0.41	0.25	–0.21	–0.18	–0.27	0.17	–0.04	–0.45	0.11	**0.50**	**–0.60**
Percentage dominant taxon	0.40	–0.01	**0.54**	–0.24	0.33	0.00	0.01	0.06	–0.11	–0.39	0.35

Table 7-5. Kendall tau nonparametric correlations analyses performed to examine associations between commonly used biological metrics and precipitation at long-term reference sites from three states. Entries are in bold text if *r* ≥ ±0.5 and are highlighted in gray if they are in a direction opposite of what is expected. SON = September, October, November (cont.)

		Utah						Maine				North Carolina
		4927250	4951200		4936750		5940440	56817	57011	57065		NC0109
Biological metric		PRISM mean annual	PRISM mean annual	Observed SON	PRISM mean annual	Observed SON	PRISM mean annual	PRISM Mean annual	PRISM mean annual	PRISM mean annual	Observed SON	PRISM mean annual
Percentage tolerant individuals		–0.04	0.00	–0.04	0.35	–0.03	–0.11	–0.15	0.00	–0.33	–0.17	–0.20
Hilsenhoff Biotic Index		0.18	0.03	0.27	–0.30	–0.21	–0.28	–0.14	0.06	–0.11	0.06	**–0.75**
Richness	Collector filterer	0.04	0.33	0.21	0.09	–0.26	–0.07	0.03	0.13	0.27	–0.03	–0.22
	Collector gatherer	–0.06	0.28	0.19	0.08	–0.08	–0.09	0.16	–0.15	–0.15	0.26	–0.31
	Scraper/herbivore	–0.09	0.35	–0.07	**0.57**	0.23	**–0.57**	0.08	–0.11	0.23	0.00	**–0.61**
	Predator	–0.12	0.15	–0.30	0.45	0.14	0.17	0.10	0.12	–0.31	0.03	**–0.69**
	Swimmer	0.03	0.19	–0.06	–0.42	–0.22	–0.37	0.14	0.29	–0.13	0.44	–0.16
	OCH	0.36	–0.01	–0.24	0.09	0.05	–0.35	0.09	0.15	–0.39	0.15	–0.02
	Depositional	–0.02	–0.09	–0.27	0.26	0.26	--	0.15	–0.39	–0.25	0.19	–0.06
	Erosional	–0.03	0.14	–0.01	0.30	0.00	0.03	0.06	0.14	–0.08	–0.03	0.08
Percentage individuals	Collector filterer	–0.18	0.32	–0.01	0.18	–0.09	0.00	–0.10	0.15	0.28	0.33	0.45
	Collector gatherer	0.26	0.36	0.30	–0.36	–0.03	0.06	0.18	0.09	**–0.50**	–0.33	0.13
	Scraper/herbivore	–0.10	–0.41	–0.34	0.39	0.18	–0.33	0.08	0.09	–0.06	–0.11	0.05
	Predator	–0.35	0.16	–0.12	–0.27	–0.36	0.39	–0.05	–0.12	0.06	0.00	**–0.56**
	Swimmer	–0.04	–0.08	0.08	–0.18	**–0.58**	0.06	0.08	0.24	0.00	–0.06	0.42
	OCH	–0.12	–0.17	0.10	0.23	0.07	–0.17	0.00	0.24	–0.33	0.28	–0.13
	Depositional	0.07	–0.32	–0.08	0.32	0.32	--	0.08	–0.12	–0.14	0.25	0.09
	Erosional	–0.28	–0.23	–0.16	0.24	0.09	–0.17	–0.11	–0.12	0.11	0.39	0.35

Table 7-6. Kendall tau nonparametric correlations analyses performed to examine associations between commonly used biological metrics and year and flow at long-term reference sites from three states. Entries are in bold text if $r \geq \pm 0.5$ and are highlighted in gray if they are in a direction opposite of what is expected. SON = September, October, November

Biological metric	Utah								Maine						North Carolina	
	4927250		4951200		4936750		5940440		56817		57011		57065		NC0109	
	Mean annual	Mean SON	Mean annual	Mean SON	Mean annual	Mean SON	Mean annual	Mean SON	Mean annual	Mean SON	Mean annual	Mean SON	Mean annual	Mean SON	Mean annual	Mean SON
No. cold-water taxa	0.19	0.14	--	--	--	--	–0.03	–0.15	0.14	0.03	–0.07	0.23	--	--	**0.76**	**0.68**
Percentage cold-water individuals	0.22	0.34	--	--	--	--	**0.56**	**0.56**	0.08	–0.03	–0.06	0.24	--	--	0.35	0.45
No. warm-water taxa	0.03	0.02	--	--	--	--	--	--	–0.02	–0.04	0.05	–0.11	--	--	**–0.54**	**–0.50**
Percentage warm-water individuals	–0.07	–0.01	--	--	--	--	--	---	–0.11	0.11	–0.15	0.09	--	--	–0.16	–0.42
Total No. taxa	0.01	–0.16	--	--	--	--	–0.20	–0.38	0.07	0.02	0.14	–0.11	--	--	**–0.67**	–0.45
No. EPT taxa	0.00	–0.05	--	--	--	--	0.15	0.03	0.01	–0.03	0.18	–0.12	--	--	–0.02	–0.06
No. Ephemeroptera taxa	0.16	–0.01	--	--	--	--	–0.17	–0.30	0.04	0.02	0.34	0.06	--	--	0.02	0.02
No. Plecoptera taxa	0.04	0.09	--	--	--	--	0.26	0.20	0.02	0.06	–0.25	0.04	--	--	0.23	**0.51**
No. Trichoptera taxa	–0.08	–0.10	--	--	--	--	–0.03	–0.17	0.04	–0.03	0.14	–0.29	--	--	–0.06	–0.26
No. intolerant taxa	0.05	–0.06	--	--	--	--	–0.06	–0.12	0.20	–0.04	–0.03	–0.06	--	--	0.08	–0.08
Percentage EPT individuals	–0.22	–0.25	--	--	--	--	0.56	0.33	–0.11	0.11	–0.09	0.15	--	--	**0.56**	**0.60**
Percentage Ephemeroptera individuals	0.26	0.26	--	--	--	--	**0.56**	0.22	0.10	0.01	0.18	0.18	--	--	**0.53**	**0.56**
Shannon-Wiener Diversity Index	–0.26	–0.47	--	--	--	--	–0.22	–0.22	0.07	0.01	0.00	0.00	--	--	**–0.71**	**–0.75**
Percentage noninsect individuals	–0.37	–0.34	--	--	--	--	0.39	0.06	–0.06	–0.09	–0.42	–0.20	--	--	**–0.71**	b

Table 7-6. Kendall tau nonparametric correlations analyses performed to examine associations between commonly used biological metrics and year and flow at long-term reference sites from three states. Entries are in bold text if *r* ≥ ±0.5 and are highlighted in gray if they are in a direction opposite of what is expected. SON = September, October, November (cont.)

		Utah								Maine						North Carolina	
		4927250		4951200		4936750		5940440		56817		57011		57065		NC0109	
Biological metric		Mean annual	Mean SON	Mean annual	Mean SON	Mean annual	Mean SON	Mean annual	Mean SON	Mean annual	Mean SON	Mean annual	Mean SON	Mean annual	Mean SON	Mean annual	Mean SON
Percentage dominant taxon		0.44	0.44	--	--	--	--	0.33	0.22	0.00	–0.05	0.03	–0.15	--	--	0.31	**0.56**
Percentage tolerant individuals		–0.17	–0.35	--	--	--	--	–0.04	–0.25	–0.22	–0.04	–0.03	0.21	--	--	–0.16	–0.05
Hilsenhoff Biotic Index		0.34	**0.51**	--	--	--	--	–0.39	–0.39	–0.10	–0.15	0.09	–0.27	--	--	**–0.56**	**–0.67**
Richness	Collector filterer	–0.08	–0.16	--	--	--	--	–0.15	–0.15	0.00	–0.09	0.25	–0.34	--	--	–0.26	–0.18
	Collector gatherer	0.13	–0.01	--	--	--	--	–0.09	–0.34	0.14	0.14	–0.06	0.00	--	--	–0.43	–0.31
	Scraper/herbivore	–0.06	–0.23	--	--	--	--	**–0.57**	**–0.70**	0.06	0.07	–0.11	–0.17	--	--	**–0.65**	**–0.65**
	Predator	0.07	–0.04	--	--	--	--	0.17	0.10	0.02	0.13	0.09	–0.03	--	--	**–0.72**	**–0.65**
	Swimmer	0.24	0.03	--	--	--	--	–0.45	**–0.60**	0.01	–0.15	0.32	0.00	--	--	0.00	–0.16
	OCH	0.09	–0.01	--	--	--	--	0.00	–0.35	0.14	0.21	0.09	–0.12	--	--	–0.17	0.17
	Depositional	0.25	0.16	--	--	--	--	--	--	0.00	0.01	–0.42	0.02	--	--	–0.25	–0.25
	Erosional	–0.16	–0.22	--	--	--	--	–0.03	–0.15	0.06	–0.07	0.17	–0.41	--	--	–0.04	–0.04
Percentage individuals	Collector filterer	–0.37	–0.34	--	--	--	--	–0.22	–0.11	–0.11	–0.13	0.24	–0.12	--	--	0.27	**0.53**
	Collector gatherer	0.49	**0.57**	--	--	--	--	0.17	0.17	0.15	–0.04	0.06	0.24	--	--	–0.05	0.05
	Scraper/herbivore	–0.26	**–0.53**	--	--	--	--	–0.44	–0.33	–0.02	0.05	0.00	0.06	--	--	0.24	0.20
	Predator	–0.28	–0.25	--	--	--	--	**0.61**	0.39	–0.11	0.19	–0.09	0.27	--	--	–0.45	**–0.71**
	Swimmer	0.12	0.06	--	--	--	--	**0.50**	0.28	–0.01	–0.13	0.21	0.15	--	--	0.38	0.27
	OCH	–0.32	**–0.55**	--	--	--	--	0.06	–0.17	0.06	0.27	0.15	0.33	--	--	–0.16	–0.13
	Depositional	0.23	0.14	--	--	--	--	--	--	–0.04	0.12	–0.15	0.21	--	--	–0.02	–0.05
	Erosional	**–0.50**	**–0.59**	--	--	--	--	–0.17	–0.28	–0.12	–0.04	–0.03	0.03	--	--	**0.53**	**0.56**

Table 7-7. Mean metric values (±1 SD) for sites in three states in coldest, normal, and hottest year samples. Year groups are based on PRISM mean annual air temperature values. One-way ANOVA was done to evaluate differences in mean metric values. Entries with superscripts have significant differences across year groups; those entries with different superscripts are significantly different from each other (e.g., coldest total no. taxa vs. normal and hottest total no. taxa)

Location	Year group	No. total taxa	No. EPT taxa	HBI	No. cold-water taxa	No. warm-water taxa	% cold-water individuals	% warm-water individuals
Utah								
4927250	Coldest	**27.5 ± 3.5**^{A}	**17.4 ± 2.1**^{A}		**4.9 ± 1.1**^{A}	2.3 ± 0.8	6.5 ± 5.4	0.6 ± 0.5
	Normal	**21.5 ± 7.8**^{AB}	**13.6 ± 4.9**^{AB}		**3.4 ± 1.1**^{A}	1.1 ± 0.7	6.7 ± 7.4	0.4 ± 0.3
	Hottest	**17.2 ± 3.3**^{B}	**8.8 ± 2.2**^{B}		**1.0 ± 0.7**^{B}	1.0 ± 1.2	1.0 ± 1.1	0.3 ± 0.4
4951200	Coldest	**22.8 ± 6.6**^{A}	**12.3 ± 3.9**^{A}		**4.5 ± 2.4**^{A}	**1.5 ± 0.6**^{A}	**15.7 ± 10.9**^{AB}	7.7 ± 6.7
	Normal	**19.8 ± 3.2**^{A}	**9.5 ± 2.6**^{A}		**5.3 ± 1.2**^{A}	**1.5 ± 0.8**^{A}	**23.4 ± 15.6**^{A}	18.1 ± 15.3
	Hottest	**14.5 ± 1.9**^{B}	**5.3 ± 1.5**^{B}		**0.8 ± 0.5**^{B}	**3.8 ± 1.3**^{B}	**0.2 ± 0.2**^{B}	27.8 ± 19.4
4936750	Coldest	22.3 ± 6.1	13.7 ± 3.2		6.3 ± 1.5	0.3 ± 0.6	24.3 ± 4.1	0.03 ± 0.1
	Normal	25.7 ± 4.0	15.5 ± 1.4		6.3 ± 1.0	0.7 ± 0.8	14.9 ± 6.8	0.1 ± 0.2
	Hottest	24.3 ± 8.7	14.0 ± 6.6		5.7 ± 2.9	0.7 ± 1.2	17.7 ± 8.5	0.1 ± 0.2
5940440	Coldest	23.0 ± 7.0	14.3 ± 4.0		4.0 ± 2.6	--	12.1 ± 6.2	--
	Normal	20.0 ± 2.6	12.7 ± 2.1		3.3 ± 0.6	--	10.0 ± 9.2	--
	Hottest	19.3 ± 3.5	11.0 ± 1.0		3.3 ± 1.2	--	8.4 ± 5.9	--
Maine								
56817	Coldest	20.9 ± 4.3	12.3 ± 2.6	4.0 ± 0.5	0.5 ± 0.5	6.7 ± 2.2	0.5 ± 0.6	15.1 ± 6.9
	Normal	20.8 ± 5.4	12.7 ± 3.7	3.9 ± 0.5	0.5 ± 0.8	7.1 ± 2.5	0.8 ± 1.7	17.7 ± 8.7
	Hottest	24.1 ± 3.8	14.3 ± 2.3	3.8 ± 0.4	1.0 ± 0.5	8.6 ± 2.5	0.9 ± 0.8	23.7 ± 14.4
57011	Coldest	21.7 ± 4.8	9.8 ± 1.3	5.0 ± 0.8	0.8 ± 0.3	6.4 ± 2.0	3.0 ± 5.2	23.5 ± 15.9
	Normal	24.1 ± 10.4	10.0 ± 3.7	3.9 ± 0.9	1.6 ± 0.6	7.3 ± 2.3	6.1 ± 6.0	50.0 ± 12.0
	Hottest	25.2 ± 3.4	11.5 ± 1.1	4.4 ± 0.4	1.2 ± 0.6	8.5 ± 1.6	1.9 ± 0.4	40.8 ± 12.8
57065	Coldest	22.1 ± 8.0	8.9 ± 2.6	4.3 ± 0.3	2.4 ± 1.2	6.3 ± 0.6	7.8 ± 6.4	44.0 ± 22.5
	Normal	21.7 ± 3.5	8.2 ± 1.8	5.1 ± 0.9	1.7 ± 0.3	6.8 ± 1.5	5.3 ± 5.9	32.8 ± 10.8
	Hottest	18.4 ± 3.7	6.8 ± 2.0	4.8 ± 1.3	1.6 ± 0.7	4.8 ± 1.3	5.0 ± 3.3	46.6 ± 17.6

Table 7-7. Mean metric values (±1 SD) for sites in three states in coldest, normal, and hottest year samples. Year groups are based on PRISM mean annual air temperature values. One-way ANOVA was done to evaluate differences in mean metric values. Entries with superscripts have significant differences across year groups; those entries with different superscripts are significantly different from each other (e.g., coldest total no. taxa vs. normal and hottest total no. taxa) (cont.)

Location	Year group	No. total taxa	No. EPT taxa	HBI	No. cold-water taxa	No. warm-water taxa	% cold-water individuals	% warm-water individuals
North Carolina								
NC0109	Coldest	86.0 ± 7.0	34.0 ± 1.7	4.5 ± 0.4	4.3 ± 1.5	8.3 ± 0.6	2.3 ± 0.7	7.7 ± 2.5
	Normal	84.2 ± 6.8	34.4 ± 3.8	4.2 ± 0.7	5.4 ± 1.7	7.4 ± 1.7	3.6 ± 2.9	7.6 ± 2.5
	Hottest	84.7 ± 21.5	34.3 ± 4.0	4.4 ± 0.5	4.0 ± 1.7	7.3 ± 2.3	2.2 ± 1.0	7.0 ± 1.3

Table 7-8. Mean metric values (±1 SD) for sites in three states in driest, normal, and wettest flow year samples. Year groups are based on mean annual flow values from USGS gages. One-way ANOVA was done to evaluate differences in mean metric values. Groups with no superscripts are not significantly different (p < 0.05). Bolded entries with superscripts have significant differences across year groups; those entries with different superscripts are significantly different from each other (e.g., lowest no. EPT taxa vs. highest no. EPT taxa)

Location	Year group	No. total taxa	No. EPT taxa	HBI	No. cold-water taxa	No. warm-water taxa	% cold-water individuals	% warm-water individuals
Utah								
4927250	Driest	21.0 ± 7.8	13.6 ± 5.4		2.6 ± 1.3	1.0 ± 0.7	3.7 ± 4.5	0.4 ± 0.3
	Normal	22.5 ± 7.1	12.6 ± 5.0		2.9 ± 2.3	1.7 ± 1.1	2.9 ± 2.6	0.5 ± 0.4
	Wettest	22.3 ± 6.6	14.0 ± 4.8		4.1 ± 1.5	1.5 ± 1.2	9.1 ± 8.8	0.4 ± 0.4
4951200	Driest	16.8 ± 2.5	**6.3 ± 1.7**^{A}		2.5 ± 2.4	3.0 ± 1.8	7.1 ± 8.9	17.9 ± 10.0
	Normal	18.3 ± 3.9	**8.7 ± 2.5**^{AB}		4.2 ± 2.1	1.5 ± 0.8	20.7 ± 18.1	24.9 ± 20.5
	Wettest	14.5 ± 7.3	**12.5 ± 4.7**^{B}		4.5 ± 3.1	2.3 ± 1.3	12.8 ± 13.4	7.4 ± 5.4
4936750	Driest	20.7 ± 3.2	12.3 ± 2.1		5.0 ± 0.8	0.5 ± 0.6	**11.2 ± 6.3**^{A}	0.05 ± 0.1
	Normal	24.8 ± 6.1	15.0 ± 4.2		6.8 ± 2.2	0.5 ± 1.0	**23.4 ± 3.1**^{B}	0.10 ± 0.2
	Wettest	27.7 ± 5.1	16.3 ± 1.5		6.8 ± 0.9	0.8 ± 1.0	**19.3 ± 6.6**^{AB}	0.15 ± 0.3
5940440	Driest	19.3 ± 0.6	11.3 ± 0.6		3.0 ± 1.0	--	5.3 ± 2.1	--
	Normal	23.3 ± 7.5	13.7 ± 4.7		4.3 ± 2.5	--	10.9 ± 6.8	--
	Wettest	19.7 ± 2.9	13.0 ± 1.7		3.3 ± 0.6	--	14.4 ± 7.4	--
Maine								
56817	Driest	22.2 ± 4.4	13.4 ± 3.0	3.9 ± 0.5	0.7 ± 0.5	8.0 ± 2.4	0.7 ± 0.5	22.4 ± 13.9
	Normal	20.9 ± 2.8	12.6 ± 2.3	3.9 ± 0.4	0.4 ± 0.4	6.8 ± 1.8	0.2 ± 0.3	16.4 ± 8.1
	Wettest	22.7 ± 6.9	13.3 ± 4.1	3.9 ± 0.5	0.9 ± 0.9	7.7 ± 3.3	1.4 ± 1.9	18.1 ± 9.8

Table 7-8. Mean metric values (±1 SD) for sites in three states in driest, normal, and wettest flow year samples. Year groups are based on mean annual flow values from USGS gages. One-way ANOVA was done to evaluate differences in mean metric values. Groups with no superscripts are not significantly different (*p* < 0.05). Bolded entries with superscripts have significant differences across year groups; those entries with different superscripts are significantly different from each other (e.g., driest no. EPT taxa vs. wettest no. EPT taxa) (cont.)

Location	Year group	No. total taxa	No. EPT taxa	HBI	No. cold-water taxa	No. warm-water taxa	% Cold-water individuals	% Warm-water individuals
57011	Driest	26.3 ± 6.2	10.8 ± 2.4	4.3 ± 0.9	1.3 ± 0.3	7.9 ± 2.5	2.3 ± 1.3	43.0 ± 24.3
	Normal	20.5 ± 5.6	9.3 ± 2.2	4.5 ± 1.2	1.1 ± 0.7	6.9 ± 1.7	4.4 ± 7.2	32.8 ± 15.6
	Wettest	24.2 ± 7.7	11.3 ± 2.4	4.5 ± 0.5	1.2 ± 0.8	7.3 ± 2.3	4.2 ± 4.5	38.5 ± 12.0
57065	Driest	20.3 ± 6.5	8.0 ± 2.6	4.8 ± 1.3	2.4 ± 1.2	6.1 ± 0.5	7.5 ± 6.7	56.1 ± 16.0
	Normal	23.4 ± 6.0	8.1 ± 3.0	4.7 ± 0.3	1.6 ± 0.7	6.1 ± 2.5	3.1 ± 1.0	28.1 ± 3.8
	Wettest	18.4 ± 2.2	7.8 ± 1.3	4.7 ± 1.2	1.7 ± 0.3	5.7 ± 0.9	7.6 ± 5.3	39.1 ± 15.1
North Carolina								
NC0109	Driest	95.0 ± 11.1	33.7 ± 1.5	4.7 ± 0.7	4.0 ± 1.0	**9.3 ± 1.2**^{A}	2.7 ± 1.5	8.0 ± 3.0
	Normal	79.4 ± 8.8	33.0 ± 3.0	4.2 ± 0.3	4.6 ± 1.3	**6.6 ± 0.9**^{B}	2.0 ± 0.9	6.7 ± 1.2
	Wettest	83.7 ± 10.0	37.0 ± 3.5	4.2 ± 0.9	5.7 ± 2.5	**7.7 ± 1.5**^{AB}	4.5 ± 3.3	8.2 ± 2.4

For Maine and North Carolina, abundance or richness of cold-water taxa was more often related to precipitation (see Table 7-5), though trends were not always significant. While long-term increasing trends in temperature already can be demonstrated for many regions (see Sections 3.1, 4.1, 5.1, and 6.1), this is seldom the case for precipitation or flow-related variables. Long-term data for flow (e.g., IHA) variables tend to be scarcer; and climate change projections for precipitation are variable among regions. Nevertheless, the importance of ongoing changes in precipitation and its effects in combination with temperature on flow regime should not be discounted.

Several biological metrics, evaluated for differences between years partitioned based on temperature (hottest/coldest/normal years) or precipitation (wettest/driest/normal years) regime, showed patterns in one or another state, but only a few showed statistically significant patterns at sites in more than one state, and none showed common patterns among all states. Overall, more metrics were significantly associated with temperature-related variables than with precipitation variables (see Tables 7-7 and 7-8).

Results of ANOVA testing for differences in ecological trait and scenario metrics between year groups representing surrogates of future climate condition also varied among sites. At Utah Stations 4927250 (Weber) and 4951200 (Virgin), hottest-year samples had significantly fewer cold-water taxa than coldest-year samples (see Table 7-7). The greatest differences generally occurred between hottest- and coldest-year samples, while normal-year samples were variable. Warm-water taxa showed even fewer responses, increasing during hottest years only at Colorado Plateau station 4951200 (Virgin) of the four reference stations tested (see Table 7-7). Cold-water taxa were least abundant during the driest years and more abundant during wet or normal years at Utah Station 4936750 (Duchesne), but did not respond differently among wettest, driest, and normal years for other Utah stations (see Table 7-8). In contrast to Utah, in Maine, there was greater response to wet/dry years than to temperature differences. Cold-water taxa, which were present in low numbers at the sites evaluated, were slightly more abundant and diverse during wet years at the longest-term reference station (Sheepscot), though warm-water taxa showed no response to a range of annual precipitation (see Table 7-8). No significant responses of cold-water taxa over time or to temperature or precipitation were found at the few other reference stations that could be tested (see Table 7-8).

Other biological metrics that were sometimes responsive to climate variables include functional feeding groups (e.g., predators, collector-filterers) or life history habits (e.g., swimmers, climbers). Feeding, life habit, and other functional trait groups are often included as metrics in state multimetric indices (MMIs). It is, thus, recommended that, on a case by case basis, the vulnerability of this class of metrics be evaluated through trend and correlation analysis, as well as through assessment of composition by temperature sensitive taxa.

The abundance and richness of EPT taxa and of subsets of this taxonomic group also were responsive to variations in climate variables. In Utah, the richness of EPT and some component taxa decreased with year and/or with temperature at one or two of the stations tested, but not at Maine or North Carolina locations (see Table 7-5). In contrast, EPT taxa increased with increasing precipitation at one Utah station. In North Carolina, EPT taxa also increased with increasing precipitation. At one station in Maine (5011), the abundance of EPT taxa increased with increasing temperature. This would be counter to expectations if increasing temperatures are equated with increasing stress; however, this followed the increase in warm-water taxa at this location, and many abundant EPT taxa at this location are warm-water taxa (see Table 4-9). EPT taxa are generally considered sensitive and are included in many state condition indices and models. However, it appears possible from our study results that at least some portions of the increases or decreases seen in richness or abundance of EPT taxa with year, temperature, or precipitation may be related to increases or decreases in the cold or warm-water EPT taxa that are included in the metric. Given that we consistently found a moderate relationship between temperature sensitivity and sensitivity to organic pollution, it is also possible that some of the observed responses are related to pollution stress. This aspect of confounding was controlled to the extent possible through use of only reference stations. However, a few of the stations analyzed had levels of urban and/or agricultural land uses that would suggest possible impact (e.g., all three Maine stations).

Our spatially variable results raise the question of how widely applicable our study results are to the regions within which the long-term stations occurred, and across regions and states. Overall, spatial consistency in biological responses could be used as evidence that a particular trend or relationship is real and widely occurring. It would add strength to making regional inferences regarding particular biological responses or the value of particular indicators or climate change responses, even though the underlying station selection process was not random, meaning that the regional representativeness of results at the individual long-term stations cannot be determined. To decide how these results can be interpreted with regard to the climate change vulnerabilities of biomonitoring programs and possible adaptations, it is important to consider several contributing reasons for the inconsistencies. These include intrinsic data limitations, other contributing or confounding factors, and differences in regional characteristics that can alter the influence of climate variables.

The ecological traits of temperature and hydrologic preferences or sensitivities (e.g., Poff et al., 2006b) provide the most direct link to climate impacts. Other traits such as feeding types, habit, or morphology are also important, but defining expectations for responses to the effects of climate change is more challenging. For example, responses of some feeding types to climate change may be indirect through effects on food resources (phytoplankton, periphyton, allochthonous organic matter) (e.g., Hargrave et al., 2009; Montes-Hugo et al., 2009; Moline et al., 2004; Tuchman et al., 2002). This study evaluated many traits and trait suites for relationships to climate change effects, though not all potentially relevant and fruitful analyses were possible due to limitations of the available biomonitoring data.

Grouping macroinvertebrates based on temperature preferences and tolerances is expected to (1) have a greater chance of detecting temperature-related climate change effects if they exist, (2) be interpretable with regard to causal relationships, (3) offer predictive ability and transferability to other regions, and (4) serve as a basis for developing adaptive responses (Verbeck et al., 2008a, 2008b; Poff et al., 2006b; Lamouroux et al., 2004).

7.2.2. Factors Contributing to Spatial Variability in Observed Biological Responses

We found differences in the distributions of thermal preference taxa between ecoregions, largely related to elevation differences, in all states tested. In Utah, distributions of the cold-water-preference taxa were significantly higher in the Wasatch Uinta ecoregion and at higher elevation sites (see Section 3.7). Sites in the Colorado Plateau ecoregion and at lower elevations had significantly more warm-water taxa, but numbers of warm-water taxa were low at the Utah reference sites. In Maine, the Northeastern Highlands sites had the highest mean number of cold-water taxa, followed closely by the Northeastern Coastal Zone sites (see Section 4.7). Overall, the number of cold-water taxa in all the Maine ecoregions evaluated was low (1 to 2 taxa). The mean number of warm-water-preference taxa at sites in the Laurentian

Plains and Hills was significantly higher than at sites in other ecoregions, while the Northeastern Highlands sites had the lowest mean number of warm-water-preference taxa. These observed ecoregional differences appear to be driven by elevation: there are more cold-water taxa at higher elevation (>150 m) sites and more warm-water-preference taxa at lower elevation (<150 m) sites. Although it was originally assumed that the high (northern) latitude of Maine also would influence composition by cold-water taxa, apparently elevation is a more influential factor. In North Carolina, ecoregions also vary in the predominance of cold and warm-water taxa. The richness of cold-water taxa is, on average, higher in the Mountain ecoregion than in the other two ecoregions (see Section 5-7). The distribution of warm-water taxa is significantly different between all three ecoregions, with the highest abundance occurring in the Coastal ecoregion and the lowest number occurring in the Mountain ecoregion. This distributional pattern is reinforced by the finding that significantly more cold-water taxa occur at higher elevation sites than at lower elevations. Conversely, median richness and abundance of warm-water taxa is greater at lower elevation sites.

The prevalence and distribution of cold and warm-water taxa also varied predictably with stream order. First- and second-order streams in Utah had slightly greater relative abundance and richness of cold-water taxa, and fewer warm-water taxa, compared to third- or higher-order streams. These results suggest that effects are likely to vary spatially within states, reflecting spatial differences in vulnerabilities. Biotic assemblages in the Wasatch and Uinta Mountains and at higher elevations may be more vulnerable to the increasing temperatures that are predicted to occur. On the other hand, many of the higher elevation stations evaluated in Utah were also mid-order streams, and may not contain the greatest proportion of cold-preference taxa, but may represent transitional areas to higher elevation headwater reaches that may be vulnerable if they harbor taxa near thermal thresholds.

As observed in Utah, first- and second-order streams in Maine had slightly greater relative abundances and richness of cold-water-preference taxa, while fourth- and higher-order streams had more warm-water-preference taxa. Third-order streams appeared transitional in temperature preference composition. Based on the distribution of cold-water-preference taxa, it might be expected that biotic assemblages at Northeastern Highland and other higher elevation locations, especially in lower-order streams, will be more vulnerable to increasing temperatures. Unfortunately, none of the reference sites located in the Northeastern Highlands have enough long-term data to support trend analyses. The three reference sites that had enough data to analyze were located in the Laurentian Plains and Hills and Northeast Coastal Zone ecoregions and were dominated by warmer-water-preference taxa.

Distribution of cold and warm-water taxa was also related to watershed size. The smaller watersheds in North Carolina (<35 mi^2) had a greater proportion of cold-water taxa (based on both abundance and richness), while larger watersheds (>100 mi^2) had a greater proportion of warm-water taxa (see Section 5-7). Based on the results from the cold- and warm-water taxa distribution analysis, it is likely that biotic assemblages at Mountain and higher elevation sites, and in smaller watersheds, will be more vulnerable to increasing temperatures than other North Carolina sites because greater numbers of cold-water taxa inhabit these sites. However, in North Carolina, few trends over time were found for cold or warm-water taxa. This may be attributable to the more limited time series of data available from North Carolina (see Section 7.3.1), as well as to the use of categorical rather than abundance data (though this would not affect evaluation of richness trends).

Despite the spatial variability of results, this study supports the concept that not all regions are equally threatened or responsive to climate change. There is regional variability in climate combined with spatial variability in vulnerability[9] and resilience of the affected aquatic ecosystems. Many factors can influence susceptibility to changing water temperature or hydrologic regime from climate change, such as elevation (Chessman, 2009; Diaz et al., 2008; Cereghino et al., 2003), and stream order (Cereghino et al., 2003; Minshall et al., 1985) as observed in our study results, as well as other factors such as degree of ground water influence, or factors that affect water depth and flow rate, such as water withdrawals (Chessman, 2009; Poff et al., 2006a; Poff, 1997).

7.2.3. Benthic Inferred Temperature

We calculated benthic inferred temperatures for three sites—the Weber River site (UT 4927250) in Utah, the Sheepscot River site (ME 56817) in Maine, and the New River site

[9]Vulnerability is generally defined as a combination of exposure (e.g., the expected climate changes in temperature and precipitation); sensitivity or the degree of responses to the exposures; and resilience or ability of the communities (or habitats) to adapt and cope with the exposures and responses (see also Poff et al., 2010). We refer to the vulnerability of the habitat (features of the natural landscape), as well as the vulnerability of the biotic communities. Vulnerability can be thought about on different scales, e.g., the biological assemblage as a whole, individual species, particular sites, stream types, etc.

(NC0109) in North Carolina. These sites had the most number of years of biological data. Benthic inferred temperature is based on relative abundance and temperature optima data for macroinvertebrate taxa that occur in each sample. To make the calculation, the temperature optima values for each taxon are multiplied by the relative abundance of that taxon, then the products of those calculations are summed over all taxa in the sample and divided by the summed relative abundances of all the taxa in the sample. The temperature optima values used in these calculations were derived from weighted averaging or maximum likelihood modeling on appropriate subsets of the state biomonitoring data, as described in Section 2.2.1.

We calculated benthic inferred temperatures at these sites to evaluate how closely trends in benthic inferred temperatures tracked observed changes in air temperature over the period of biological record. In addition to direction and amount of change over time, actual temperature values were also important. We compared benthic inferred temperatures to air temperature measurements because the air temperature measurements were derived from independent data sets[10]. Thus, it provided a way to "test" how well thermal optima calculations captured changes in observed temperatures over the time periods being evaluated.

To make these comparisons, we plotted benthic inferred temperature and air temperature measurements versus year. At the Weber River site (UT 4927250), we compared benthic inferred temperature to observed mean September/October air temperature values from the nearest weather station[11] and to PRISM mean annual air temperature. At the Sheepscot River site (ME 56817), we compared benthic inferred temperature to observed mean July/August air temperature values from the nearest weather station[12] and to PRISM mean annual air temperature. At the New River site (NC0109), we were limited to comparing benthic inferred temperature to PRISM mean annual air temperature; temperature data from the nearest weather station was not available for the period of biological record. We also experimented with

[10]The thermal optima calculations are based on instantaneous water temperature measurements that were taken at the time of the biological sampling event.

[11]We chose this time period because the thermal optima calculations in Utah are based on a subset of fall data. We did not include November air temperatures in our comparison because the November biological sampling events took place early in the month. Plus the inclusion of November temperatures would have substantially changed the observed air temperature values, because on average, November air temperatures are ≥10°C lower than September and October temperatures.

[12]We chose this time period because the thermal optima calculations in Maine are based on a subset of data collected from July−September. We did not include September air temperatures in our comparison because the September collection events took place early in the month. Plus the inclusion of September temperatures would have substantially changed the observed air temperature values, because on average, September air temperatures are approximately 5°C lower than July and August temperatures.

grouping data from multiple sites (Weber River—UT 4927250; Virgin River—UT 4951200; Duchesne River—UT 4936750) on the same plot to evaluate how site-specific differences can influence overall trends in benthic inferred temperature.

Results show that benthic inferred temperatures are less variable than seasonal and annual air temperature; and when they do change, they vary on a much smaller scale (generally less than 1°C) (see Figure 7-1). Unless there is a large shift in the composition of the assemblage towards cold or warm-water taxa, as reflected in the thermal optima values of the taxa, benthic inferred temperatures will stay relatively stable over time, so this is not unexpected. In general, patterns in the benthic inferred temperatures track fairly closely with patterns in the seasonal air temperature data, although during some years, there appears to be a lag effect in the biological data (see Figure 7-1). At both the Sheepscot River site (ME 56817) and the Weber River site (UT 4927250), benthic inferred temperature values are similar to the observed seasonal temperature values (see Figure 7-1).

The PRISM mean annual air temperature values are lower than the benthic inferred temperatures at all three sites (see Figure 7-2). At the Sheepscot River site (ME 56817) and the Weber River site (UT 4927250), mean annual air temperature, which is less variable than the seasonal air temperatures, varies by greater amounts than the benthic inferred temperatures, while at the New River site (NC0109), benthic inferred temperatures are more variable (see Figure 7-2). Our evaluation of trends in benthic inferred temperatures at the Weber River site (UT 4927250) and the New River site (NC0109) was hindered by gaps in the biological data. At all sites, our trend analyses were somewhat limited by the relatively short time period for which biological data are available.

Site-specific differences were evident (i.e., the overall trend line is not very reflective of the trend that occurred at the Weber River site [UT 4927250]) in the three Utah sites (see Figure 7-3). The overall benthic inferred temperature trend for these Utah sites was equivalent to a rate of increase of approximately 3^{o}C in 25 years. This corresponds well with the magnitude of air temperature increases observed for the period, suggesting that the estimates of benthic invertebrate temperature optima were generally appropriate, and that using benthic invertebrate occurrence and abundance coupled with temperature preferences provides evidence of benthic community changes over time related to long-term changes in temperature. With a large enough

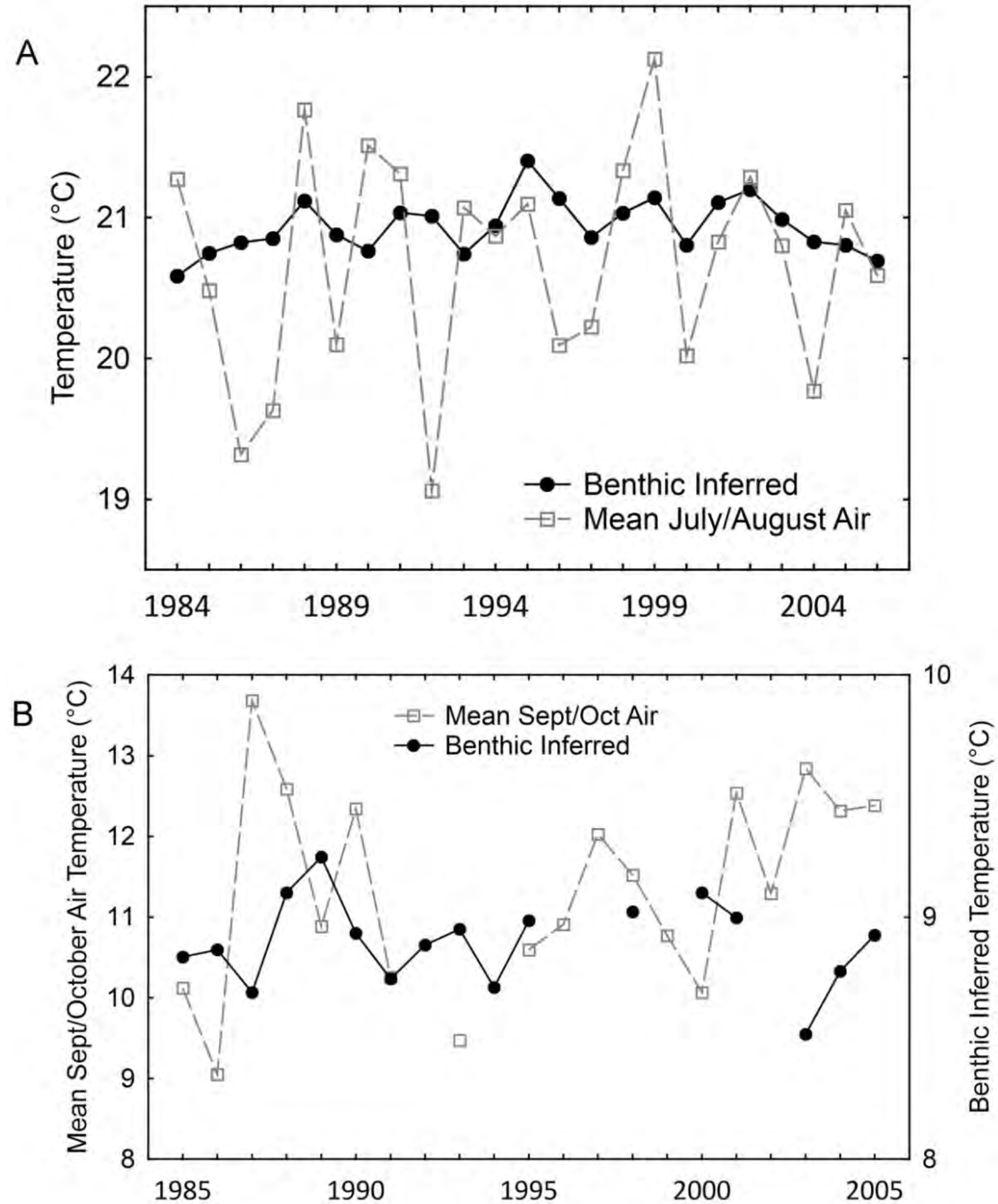

Figure 7-1. Comparison of trends in benthic inferred temperature and seasonal observed air temperatures at (A) the Sheepscot River site (ME 56817); and (B) the Weber River site (UT 4927250).

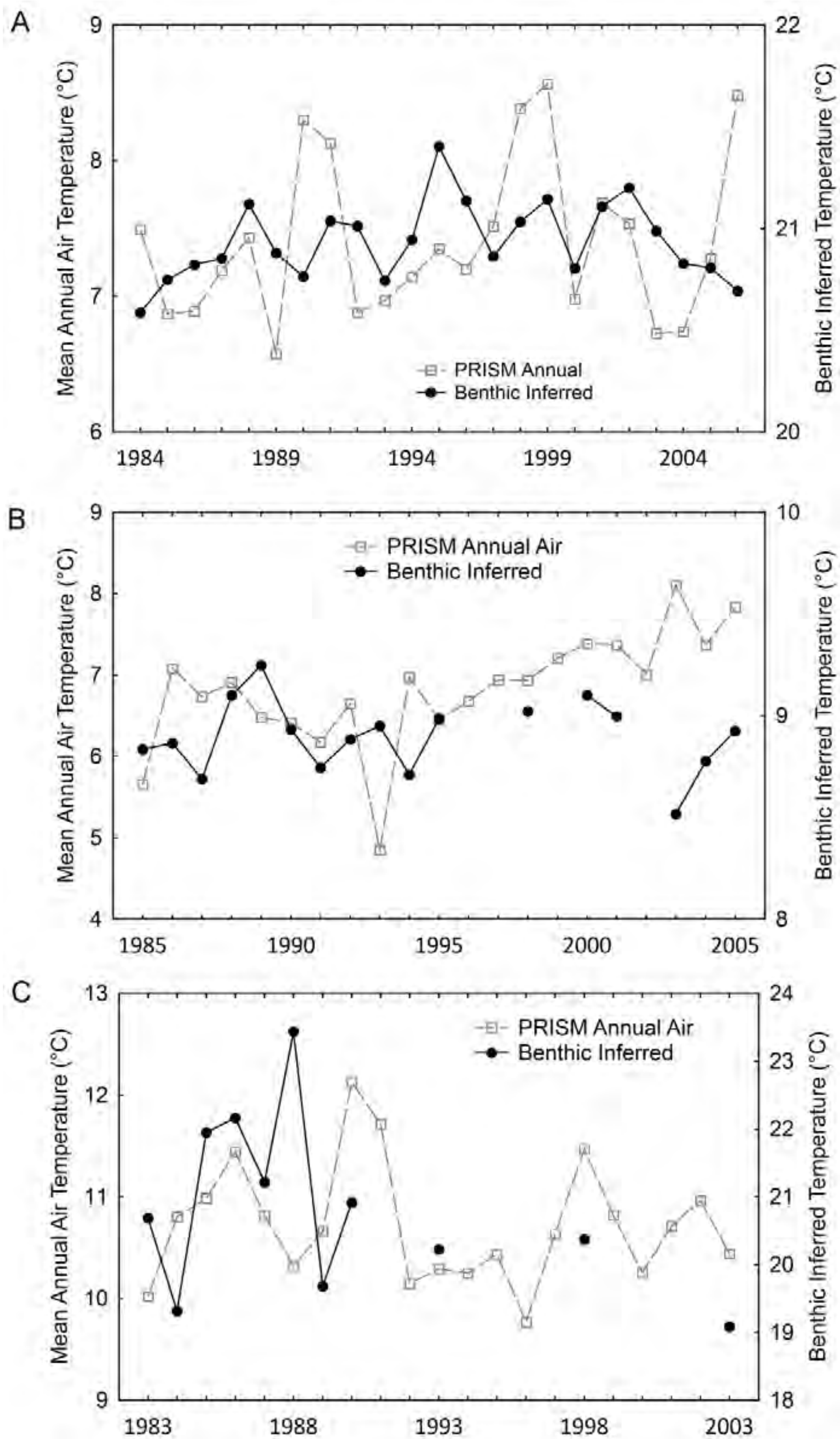

Figure 7-2. Comparison of trends in benthic inferred temperature and PRISM mean annual air temperatures at: (A) the Sheepscot River site (ME 56817); (B) the Weber River site (UT 4927250); and (C) the New River site (NC0109).

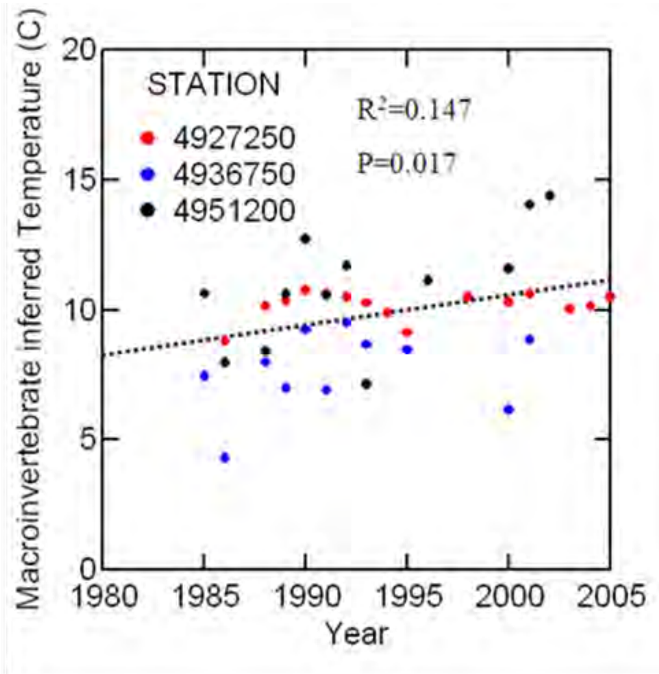

Figure 7-3. Benthic macroinvertebrate inferred temperature trend for selected reference sites in Utah. Only samples collected in October and November were used in these calculations.

data set, this type of analysis could be informative of long-term trends that are more widely applicable than our analyses that were limited to data from single sites.

7.2.4. Basis for Inferring Climate Change Associations

Biological data reflect responses to interannual variations (e.g., year-to-year variations in temperature, precipitation regime, etc.) and to multiyear to multidecadal "cyclic" climate variations, such as the NAO, the Pacific Decadal Oscillation (PDO), or the El Niño Southern Oscillation (ENSO) that drive differences in water temperature and hydrologic regimes in a manner similar to the mechanisms linking to long-term climate change responses. The NAO, for example, affects mainly winter weather conditions on decadal time scales (Hurrell, 1995). The PDO, which influences western and southwestern regions, is generally considered to be a much longer term, multidecadal phenomenon (Brown and Comrie, 2004; Mantua et al., 1997), while ENSO is found to vary in the range of multiple years to a decade or more (e.g., Brown and Comrie, 2004).

A rigorous approach, were it supported by available data, could examine what components of observable temporal variation in biological responses are attributable to long-term directional climate change, and then apply general linear modeling or another comparable approach to partition the variation within the observed biological responses between interannual or cyclic and long-term directional climatic sources. However, most state biomonitoring data sets, even the most critically developed (sensu Yoder and Barbour, 2009) and long term, such as those analyzed in these pilot studies, are limited in duration and frequency of sampling. These data are not able to support linear modeling, especially of several separate variables, because the average scope of available data is typically 20 years or less, with 10 to fewer than 20 annual data points over that time span. We explored an alternative analysis, examining correlations between indices of known cyclic climatic variation (e.g., the NAO, PDO, and ENSO) with biological metrics, focusing on those that also showed long-term temporal responses, as well as correlations with temperature or precipitation[13]. In general, responses varied by state and region, but most of the results were weak or not significant. In Utah, there were some intriguing relationships found at individual long-term reference stations between trait groups (e.g., warm-water-preference taxa, perennial taxa) and either the ENSO or PDO annual or monthly indices. However, none of these were consistent spatially; therefore, no particular trait or taxonomic group is a strong indicator of PDO or ENSO responses. The complexity of the patterns compared to the relatively short (20 years or fewer) data sets suggests the importance of further investigation and long-term monitoring, including further study on the relative contributions of each index.

While it is important to consider NAO, PDO, and/or ENSO when evaluating biomonitoring (or any other) data sets for climate change effects, there are still some practical limitations, particularly in the biomonitoring application. Analyses would require data spanning multiple (2−3) multidecadal cycles to be able to model the cycle-associated responses and extract the residual long-term trend on a rigorous basis. The Maine Station 56817 (Sheepscot) data series spanned 23 years, and this is long compared to most existing available biomonitoring data. It also is likely that variations in the effects of the NAO interact with long-term climate change effects, potentially damping increasing temperatures in negative years and augmenting them in positive years (Durance and Ormerod, 2007). This is important, because the composite of

[13]Detailed results are available upon request.

climate effects may underestimate long-term climate impacts during some periods, or overestimate them during others. It would take proportionately more (longer-term) data to separate these and confidently define the long-term climate change component.

Because the nature of most bioassessment data limit the ability to separate the magnitude of observed trends among interannual, cyclical, and long-term directional climate effects, the results obtained in this study cannot be interpreted as entirely attributable to directional climate change. However, the net response of benthic or other aquatic community metrics to climate sensitive variables, including water temperature and hydrologic patterns, can reasonably and effectively be used to address the primary questions of this study. The direction and nature of the observed climate responses can be applied to characterize the types of responses that can be expected due to climate change, to identify the most sensitive indicators to climate change, and to understand implications to multimetric indices or predictive models and their application by managers to characterize the condition of stream resources for decision making. These effects may be viewed in some respects as maximum estimates of probable effects, because multiple components of climate change could be included, though at times, the resulting estimates may also be undervalued.

7.2.5. Other Sources of Potential Spatial Confounding

There are other potential sources of spatial confounding of temporal trends, which were tested in this study. Land use and land cover within a 1-km buffer of individual reference sites indicated that anthropogenic influences were higher than desired (>5% urban or >10% agricultural) at most sites. Though stations were initially screened at 1, 2, and 5% urban, and 5 and 10% agricultural land use levels, final levels applied were 5% urban/10% agricultural in Maine and North Carolina, and 2% urban/10% agricultural in Utah, based largely on the practical need to not eliminate all stations with data that could be used for long-term analyses. The urban land uses surrounding these sites generally consisted of low-intensity and open-space development, and the agricultural land uses were mostly pasture/hay, with occasional cultivated crops. Although higher than considered desirable for reference conditions, these final land use criteria are more conservative than those used in several states. Georgia, Alabama, and South Carolina apply land use criteria for selecting reference stations of <15% urban/<20% agricultural for high gradient streams, and <15% urban/<30% agricultural in low gradient streams (Barbour and Gerritsen, 2006). It will take additional analysis to determine on an objective level whether these criteria are adequate to minimize confounding of climate change effects.

It is reasonable and sometimes necessary to use less than "natural" conditions as a baseline for spatial comparisons. For example, accessibility of a site for frequent (e.g., annual) long-term sampling can be an important practical consideration. For example, the longest term reference station in Maine, 56817 (Sheepscot), is generally (though not always) categorized as an "A" station by Maine DEP, but is surrounded by about 16 urban and 23% agricultural land uses. Though higher than would be considered ideal for "unconfounded" analyses, the level of urban land use was stable over time (at about 16%), although forested conditions decreased from 84 to 57%, while agricultural land use increased 0 to 23%. At Maine's Station 57065, there was an increase from 0 to 16% urban land use, but a decrease from 4 to 0% agricultural land use. At Maine's Station 57011, urban land use increased from about 4 to 9%, and agricultural use from 0 to 18.5% with the changes coming from both forested and wetland uses. It is possible that such land use changes may have contributed to trends observed at these sites. It is recommended for all sampling stations, but especially for reference stations, that quantification of land-use categories be documented. This will support tracking changes in land uses over time (although land-use data are often only available at infrequent intervals), which will aid in separating this from degradation due to climate change effects (and other stressors).

We further explored these relationships by using correlation analyses to determine whether any available chemistry and habitat variables were significantly correlated with biological metrics. Data availability limited this pursuit. For example, Utah only had chemistry data. At two of the Utah long-term reference stations (Stations 5940440—Beaver and 4936750—Duschesne), some of the temperature preference metrics were significantly correlated with water chemistry variables (see Sections 3.6.3.1 and 3.6.4.1). Many of the correlations were driven by outliers, but a few of the water chemistry variables, notably chloride, may have influenced trends in the biological assemblage. Chloride could be an indirect indicator of human development, as increases are sometimes associated with increasing road development and/or increasing application of road salt over time (TRC, 1991). However, chloride concentrations may also vary naturally with drought conditions.

In Maine, limited chemistry and habitat information were available (mainly in situ water quality measurements and visual substrate estimates). At Site 56187 (Sheepscot), yearly trends in the biological data were likely influenced by nonpoint-source pollution (Maine DEP, personal communication), but we lack the long-term chemistry data necessary to confirm this possibility. Some of the habitat variables at Site 56817 also showed trends over time. Percentage boulders and percentage gravel were significantly correlated with some of the biological variables. However, based on conversations with Maine DEP, it appears that this "trend" actually reflects observer bias, and it is not considered a real change over time in substrate characteristics. A similar example occurred in North Carolina, where visual substrate estimates for one site showed a fairly dramatic yearly trend. Scientists at NCDENR believe this also to be observer bias. More problematically, there were some fairly dramatic trends in canopy cover and water chemistry found at some North Carolina sites, which turned out to be due to data entry errors. This seems a minor but important cautionary note, as the "false" trend in canopy cover seemed feasible (increasing cover over time would be possible if there were an earlier instance of logging), and a (nonsignificant) trend of decreasing water temperature over time appeared to be logically consistent with increasing canopy cover. In the end, this very "appealing" discovery was false.

7.3. CHARACTERISTICS OF EXISTING BIOASSESSMENT PROGRAMS RELEVANT TO DISCERNING CLIMATE CHANGE TRENDS

There are some inherent qualities of biomonitoring data that limit the ability to define long-term trends, and to consider results representative of larger regions. We discuss these limitations in the context of existing program objectives and understanding how biomonitoring programs are likely to be affected by climate change in the future.

7.3.1. Sufficiency and Limitations of Data to Define and Partition Long-Term Trends

State and tribal bioassessment programs establish reference stations across their jurisdictions for reference-based comparisons to assess condition, detect impairment, and identify causes. The main objectives of these programs focus on spatial comparisons, and program design elements reflect this. Assessment designs generally include random sampling within a stream reach or watershed, or a combination of random plus some targeted sampling. Random sampling tends to maximize spatial sources of variation. Rotating basin sampling designs are often used, which typically include sampling once every 5 years. Collections are usually of one sample per location per year, with measurements of few covariates.

In contrast to the original spatial objectives of biomonitoring designs, detection of climate change requires evaluation of trends over time, whether at a specific location or for a defined area or stratum. There are some commonly observed limitations of many existing biomonitoring programs with regard to assessment of trends. Despite the relatively large numbers and broad spatial distribution of sampling stations in the biomonitoring data sets analyzed (see Figures 3-6, 4-6, 5-6), few are sampled in more than one or a few years over the entire period of record (see Table 7-9). As a result, there are a limited number of stations with long-term data from which to analyze temporal trends. In addition, samples are often not collected from the same sites every year (see Table 7-10), so many data sets have discontinuities, making trend detection more difficult. In addition, trend analyses should be conducted using data from "reference" or minimally affected stations to minimize influences from conventional stressors. This study also found that climate change responses can differ among regions (see summary in Section 7.2), potentially making it necessary to partition analyses by ecoregion or other classification. However, there are seldom more than one or two long-term sites within a particular region, and many regions have no long-term reference stations.

Table 7-9. Average distribution of reference and total stations by state, categorized by duration of sampling

Years sampled	Maine		North Carolina		Utah		Average		
	Ref	Total	Ref	Total	Ref	Total	Ref	Total	% Ref
1 to 4	57	696	89	2,530	61	482	207	3,708	5.6
5 to 9	7	40	13	223	1	41	21	304	6.9
≥10	2	6	3	33	4	26	9	65	13.8
Total	66	742	105	2,786	66	549	237	4,077	5.8

Table 7-10. Time periods for which biological data were available at the long-term monitoring sites in Utah (UT), Maine (ME), and North Carolina (NC). Data used in these analyses were limited to autumn (September−November) kick-method samples in the Utah data set, summer (July–September) rock-basket samples in the Maine data set, and summer (July–August) standard qualitative samples in the North Carolina data set

Station ID	Water body	Number of years of data analyzed	Years
UT 4927250	Weber	17	1985–1995, 1998, 2000, 2001, 2003–2005
UT 4951200	Virgin	14	1985–1993, 1996, 2000–2002, 2004
UT 4936750	Duchesne	12	1985–1993, 1995, 2000, 2001
UT 5940440	Beaver	9	1996–1998, 2000–2005
ME 56817	Sheepscot	22	1985–2006
ME 57011	W. Br. Sheepscot	12	1995–2006
ME 57065	Duck	9	1997–2005
NC 0109	New	11	1983–1990, 1993, 1998, 2003

The limited number of "reference" stations with adequate long-term data records within each ecoregion or other stratum of interest reduces the ability (1) to confirm regional trends, (2) assert the strength of any trends discerned, and (3) to compare biological responses between regions. Essentially, the low number of stations with sufficient long-term data limits replication for testing of climate change effects. The small number of reference locations with long-term data is a surprising but important finding that likely applies to many other biomonitoring data sets.

A related factor is the actual length of the long-term data record. Reference locations in this study yielded some valuable results, but also many nonsignificant patterns. It appears in several of these cases that the length of the data record along with the number of years sampled within the period is not sufficient to detect trends given the year-to-year variability of the metrics being tested. As examples, the longest-term reference station in North Carolina, NC0109, had 11 years of data over a 21-year time span (1983−2003); the longest-term reference station in Maine had 23 years of data over a 23-year time span (1984−2006); and three long-term reference stations in Utah had 19 years of data over a 21-year span (1985−2005, station 4927250—Weber), 15 years of data over a 20-year span (1985−2004, station 4951200—Virgin), and 14 years of data over an 18-year span (1985−2002, station 4936750—Duchesne).

Data durations of about 13−20 years appear in the literature as an apparent minimum. For example, analyzing an 18-year data set from a large number of streams in the UK, Durance and Ormerod (2008) found significantly increasing temperature trends and significant correlations of some invertebrate variables with temperature, although they concluded that water quality improvements confounded interpretation of results. Chessman (2009) found significant climate change trends in benthic invertebrate taxonomic families and trait groups within a 13-year data record in New South Wales, Australia. Daufresne et al. (2004) defined aquatic community trends in the Rhone River based on data durations of 20 (macroinvertebrates) to 21 (fish) years. Although Daufresne et al. (2004) found several meaningful community patterns and showed statistically significant trends in temperature, trends related to flow parameters were generally not found to be significant based on the same duration of data. Two possibilities are (1) in the Rhone River there were no temporal trends in flow and/or no relationships between flow and invertebrate or fish communities; or (2) given the typically high variability of hydrologic variables, the 20 to 21-year duration of data was adequate to discern temperature trends but not to detect flow-related responses.

7.3.2. Other Biomonitoring Methods Considerations

Each of the states analyzed in this study use different collection methods that range from single or multihabitat kicknet samples to different types of artificial substrate samples (see Sections 3.2 through 6.2 for the specific sampling methods employed by each state evaluated in this study). Some methods are likely to be more effective than others for certain applications (e.g., Flotemersch et al., 2006), but it is still unclear which sampling protocol is best suited for detecting climate change effects. Long-term changes in climate variables are expected to contribute to a wide range of in-stream changes that can contribute to biological responses, such as drought or flood-related changes in flows, and associated changes in nutrient loadings, sediment loadings, habitat availability, and other interrelated factors. Given these considerations, the ability to examine the full spectrum of naturally occurring biological community components may be advantageous. In-stream multihabitat sampling may be more likely to provide realistic estimates of abundance or richness of a broader spectrum of indicator taxa.

Use of artificial substrates were favored for pollution detection on the premise that application of a uniform substrate eliminates the substrate variation among stations as a variable that would confound detection of community responses to a pollution discharge or other disturbance (e.g., Barbour et al., 1999; Cairns, 1982). But with the additional objectives of testing for climate change effects, artificial substrates may be less advantageous. For example, in Maine, rock baskets are placed in run habitats that will have sufficient water for the entire deployment period. If drought conditions or altered seasonal precipitation leads to reduced flows and a loss of edge habitat, the rock baskets are less likely to reveal the potential loss of edge taxa. Even protocols that sample only riffles may be less likely to collect edge-specialized fauna. However, the multiple habitat protocol used in North Carolina is more likely to detect such shifts.

On the other hand, there is a significant disadvantage to changes in sampling methods, due to the disruption it causes in temporal patterns that might otherwise be observed. Because of this, any consideration of changing sampling methods should at least be accompanied by a period of time in which both methods are applied simultaneously in order to develop translation models. Even with some “side-by-side” sampling, translational models used to correct species abundance for sampling method may not always be effective or overcome inherent sampling biases. For example, if rock baskets do not effectively collect edge taxa, then no factor can be defined that would translate multiple years of near-zero results into meaningful estimates of abundance.

Because of considerations such as these that bear on the consistency of results, states have a vested interest in continued use of their own methods to assure that new data are meaningful to their program. Additional sampling might be considered in representative and/or especially vulnerable regions as an adjunct to standard biomonitoring methods. For instance, in streams with a high likelihood of transitioning from perennial to intermittent status, collection of samples from edge habitats could be considered.

Another potential hindrance to effective detection of climate change trends is relatively low sampling effort and the lack of replication in station sampling. In most biomonitoring programs, the concept of collection of replicate samples is relinquished in favor of collecting single composite samples. The composites can be either of multiple artificial substrates (e.g., in Ohio, 5 Hester-Dendy samples per station are composited and processed as a single unit [DeShon, 1995]); or a single sample unit can be a composite of collections made in multiple representative habitats (NCDENR, 2006). In general, increasing the number of samples collected and composited for a site has been found to decrease variance among "replicate" (similar) sites and increase the precision of characterizing the assemblage at the site (Cao et al., 2003; Diamond et al., 1996). Multihabitat sampling, applied in many biomonitoring programs (e.g., Utah, North Carolina) is considered to yield representative and, therefore, precise samples (Barbour et al., 2006; Hering, 2004). Though replication is considered necessary to determine the precision of the sampling method (Barbour et al., 2000), it is often only accomplished on about 10% of collections (e.g., Stribling et al., 2008; Barbour et al., 2006; Flotemersch et al., 2006). However, with regard to detecting climate change temporal trends, knowledge of spatial variation within a station (or stream reach), as well as between sites within a watershed or ecoregion, may be valuable.

There are some environmental variables that can be measured along with biological samples to aid in interpretation of results. For example, a detailed assessment of substrate and related habitat condition, as was used in EMAP (Lazorchak et al., 1998), is valuable in differentiating habitat disturbance from other stressors. If biomonitoring programs consider climate change as an additional stressor, it would be valuable to have good information on water temperatures and flows from biological collection sites. Existing sampling protocols usually include concurrent point measurements of temperature, and sometimes also of pH, DO, and conductivity, as these values are relatively easy to obtain with portable sondes. However, the analyses conducted in this study illustrate that point measurements of temperature are not a good measure of the stream conditions to which an aquatic community is exposed. They tend to include a large amount of variation from time of day as well as date during the seasonal index period when that measurement happened to be taken.

In this study, the lack of long-term, site-specific temperature and flow data impaired the ability to conduct weighted-average modeling (or use of related approaches) to determine temperature or flow parameter preferences for many taxa. It also made it difficult to conduct simple trend and correlation analyses (see Sections 3 through 5). It would be beneficial to consider deploying in situ equipment to obtain continuous water temperature and flow measurements at as many climate change monitoring sites as possible. Though such equipment is widely available and much less expensive than it used to be, the sometimes severe resource limitations experienced by states and tribes may limit the extent to which this recommendation can be applied. Priorities could be set based on regional assessments of relative vulnerability to climate change. For example, a limited number of deployments could be done at reference locations in higher elevations, and/or in lower-order streams. There is also high value in continued operation of USGS long-term flow and temperature gages.

7.4. REFERENCE STATION VULNERABILITIES

Several program elements in addition to biologic indicators need to be considered for effective program management and adaptation in relation to climate change. The use of reference stations and comparison to reference conditions are central to bioassessment. There are two components of reference station vulnerability to climate change that are apparent from this study. One is the negative drift of the biologically based characterization of reference condition over time that will likely result from climate change effects on component biota. The other is the threat to the quality status of reference stations from other global stressors, in particular encroaching developed land uses. We, therefore, examined potential vulnerabilities in the definition of reference conditions, in the synergistic effects between climate change and land use, and in the vulnerability of reference sites to encroaching developed land uses.

7.4.1. Vulnerabilities in Assessing Reference Condition

Reference station comparisons are central to bioassessment. Both in the United States (Clean Water Act) and in Europe (Water Framework Directive), the determination of ecological status and integrity is based on a comparative approach ("reference based comparisons") requiring reference locations that can be used to set expectations for "natural" conditions and associated variability (Barbour and Gerritsen, 2006; Stoddard et al., 2006; Verdonschot. 2006; Nijboer et al., 2004; Wallin et al., 2003). Impairment in the regulatory context represents an unacceptable level of departure from this "expected" reference condition. Climate change can alter the biological conditions at reference stations, and thereby influence reference-based comparisons and the decisions that are based on those comparisons.

The exploratory analyses conducted using North Carolina protocols (see Section 5.8) illustrate expectations for drift over time in the biological status of reference stations that could impact impairment decisions. As cold-water taxa are lost from North Carolina biomonitoring stations due to warming temperatures, and possibly also to related decreasing flows especially during the summer, the percentage of stations that are characterized as excellent or good decreases (see Figure 5-36). The net effect, even with only 50% loss of cold-water taxa, is that the average condition of reference stations has drifted down the condition scale to be closer to test stations. The implications of this reference station condition drift is that in reference-based comparisons used to judge the status of test locations, the condition of test locations will be more similar to and, therefore, more difficult to differentiate from reference conditions. From this, it should be less likely to characterize a test location as being impaired, and more difficult to recognize sources of impairment.

This analysis was based on our study findings showing that cold-water taxa decrease, and also that warm-water taxa increase over time and/or with increasing temperature or decreasing flow or precipitation, at some, though not all, long-term biomonitoring stations. We acknowledge that this basic finding was not universal, and so this threat to reference status may be more important to consider in more vulnerable regions where the benthic communities are composed of a greater proportion of cold-water taxa. The study supports the inference that temperature-preference taxa can be expected to respond as climate changes progress in the future, because when the responses of temperature preference trait groups were observed, they were consistent with expectations based on the direction and magnitude of temperature or flow/precipitation changes that occurred at the stations tested, they occurred at locations that based on elevation, stream size, and/or ecoregion were composed of sufficient cold-water taxa for responses to be testable, and were not limited in trend detection by shorter data durations. We also acknowledge that a 50 to 100% loss/replacement of cold-water taxa may be more extreme than what will occur at existing biomonitoring sites in the near term. This approach is only intended to show the direction and extent of alterations that can be expected from the types of biological responses occurring as a result of climate change effects.

Given this expected effect of climate change in altering reference baseline conditions and its implications to reference-based comparisons, it would be valuable to be able to characterize reference conditions on a more complete and objective condition scale than is represented by the "impaired/not impaired" decision approach. The BCG (Davies and Jackson, 2006) captures the full range of biological conditions, from natural/undisturbed to completely impaired. The more numerous, subtle and well-defined levels captured in the BCG delineate a meaningful and scaled framework for characterizing existing reference conditions, and within which changes in reference condition attributable to climate change could be judged. A BCG would allow reference stations to be more accurately characterized, would support evaluation of reference station condition or drift over time, and would similarly support characterization of nonreference station changes over time.

7.4.2. Synergistic Effects between Climate Change and Land Use

Though slightly different in geographic scale, both climate and land-use change can be considered large-scale impacts (Hamilton et al., 2010a). Global climate change drivers are well described (IPCC, 2007c). Land-use change is generally considered a landscape-scale stressor, but is driven by global population growth (Nakićenović and Swart, 2000). Land-use changes, such as urban/suburban land development, have encroached on and impaired reference stations across the United States. However, documentation of such problems has been sparse and likely has been handled on a local, case-by-case basis.

The successful use of biomonitoring data for evaluating pollution impairment in the context of climate change is in part related to understanding synergistic effects between climate change and conventional stressors, and how they can be separated. These synergistic effects can impact approaches used for attributing causes through the stressor identification process (see U.S. EPA, 2000). Synergistic effects between climate change and other stressors are increasingly documented (Clement et al., 2008; Collier, 2008; Kaushal et al., 2008).

We examined the relative responses to climate change compared to land-use change (urbanization) through analyses of existing biomonitoring data. Hydrologic response variables play important roles in defining habitat conditions and structuring aquatic communities (e.g., Poff et al., 1997) and are responsive to both climate change and urbanization.

Flow data from USGS gages in the Baltimore-Washington, DC area (Mid-Atlantic region) were used in this case study. The main question that was addressed was how hydrologic response to climatic change in the Mid-Atlantic would compare with land use impacts. Data preparation involved gathering historical flow and precipitation data for urban and forested sites, calculating Baker's Flashiness Index (Baker et al., 2004) and IHA parameters for these sites, and identifying which historical years of data had conditions that most resembled those that are projected to occur in the future. Data were analyzed using ANOVA analyses.

ANOVA results are shown for one example high flow metrics in Figure 7-4 and for one low flow metric in Figure 7-5. Tables 7-11 and 7-12 summarize complete results. All plots of the ANOVA results for the IHA parameters are available on request. Results show differences in the types of hydrologic variables (IHA, sensu Richter et al., 1996) that are likely to be most responsive to either climate change or urbanization effects. High flow metrics, such as flashiness, high-pulse-count duration, 1-day maximum flow, and others, tend to strongly reflect urbanization, swamping inputs from climate change effects. In comparison, several low-flow metrics, such as 1-, 3-, and 7-day minimum flows and low-pulse count, show responses to climate change effects more so than to land use (see Table 7-12). Where future climate change effects are small compared to land use, expectations are for more frequent, shorter, higher flows in urban-affected streams. Where future climate change effects are large compared to land-use effects, expectations are for more frequent, longer, lower flows. Accordingly, low-flow parameters should be selected as sensitive climate change indicators, and low-flow effects on biota are correspondingly expected to be most influential.

We further evaluated the relative effects of climate change and urbanization on stream condition through benthic invertebrate responses, using the sampling results from the Piedmont regions of North Carolina as a test case. The study area has undergone rapid population growth and urbanization since 1945, which has contributed to flashier streams and altered habitat. Data preparation for the study involved developing OTUs, calculating taxa richness-based metrics, calculating IHA parameters (Richter et al., 1996) and Baker's Flashiness Index (Baker et al., 2004) for 67 biological sampling sites that were associated with USGS gage stations, and dividing the sites into natural, urban, agricultural and other land use categories based on examination of the watersheds in Google Earth.

The main objective of this study was to assess the response of macroinvertebrates in urban and nonurban streams to hydrologic changes. We used number of EPT taxa as the principal response metric and flashiness (the sum of daily flow changes divided by total flow), low pulse count (number of events per year where flow is below the 25th percentile), and 1-day minimum flow as the hydrologic indicators. Flashiness is predicted to increase with urbanization

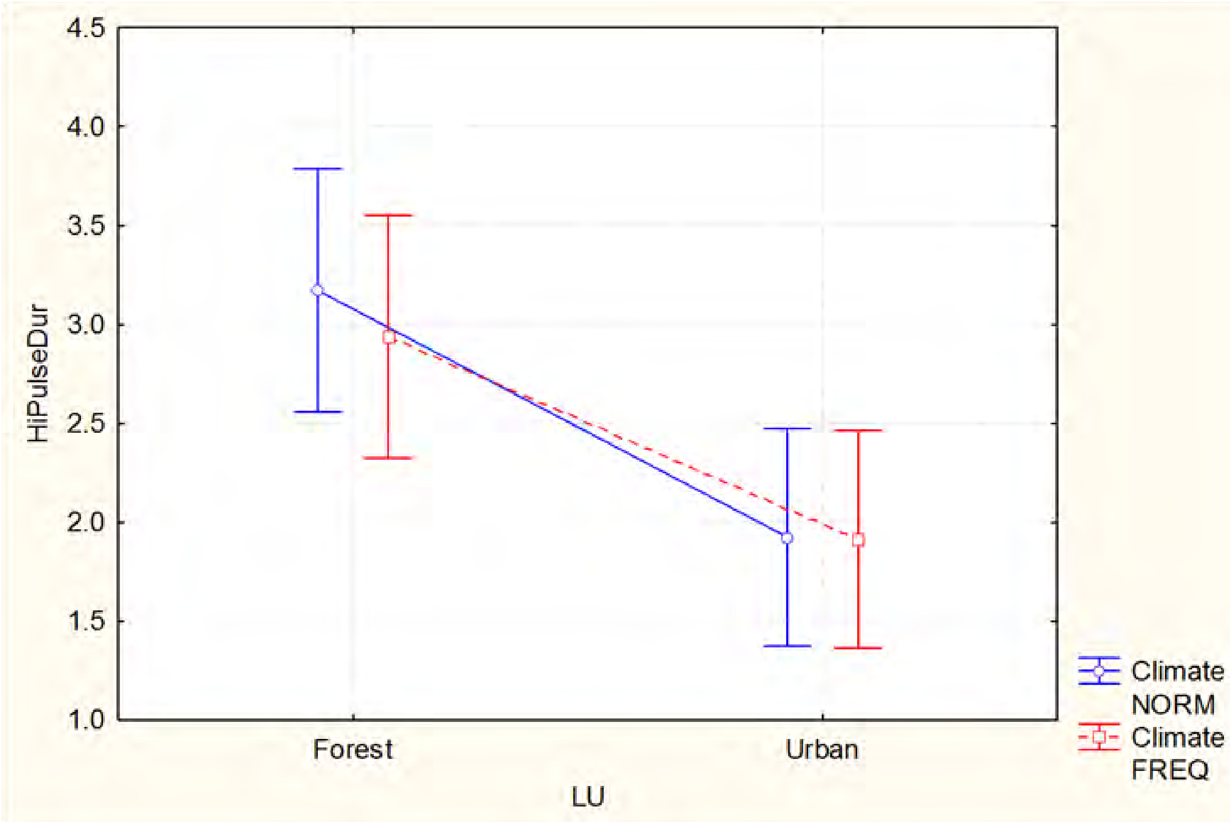

Figure 7-4. ANOVA results for high-pulse duration (days) at forested and urban sites.

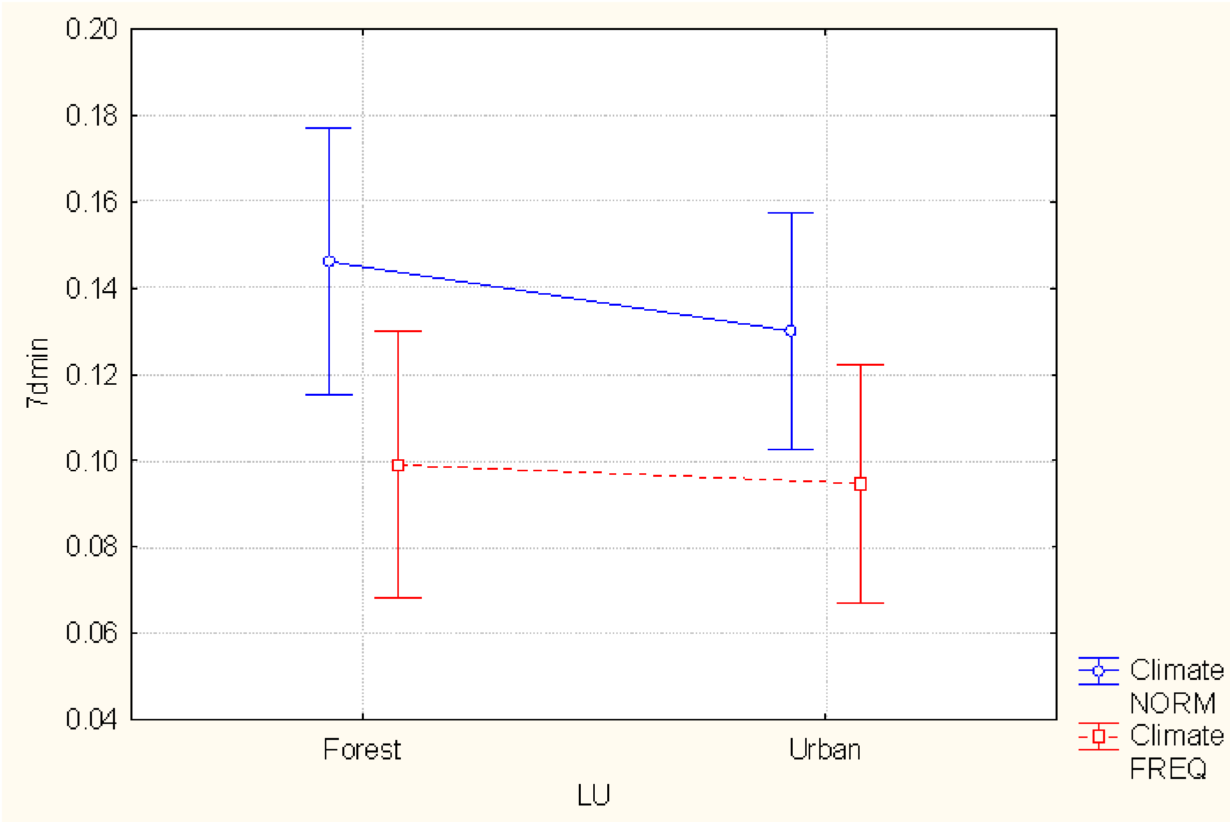

Figure 7-5. ANOVA results for 7-day minimum flow (standardized by mean annual flow) at forested and urban sites.

Table 7-11. Summary of ANOVA results for high-flow IHA metrics. Land use effects are greater than climate effects for most high-flow metrics tested

High flow metrics	Land use	Climate
Flashiness	Y	N
High-pulse count/duration	Y	N
1-day maximum	Y	N
3 or 7-day maximum	N	N
Rise rate/fall rate	Y	N
Reversals	Y	N
High flood peak/frequency/duration	Y	N
Small flood peak/duration	Y	N

Table 7-12. Summary of ANOVA results for low-flow IHA metrics. Climate effects are greater than land use effects for most low-flow metrics tested

High flow metrics	Land use	Climate
Low pulse count	Y	Y
Low pulse duration	Y	N
1, 3, or 7-day minimum	N	Y
Extreme low peak	N	N
Extreme low frequency/duration	Y	Y

but not with climate change, while low-pulse count and 1-day minimum flow are predicted to increase with climate change.

EPT taxa respond to both high-flow metrics (flashiness) and to low-flow metrics. For example, extreme increases in frequency of low-flow pulses (>20/*y*) are associated with EPT taxa loss (see Figure 7-6), though low-pulse count did not differ much between the natural and urban streams in this analysis. There was a strong association of decreasing richness of EPT taxa with increasing flashiness (see Figure 7-7), as well as confirmation of the greater flashiness of urban streams. The flashiest urban streams had poorer conditions than the moderately flashy urban streams. In the plots, it appears that there may be a possible threshold at 0.5 (sites that had flashiness values of less the 0.5 generally showed no relationship, while sites with flashiness values greater than 0.5 generally showed strong relationships).

Natural and urban streams did not differ greatly in low-pulse count, although the Smith River is an important exception. This site is dominated by natural land cover but has extremely high low-pulse counts (28−44 per year) because it is regulated by a peaking hydropower dam. Overall results show that there was not a strong relationship between low-pulse count and number of EPT taxa (see Figure 7-6). Low-pulse count was most strongly associated with EPT taxa loss when there was an extreme increase in frequency of low pulses (>20 per year).

In this component of the study, urban conditions were compared with natural stream conditions, and the urban streams had lower 1-day minimum flows than natural streams (see Figure 7-8). However, within the urban sites, there was no association between number of EPT taxa and minimum flow. There is an apparent threshold response below minimum flows of

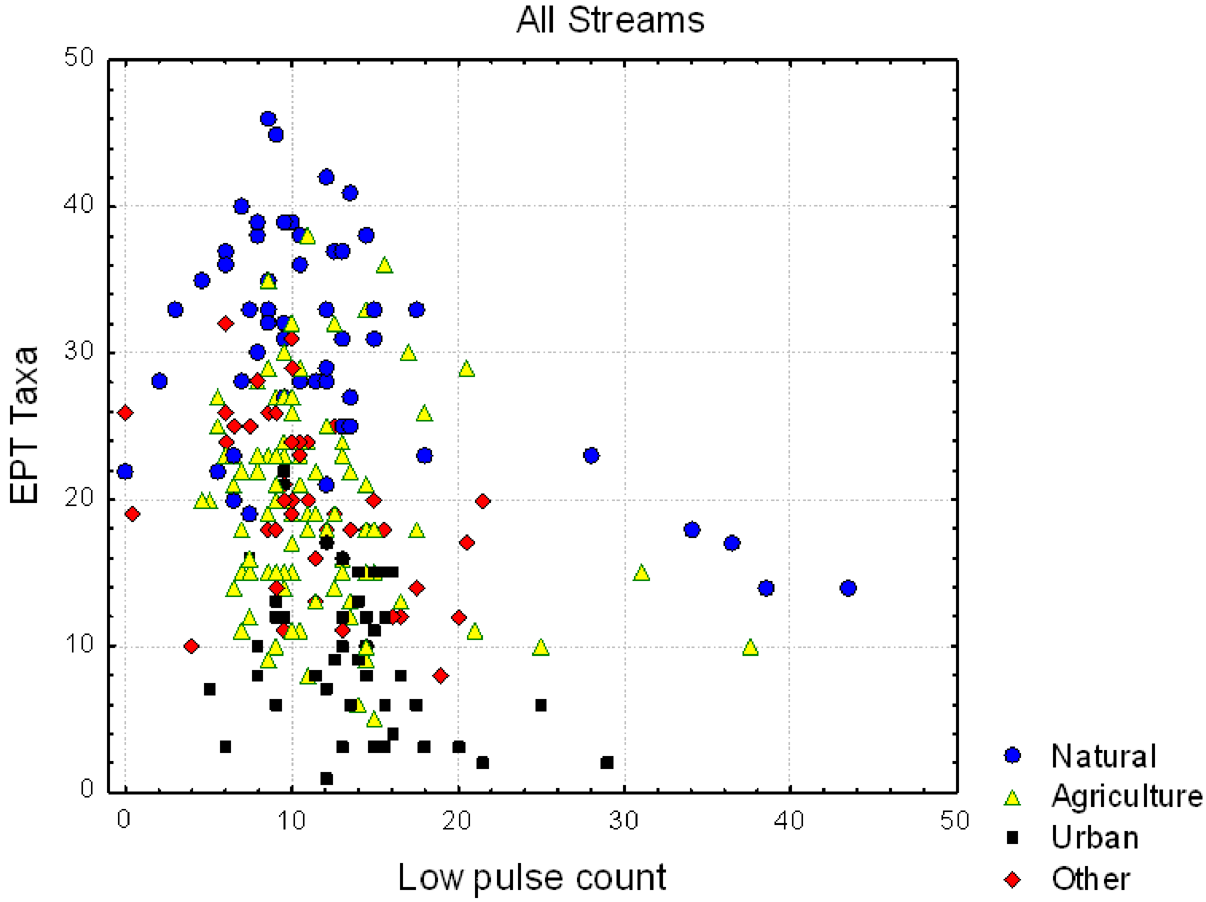

Figure 7-6. Relationship between richness of EPT taxa and low-pulse count of the stream for stream types in the North Carolina Piedmont.

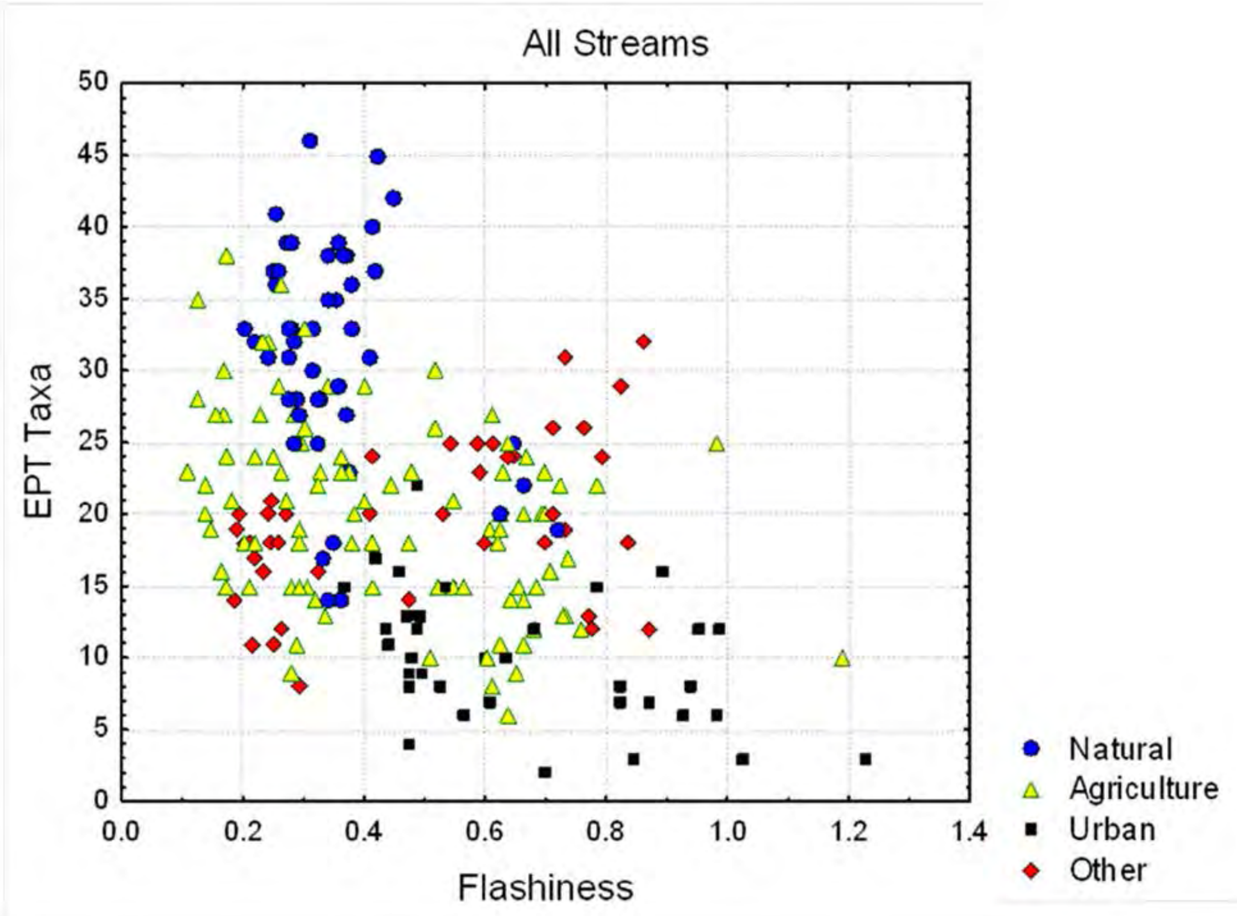

Figure 7-7. Relationship between richness of EPT taxa and flashiness (Baker's index) of the stream for stream types in the North Carolina Piedmont.

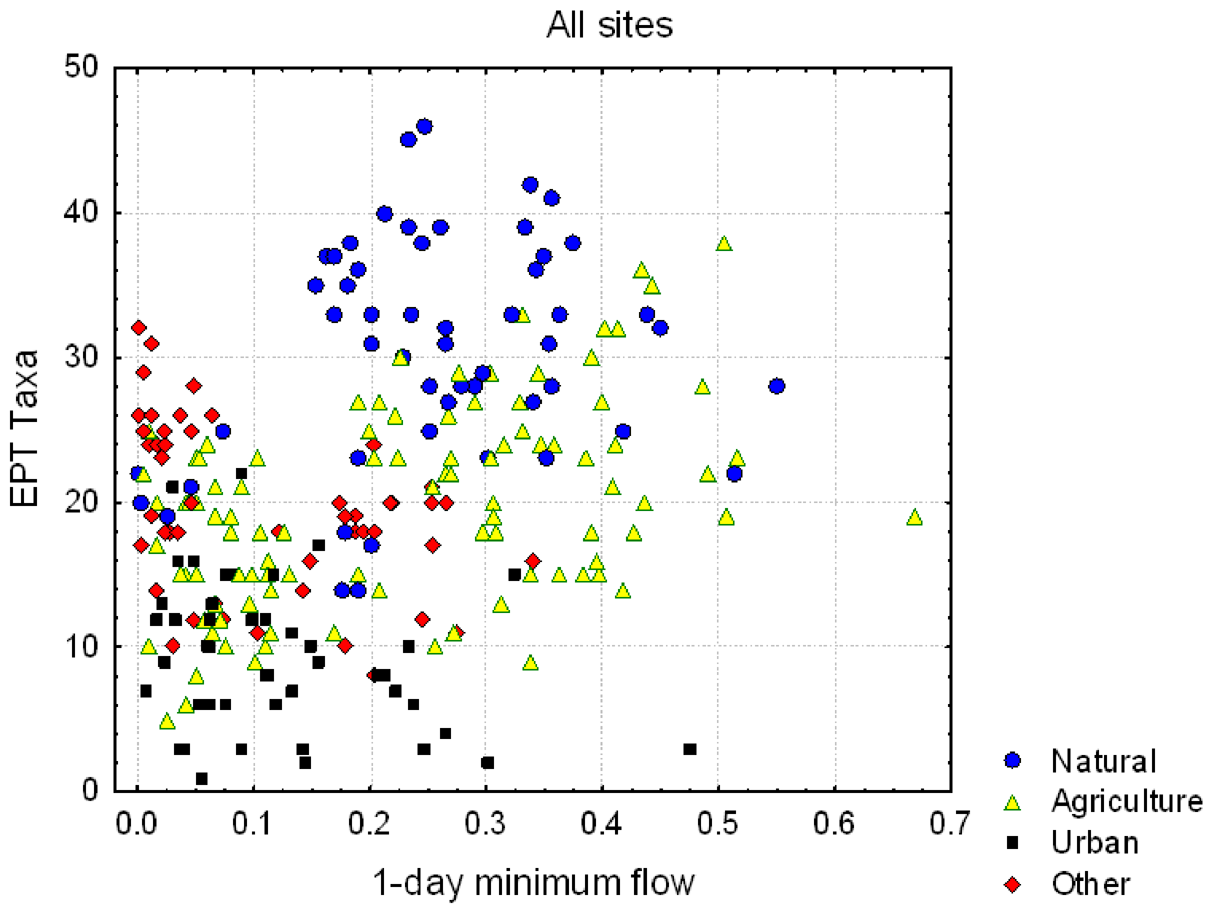

Figure 7-8. Relationship between richness of EPT taxa and 1-day minimum flow of the stream for stream types in the North Carolina Piedmont.

about 15% in natural streams, where richness of EPT taxa is lower and less variable compared to higher flows, but this is confounded by the association of minimum flows with flashiness.

There were several conclusions that were drawn from this study, and also several questions that remained unanswered. We are aware the flow regime is a causal link that changes habitat, but we are uncertain as to whether or not it is a direct stressor. In this study, intermediate-term changes in flow were not associated with taxa change within streams, but this analysis has low power. The biological responses that are seen indicate that natural stream communities are highly resilient within the range of natural hydrologic variability. Because of this resilience, effects from hydrologic changes associated with climate change are unlikely unless these changes are truly extreme, such as those that occurred in the regulated river in this study. Future climatic changes are likely to be beyond the variability observed in the recent past.

Therefore, we have not seen anything as extreme as is predicted to occur, and this makes it difficult to predict future impacts. These results suggest that natural streams are more resilient to hydrologic changes within the range of recent past climate. Large changes in minimum or low flows may take much longer to become biologically meaningful, and in the shorter term, temperature effects may be more important.

7.4.3. Future Vulnerabilities of Reference Stations to Land Use

References stations are vulnerable to human-induced changes to the surrounding landscape. We evaluated current and future vulnerabilities of existing reference stations to urban/suburban development for three study states (Maine, Utah, and North Carolina), as well as for Florida as a case study representing a high level of population growth. Data on current and future land uses comes from the Integrated Climate and Land Use Scenarios (ICLUS) project (Bierwagen et al., 2010). Future land-use scenarios are consistent with the IPCC Special Report on Emissions Scenarios social, economic, and demographic storylines used in global climate models (U.S. EPA 2009; Nakicenovic and Swart, 2000). The ICLUS scenarios consider different levels of population growth, with different assumptions about development patterns (U.S. EPA 2009). The two most extreme scenarios are A2, which has high population growth rates and business-as-usual development patterns and B1, which has low population growth rates and compact development patterns. The base case uses medium growth and migration rates, along with a business-as-usual development pattern. We used a total of 248 reference sites compiled from Maine, Utah, and North Carolina to examine their vulnerability to current and future land use. The number and distribution of reference stations for these states are discussed in Sections 3, 4, and 5 of this report. Florida DEP has about 308 sampling locations, with 58 reference sites designated as “exceptional” (see Figure 7-9).

Urbanization affects stream conditions through alterations in hydrology and geomorphology, with typically increased loading of nutrients, metals, pesticides, and other contaminants; these effects are associated with increases in impervious surface (Paul and Meyers, 2001). To estimate the degree of urbanization representing a threshold of impairment for the Florida case study, the relationship between human population density and Ephemeroptera (mayfly) taxon richness developed from analyses in New England were used (see Figure 7-10) (Snook et al., 2007). At low population densities, up to approximately 50 persons

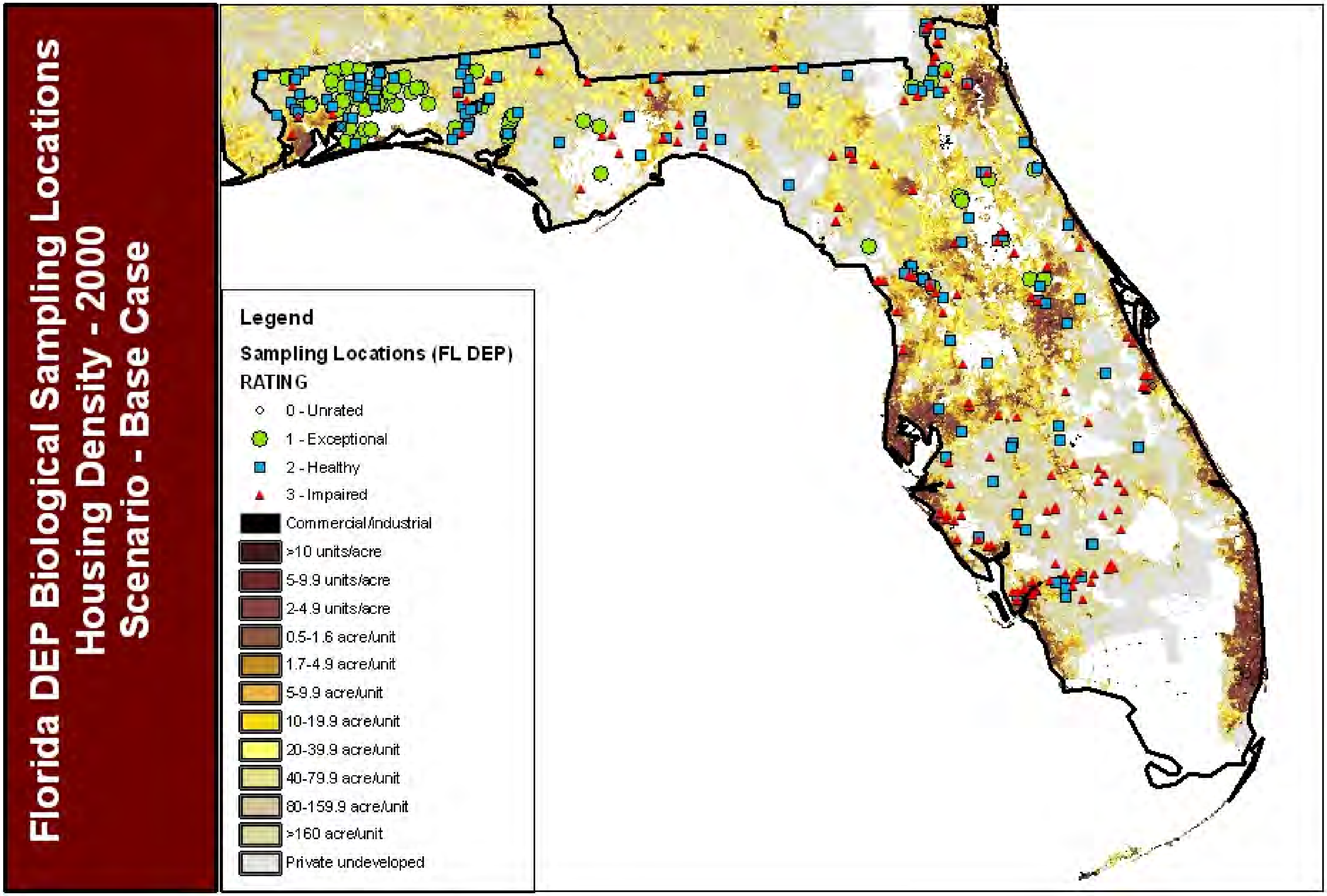

Figure 7-9. Florida's biomonitoring sampling stations, including "exceptional" reference locations (light green dots), shown in relation to current land use.

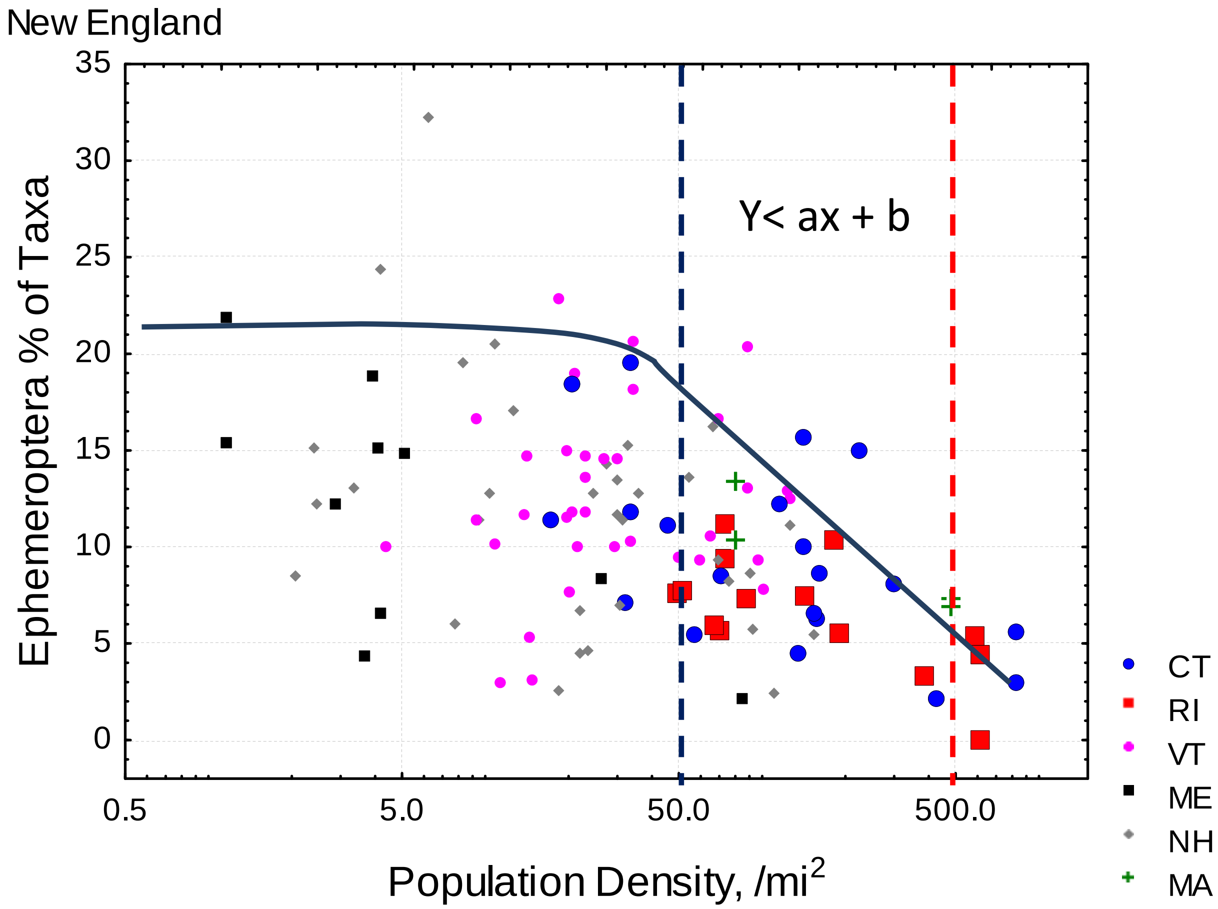

Figure 7-10. Relationship between human population density (i.e., degree of urban development) and Ephemeroptera (mayfly) taxon richness among six New England states (from Snook et al., 2007).

(~25 houses) per square mile, there are few detectable biological responses. From 50−500 people (25−250 houses) per square mile corresponds to a degradation gradient, and above 500 people (250 houses) per square mile, New England streams are degraded. Therefore, a threshold of housing density >25 houses per square mile was selected to indicate potential degradation. Using the land use composition within a 1-km (0.62-mi) radius buffer around each reference station, vulnerability was defined as ≥20% of the buffer with a land use at or above the threshold of housing density.

For the analysis conducted for Maine, Utah, and North Carolina, urban and suburban (>0.6 units/acre, or about 384 per square mile) was used. However, a threshold of 10% of development within a 1-km buffer was used to reflect expectations for impacts to the biological communities from urbanization (Schueler, 1994; Booth and Jackson, 1997; Wang et al., 2001). These differences in thresholds may account for some of the differences in results between the evaluation of the three study state reference stations and the Florida case study. Given the low threshold of development used and the high population growth rates for Florida, we take the Florida results to represent a worst-case scenario.

Among the 58 "exceptional"-grade reference stations in Florida under year 2000 conditions, 19% of the stations can be classified as vulnerable to land-use impacts (see Table 7-13). That is, nearly 1/5 of Florida reference stations may already exhibit impacts from urbanization. Within the next 2 decades, more than one third of existing reference stations will be vulnerable, and by 2100, nearly half of current reference stations may be impacted by urbanization under the base case and A2 scenarios. This level of vulnerability is significant. The spatial distribution of this vulnerability is broad. In Florida, most sampling stations are in the northern half of the state. Future projections of urbanization generally follow current patterns of development, with particularly dense future development projected for the northern half of the Florida peninsula. The only reference locations that appear to be protected from future land development are those largely surrounded by water, and/or those within government-owned or protected lands that cannot be developed. In Florida, this represents about 17% of existing reference locations.

The results for Maine, North Carolina, and Utah show a somewhat lesser degree of vulnerability. Under current (2000) conditions, 22% reference locations in these three states have greater than 10% urban/suburban densities within a 1-km^2 neighborhood (see Table 7-14). Under the worst case (A2) scenario, future housing development increased to 34% by 2100. The maximum amount of suburban and urban development within the 1-km^2 neighborhood in 2000 was 58%; this increased to 99% by 2050. The average amount of development increased from 22% in 2000 to 28% in 2050 and 34% in 2100 using the A2 scenario, while it leveled off at 26% using a lower population growth and higher development density scenario (B1) (see Table 7-14). The results for Utah are difficult to interpret, and the projections not very meaningful, as the number of reference sites falling within the 10% development threshold as calculated for a 1-km^2 neighborhood was very small.

Table 7-13. Percentage of existing Florida reference stations (*n* = 58, classified as "exceptional"), that have >20% developed land use (with 25 houses per square mile (9.65 houses per square kilometer) or more, Categories 5–12 in the ICLUS data set) within a 1-km buffer surrounding the station, for current and decadal time periods through 2100

Year	Scenario		
	BC (%)	A2 (%)	B1 (%)
2000	19.0	19.0	19.0
2010	36.2	34.5	36.2
2020	36.2	36.2	36.2
2030	37.9	37.9	36.2
2040	41.4	39.7	36.2
2050	44.8	44.8	36.2
2060	44.8	44.8	36.2
2070	44.8	44.8	36.2
2080	44.8	44.8	36.2
2090	44.8	44.8	36.2
2100	44.8	48.3	36.2

Table 7-14. Percentage urban and suburban development within a 1-km^2 area surrounding reference sites, for all sites and for sites at or above the impact threshold of 10%. Number of sites is shown in parentheses. Scenario A2 has high population growth and a business-as-usual development pattern; Scenario B1 has low population growth and a compact development pattern (U.S. EPA, 2009)

	Area	2000	A2 2050	A2 2100	B1 2050	B1 2100
Mean of reference sites (≥10% threshold)	Combined	22% (35)	28% (37)	34% (45)	26% (37)	26% (37)
	Maine	23% (26)	24% (26)	30% (32)	23% (26)	23% (26)
	North Carolina	20% (9)	27% (9)	40% (10)	24% (9)	24% (9)
	Utah	0% (0)	87% (2)	64% (3)	77% (2)	77% (2)

The specific patterns of reference station distribution and vulnerability to land development will vary among states, although there are widely applicable lessons from these results. The high level of current vulnerability to urbanization (about 20% in all states tested except Utah) highlights the difficulties in siting reference locations in many areas and the probability of encountering substantial existing urban influences, which impact baseline reference conditions. This evidence suggests that protection of reference stations is of substantial importance. Options for protection may differ regionally and include zoning changes, limitations to development within buffer zones of selected stream reaches, incorporation into land protection programs (U.S. EPA, 2011), or other sociological, economic, and/or political solutions. If alternatives for protecting reference locations are limited or costly, it may be that reference stations in already protected areas, such as national parks, other government lands, or in otherwise inaccessible areas may represent the only "protected" references. This is likely to leave many watersheds and regional ecotypes without good reference conditions for comparison. In Florida, this would reduce the ratio of reference sites to total sampling sites from 19 to 3%. If reference sites are too scarce, they will be unrepresentative.

The need to protect reference locations is an important issue for the future of bioassessment. If reference stations become urbanized, the ability to detect climate change, and separate climate responses from conventional stressors in order to continue to manage resources, set permit limits, and meet CWA requires, may be hampered. It may become important to consider and promote more broad-based alternatives than just local or state-specific protections, such as regional cooperation in the establishment and monitoring of long-term fixed "sentinel" locations.

7.5. IMPLICATIONS TO MULTIMETRIC INDICES, PREDICTIVE MODELS, AND IMPAIRMENT/LISTING DECISIONS

7.5.1. Conclusions Across Pilot Study States

Among the four states evaluated in this study, three of them—Maine, North Carolina, and Ohio—use some form of MMI. Utah uses a predictive model, RIVPACS, for assessing wadeable streams. These states are representative of major regions of the United States, encompassing large-scale variations in climate, climate change projections, geography, topography, geology, and hydrology. State-specific analysis results also inform a regional view of climate change implications to commonly used MMIs and predictive models.

MMIs are generally structured as a composite of biological metrics selected to capture ecologically important community structural or functional characteristics and have been applied to fish and benthic macroinvertebrate communities (Norris and Barbour, 2009; Bohmer et al., 2004; Sandin and Johnson, 2000; Barbour et al, 1995; Yoder and Rankin, 1995; DeShon, 1995; Karr, 1991). Component metrics are selected based on their responsiveness to the environmental impacts most often evaluated. Results of this study suggest that climate changes in temperature and flow conditions can elicit responses in these commonly use metrics through their temperature preference traits, and potentially through their flow preferences as well, in ways that can influence the outcomes of MMI condition scores. This means that the commonly used biological indicators of environmental condition are not only linked to the conventional stressors usually evaluated, but also to changing climate variables. At least in the most vulnerable regions (e.g., higher elevations, ecoregions composed of a high proportion of cold-water taxa, smaller watersheds or stream sizes), the scoring of station condition that relies on MMIs can be altered by climate change effects. The importance of this finding is that the scoring of stations according to their apparent biological status becomes the basis for impairment decisions and associate management actions.

There is much variation among states and tribes in the particular components included in MMIs or predictive models, because, as a rule, they are calibrated to the state, or more often, to regions within a state to account for predictable (natural) variability (Barbour and Gerritsen, 2006). Added to this index variability is the regional variability in both climate change projections and associated biological responses. These sources of variability make generalizations about the implications of climate change for bioassessment indices challenging. However, there are some commonalities among states, such as the categories of metrics used, which we use to investigate vulnerabilities of these approaches to climate change.

There are a variety of regional differences in biological responses evident from this study. More and stronger trends and responses were found in Utah, largely related to temperature changes. Fewer significant trends were found in North Carolina, and more were related to precipitation or flow (see also Section 7.2). There is much spatial variation in these patterns, in part due to ecoregional, geographic, and climatological variations, and in part attributable to limitations of the available data. The results point to several conclusions. One is the importance of categorizing taxa based on ecological traits, especially temperature sensitivities, in order to evaluate responses to climate change variables and to estimate future vulnerabilities to climate change. It is a relatively consistent finding that biological metrics and indices used by states and tribes are either composites of cold and warm-water taxa, or are dominated by one or the other.

This composition defines the nature of responses and, therefore, the vulnerability of the metric or index to climate change effects. The richness of cold-water taxa is a metric that was often responsive, especially at higher elevations, where high-elevation communities tend to have more cold-water taxa. Metrics using cold-water taxa will help identify climate change "sensitive" or vulnerable areas. Such information would assist in detecting climate change effects and in identifying sites to monitor these changes.

For example, in Maine, several EPT metrics (e.g., EPT richness, Plecoptera abundance and richness, Ephemeroptera abundance and relative abundance) are incorporated into their linear discriminant model. We have found these taxonomic metrics are composed of varying combinations of both cold and warm-water taxa, and in relationship to this, predicting their responses to increasing temperatures and changing hydrologic regimes resulting from climate change is complex. As summarized in Section 4.8, due to the greater prevalence of warm-water taxa at the low-elevation long term site evaluated, increases in abundance of warm-water EPT taxa could results in increasing values of some of these metrics, while losses of the cold-water EPT taxa could reduce the abundance or richness of other EPT metrics. In addition, taxa replacements could have variable results. An additional factor is that not all of the EPT metrics that are components of the linear discriminant model have a simple linear relationship with site class condition. For example, Ephemeroptera abundances increase initially as station condition degrades from Class A to B, and then declines again with further reduction in station condition status. Through this mechanism, increases or decreases in EPT taxa through temperature or flow preferences could have either positive or negative effects on the final station condition decision. Another example is that in Maine, there is an additional consideration associated with the use of a group of "Class A indicator taxa" as one of the ways of separating Class A from B condition ratings. Maine's Class A indicator taxa are fairly evenly divided between cold and warm-water-preference taxa. Therefore, application of this metric with increasing temperature could confound results, because some of the Class A indicators could decline with increasing temperatures, while others could increase.

Predictive models use regional reference conditions to develop relationships between environmental predictor variables and macroinvertebrate taxon occurrence from which predictions for an "expected" (E) community are based. A commonly applied model for macroinvertebrate communities is RIVPACS (Wright, 2000). An important assumption is that the predictor variables are minimally affected by human disturbance and are relatively invariant over an ecologically relevant time (USU, 2009; Tetra Tech, 2008; Hawkins et al., 2000; Wright, 2000; Wright et al., 1984). The E community is then compared to various "observed" (O) communities at nonreference locations. A basis for comparison is that any differences between O and E communities reflect biological responses to the range of environmental pollutants or alterations that are intended to be evaluated. This is similar to the MMI approach.

In Utah, evidence of responses of temperature trait and taxonomic groups to temperature increases, and to a lesser extent with changes in precipitation, was somewhat stronger and more widespread (though not consistent at all stations). In particular, responsive groups that should be tracked in the future include total taxa, EPT and EPT-related metrics, and thermal preference metrics. But our examination of corresponding impacts to the Utah RIVPACS model responses showed minimal changes in O/E ratios (see Section 3.8), suggesting that predictive models used by states may be more resilient to climate change than MMIs. This is in part because they incorporate long-term (e.g., 30-year) averages of environmental predictor variables, including climate parameters.

On the other hand, the Utah results on trends in biological trait and taxa groups can also reflect on potential vulnerabilities of MMIs used by other southwestern states. The EPT trends at some (though not all) higher elevation stations in Utah indicate fairly predictable losses of EPT taxa over time in response to increasing temperatures. These losses are in the magnitude of up to a 25% loss of EPT taxa with current scenarios of temperature increases by 2050, attributable to the loss of cold-water EPT taxa components. Changes of this magnitude could result in notable responses in MMIs. Note that over the long term, it is also possible that increases in warm-water EPT taxa could result in taxa replacements, as both decreases in cold-water EPT taxa and increases in warm-water EPT taxa were observed at some stations (see Section 3.5).

In North Carolina, even more than temperature, expected climate changes in flow had important influences on the biological assemblage, including biological metrics that are used in the MMI to assess condition status. The very limited long-term data mean that we cannot conclude that the climate change responses are widespread. However, as examples of the types of biological response that could be expected in the future with continued climate changes in flow and temperature, we show that losses of cold-water EPT taxa can lead to changes in bioclassification scores, with the highest quality stations (those currently classified as excellent to good) being the most vulnerable (see Section 5.8). In addition, the linkage between temperature preferences and tolerance to organic enrichment means that increases in warm-water taxa, and/or losses of cold taxa can alter HBI scores, and this will also alter bioclassification scoring. The maximum effect appears to be decreases of one bioclassification level (e.g., from excellent to good, or from good to fair).

In Ohio, the MMI and the determination of the final station rating are also potentially vulnerable to climate change because of the positive association between temperature sensitivity and pollution tolerance. Percentage of tolerant taxa is one of the metrics used in the Ohio MMI. There are also several EPT metrics in the Ohio MMI, including EPT taxa richness, Ephemeroptera and Trichoptera richness, and relative abundance of Ephemeroptera and Trichoptera taxa. These metrics contribute to the potential vulnerability of the Ohio MMI through the relative contribution of cold-water taxa within these groups, with the most plausible expectation being for a decline in bioassessment scores due to losses of sensitive taxa and/or increases in tolerant taxa. However in Ohio, the biological condition of reference sites has improved over the last 30 years (see Section 6.5). Climate change effects may be a contributing component to these observed trends, or may be decreasing the magnitude of the positive response. However, there is evidence that the trends have been driven largely by other environmental factors, and in particular, management efforts that have reduced pollutant loadings and better agricultural practices (see Section 6.8). Thus, in Ohio, the relative vulnerability of the bioassessment process and the MMI in particular is difficult to assess, as are approaches that could be applied to adapt metrics to assist in tracking climate change and partition its effects from other sources.

Overall, the vulnerabilities of MMIs used to estimate bioassessment station condition scores appear directly related to responses of thermal preference trait groups to both temperature and flow changes. Responses mediated through hydrologic preference traits may be equally important, but due especially to limited availability of associated flow and biological data, we were unable to sufficiently develop hydrologic indicator groups to examine these responses. In addition, MMIs appear indirectly vulnerable to climate change influences through the correspondence between the general biological sensitivities to pollution and temperature preferences. Because many metrics commonly used in MMIs can be comprised predominantly of cold or warm-water taxa, or of both, the changes in these metrics alter MMIs through shifts in the proportion of cold to warm water-preference taxa.

Another widespread and related finding is the moderate but significant relationship between temperature sensitivity and sensitivity to organic pollution. Metrics selected because the composite taxa were considered to be generally sensitive, such as EPT taxa, or generally tolerant, such as Diptera taxa, or to represent responses to conventional pollutants (e.g., organic pollution as in the HBI), also have demonstrable sensitivities to climate-related changes in temperature and flow conditions. We have shown these sensitivities to be related, at least in part, to the predominance of cold and/or warm-water taxa at a location. Assemblage composition by cold and warm-water taxa may be related to ecoregion, latitude, watershed size, and/or stream order, and is also clearly affected by elevation. This association between temperature and pollution sensitivities will affect how indices are interpreted with regard to the conventional stressors for which the indices were originally developed.

From more limited evidence, it also appears that the ability to categorize taxa according to flow preferences and requirements could be useful. However, there are generally fewer data available for this analysis. We augmented the approach of grouping taxa by traits responsive to one climate variable (temperature) through consideration of a suite of traits. This was useful in some cases, though it produced fewer significant results. This was probably due to the fact that fewer taxa were included when categorized by a suite of several traits, resulting in more limited and/or more variable data and smaller sample sizes with which to test responses. Still, this is potentially a useful approach to apply as more data become available.

7.5.2. Recommendations for Modifying Metrics

In general, biological metrics (indicators) are selected for their diagnostic value (Verdonschot and Moog, 2006). However, the effects of global climate changes in temperature and precipitation on biological metrics have, until now, been largely untested, because climate change was not considered a "stressor of concern" until recently (Hamilton et al., 2010a). Given our demonstrations of the vulnerabilities of traditional metrics to climate change, and associated impacts to the classification of station conditions, it is important that state and tribal biomonitoring programs consider adopting modified metrics with the purpose of tracking climate-associated changes in MMI outputs (Hamilton et al., 2010b). This will support making inferences about causes, helping differentiate climate change from other stressors as part of a weight-of-evidence evaluation. It will allow resource managers to more effectively make management and regulatory decisions on the basis of biomonitoring results in the face of climate change impacts (Hamilton et al., 2010a).

The focus here is on the relative contribution of cold- and warm-water ecological trait groups to the composition of traditional metrics. The general recommendation is that cold and warm water components of traditional metrics be documented and tracked separately. A recommended approach for incorporating modified metrics into a biomonitoring data analysis regime is to continue calculating the traditional metric (e.g., EPT richness, HBI), while adding new cold and warm water metrics. Proportional changes in cold and warm-water taxa would provide a basis for estimating how much of the change in the traditional metric can be accounted for by changes in temperature trait groups. This provides a basis for comparing potential climate change effects to those of other stressors in a weight-of-evidence assessment. Comparisons could be made over time and among locations or groups of sites (both reference and nonreference). An option for tracking climate-related changes is to put traditional and modified metrics on the same plot and compare their trends over time (i.e., Figure 7-11). Another option that requires further testing is to track the ratio of the cold- or warm-modified metric to the traditional metric. For example, separate tracking of cold-to-total EPT and warm-to-total EPT richness metrics was able to account for trends in total EPT richness over time in circumstances where changes in total EPT richness were caused by losses of cold-water taxa, and where changes include both losses of cold-water taxa plus gains of warm-water taxa (i.e., taxon replacements) (Hamilton et al., 2010b).

We examined evidence in this study for the value of adopting temperature-modified metrics for diversity and total taxa richness metrics; for EPT-related metrics; and for pollution tolerance metrics, such as the HBI or related indices. However, the principle of partitioning metrics to separate component taxa based on cold or warm water should be considered for other biological metrics (Hamilton et al., 2010b). These could include trait metrics related to functional feeding groups (e.g., predators, collector-filterers) or life history habits (e.g., swimmers, climbers). Such metric modification should be considered on a state or region-specific basis, in particular for climate-vulnerable regions (e.g., high elevations, low-order streams, small watersheds). In addition, an OCH taxa metric may be valuable to track taxa that are robust to warmer conditions and/or more intermittent flows. This may be especially valuable in regions at lower elevations, where temperature increases may be large, and/or where summer flow conditions are likely to be especially vulnerable to climate change effects.

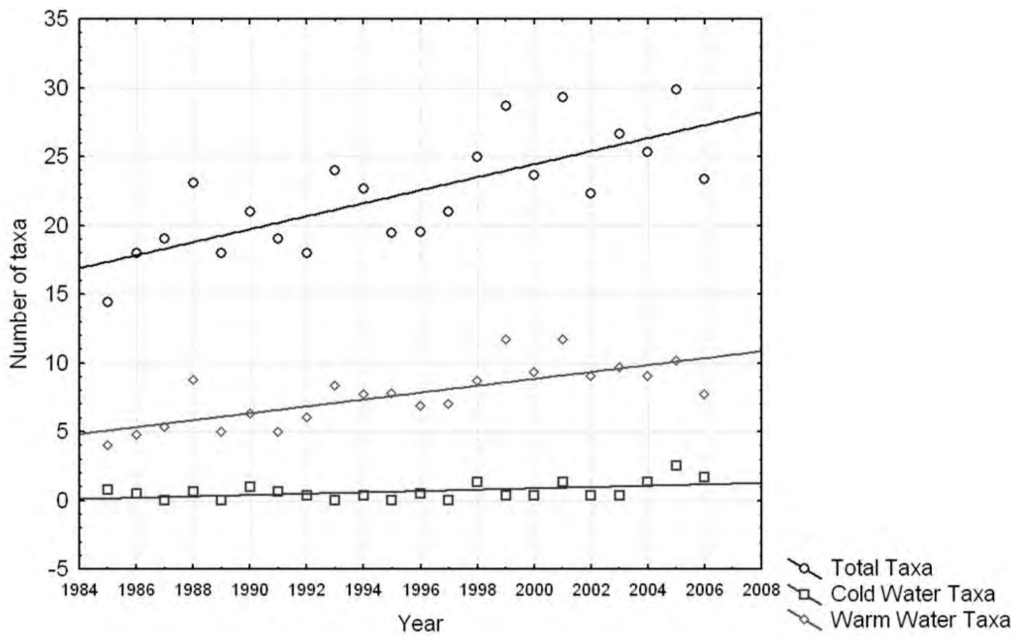

Figure 7-11. Method for tracking changes in cold- and warm-water-preference taxa and commonly used metrics (in this case, total number of taxa at Maine site 56817 [Sheepscot] over time).

We cannot yet make strong suggestions for metrics related to hydrologic sensitivity, in part because the lack of flow data corresponding to biological collections has limited ability to calculate flow metric preferences by taxon. However, hydrology-related trait characterizations can be based on known life history traits coupled with regional observations and literature information, as with the intermittent taxa metric used in North Carolina. A metric that accounts for tolerance to intermittent flows, requirement for perennial flows, or some similar hydrologic-preference metric, may become valuable as changes in flow conditions are more evident. Such a metric would have to be calibrated by region.

Calculation of modified metrics for incorporation into biomonitoring data evaluation will require designation of cold- and warm-water ecological trait groups. Cold and warm-water taxa lists must be developed on a state- or region-specific basis, which is a substantial undertaking. The efforts initiated in this study, including the process of applying weighted average or maximum likelihood modeling in concert with literature information and best professional judgment to estimate temperature preferences by taxon from biomonitoring data, and the development of a traits database that documents the temperature preferences and tolerance results calculated for the three states analyzed in this study (see Stamp et al., 2010; U.S. EPA, 2012), can be used as a starting point for future state efforts.

7.6. SENTINEL MONITORING NETWORK

Results of this study have demonstrated the importance of accounting for climate change effects in order to maintain sound bioassessment decision making. The next step is to consider possibilities for augmenting existing programs to address this need. Section 7.3 discusses characteristics of a biomonitoring program and their inherent limitations with regard to detecting trends that might be associated with climate change. Approaches to address some of those limitations are discussed here.

A monitoring network designed to detect climate change effects needs to account for regional variations in numerous factors, including climate, geology (including soils), topography, elevation, latitude, vegetation, etc. Such conditions often cross state and tribal boundaries. Therefore, this kind of monitoring network may require collaboration among states and tribes with regard to technical considerations (e.g., site selection, sampling methods) and funding. Regional and national coordination will be important to facilitate this process.

Thorough coverage across ecoregions and other environmental variants would require a large network of sites. A modest initial effort for sentinel site monitoring could focus on highly vulnerable areas and watershed types. Because not all watersheds or community types would be represented by such selective establishment of a sentinel site monitoring network, the classification of conditions and transferability of bioassessment results will be integral for extrapolation to other areas (e.g., Allan et al., 1997; Gerritsen et al., 2000; Wu and Li, 2006).

In order to separate climate change effects from other stressors, both reference and some portion of impaired sites should be measured over time. Thus, an ideal network of sentinel sites would be established along the BCG and be anchored in reference conditions. This would support an analysis approach in which temporal trends at reference sites could be compared to temporal trends at impaired sites, in order to differentiate between climate effects and conventional stressors, as illustrated in Figure 7-12. Different levels of stressor effects could also be compared, and synergistic effects could be considered (see Figure 7-12).

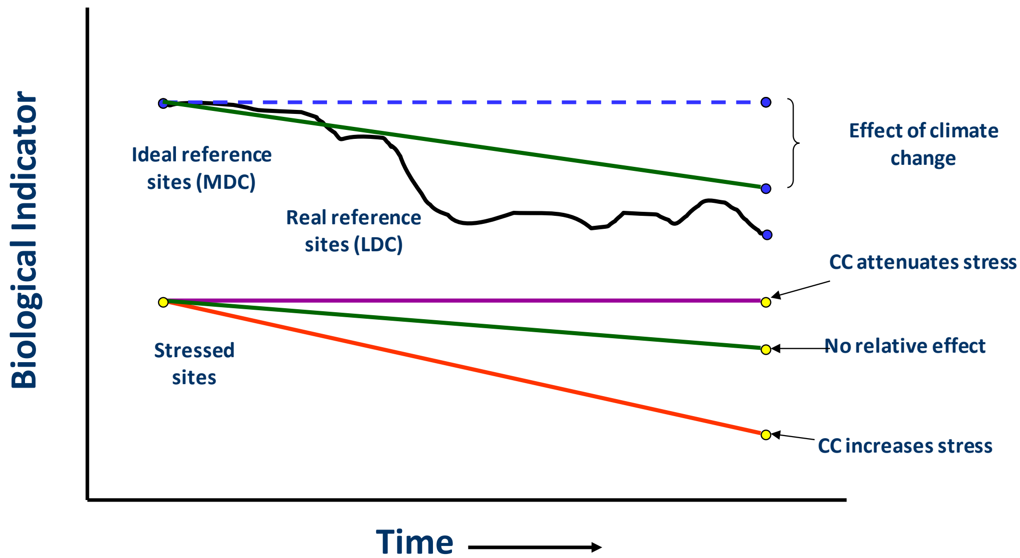

Figure 7-12. Conceptual model showing relationship between climate change trends and reference and stressed sites with an overlay of temporal variation on the trend (black line). "MDC" = minimally disturbed condition; "LDC" = least disturbed condition.

It is possible that in a monitoring context, as opposed to a controlled study, synergisms between climate change and conventional stressor responses could not be fully partitioned. Inference using literature studies, especially through use of CADDIS and the stressor identification process (Suter et al., 2002; U.S. EPA, 2000) would contribute to data interpretation in a weight-of-evidence approach. The efficacy of conducting long-term sampling along the BCG should be considered through interactions with state and tribal biomonitoring managers, consideration of avenues of funding support, and finally, through practical evaluation of existing opportunities for establishing such a sentinel site monitoring network in representative and vulnerable regions.

If a sentinel site monitoring network along the BCG is infeasible, a less resource-intensive alternative would be to establish long-term sentinel sites only at high-quality reference locations. Lack of trend data from nonreference sentinel locations would present some limitations to separating climate change from other stressors responses. Selection of such locations would face some of the same difficulties as any reference selection effort conducted by individual states. However, the larger spatial scale and regional perspective necessary for implementation would offer opportunities to search for and select least-affected locations from a larger area and share results across jurisdictional boundaries.

While typical bioassessment approaches include sampling watersheds on a (typically) 5-year rotating basis, biomonitoring at sentinel sites should be considered on a regular, repeating basis, annually if possible. With less frequent data, temporal variations from interannual and cyclic climatic sources would greatly extend the time frame needed to describe climate change responses.

Another consideration for sentinel site monitoring for climate change is the inclusion of continued monitoring at targeted locations, even if initial site selection is probability-based, rather than only application of a probability-based sampling approach in which all sites are reselected each year. Probability sampling has important strengths in capturing the (often large) range of variability within a defined stratum, such as low-order stream reaches (Barbour and Gerritsen, 2006; Hughes et al., 2000). It also provides valuable data about the status of our nation's waters at any given time (Hughes et al., 2000; Paulsen et al., 1998). This is important for defining the range of conditions within the stratum at any one time, but it requires replication (multiple reference sites) within the stratum. Reference conditions are often established based on a population of reference locations that together reflect the range of natural variability for a region (Barbour and Gerritsen, 2006). Combining reference stations across major physiographic, geomorphic or climatological regions inflates the range of measured variation in biological parameters from predictable, natural sources (Barbour and Gerritsen, 2006). It is, thus, important to account for predictable, natural sources of variation. This will affect how many reference stations within a defined area must be sampled, how frequently they must be sampled, and the sampling duration needed to have the power to detect climate change response trends. In the current study, groups of reference stations analyzed were typically not of sufficient duration to define statistically significant trends within the context of natural spatial and interannual variation.

We found high among-site variability within ecoregions despite the expectation that partitioning by ecoregion should control major predictable sources of variation. This maximizes the effects of "natural" site (spatial) variability on the detection of temporal trends and greatly extends the time it will take to discern climate change effects. This suggests a trade-off between gaining knowledge about regional status and knowledge about long-term trends.

Climate change trends observed from single fixed locations may not be transferable to corresponding regions or strata because they do not account for the real range of conditions that defines the stratum. However, replication of targeted locations within a region or stratum would account for natural spatial variability. Combining some fixed with random sites in a predetermined sampling pattern may be the most likely design that accomplishes both trend detection and representation (Urquhart et al., 1998). One observation that stands out regarding the Maine, North Carolina, and Utah reference locations is that most of these have more frequent annual sampling than would be the case if they were only sampled on a “rotating basin” basis. Utah adopted a rotating basin sampling scheme as well as a probability-based station selection approach within the last decade (Utah DEQ, 2006). However, they maintain regular annual sampling at a small number of fixed locations with long-term historic records. Whether by formal decision or historic happenstance, some other states also have regularly sampled stations outside of rotating and/or probabilistic designs.

The selection of an index period will also be affected by climate change. Projected climate changes are likely to impact seasonal patterns through changes in flow conditions as well as in temperature regimes. These will influence a variety of biological processes, including rates of development, timing of emergence, and other components of reproduction (Seebens et al., 2009; Harper and Pecarsky, 2006; Poff et al., 2002; Vannote and Sweeney, 1980). This may have several ramifications to biomonitoring designs. If samples are collected at a fixed time during the year, then in the future, sampling may yield lower abundances of some species, different species composition, or different relative abundances. This impacts temporal comparisons. Also, spatial comparisons may now be based on communities of more limited seasonal diversity. More extreme or extended summer low flows may, over the long term, become an impediment to sampling for states that use summer or fall index periods. This may be a particular concern in perennial streams vulnerable to a shift to intermittent conditions in the future. Biological responses to reductions in flow can represent legitimate responses to climate change. However, the eventual inability to sample during a late-season index period in some stream locations must be considered and planned for. Though highly unlikely due to resource limitations, sampling more than once per year, including once during the spring/high flow index period, could provide valuable information on components of the benthic community that emerge early in summer.

Many different groups are considering, or have already started, monitoring for climate change effects. If possible, collaboration among at least some groups, particularly among bordering states, would have many potential benefits. Some duplication of effort could be avoided, results could be integrated in a more meaningful way, and resources could potentially be saved. Collaboration would foster consistency across groups in types of data collected, as well as potential use of a common database. Efforts to discuss and establish a sentinel monitoring network might facilitate collaboration among existing efforts. A common vision of sampling and agreement on types of data that could be incorporated into a common database related to a potential climate change monitoring network could have a better chance of success.

7.7. CLIMATE CHANGE IMPLICATIONS FOR ENVIRONMENTAL MANAGEMENT

The components of bioassessment programs that may be affected by climate change include assessment design, implementation, and environmental management (see Figure 7-13). Awareness that climate change can have widespread effects on biological communities introduces additional uncertainty into a system that requires interpretable patterns of biological indicator responses to "conventional" stressors. This has the potential to cast doubt on assertions of stressor-response relationships that are being evaluated within a regulatory context. It also highlights that the biomonitoring tools applied must be appropriately tailored to the types of stressors expected. With increasing knowledge of the types of climate change effects that are appearing to different degrees in regions around the country, and of the categories of organisms that are showing the most predictable responses, it becomes important to adjust assessment tools to changing biota to enable a clearer interpretation of stressor identification and causal analysis. One of the central objectives of state programs for establishing a reference condition baseline and conducting ongoing biomonitoring at reference and nonreference locations is to detect locations, or stream reaches, that are sufficiently different from the established baseline to be considered impaired. The approach and specific criteria used to make impairment decisions are established by states and tribes, and vary among regions to reflect the appropriate range of natural variability (Barbour and Gerritsen, 2006). But the assumptions inherent in the almost universally applied reference comparison approach include that the stressors likely to impair streams and rivers within a region are accounted for within the sampling and analysis scheme applied, and that if a real impairment exists, it can be detected with a reasonable level of confidence. The concept that all stressors must be accounted for presents an unusual problem with regard to climate change effects, because climate change effects are "global," so reference stations are equally at risk. This threatens the reference comparison paradigm.

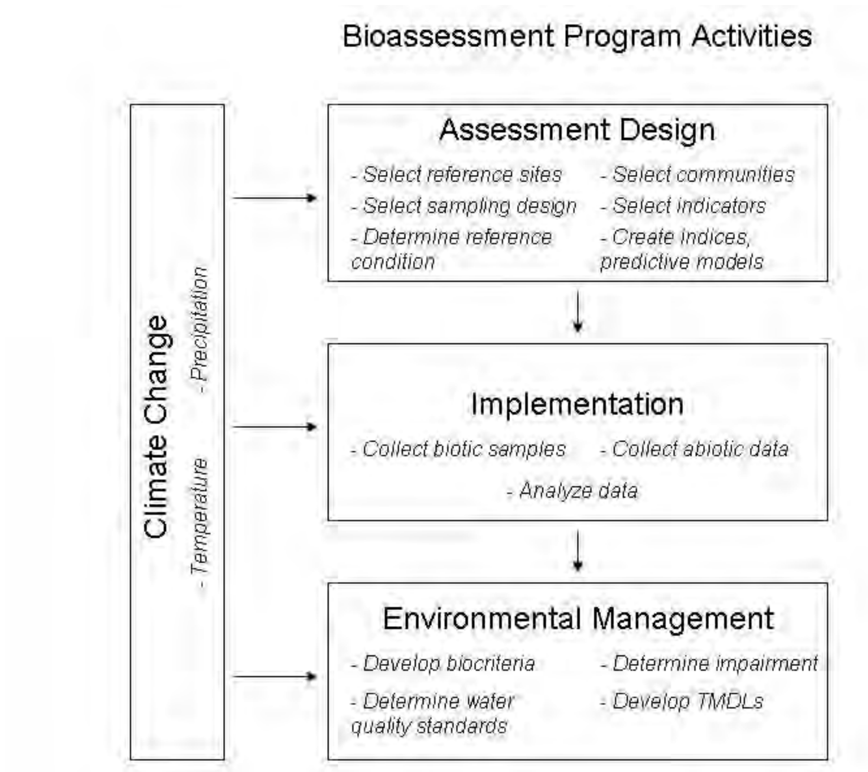

Figure 7-13. Climate change can affect many bioassessment program activities from the initial assessment design, to collecting and analyzing data, and to developing responses to assessment outcomes.

7.7.1. Impairment Listings and Total Maximum Daily Load (TMDL) Development

Results of this study reveal changes in biological indicators and within specific ecological traits groups that are reasonably attributable to climate change effects and are likely to interfere with impairment determinations. Trends in cold- and warm-water trait groups result in corresponding changes in biological metrics used by states, such as EPT taxa richness or abundance in the HBI index. The observed and projected changes in biological metrics are sufficient to downgrade reference station condition. Degradation of reference station condition is essentially causing references stations to become more similar to nonreference stations, and diminishes the ability to detect impairment. These findings imply that unless metrics are modified so that climate effects can be tracked and thresholds for defining impairment re-evaluated, degraded reference conditions will cause fewer stream reaches to be defined as impaired, at least in the most climate-vulnerable watersheds. Where this occurs, fewer corrective actions would be taken, and greater long-term degradation of stream conditions could result (see also Hamilton et al., 2010a).

When a stream segment is found to be impaired, TMDLs of pollutants are developed by states, and the cause(s) of the impairment are identified through the stressor identification process (U.S. EPA, 2000; Suter et al., 2002). In permitting (e.g., the National Pollutant Discharge Elimination System [NPDES]), discharge limits must be set considering any existing TMDLs. Beyond the possibility of underprotection with fewer impairment listings and fewer requirements for TMDLs, there may be other climate change implications to TMDL development. Climate change scenarios show greater variability in runoff and flow, which may result in greater uncertainty in loadings expected from nonpoint sources. Critical low flows also drive TMDLs, and these may become uncertain and more difficult to predict. The identification of culpable stressors is also complicated by the effects of climate change on biological indicators.

The main approaches pertinent to preserving the ability to detect impairment include adopting climate change-related modifications of biological metrics, associated re-evaluation of impairment thresholds, and reference station classification and protection. These actions are directed at improving the ability to track effects of climate variables, compare these between reference and nonreference locations, and, thus, increase the information brought to bear on differentiating climate change from other stressors and detecting conventional stressor impairment. The stressor identification process, tailored to include detailed climate change information, would facilitate partitioning biological responses between climate change and other stressors.

The paradigm for conventional stressor identification is based on spatial (reference/nonreference) comparisons, combined with a weight-of-evidence evaluation of potential causes, augmented by research and other literature-based knowledge of major cause-effect expectations (Suter et al., 2002; U.S. EPA, 2000). The need to partition climate change effects could add a relatively extensive time component to this framework if the process were to rely primarily on site-specific, long-term field data. However, it is impractical and undesirable from a decision-maker's point of view to obtain this degree of detailed, long-term sampling for every case of impairment assessment. From a practical perspective, it also is likely to be outside of the level of resources available to most states or tribes for routine bioassessment sampling. An alternative approach includes monitoring a more limited network of sentinel sites (see Section 7.6). Documentation of trends from monitoring data, other aspects of weight-of-evidence evaluation of potential causes, and an expanded knowledge database on biological responses to climate change could be included in an expanded stressor identification process.

With regard to other vulnerabilities in the TMDL development process, there is a need for watershed-specific modeling to predict how flow dynamics change with climate, to provide support for estimating future changes in low flows, and to modify loading calculations and limitations accordingly.

7.7.2. Impacts on the Development of Water-quality standards and Biocriteria

Biological responses to climate change will likely impact water-quality standards and biocriteria through shifts in baseline conditions. This study illustrates several avenues through which climate change is affecting stream communities in ways that have implications for biocriteria programs. The cascading effects of climate change-related trends in temperature and precipitation on watershed conditions, water quality, and aquatic biological communities, will lead to shifting, most often degrading, baseline conditions. Decreases in mean abundances and/or species richness of cold water or other sensitive taxa and trait groups, increases in warm water or other tolerant taxa and groups, and also increases in variability of these indicators drive reference sites to greater similarity with nonreference areas, as well as greater difficulty in establishing statistical differentiation (see also U.S. EPA, 2008). As a result, reference-based standards will be liable to progressive underprotection.

Given the types of biological responses observed in this study, climate change can be expected to alter some uses and their attainability, especially in vulnerable streams or regions. For example, some cold-water streams could take on cool-water characteristics, with declining abundances and/or richness of sensitive cold-water taxa, possible increases in warm-water taxa, and other changes potentially related to altered hydrologic patterns. Regulated parameters such as temperature, DO, ammonia, and pH may also be sensitive to climate change effects, and their values may need to be adjusted relative to revised designated uses.

There are numerous criteria, both biological and chemical, that are addressed in water-quality standards, and which may be affected by climate change (see Table 7-15). Biocriteria are of particular interest, as they tie closely to the indices and thresholds used to determine condition and impairment. The climate-related causes of drifting (degrading) baseline conditions cannot be directly controlled, but can be assessed, at least to the degree resources allow. Necessary steps would include documentation of reference conditions, tracking of changes in reference conditions over time, and to the extent possible, protection of reference conditions from other encroaching impacts, particularly land-use changes. This may be extended to include repetitive regional monitoring of sentinel sites, carefully chosen to represent the best conditions of the most vulnerable regional watersheds. Further efforts to address climate change impacts on standards would require examination of which water-quality standards are resilient to climate change impacts and will remain protective, and identification of susceptible standards that may need adjustment.

For watersheds that are found to be particularly vulnerable to climate change effects and are characterized by particularly vulnerable trait groups, more refined aquatic life uses should be considered for application. Refinement of aquatic life uses can be applied to guard against lowering of water quality protective standards. Uses are designated for a stream segment based on conditions at similar reference stream segments, using information on habitat characteristic and associated biological communities, and potentially also consideration of economics and human-related conditions. Criteria are set to protect designated uses, and often differ between use levels. Application of refined aquatic uses could provide a greater number of more narrowly defined categories, which could accommodate potentially “irreversible” changes (e.g., increased temperatures driven by long-term climate change), but with sufficient scope to maintain protection, and also support antidegradation from regulated causes.

Climate change effects that contribute to degradation of water quality and biological resource condition bring into question how antidegradation policies can be managed considering the additional influences of climate change. High quality water bodies may be most

Table 7-15. Variables addressed in criteria and pathways through which they may be affected by climate change (from Hamilton et al., 2010a)

Criteria	Climate change impacts
Pathogens	Increased heavy precipitation and warming water temperatures may require the evaluation of potential pathogen viability, growth, and migration.
Sediments	Changing runoff patterns and more intense precipitation events will alter sediment transport by potentially increasing erosion and runoff.
Temperature	Warming water temperatures from warming air temperatures may directly threaten the thermal tolerances of temperature-sensitive aquatic life and result in the emergence of HABs, invasion of exotic species, and habitat alteration.
Nutrients	Warming temperatures may enhance the deleterious effects of nutrients by decreasing oxygen levels through eutrophication (hypoxia), intensified stratification, and extended growing seasons.
Chemical	Some pollutants (e.g., ammonia) are made more toxic by higher temperatures, and also by pH, which may be altered as a result of climate change.
Biological	Climate changes such as temperature increases may impact species distribution and population abundance, especially of sensitive and cold-water species in favor of warm-tolerant species including invasive species. This could have cascading effects throughout the ecosystem.
Flow	Changing flow patterns from altered precipitation regimes are projected to increase erosion, sediment and nutrient loads, pathogen transport, and stress infrastructure. Depending on the region, climate change is also projected to change flood patterns and/or drought and associated habitat disturbance.
Salinity	Sea level rise will inundate natural and manmade systems resulting in alteration and/or loss of coastal and estuarine wetland, decreased storm buffering capacity, greater shoreline erosion, and loss of habitat of high value aquatic resources such as coral reefs and barrier islands. Salt water intrusion may also affect groundwater.
pH	Ocean pH levels have risen from increased atmospheric CO_2, resulting in deleterious effects on calcium formation of marine organisms and dependent communities, and may also reverse calcification of coral skeletons.

vulnerable to climate change degradation, making application of antidegradation policies in vulnerable water bodies important. Management approaches and special considerations for implementation of antidegradation policies may need attention. In addition, the application of use attainability analyses on vulnerable water bodies may be pertinent for characterizing climate change effects.

7.8. CONCLUSIONS

Climate change will affect many of the components of bioassessment programs, including assessment design, implementation, and environmental management. Implementing the recommendations derived from the results in this study can improve the resilience of bioassessment programs and ensure that management goals can be met under changing climatic conditions. These steps can help manage the risks associated with not meeting goals, even though the magnitude and timing of climate change effects on aquatic resources is uncertain.

There are four main sets of recommendations from this study specific to adaptations of biomonitoring programs:

1. Multimetric indices should be revised to reflect the sensitivity of taxa and trait groups to climate change effects; predictive models should also reflect these changes in indicators and periodically revise the expected community composition used in the analysis. At present, the most accessible information relates to temperature sensitivities and preferences; however, sensitivities to changing hydrologic conditions should be pursued in the future.

2. A monitoring network to detect climate change effects should be set up, at least for the most climate-vulnerable regions. This network will need to be more comprehensive spatially and sampled more frequently than current bioassessment sites. Detecting climate change at these monitoring sites requires that they are protected from other stressors.

3. Abiotic data needs to be collected more frequently and at more sites; a monitoring network to detect climate change effects should incorporate abiotic data collection as well, including water temperature and flow. The value of better water temperature and flow data is great, and consideration should be given to deploying in situ temperature and flow meters.

4. TMDLs and water-quality standards should be examined to ensure that these remain protective of aquatic life uses under changing climatic conditions.

We have some additional recommendations for further study and collaboration that would enhance our ability to track climate change effects and separate these from other stressor responses in the context of biomonitoring:

1. The use of thermal-preference metrics for detecting climate-related trends should be further explored. Monitoring of thermal-preference metrics will increase the probability of detecting community responses to warming trends and reduce the likelihood that they will be obscured by taxonomic variability.

2. The lists of cold and warm-water taxa developed in this study should be refined and extended to more states and regions. Refinements can be made by using continuous water-temperature data instead of instantaneous water-temperature data, by calculating propensity scores to help improve the robustness of the analyses (Yuan, 2010), and by using species-level OTUs for genera in which differences in which species-level thermal preferences are known to occur.

3. Continue to further our knowledge of traits and how they relate to climate change. More information is needed about which traits are most important in the context of climate change, the influence of each trait on an organism's ability to adapt, and which combinations of traits are most adaptive to particular environmental conditions (Stamp et al., 2010). A key component of furthering the traits-based framework will be expansion and unification of existing trait databases (Statzner and Beche, 2010).

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http://www.prismclimate.org

USGS
http://waterdata.usgs.gov/nwis/rt

Utah Climate Center
http://climate.usurf.usu.edu/products/data.php

National Center for Atmospheric Research
http://rcpm.ucar.edu

APPENDIX A

TAXONOMIC CORRECTIONS AND EVALUATION

A.1. TAXONOMIC CORRECTIONS AND EVALUATIONS PERFORMED ON THE OHIO DATA SET

The Midwest Biodiversity Institute (MBI) developed a list of possible taxa that could affect the Invertebrate Condition Index (ICI) scoring via taxonomic refinement (splitting or lumping of taxa). MBI then conferred with senior Ohio Environmental Protection Agency (EPA) taxonomists (Mike Bolton and Jack Freda) to determine how to best address these changes. Their efforts primarily resulted in "combining of the" individual taxa designations of mayflies back into "*Baetis* sp." or "*Pseudocloeon* sp." as described in Table A-1. This process assured that changes found in the ICI calculated at reference sites for the historic and current periods would be reflecting biological responses to changing conditions and not changes in taxonomy. See results in Tables 6-7 and 6-8 of the main report for a summary of the impact of these taxonomic fixes on index values.

A.2. EVALUATION OF TAXA CORRECTIONS—NONMETRIC MULTIDIMENSIONAL SCALING (NMDS)

In the Maine, North Carolina, and Utah data sets, we used NMDS to evaluate whether the database 'fixes,' and in particular the taxonomic corrections and application of operational taxonomic unit (OTU) rules, were effective in minimizing changes over time due to taxonomic identification procedures rather than actual community changes. For the Ohio data set, taxonomic fixes were conducted by Ed Rankin and Chris Yoder of MBI and were straightforward, mainly recombining mayfly taxa for which refinements resulted in renaming or splitting of taxa since the historic time period during which reference communities were evaluated using the ICI. Postfacto NMDS evaluation was not deemed necessary for that application (see results in Tables 6-7 and 6-8 of the main report for a summary of the impact of these taxonomic fixes on index values). For the Maine, North Carolina, and Utah data sets, the NMDS ordinations were run before and after generating genus-level OTUs. Various grouping variables (i.e., year, month, collection method, taxonomy lab, ecoregion, watershed, etc.) were overlaid to look for trends. Figures A-1A through A-14B and Figures A-18 through A-22B show the NMDS plots that were generated as part of this exercise. Figures A-15 through A-17 show more details about number of identifications by species, genera, and families, as well as differences in total taxa identifications by laboratory. Table A-2 lists the laboratories references in Figure A-17.

Table A-1. Mayfly taxa from reference sites in Ohio that abruptly appeared (Later) or disappeared (Earlier) in the Ohio data set and explanation of change. Explanations were provided by Mike Bolton and Jack Freda of OH EPA

Taxa code	Taxon name	Appearance	Explanation of change
11010	*Acentrella* sp.	Later	Advancements in taxonomy allow this taxa to be distinguished from *Pseudocloeon* sp.
11014	*Acentrella turbida*	Later	Advancements in taxonomy allow this taxon to be distinguished from *Pseudocloeon* sp.
11015	*Acerpenna* sp.	Later	Advancements in taxonomy allow this taxon to be distinguished from Baetidae sp.
11018	*Acerpenna macdunnoughi*	Later	Advancements in taxonomy allow this taxon to be distinguished from Baetidae sp.
11020	*Acerpenna pygmaea*	Later	Advancements in taxonomy allow this taxon to be distinguished from Baetidae sp.
11110	*Acentrella parvula*	Later	Advancements in taxonomy allow this taxon to be distinguished from *Pseudocloeon* sp. or was renamed from *Pseudocloeon parvulum*
11115	*Baetis tricaudatus*	Later	Advancements in taxonomy allow this taxon to be distinguished from Baetidae sp.
11118	*Plauditus dubius*	Later	Advancements in taxonomy allow this taxon to be distinguished *Pseudocloeon* sp.
11119	*Plauditus dubius* or *P. virilis*	Later	Advancements in taxonomy allow this taxon to be distinguished *Pseudocloeon* sp.
11120	*Baetis flavistriga*	Later	Advancements in taxonomy allow this taxon to be distinguished from Baetidae sp.
11125	*Pseudocloeon frondale*	Later	Advancements in taxonomy allow this taxon to be distinguished from Baetidae sp.
11130	*Baetis intercalaris*	Later	Advancements in taxonomy allow this taxon to be distinguished from Baetidae sp.
11150	*Pseudocloeon propinquum*	Later	Advancements in taxonomy allow this taxon to be distinguished from Baetidae sp.
11155	*Plauditus punctiventris*	Later	Advancements in taxonomy allow this taxon to be distinguished *Pseudocloeon* sp.
11175	*Plauditus virilis*	Later	Advancements in taxonomy allow this taxon to be distinguished *Pseudocloeon* sp.

Table A-1. Mayfly taxa from reference sites in Ohio that abruptly appeared (Later) or disappeared (Earlier) in the Ohio data set and explanation of change. Explanations were provided by Mike Bolton and Jack Freda of OH EPA (continued)

Taxa code	Taxon name	Appearance	Explanation of change
11250	*Centroptilum* sp. (w/o hindwing pads)	Later	Advancements in taxonomy allow this taxon to be distinguished *Cloeon* sp.
11400	*Centroptilum* sp. or *Procloeon* sp. (formerly in *Cloeon*	Earlier	Advancements in taxonomy allow this taxon to be distinguished *Cloeon* sp.
11430	*Diphetor hageni*	Later	Advancements in taxonomy allow this taxon to be distinguished from Baetidae sp.
11503	*Heterocloeon curiosum*	Later	Renamed *Heterocloeon* (H.) sp., *Heterocloeon* sp.
11600	*Paracloeodes* sp. 1	Later	Advancements in taxonomy allow this taxon to be distinguished from *Paracloeodes* sp.
11625	*Paracloeodes* sp. 3	Later	Advancements in taxonomy allow this taxon to be distinguished from *Paracloeodes* sp.
11645	*Procloeon* sp.	Later	Was earlier classified as *Centroptilum* sp. or *Cloeon* sp.
11650	*Procloeon* sp. (w/hindwing pads)	Later	Was earlier classified as *Cloeon* sp.
11651	*Procloeon* sp. (w/o hindwing pads)	Later	Was earlier classified as *Centroptilum* sp.
11670	*Procloeon irrubrum*	Later	Advancements in taxonomy allow this taxon to be distinguished from *Cloeon* sp.
11700	*Acentrella* sp. or *Plauditus* sp. (formerly in *Pseudoc*)	Earlier	Renamed as *Pseudocloeon* sp.
13010	*Leucrocuta hebe*	Earlier	Renamed as *Heptagenia hebe*
13030	*Leucrocuta maculipennis*	Earlier	Renamed as *Heptagenia maculipennis*
14501	Leptophlebiidae	Earlier	Now coded as *Leptophlebia* sp.
14900	*Leptophlebia* sp.	Later	*Leptophlebia* sp.
14950	*Leptophlebia* sp. or *Paraleptophlebia* sp.	Later	Small specimens lumped

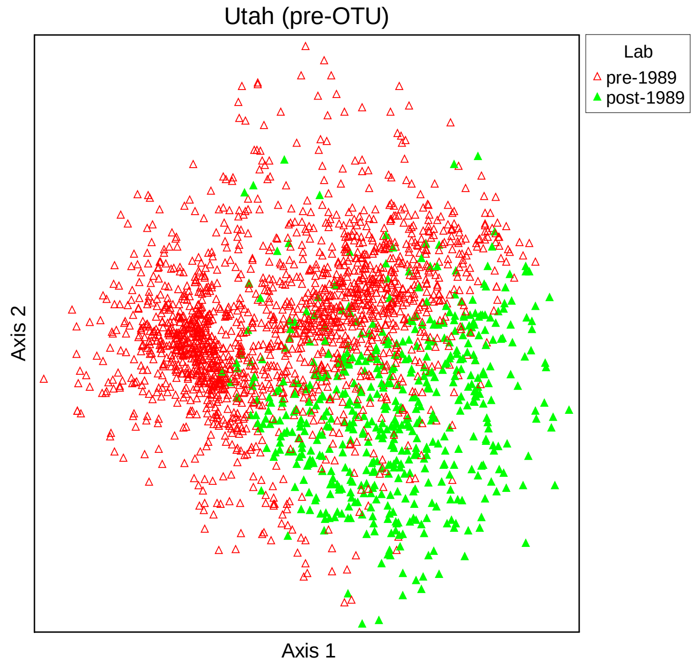

Figure A-1A. Pre-OTU (genus) NMDS plot when lab is used as the grouping variable.

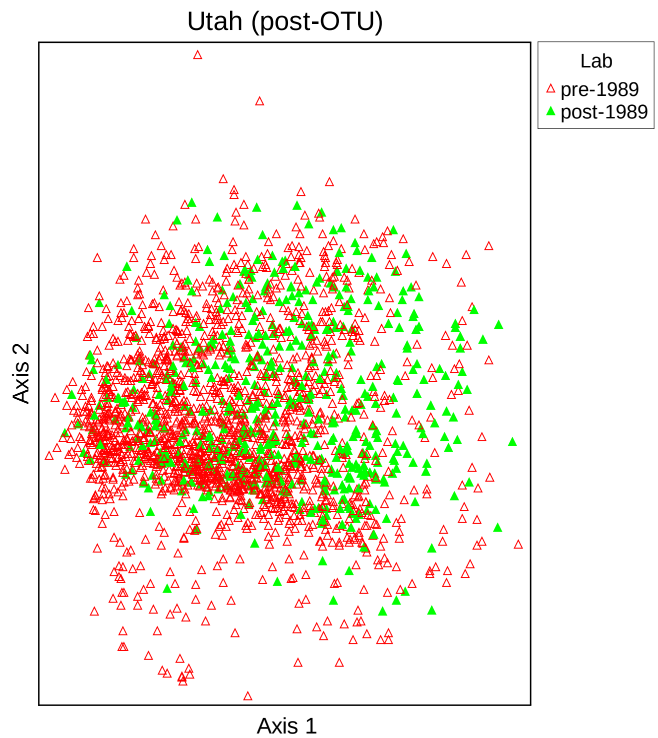

Figure A-1B. Post-OTU (genus) NMDS plot when lab is used as the grouping variable.

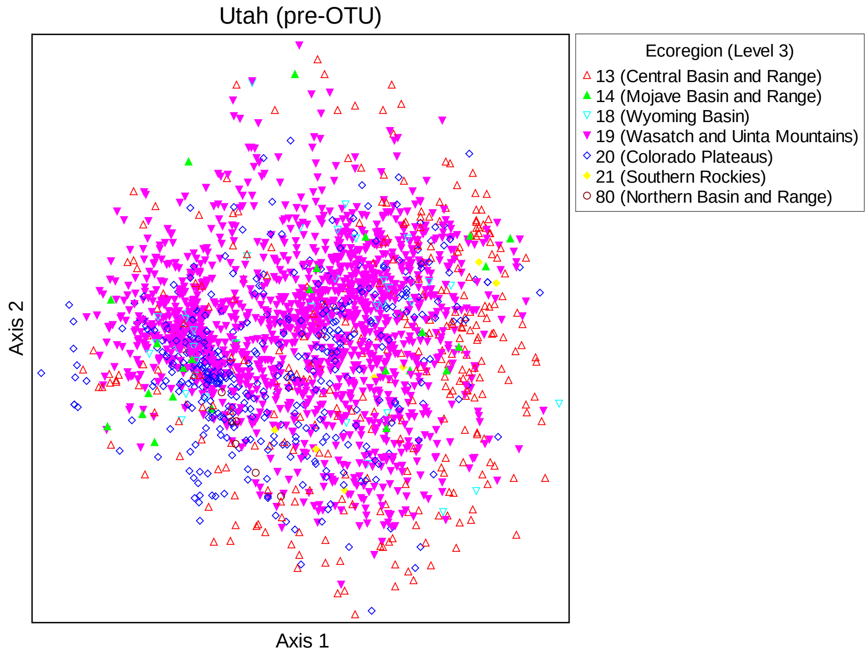

Figure A-2A. Pre-OTU (genus) NMDS plot when Level 3 ecoregion is used as the grouping variable.

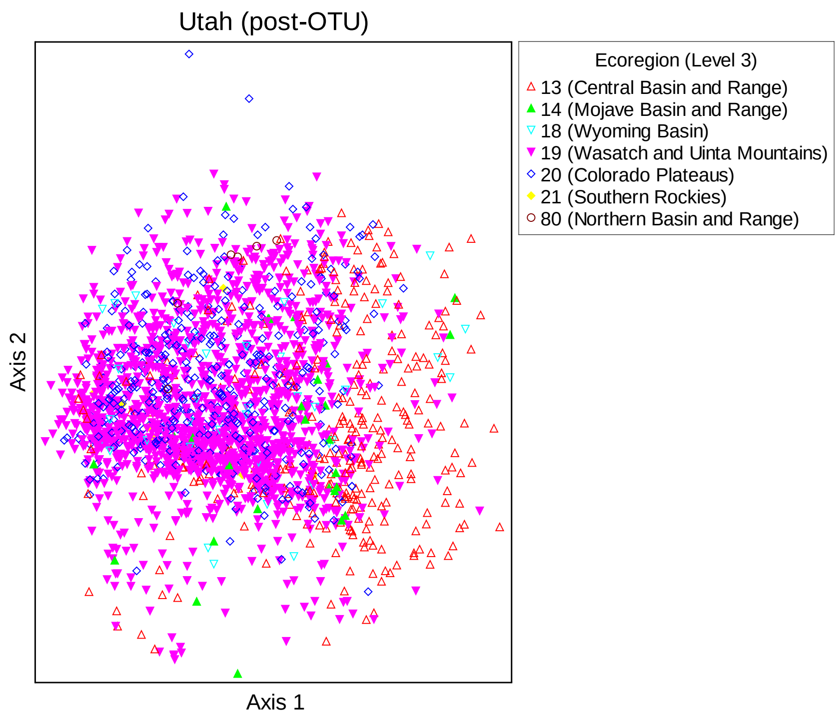

Figure A-2B. Post-OTU (genus) NMDS plot when Level 3 ecoregion is used as the grouping variable.

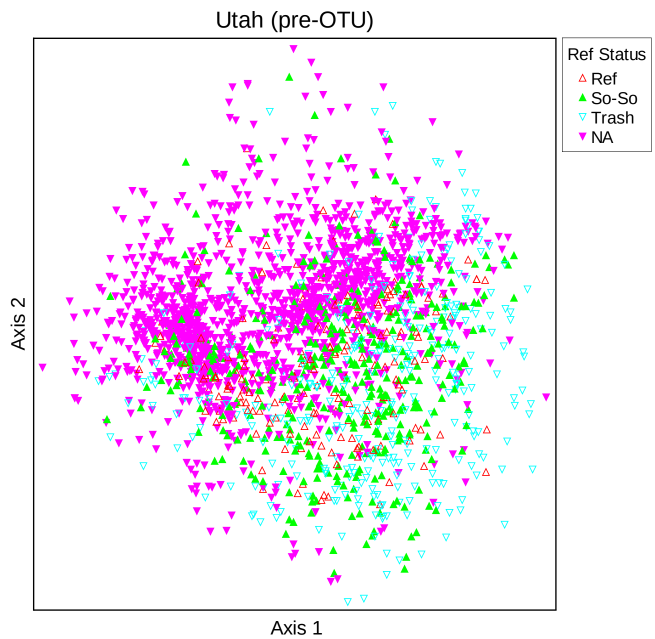

Figure A-3A. Pre-OTU (genus) NMDS plot when reference status is used as the grouping variable.

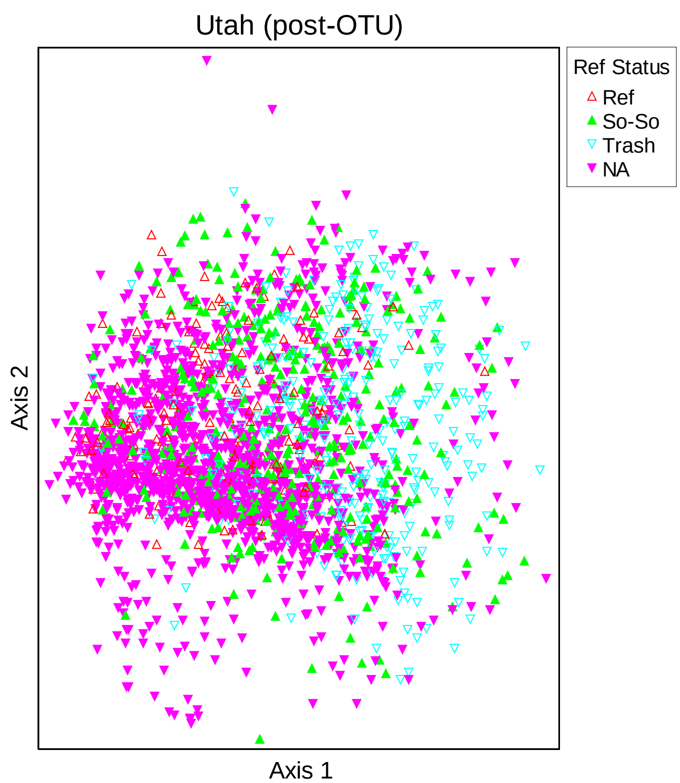

Figure A-3B. Post-OTU (genus) NMDS plot when reference status is used as the grouping variable.

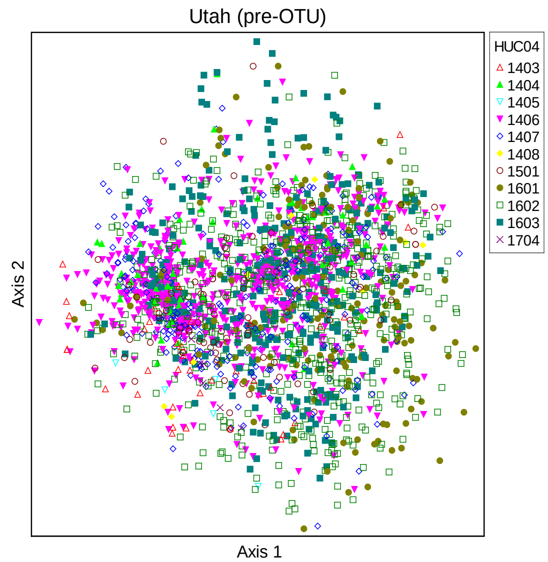

Figure A-4A. Pre-OTU (genus) NMDS plot when Hydrologic Unit Code (HUC)-04 is used as the grouping variable.

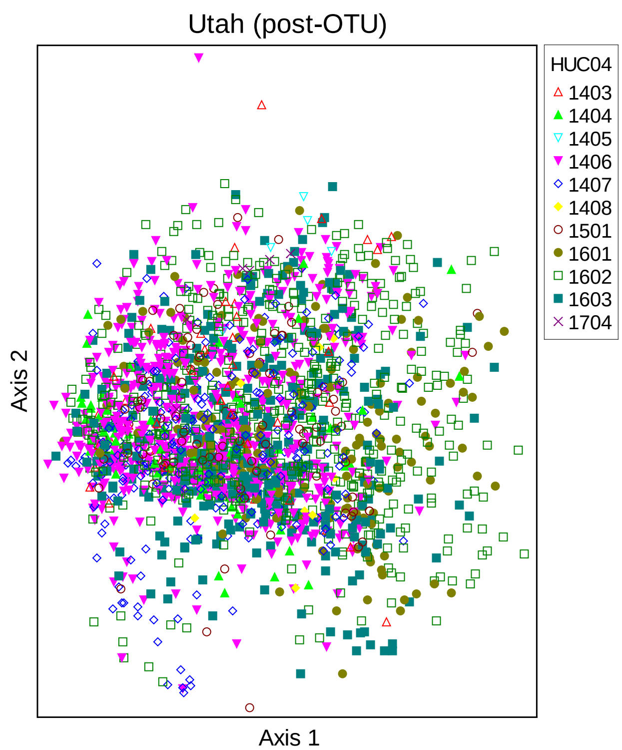

Figure A-4B. Post-OTU (genus) NMDS plot when HUC-04 is used as the grouping variable.

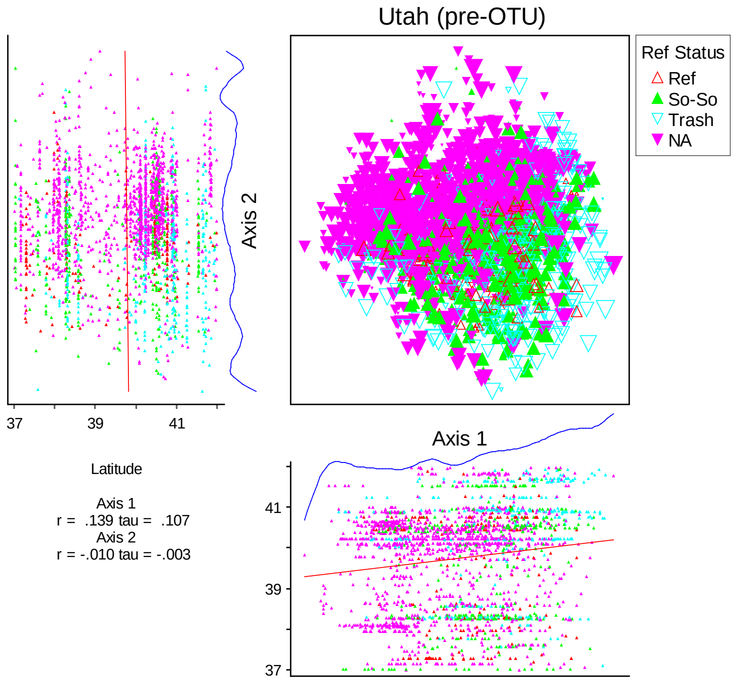

Figure A-5A. Pre-OTU (genus) NMDS plot when reference status is used as the grouping variable. Trends related to latitude are also evaluated.

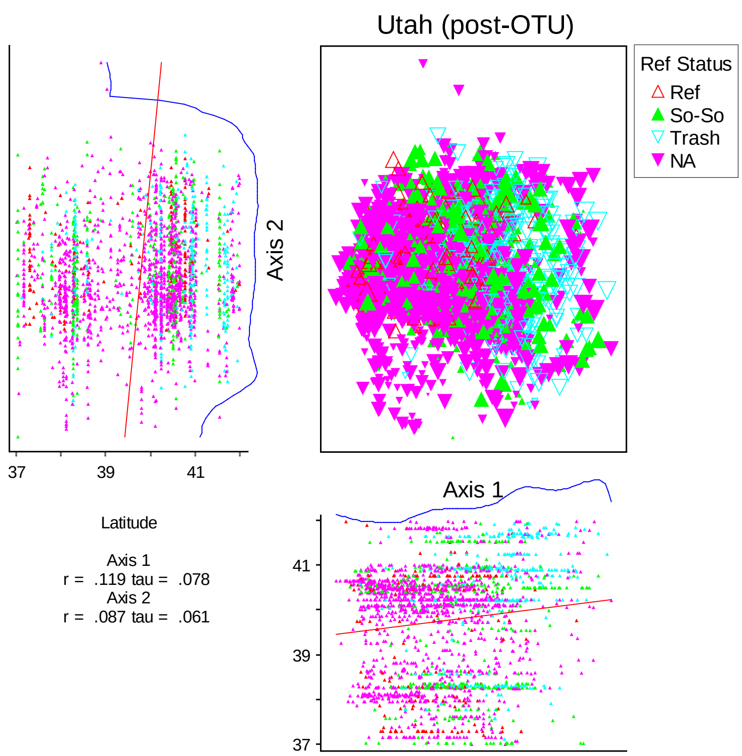

Figure A-5B. Post-OTU (genus) NMDS plot when reference status is used as the grouping variable. Trends related to latitude are also evaluated.

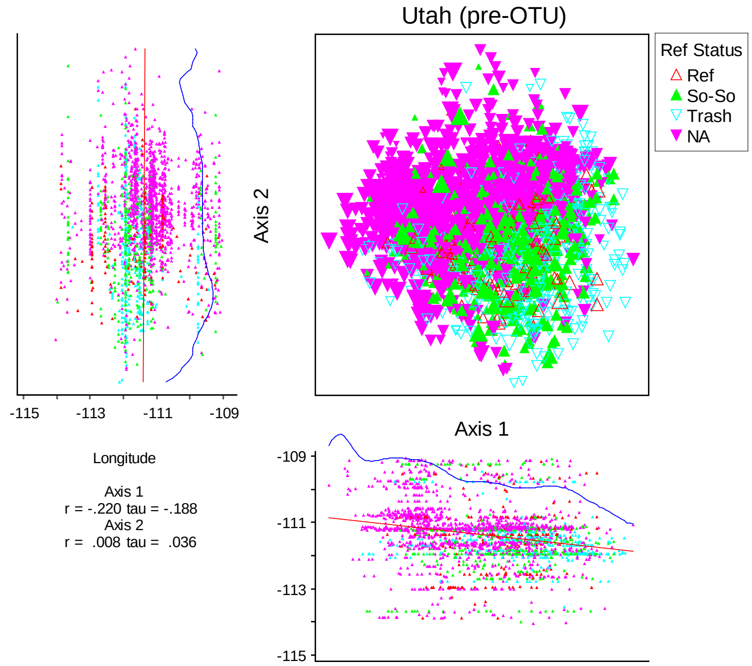

Figure A-6A. Pre-OTU (genus) NMDS plot when reference status is used as the grouping variable. Trends related to longitude are also evaluated.

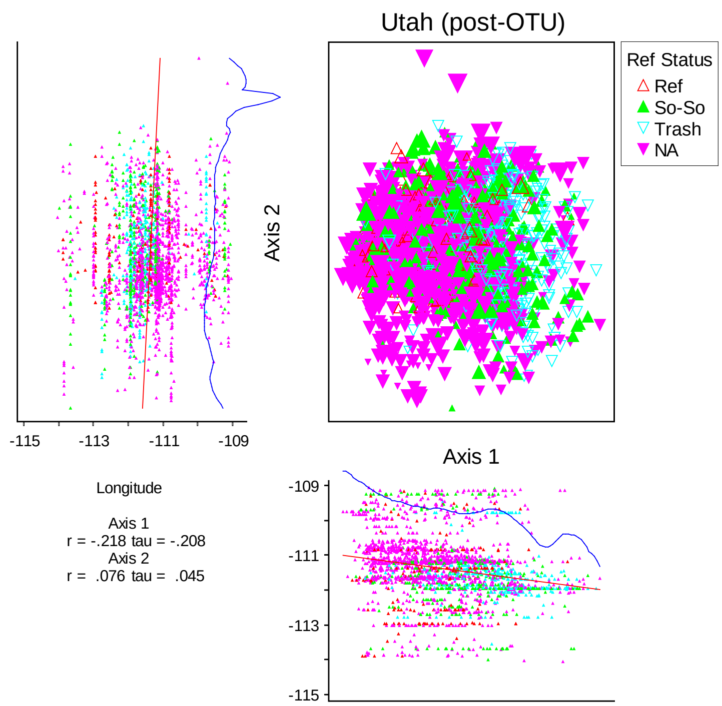

Figure A-6B. Post-OTU (genus) NMDS plot when reference status is used as the grouping variable. Trends related to longitude are also evaluated.

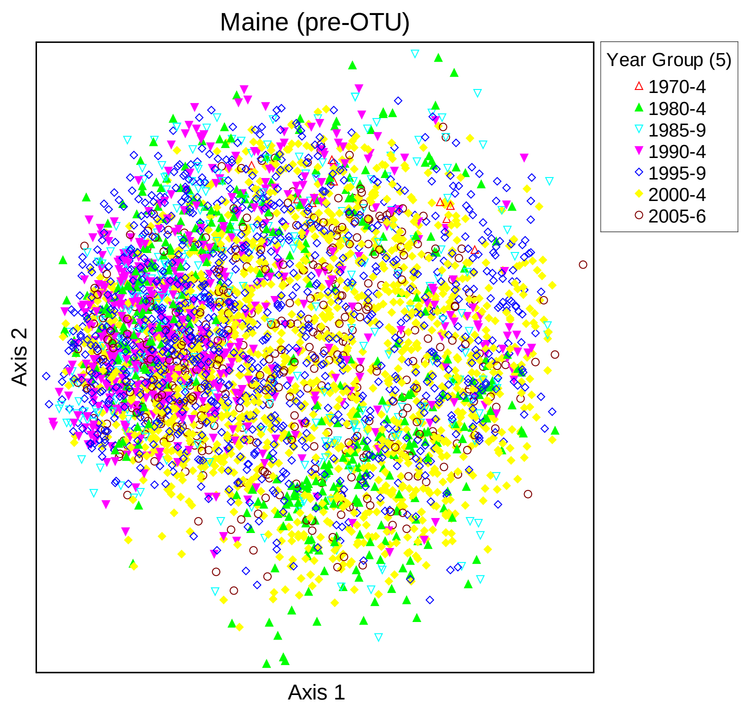

Figure A-7A. Pre-OTU (genus) NMDS plot using sample years (5-year increments) as the grouping variable.

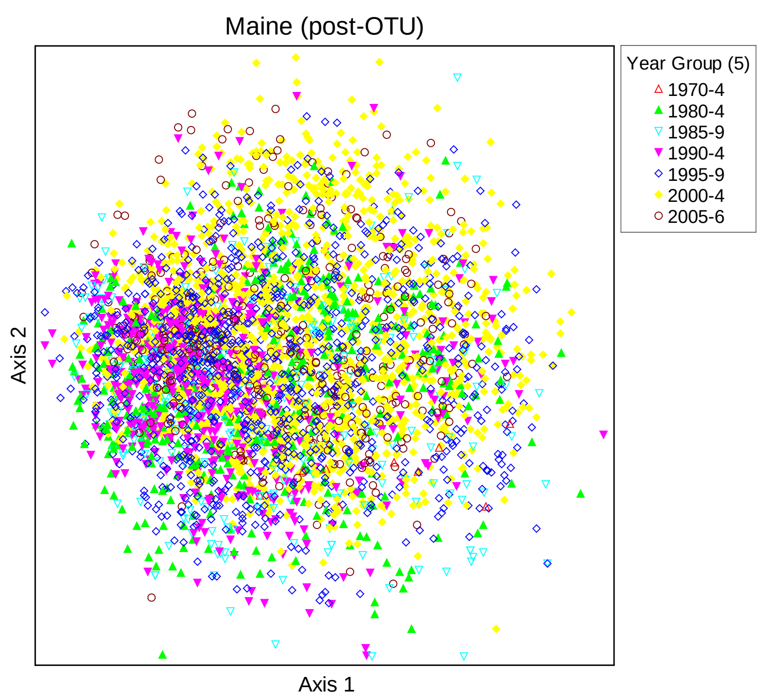

Figure A-7B. Post-OTU (genus) NMDS plot using sample years (5-year increments) as the grouping variable.

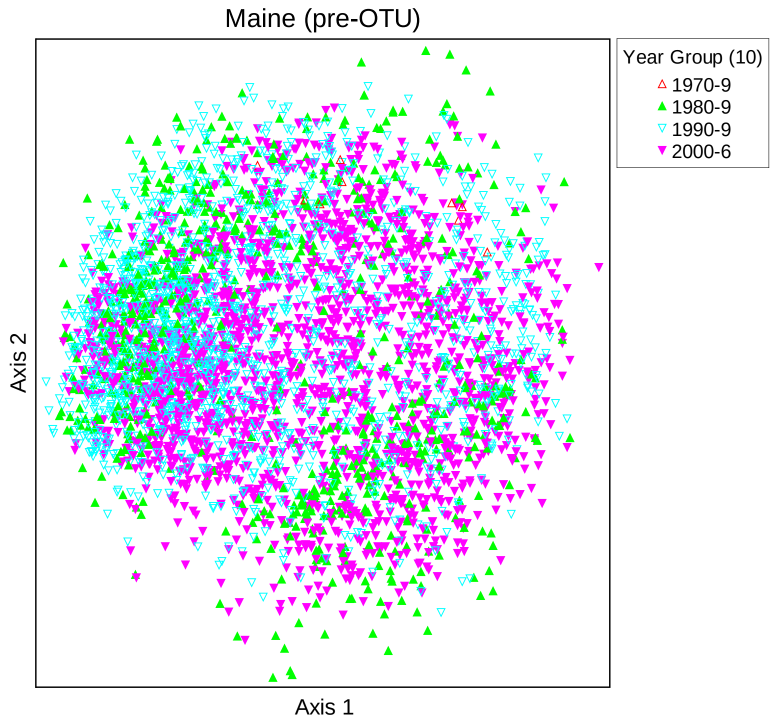

Figure A-8A. Pre-OTU (genus) NMDS plot using sample years (10-year increments) as the grouping variable.

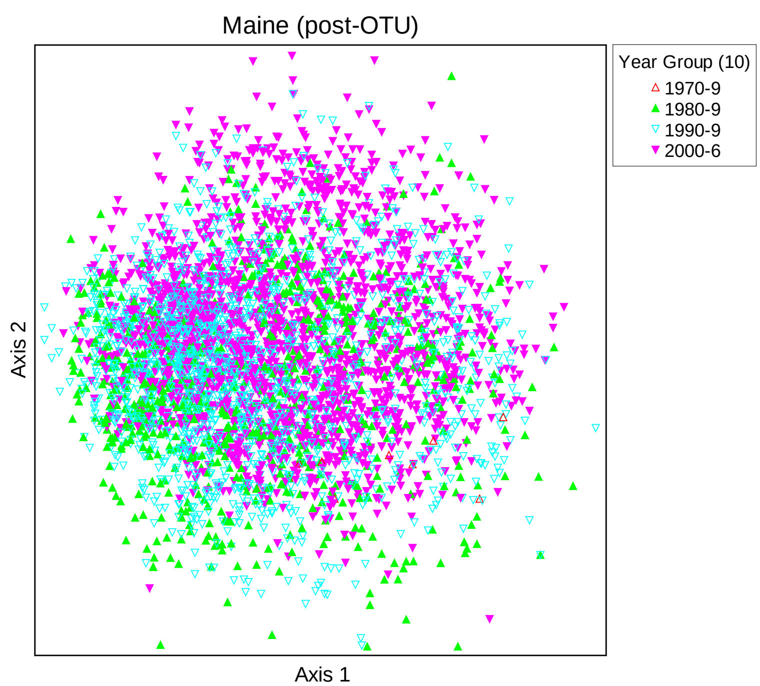

Figure A-8B. Post-OTU (genus) NMDS plot using sample years (10-year increments) as the grouping variable.

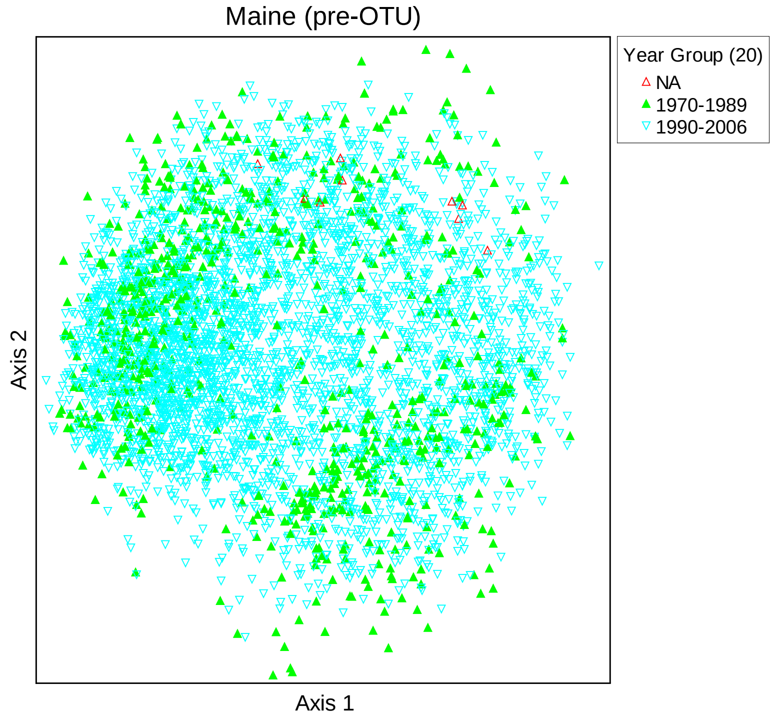

Figure A-9A. Pre-OTU (genus) NMDS plot using sample years (20-year increments) as the grouping variable.

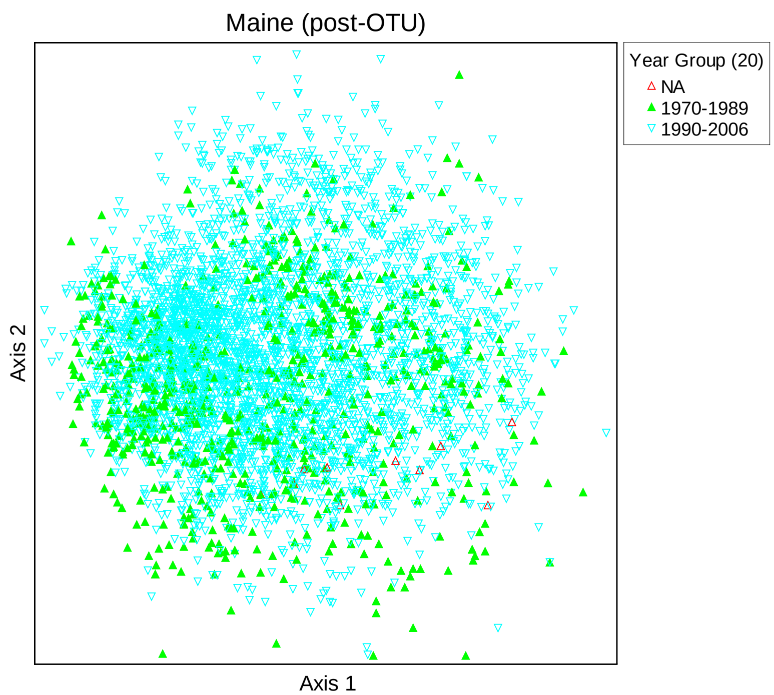

Figure A-9B. Post-OTU (genus) NMDS plot using sample years (20-year increments) as the grouping variable.

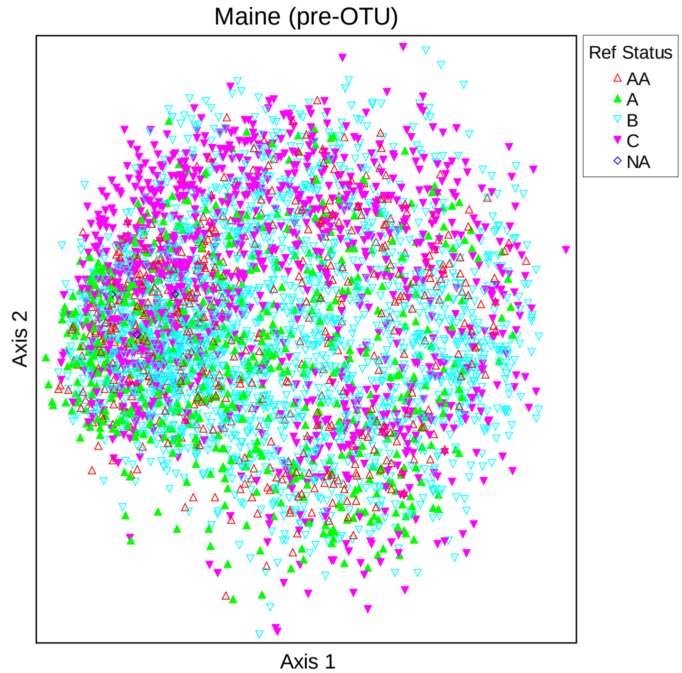

Figure A-10A. Pre-OTU (genus) NMDS plot when reference status is used as the grouping variable.

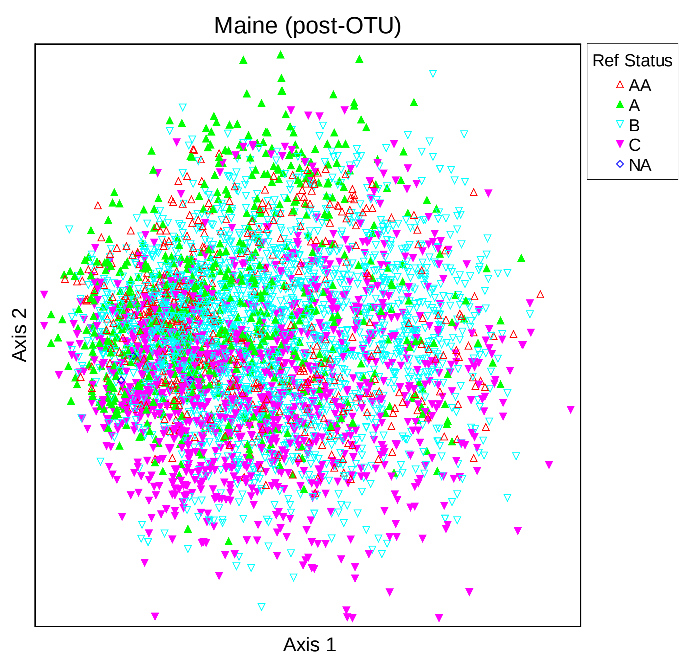

Figure A-10B. Post-OTU (genus) NMDS plot when reference status is used as the grouping variable.

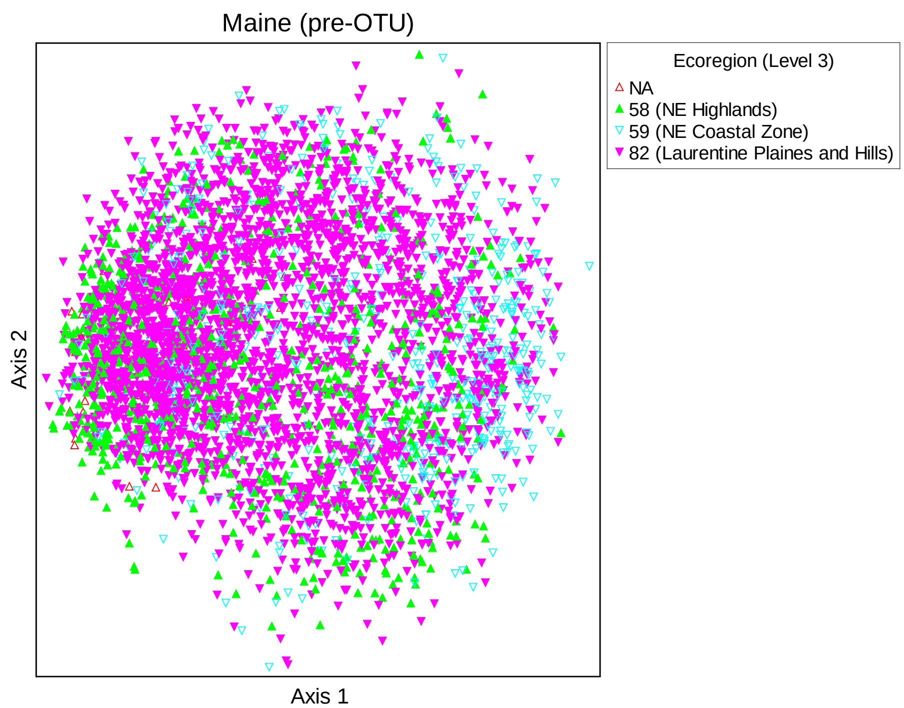

Figure A-11A. Pre-OTU (genus) NMDS plot when Level 3 ecoregion is used as the grouping variable.

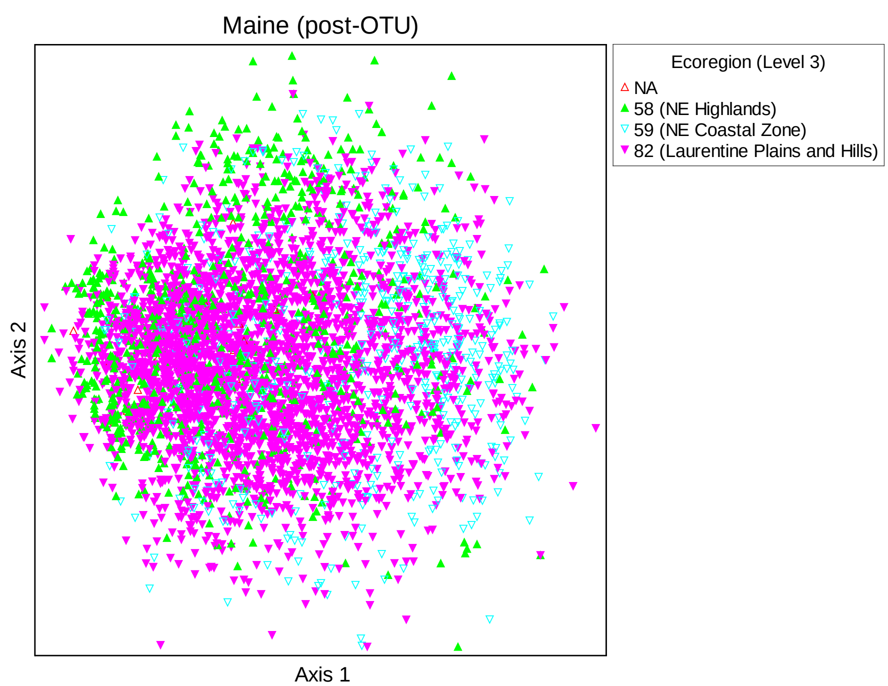

Figure A-11B. Post-OTU (genus) NMDS plot when Level 3 ecoregion is used as the grouping variable.

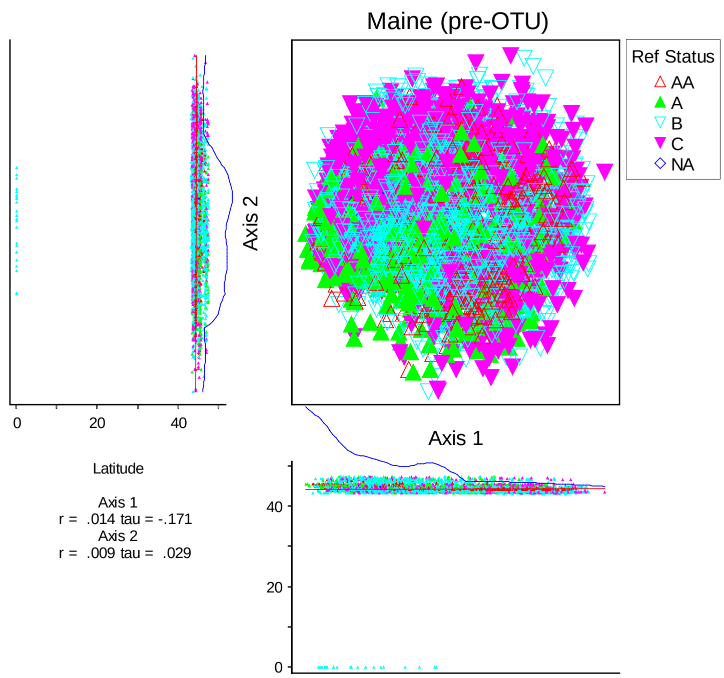

Figure A-12A. Pre-OTU (genus) NMDS plot when reference status is used as the grouping variable. Trends related to latitude are also evaluated.

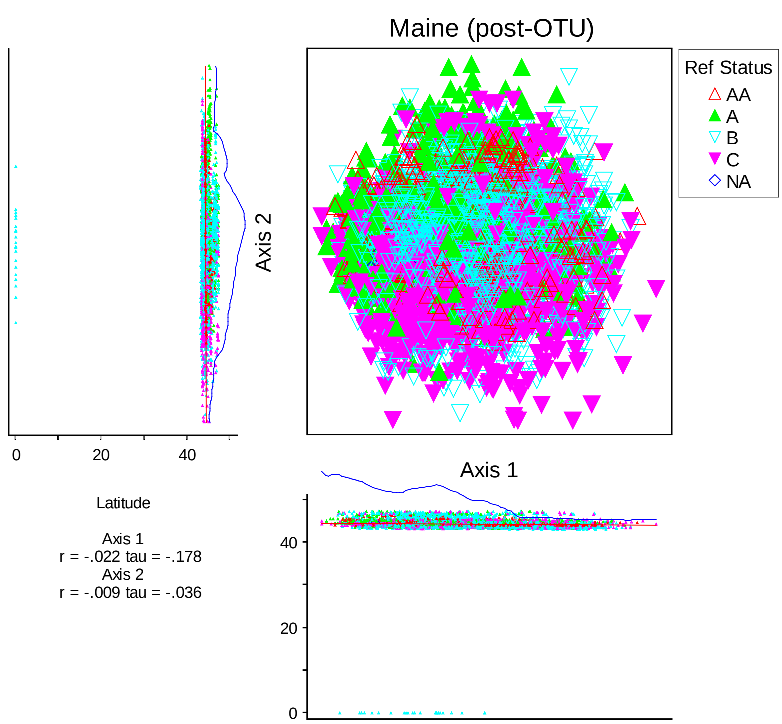

Figure A-12B. Post-OTU (genus) NMDS plot when reference status is used as the grouping variable. Trends related to latitude are also evaluated.

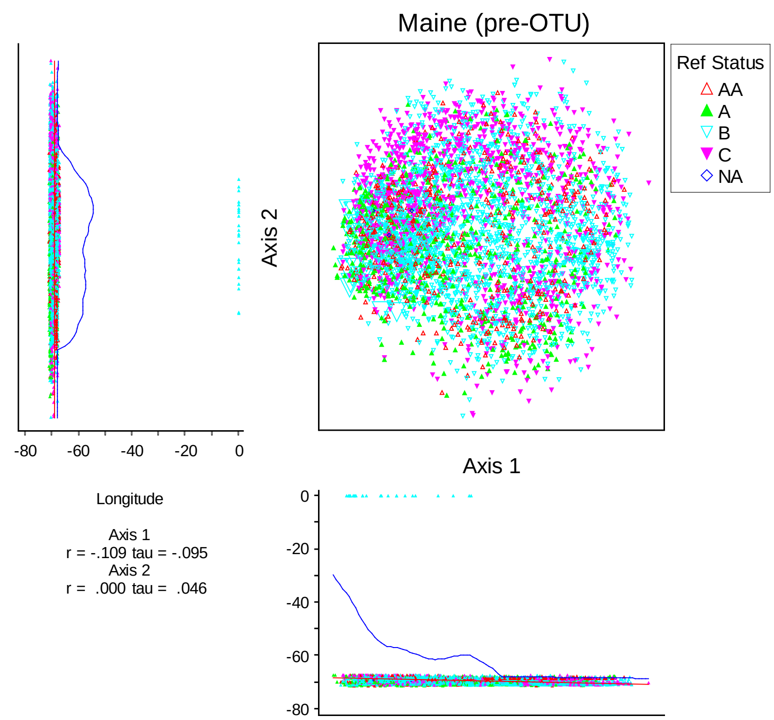

Figure A-13A. Pre-OTU (genus) NMDS plot when reference status is used as the grouping variable. Trends related to longitude are also evaluated.

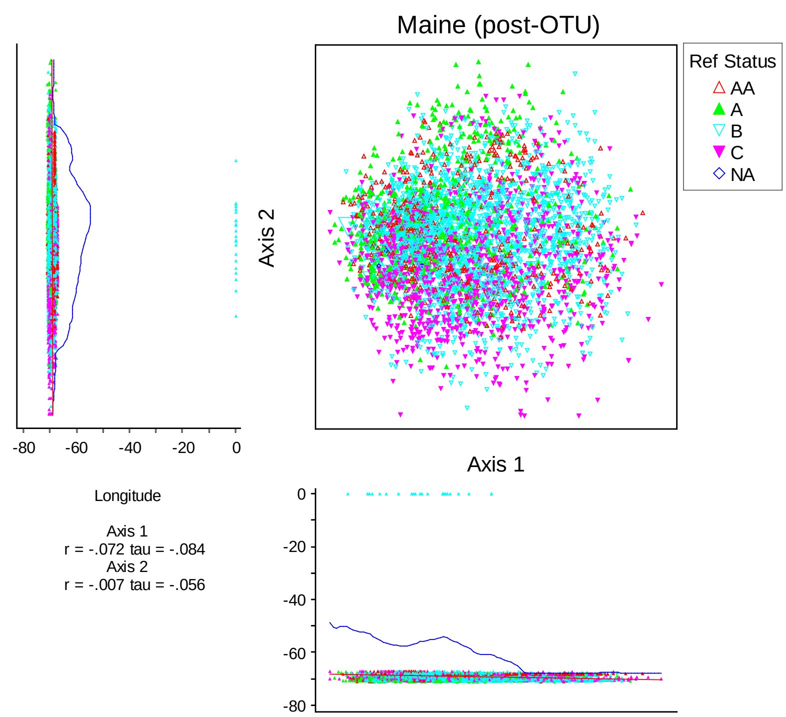

Figure A-13B. Post-OTU (genus) NMDS plot when reference status is used as the grouping variable. Trends related to longitude are also evaluated.

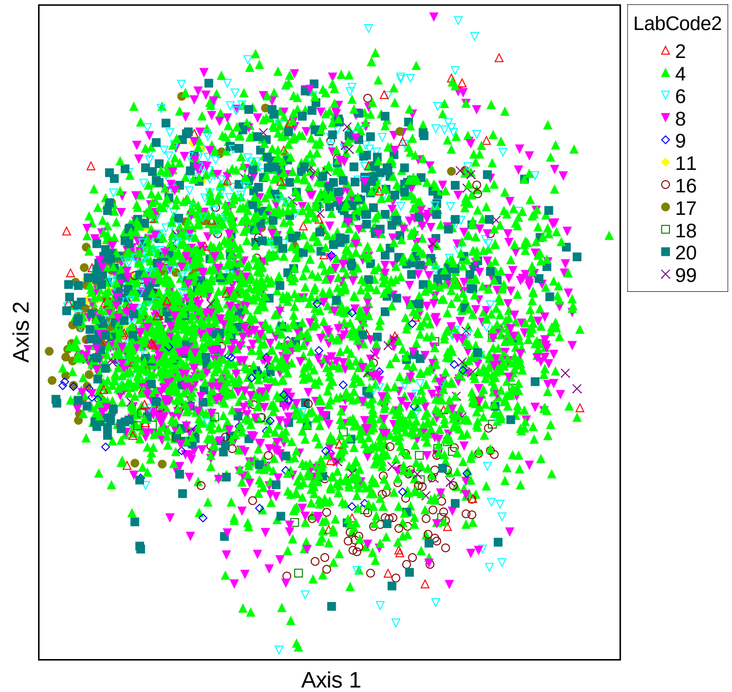

Figure A-14A. Pre-OTU (genus) NMDS plot for Maine data when lab is used as the grouping variable.

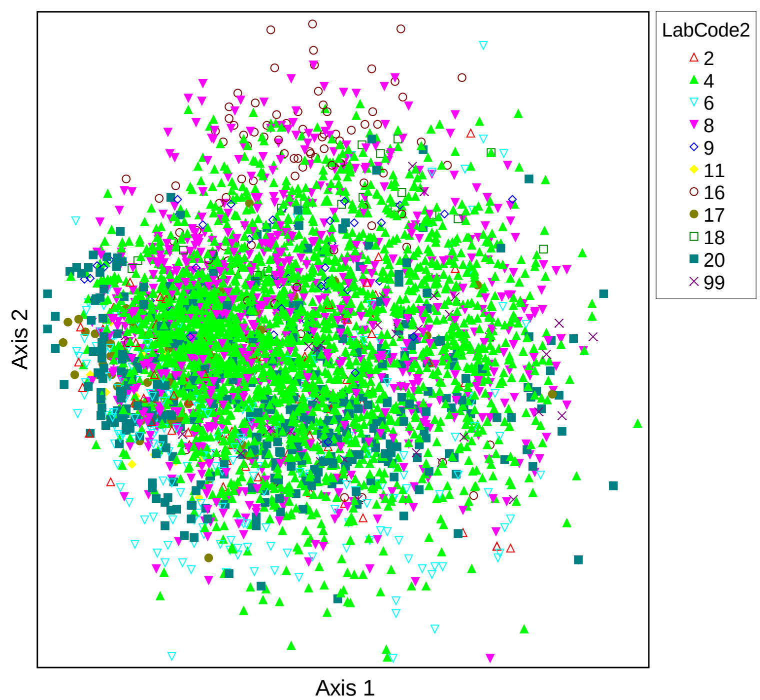

Figure A-14B. Post-OTU (genus) NMDS plot for Maine data when lab is used as the grouping variable.

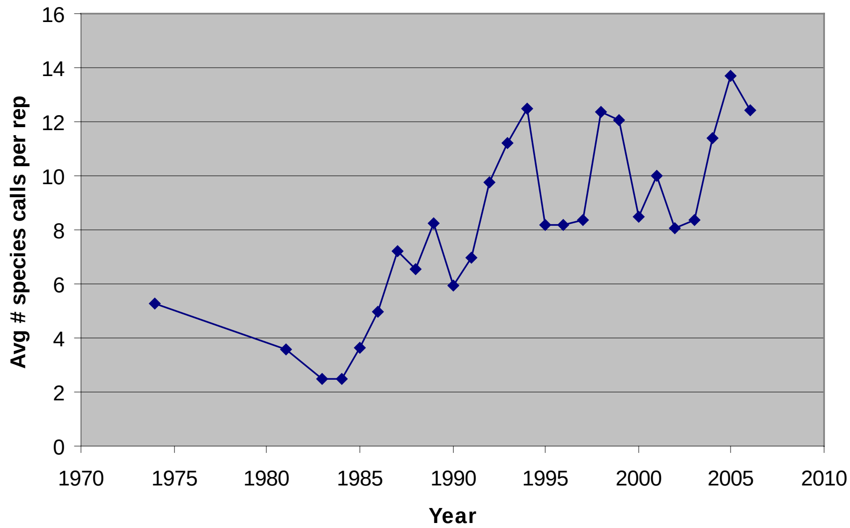

Figure A-15A. Average number of species-level identifications per replicate sample per year in the Maine database (using original data; not adjusted for OTUs).

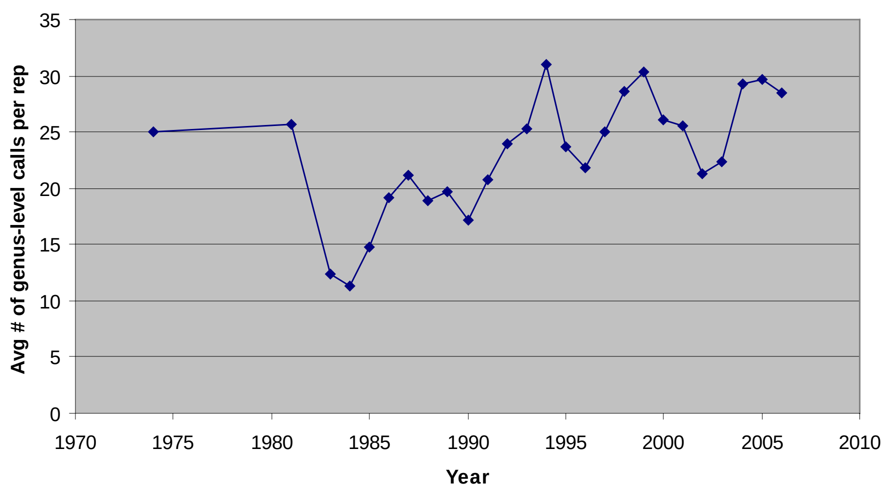

Figure A-15B. Average number of genus-level identifications per replicate sample per year in the Maine database (using original data; not adjusted for OTUs).

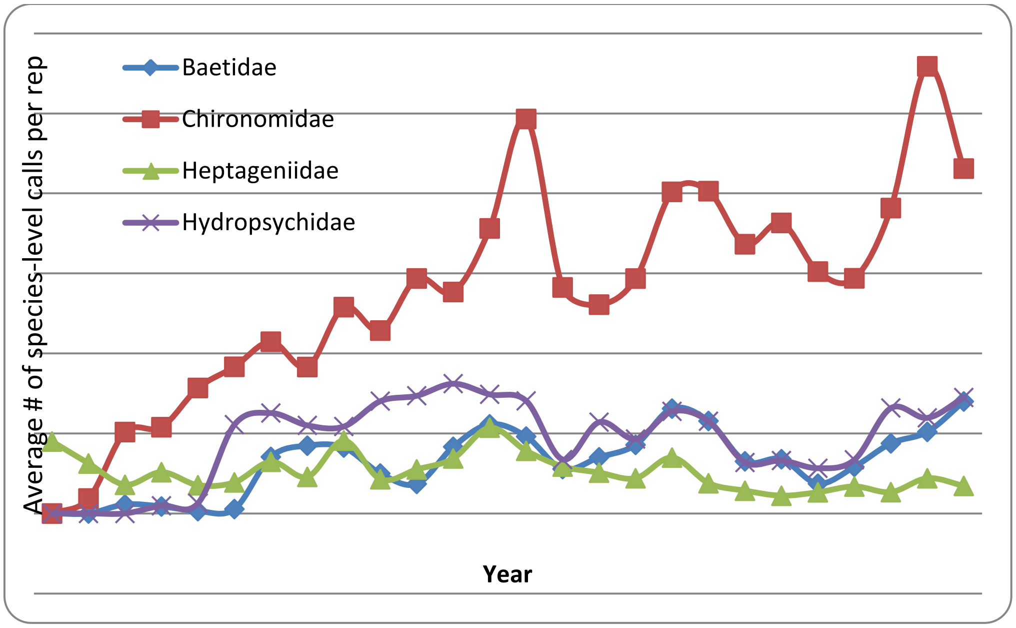

Figure A-16A. Average number of species-level identifications per replicate sample per year for selected families in the Maine database (using original data; not adjusted for OTUs).

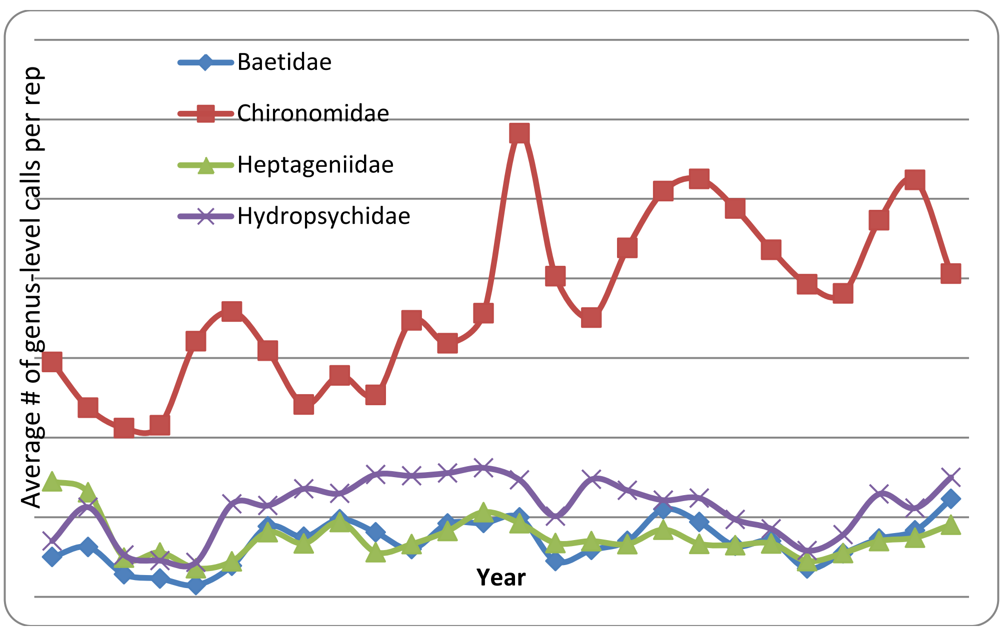

Figure A-16B. Average number of genus-level identifications per replicate sample per year for selected families in the Maine database (using original data; not adjusted for OTUs).

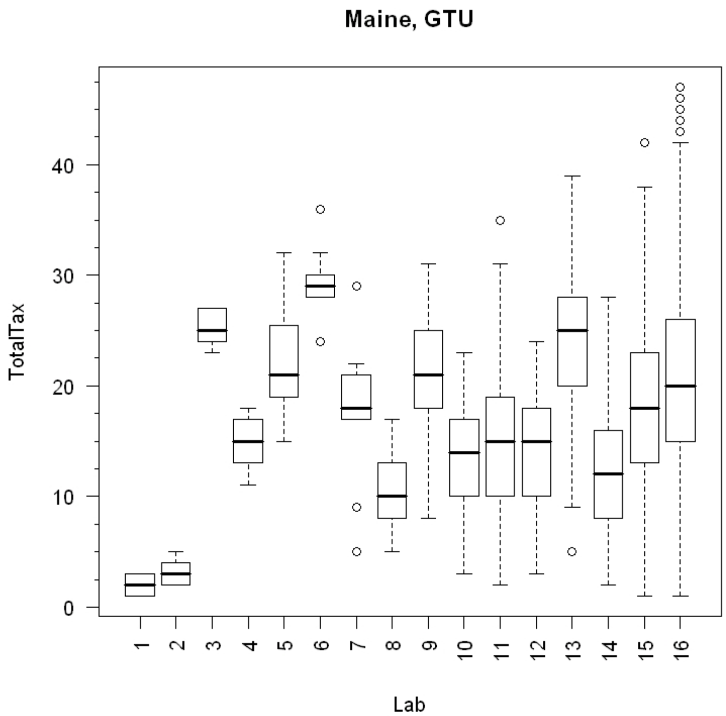

Figure A-17. Distribution of the total number of taxa (average per replicate) among laboratories in Maine.

Table A-2. List of 16 different individuals or labs that performed taxonomic analyses on Maine benthic samples during the study period 1983−2006. Per communication with Leon Tsomides Maine Department of Environmental Protection (ME DEP), some adjustments were made to taxonomy produced from different sources to assure consistency

Lab	Year_min	Year_max	#Samp	LabNum
BILLIE BESSIE	1996	1996	2	1
DAVID COURTEMANCH	1983	1983	5	2
B.A.R ENVIRONM	1994	1994	6	3
WOODWARD CLYDE	1981	1981	6	4
Unknown	1995	1995	7	5
BBL SCIENCES	2004	2004	9	6
CF RABENI	1974	1974	10	7
QST ENVIRONMENTAL (BOWATER)	1994	1996	20	8
CHRIS PINNUTO	2000	2000	22	9
NORMANDEAU	1989	1999	45	10
SUSAN DAVIES	1981	1989	74	11
NEW BRUNSWICK	1999	2001	84	12
IDAHO ECOANALYSTS	1999	2005	100	13
TERRY MINGO	1983	1987	254	14
LOTIC	1988	2006	743	15
MICHAEL WINNELL	1983	2006	2,509	16

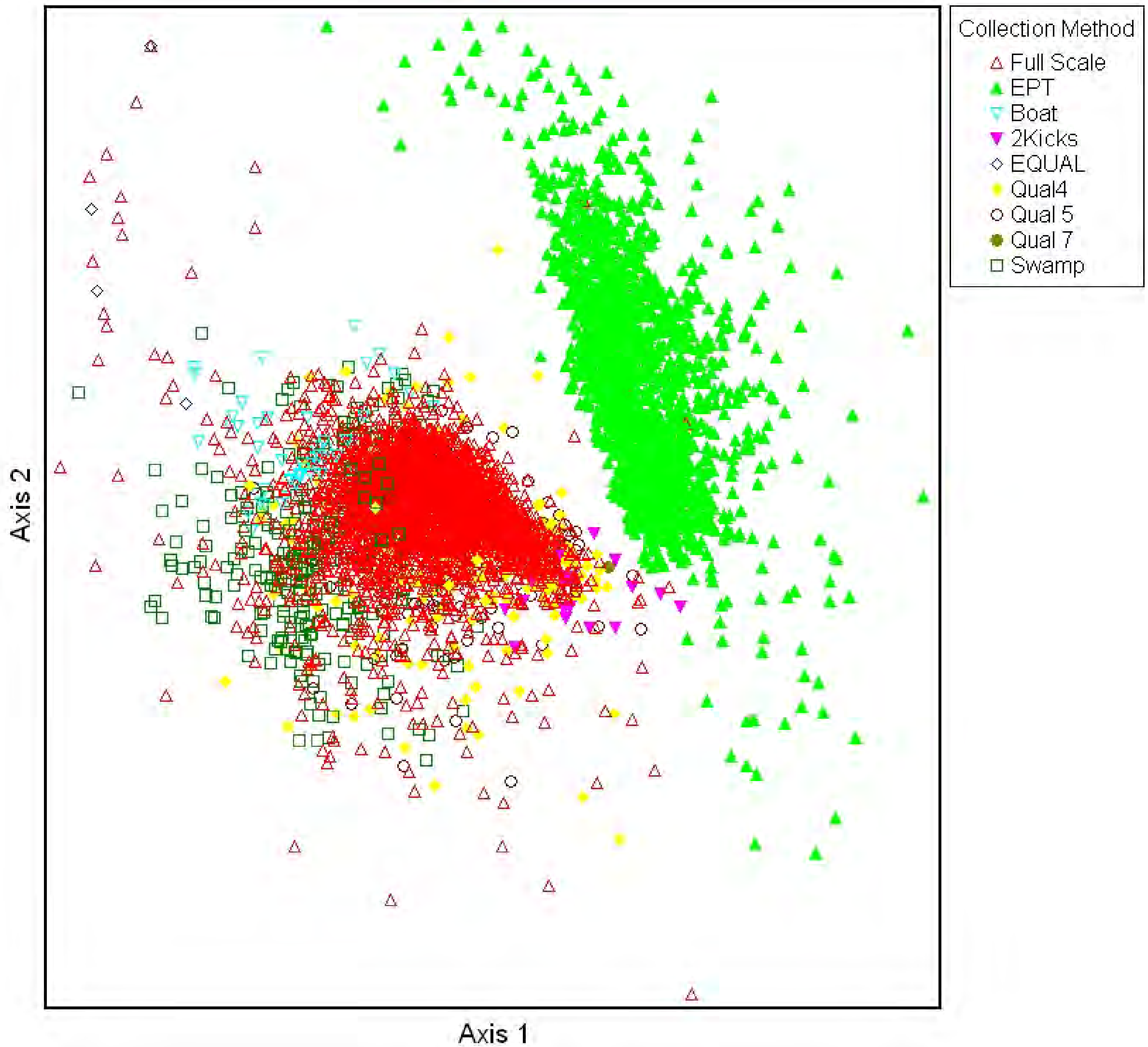

Figure A-18. Preliminary North Carolina NMDS plot (genus-level OTU) using collection method as the grouping variable.

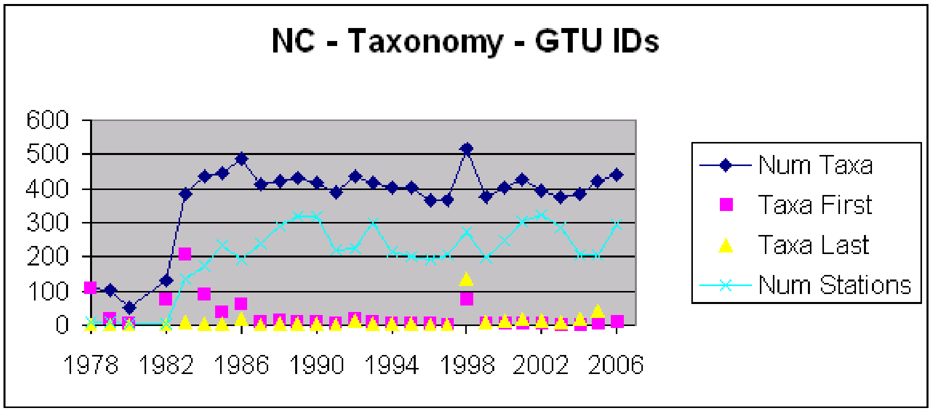

Figure A-19A. North Carolina genus-level OTU (GTU) data using all collection methods. "Num Taxa" refers to the total number of taxa recorded in a particular year; "Taxa First" refers to the number of taxa that appear in the database for the first time in a particular year; "Taxa Last" refers to the number of taxa that appear in the database for the last time in a particular year; "Num Stations" refers to the number of stations sampled in a particular year.

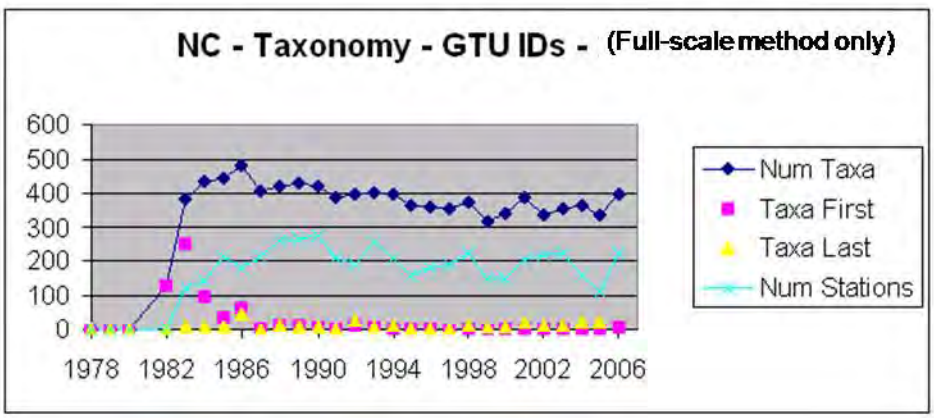

Figure A-19B. North Carolina GTU using data from only the Full-scale collection method. "Num Taxa" refers to the total number of taxa recorded in a particular year; "Taxa First" refers to the number of taxa that appear in the database for the first time in a particular year; "Taxa Last" refers to the number of taxa that appear in the database for the last time in a particular year; "Num Stations" refers to the number of stations sampled in a particular year.

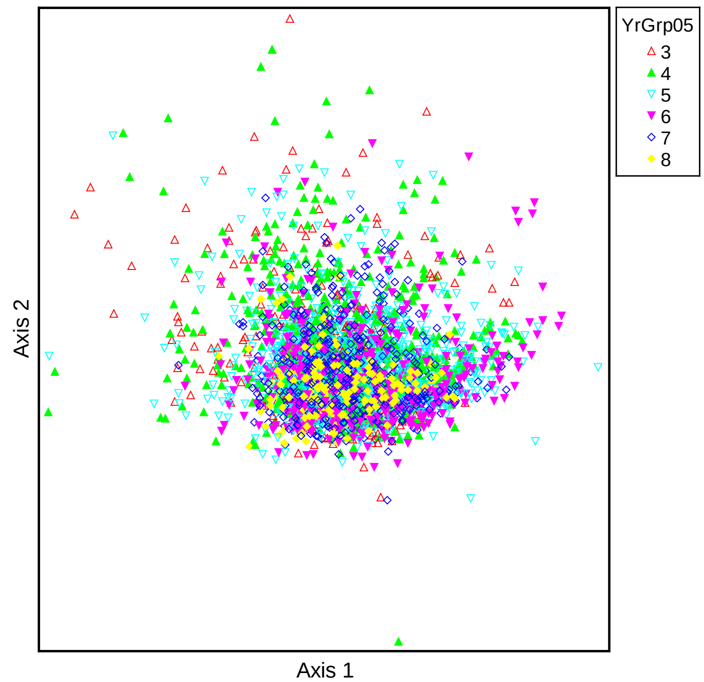

Figure A-20A. Pre-OTU (genus) NMDS plot for North Carolina data when year (5-year increments) is used as the grouping variable, and only full-scale collection method data are used.

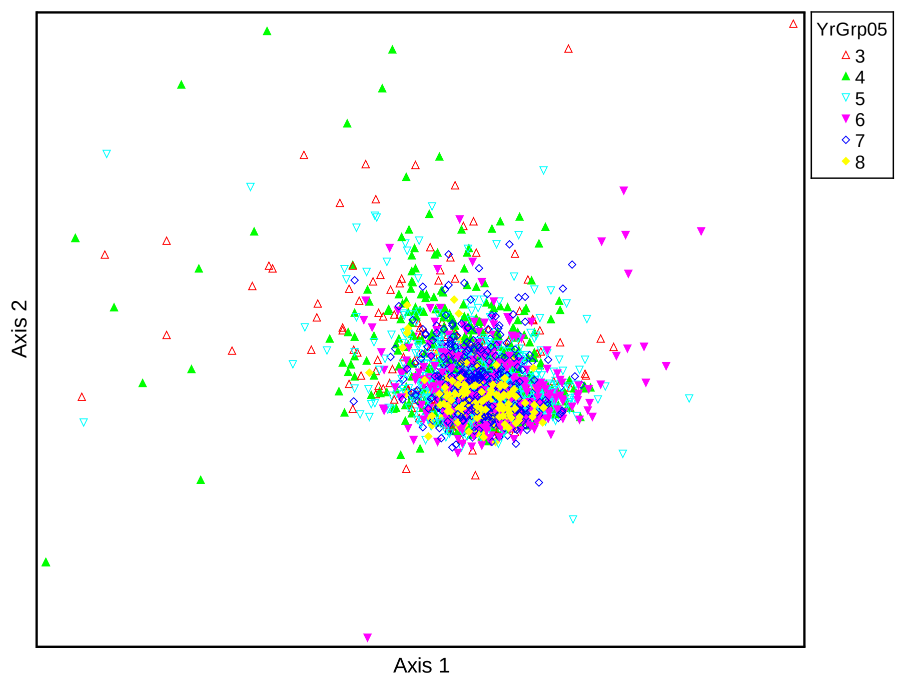

Figure A-20B. Post-OTU (genus) NMDS plot for North Carolina data when year (5-year increments) is used as the grouping variable, and only full-scale collection method data are used.

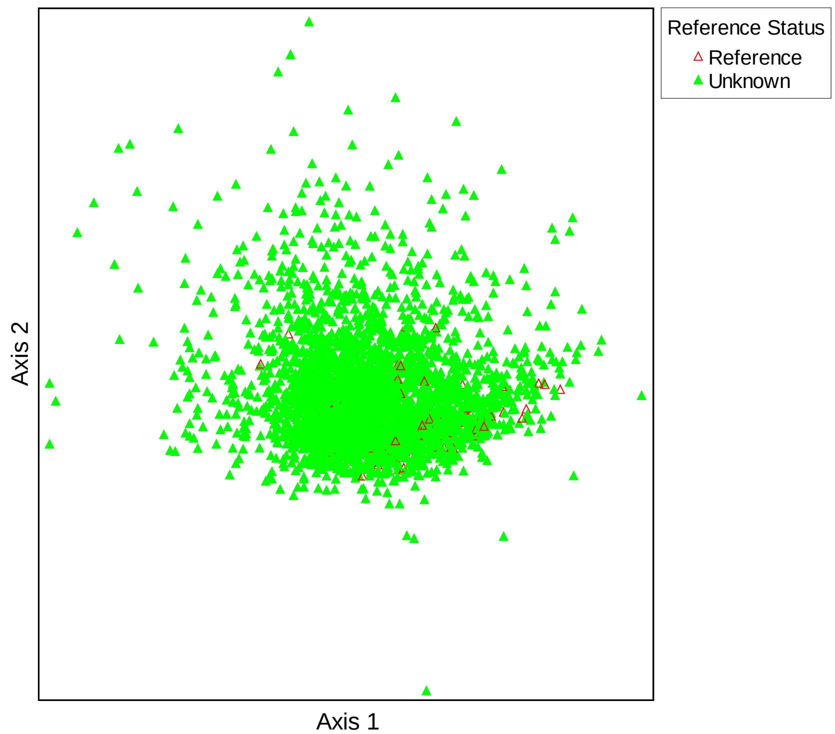

Figure A-21A. Pre-OTU (genus) NMDS plot for North Carolina data using reference status as the grouping variable, and only full-scale collection method data are used.

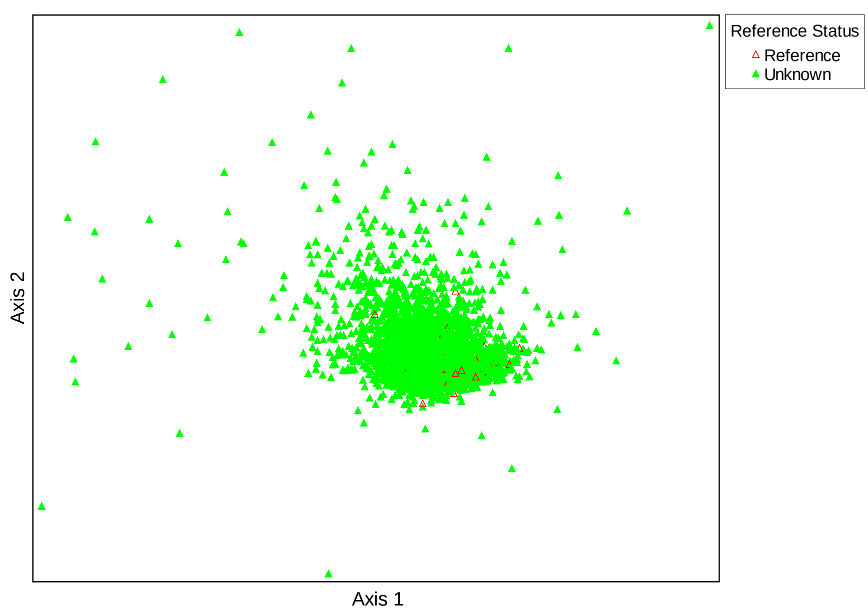

Figure A-21B. Post-OTU (genus) NMDS plot for North Carolina data using reference status as the grouping variable, and only full-scale collection method data are used.

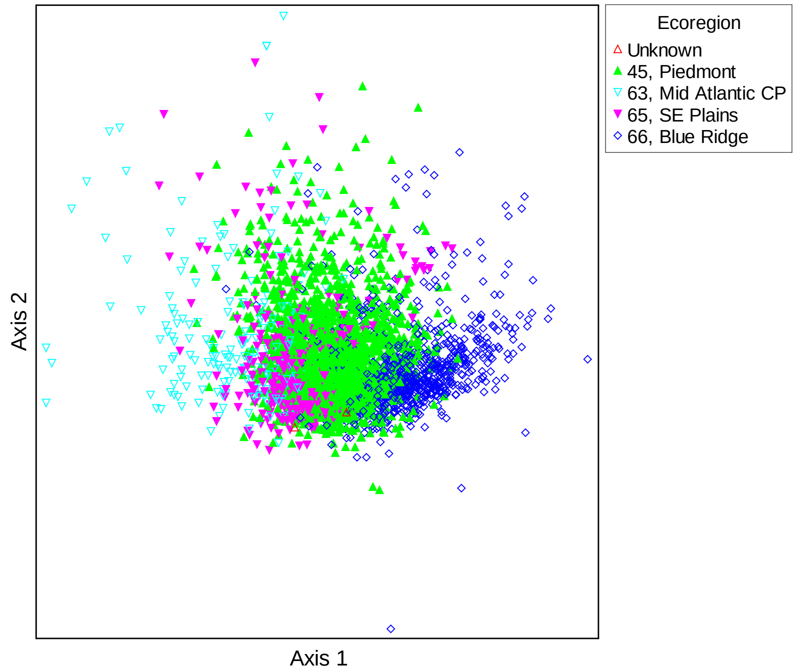

Figure A-22A. Pre-OTU (genus) NMDS plot for North Carolina data using Level 3 ecoregion as the grouping variable, and only full-scale collection method data are used.

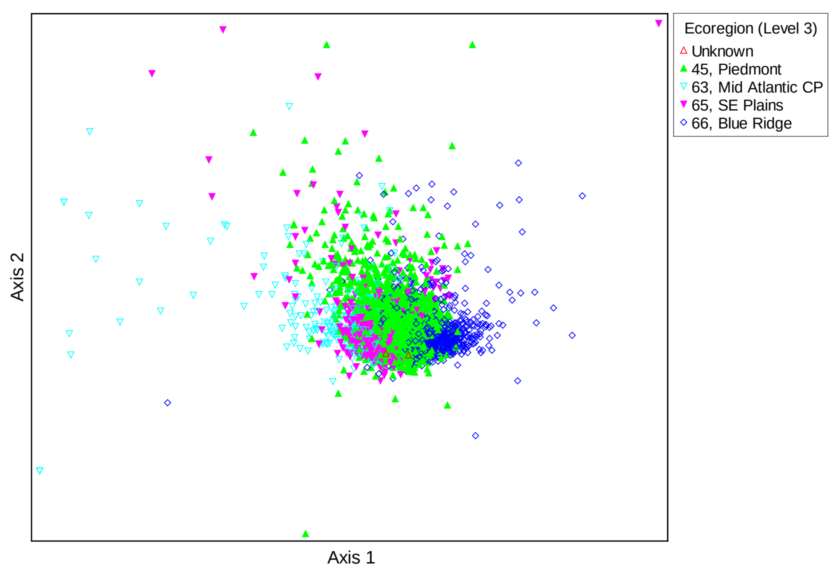

Figure A-22B. Post-OTU (genus) NMDS plot for North Carolina data using Level 3 ecoregion as the grouping variable, and only full-scale collection method data are used.

APPENDIX B

ADDITIONAL ANALYSES PERFORMED ON UTAH DATA

B.1. HYDROLOGIC ANALYSIS PERFORMED ON THE UTAH DATA SET

Figure B-1 shows the locations of the 43 Utah biological sampling stations that we associated with United States Geological Service (USGS) stream gages.

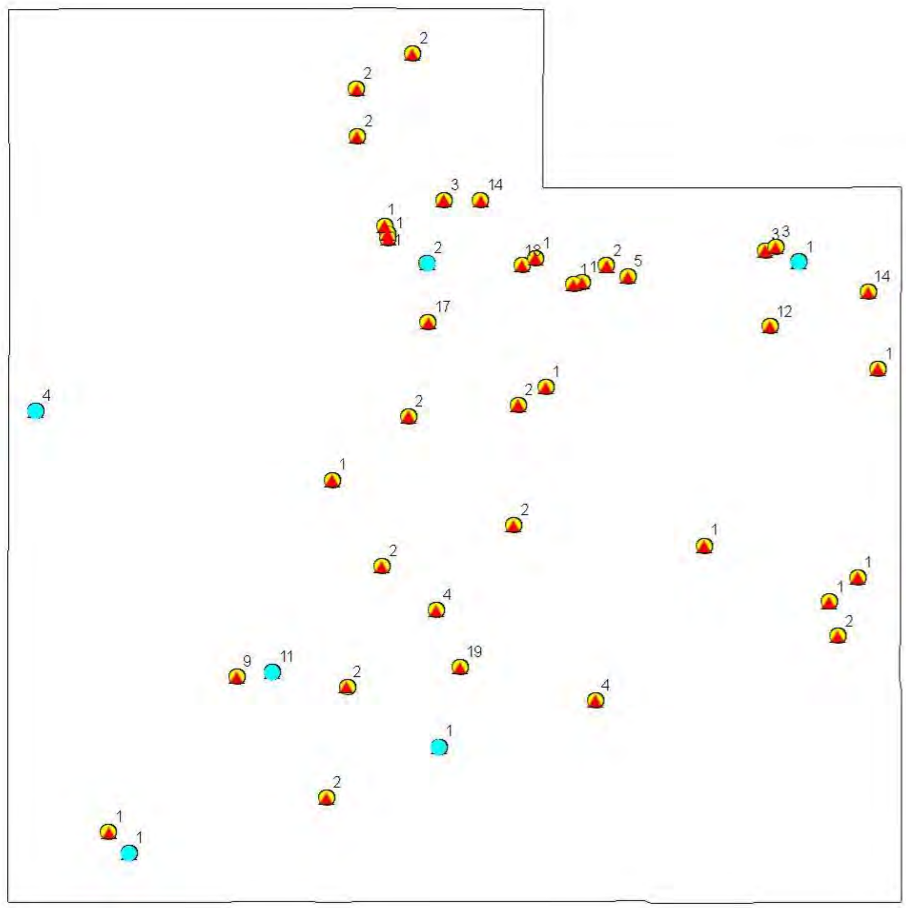

Figure B-1. Locations of the 43 Utah biological sampling stations (red triangles) and associated USGS stream gages (yellow circles). Stations that are highlighted in blue are classified as reference sites by Utah DEQ Division of Water Quality. The numbers next to the sites are the number of years of data that were available for each station.

Table B-1 shows results from the weighted-average modeling for the 3-day annual minima indicators of hydrologic alteration (IHA) parameters.

Table B-1. Weighted-average indicator values for annual minima, 3-day means

3-Day annual minima					
Taxa	**Optimum**	**Tolerance**	**Rank_opt**	**Rank_tol**	**Count**
Pisidium	0.030	0.04	1	2	16
Ambrysus	0.041	0.05	1	3	17
Mayatrichia/Neotrichia	0.045	0.03	1	2	16
Neotrichia	0.046	0.04	1	2	12
Leuctridae	0.049	0.03	1	1	24
Asellidae	0.050	0.06	1	4	45
Lymnaea	0.056	0.04	1	3	15
Zapada	0.057	0.04	1	3	35
Neothremma	0.059	0.04	1	3	19
Physella	0.060	0.06	2	5	13
Skwala	0.061	0.02	2	1	31
Petrophila	0.062	0.05	2	4	36
Coenagrionidae	0.064	0.07	2	6	36
Bibiocephala	0.065	0.01	2	1	17
Cultus	0.066	0.04	2	3	20
Serratella	0.067	0.04	2	2	11
Dytiscidae	0.068	0.04	2	2	10
Pelecypoda	0.069	0.06	2	5	44
Hesperoperla	0.069	0.05	2	4	33
Epeorus	0.070	0.04	2	2	92
Physa	0.071	0.06	2	5	54
Claassenia	0.072	0.03	3	1	12
Podmosta	0.072	0.03	3	1	10
Tipula	0.072	0.05	3	4	31
Capniidae	0.073	0.05	3	4	38
Apatania	0.073	0.02	3	1	20
Oecetis	0.073	0.04	3	2	45

Table B-1. Weighted-average indicator values for annual minima, 3-day means (continued)

3-Day annual minima					
Taxa	**Optimum**	**Tolerance**	**Rank_opt**	**Rank_tol**	**Count**
Baetidae	0.073	0.06	3	6	277
Heptagenia	0.075	0.05	3	4	58
Pteronarcella	0.076	0.04	3	2	91
Ephemerella	0.076	0.05	3	4	149
Chloroperlidae	0.076	0.04	3	2	105
Hemerodromia	0.076	0.07	3	6	103
Antocha	0.077	0.05	4	3	126
Ostracoda	0.077	0.06	4	5	96
Lepidostoma	0.077	0.05	4	4	88
Paraleptophlebia	0.078	0.04	4	2	96
Arctopsyche	0.078	0.05	4	3	99
Rhithrogena	0.078	0.04	4	3	127
Simuliidae	0.079	0.06	4	5	234
Chelifera	0.079	0.06	4	5	98
Isoperla	0.080	0.04	4	3	105
Cheumatopsyche	0.080	0.07	4	6	55
Rhyacophilidae	0.080	0.05	4	4	98
Cinygmula	0.080	0.05	4	3	90
Optioservus	0.080	0.06	4	5	148
Glossosoma	0.081	0.05	4	4	60
Acarina	0.081	0.06	4	5	268
Zaitzevia	0.081	0.05	4	4	97
Planaria	0.082	0.07	4	7	90
Leptohyphidae	0.082	0.07	5	6	133
Ameletus	0.082	0.05	5	4	26
Hydroptila	0.082	0.06	5	6	97
Nematoda	0.082	0.06	5	6	125
Hexatoma	0.082	0.03	5	2	88
Hydropsyche	0.083	0.06	5	5	232
Taenionema	0.083	0.04	5	3	29
Copepoda	0.084	0.07	5	6	35

Table B-1. Weighted-average indicator values for annual minima, 3-day means (continued)

3-Day annual minima					
Taxa	**Optimum**	**Tolerance**	**Rank_opt**	**Rank_tol**	**Count**
Microcylloepus	0.085	0.04	5	3	10
Leucotrichia	0.085	0.06	5	5	23
Chironomidae	0.085	0.07	5	6	291
Euparyphus	0.086	0.10	5	7	12
Isogenoides	0.086	0.04	6	2	19
Drunella	0.087	0.05	6	4	119
Dicranota	0.089	0.05	6	4	32
Tubificidae	0.090	0.06	6	5	107
Pteronarcys	0.090	0.03	6	1	27
Atherix	0.091	0.05	6	4	81
Planorbidae	0.091	0.08	6	7	37
Alisotrichia/Leucotricia	0.091	0.06	6	6	32
Micrasema	0.092	0.05	6	4	55
Brachycentrus	0.093	0.06	6	5	145
Hirudinea	0.094	0.09	6	7	75
Oligophlebodes	0.094	0.05	6	4	35
Forcipomyia/Probezzia	0.094	0.08	7	7	20
Agapetus/Culoptila/Protoptila	0.097	0.03	7	1	12
Pericoma	0.100	0.07	7	6	47
Bezzia	0.103	0.08	7	7	53
Helicopsyche	0.110	0.08	7	7	68
Hyalella	0.111	0.09	7	7	62
Traverella	0.116	0.03	7	1	10
Hesperophylax	0.159	0.08	7	7	12
Gammarus	0.170	0.07	7	6	15

Figures B-1 to B-4 show the ordination plots from the Nonmetric Multidimensional scaling (NMDS) and canonical correlation analysis (CCA).

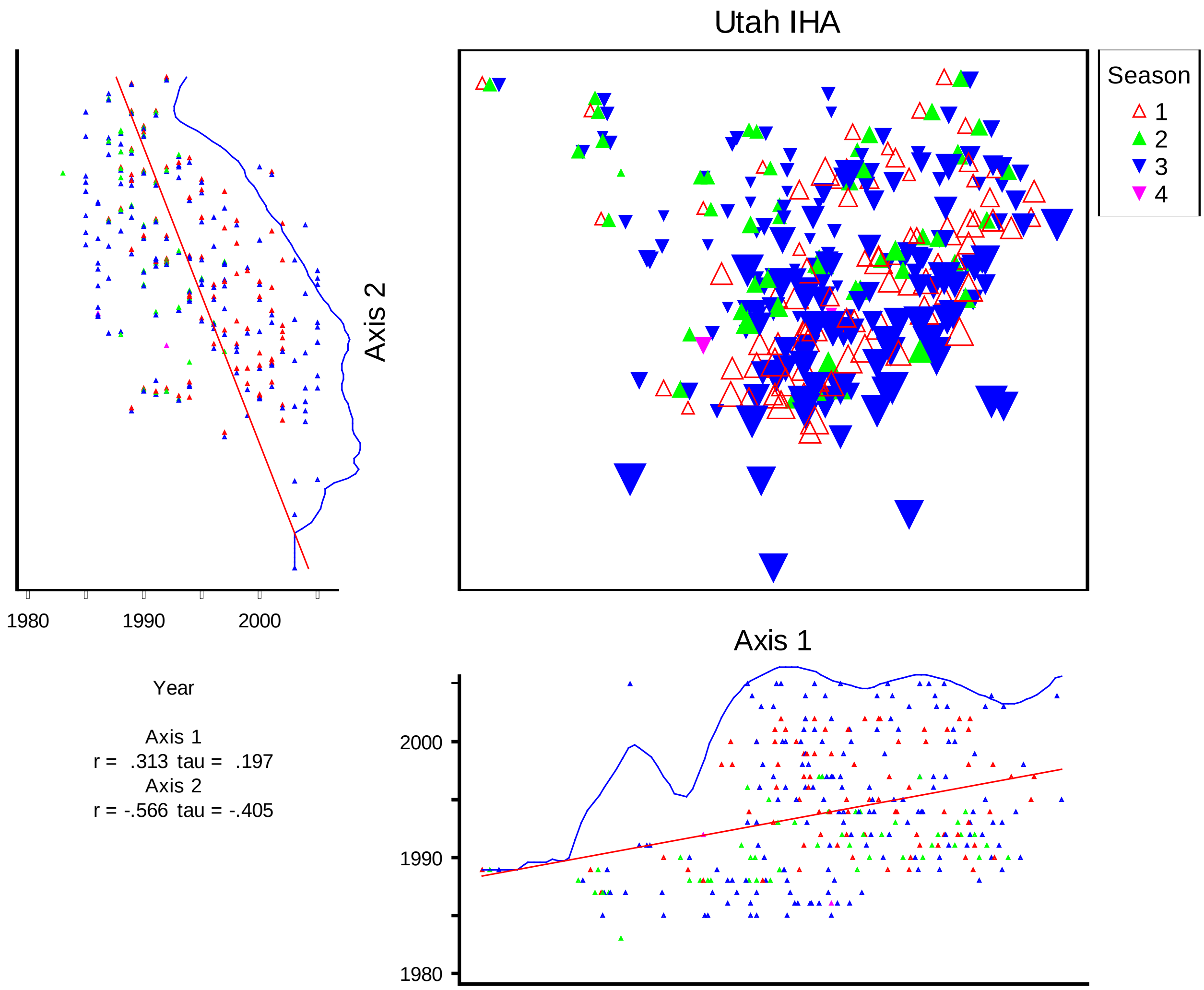

Figure B-2. Taxonomical trends in the Utah data set were examined using NMDS. Year had the strongest influence on taxonomical composition. However, when NMDS ordinations were run on a selected subset of data that only contained data from sites with multiple years of samples, the year trend was not as strong.

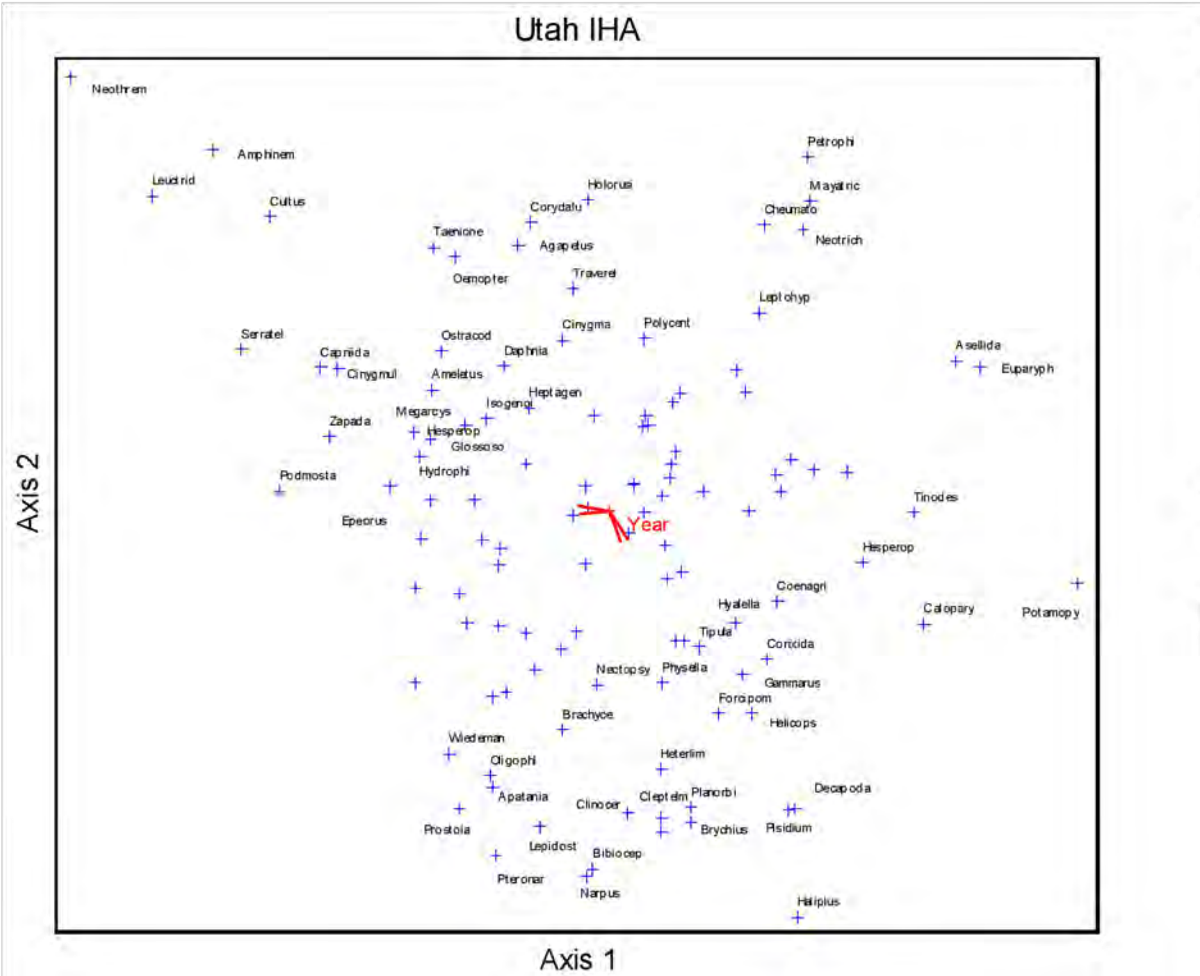

Figure B-3. Species trends along year. These were derived from the CCA analysis.

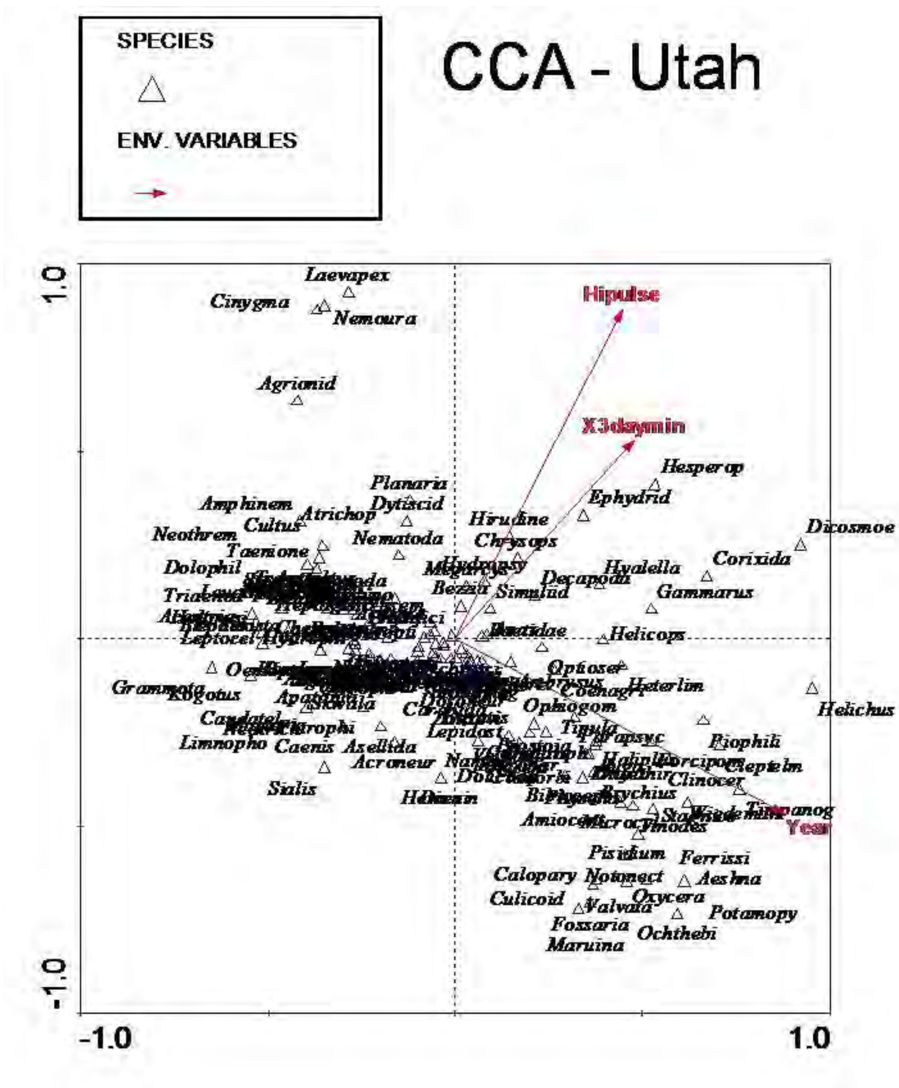

Figure B-4. CCA plot of a selected subset of the Utah biological-hydrological data.

Table B-2 shows a list of the Utah sites at which we ran correlation analyses.

B.2. 'EXTREME' ALTERATIONS OF UTAH FALL RIVPACS MODEL CLIMATE-RELATED PREDICTOR VARIABLE VALUES

We also ran some 'extreme' scenarios (i.e., doubling temperature, dividing precipitation values by two, changing freeze dates by 30 days, etc.) to explore how much the climate-related predictor variables would have to change in order to result in substantial changes to observed/expected (O/E) scores. Tables B-3 through B-8 show which scenarios were run and what the results were.

Table B-2. Data that were used in the Utah correlation analyses were gathered from these biological sampling stations/USGS gages. %URB = % urban, %AGR = % agricultural and %FOR = % forested land use within a 1-km buffer of the sites

BioStationID	USGS gage	# Years of data	Elev_ft	Eco_L3	Eco_L4	Ref status	%URB	%AGR	%FOR
4926350	10131000	14	5,573.3	Wasatch and Uinta Mountains	Mountain Valleys	TRASH	32.5	27.9	30.2
4934100	9302000	12	4,762.6	Colorado Plateaus	Uinta Basin Floor	UNKNOWN	3.9	18.4	24
4937900	9261000	14	4,766.1	Colorado Plateaus	Uinta Basin Floor	SO-SO	0	20.3	65.1
4954380	9330000	19	6,940.5	Wasatch and Uinta Mountains	Semiarid Foothills	TRASH	6.9	30.3	56
4996690	10163000	17	4,521.3	Central Basin and Range	Moist Wasatch Front Footslopes	TRASH	73.2	15.8	5.3
4998400	10154200	18	6,971.4	Wasatch and Uinta Mountains	Mid-elevation Uinta Mountains	SO-SO	5.7	0.7	93.6
5940440	10234500	11	6,249.3	Wasatch and Uinta Mountains	Semiarid Foothills	REF	3.9	0	96.1

Table B-3. Descriptions of how the climate-related predictor variables were altered in the 'extreme alteration' RIVPACS analyses

Run#	Category	Altered predictor variables	Rationale
1	Baseline	None—used original values	Get baseline values and quality control
2	Temperature	TMEAN.WS + 2 and TMEAN.NET + 2	National Center for Atmospheric Research (NCAR) annual temperature predictions (2050)
3		TMEAN.WS + 4 and TMEAN.NET + 4	NCAR annual temperature predictions (2090)
4		TMEAN.WS + 10 and TMEAN.NET + 10	Curiosity
5		TMEAN.WS + 20 and TMEAN.NET + 20	Curiosity
6	Precipitation	MEANP.PT − 0.05	NCAR annual precipitation predictions (2050)
7		MEANP.PT − 0.1	NCAR annual precipitation predictions (2090)
8		MEANP.PT − Minimum PRISM ppt14	Based on Parameter-elevation Regressions on Independent Slopes Model (PRISM) ppt14 minimum values (1975−2006)
9		MEANP.PT/2	Curiosity
10		MINP.PT/2	Curiosity
11		MEANP.PT/2 and MINP.PT/2	Curiosity
12		MINWD.WS/2	Curiosity
13	Temperature and precipitation	TMEAN.WS + 2 and TMEAN.NET + 2 and MEANP.PT − 0.05	NCAR annual temperature and precipitation predictions (2050)
14		TMEAN.WS + 4 and TMEAN.NET + 4 and MEANP.PT − 0.1	NCAR annual temperature and precipitation predictions (2090)
15	Freeze date	LST32AVE − 2	Best professional judgment
16		LST32AVE − 5	Best professional judgment
17		FST32AVE + 5	Best professional judgment
18		LST32AVE − 5 and FST32AVE + 5	Best professional judgment
19		LST32AVE − 10	Curiosity
20		FST32AVE + 10	Curiosity
21		LST32AVE − 10 and FST32AVE + 10	Curiosity
22		LST32AVE − 15	Curiosity
23		LST32AVE − 15 and FST32AVE + 15	Curiosity

Table B-3. Descriptions of how the climate-related predictor variables were altered in the 'extreme alteration' RIVPACS analyses (continued)

Run#	Category	Altered Predictor variables	Rationale
24	Combine all	LST32AVE − 1, MINP.PT − 1, MEANP.PT − 1, TMEAN.NET + 1, TMEAN.WS + 1, FST32AVE + 1, MINWD.WS − 1	Best professional judgment
25		LST32AVE − 2, MINP.PT − 2, MEANP.PT − 2, TMEAN.NET + 2, TMEAN.WS + 2, FST32AVE + 2, MINWD.WS − 1	Best professional judgment

Table B-4. Results for the scenarios in which temperature predictor variables were altered

			Baseline (original)			TMEAN.WS + 2 and TMEAN.NET + 2			
Group	**Site**	**Sample**	**O**	**E**	**O/E**	**O**	**E**	**O/E**	**Dif'ce O/E**
1	5940440	127636	14	15.09	0.93	14	14.92	0.94	0.01
7	4951200	120184	10	9.58	1.04	10	9.56	1.05	0
1	4936750	118524	15	14.04	1.07	15	14	1.07	0
6	4927250	127718	8	8.74	0.92	8	8.74	0.92	0
			Baseline (original)			**TMEAN.WS + 4 and TMEAN.NET + 4**			
Group	**Site**	**Sample**	**O**	**E**	**O/E**	**O**	**E**	**O/E**	**Dif'ce O/E**
1	5940440	127636	14	15.09	0.93	14	14.8	0.95	0.02
7	4951200	120184	10	9.58	1.04	10	9.6	1.04	0
1	4936750	118524	15	14.04	1.07	15	14	1.07	0
6	4927250	127718	8	8.74	0.92	7	8.25	0.85	−0.07
			Baseline (original)			**TMEAN.WS + 10 and TMEAN.NET + 10**			
Group	**Site**	**Sample**	**O**	**E**	**O/E**	**O**	**E**	**O/E**	**Dif'ce O/E**
1	5940440	127636	14	15.09	0.93	14	14.65	0.96	0.03
7	4951200	120184	10	9.58	1.04	10	9.61	1.04	0
1	4936750	118524	15	14.04	1.07	15	13.89	1.08	0.01
6	4927250	127718	8	8.74	0.92	7	8.24	0.85	−0.07
			Baseline (original)			**TMEAN.WS + 20 and TMEAN.NET + 20**			
Group	**Site**	**Sample**	**O**	**E**	**O/E**	**O**	**E**	**O/E**	**Dif'ce O/E**
1	5940440	127636	14	15.09	0.93	13	14.08	0.92	0
7	4951200	120184	10	9.58	1.04	10	9.63	1.04	−0.01
1	4936750	118524	15	14.04	1.07	15	13.44	1.12	0.05
6	4927250	127718	8	8.74	0.92	7	8.24	0.85	−0.07

Table B-5. Results for the scenarios in which precipitation predictor variables were altered

			Baseline (original)			MEANP.PT − 0.05			
Group	Site	Sample	O	E	O/E	O	E	O/E	Dif'ce O/E
1	5940440	127636	14	15.09	0.93	14	15.1	0.93	0
7	4951200	120184	10	9.58	1.04	10	9.59	1.04	0
1	4936750	118524	15	14.04	1.07	15	14	1.07	0
6	4927250	127718	8	8.74	0.92	8	8.75	0.91	0
			Baseline (original)			MEANP.PT − 0.1			
Group	Site	Sample	O	E	O/E	O	E	O/E	Dif'ce O/E
1	5940440	127636	14	15.09	0.93	14	15.08	0.93	0
7	4951200	120184	10	9.58	1.04	10	9.58	1.04	0
1	4936750	118524	15	14.04	1.07	15	14.01	1.07	0
6	4927250	127718	8	8.74	0.92	8	8.74	0.92	0
			Baseline (original)			MEANP.PT − Min ppt14 PRISM			
Group	Site	Sample	O	E	O/E	O	E	O/E	Dif'ce O/E
1	5940440	127636	14	15.09	0.93	14	14.78	0.95	0.02
7	4951200	120184	10	9.58	1.04	10	9.51	1.05	0.01
1	4936750	118524	15	14.04	1.07	15	13.79	1.09	0.02
6	4927250	127718	8	8.74	0.92	8	8.71	0.92	0
			Baseline (original)			MEANP.PT/2			
Group	Site	Sample	O	E	O/E	O	E	O/E	Dif'ce O/E
1	5940440	127636	14	15.09	0.93	14	14.79	0.95	0.02
7	4951200	120184	10	9.58	1.04	10	9.43	1.06	0.02
1	4936750	118524	15	14.04	1.07	15	13.8	1.09	0.02
6	4927250	127718	8	8.74	0.92	8	8.68	0.92	0.01

Table B-5. Results for the scenarios in which precipitation predictor variables were altered (continued)

			Baseline (original)			MINP.PT/2			
Group	Site	Sample	O	E	O/E	O	E	O/E	Dif'ce O/E
1	5940440	127636	14	15.09	0.93	13	13.92	0.93	0.01
7	4951200	120184	10	9.58	1.04	10	9.46	1.06	0.01
1	4936750	118524	15	14.04	1.07	15	13.58	1.1	0.04
6	4927250	127718	8	8.74	0.92	8	8.69	0.92	0.01
			Baseline (original)			MEANP.PT/2 and MINP.PT/2			
Group	Site	Sample	O	E	O/E	O	E	O/E	Dif'ce O/E
1	5940440	127636	14	15.09	0.93	13	13.69	0.95	0.02
7	4951200	120184	10	9.58	1.04	10	9.33	1.07	0.03
1	4936750	118524	15	14.04	1.07	15	13.38	1.12	0.05
6	4927250	127718	8	8.74	0.92	8	8.16	0.98	0.07
			Baseline (original)			MINWD.WS/2			
Group	Site	Sample	O	E	O/E	O	E	O/E	Dif'ce O/E
1	5940440	127636	14	15.09	0.93	13	13.81	0.94	0.01
7	4951200	120184	10	9.58	1.04	10	9.53	1.05	0.01
1	4936750	118524	15	14.04	1.07	15	13.47	1.11	0.05
6	4927250	127718	8	8.74	0.92	7	7.63	0.92	0

Table B-6. Results for the scenarios in which both temperature and precipitation predictor variables were altered

			Baseline (original)			TMEAN.WS + 2 and TMEAN.NET + 2 and MEANP.PT − 0.05			
Group	Site	Sample	O	E	O/E	O	E	O/E	Dif'ce O/E
1	5940440	127636	14	15.09	0.93	14	14.93	0.94	0.01
7	4951200	120184	10	9.58	1.04	10	9.56	1.05	0
1	4936750	118524	15	14.04	1.07	15	14.01	1.07	0
6	4927250	127718	8	8.74	0.92	7	8.24	0.85	−0.07
			Baseline (original)			TMEAN.WS + 4 and TMEAN.NET + 4 and MEANP.PT − 0.1			
Group	Site	Sample	O	E	O/E	O	E	O/E	Dif'ce O/E
1	5940440	127636	14	15.09	0.93	14	14.83	0.94	0.02
7	4951200	120184	10	9.58	1.04	10	9.58	1.04	0
1	4936750	118524	15	14.04	1.07	15	14.02	1.07	0
6	4927250	127718	8	8.74	0.92	7	8.26	0.85	−0.07

Table B-7. Results for the scenarios in which freeze date predictor variables were altered

			Baseline (original)			LST32AVE − 2			
Group	**Site**	**Sample**	**O**	**E**	**O/E**	**O**	**E**	**O/E**	**Dif'ce O/E**
1	5940440	127636	14	15.09	0.93	14	15.05	0.93	0
7	4951200	120184	10	9.58	1.04	10	9.58	1.04	0
1	4936750	118524	15	14.04	1.07	15	14.01	1.07	0
6	4927250	127718	8	8.74	0.92	7	8.25	0.85	−0.07
			Baseline (original)			**LST32AVE − 5**			
Group	**Site**	**Sample**	**O**	**E**	**O/E**	**O**	**E**	**O/E**	**Dif'ce O/E**
1	5940440	127636	14	15.09	0.93	14	14.733	0.95	0.02
7	4951200	120184	10	9.58	1.04	10	9.5648	1.05	0
1	4936750	118524	15	14.04	1.07	15	13.999	1.07	0
6	4927250	127718	8	8.74	0.92	7	8.2433	0.85	−0.07
			Baseline (original)			**FST32AVE + 5**			
Group	**Site**	**Sample**	**O**	**E**	**O/E**	**O**	**E**	**O/E**	**Dif'ce O/E**
1	5940440	127636	14	15.09	0.93	15	15.374	0.98	0.05
7	4951200	120184	10	9.58	1.04	10	9.5875	1.04	0
1	4936750	118524	15	14.04	1.07	15	14.028	1.07	0
6	4927250	127718	8	8.74	0.92	8	8.7184	0.92	0
			Baseline (original)			**LST32AVE − 5 and FST32AVE + 5**			
Group	**Site**	**Sample**	**O**	**E**	**O/E**	**O**	**E**	**O/E**	**Dif'ce O/E**
1	5940440	127636	14	15.09	0.93	13	14.128	0.92	−0.01
7	4951200	120184	10	9.58	1.04	10	9.5647	1.05	0
1	4936750	118524	15	14.04	1.07	15	13.992	1.07	0
6	4927250	127718	8	8.74	0.92	7	8.224	0.85	−0.06
			Baseline (original)			**LST32AVE − 10**			
Group	**Site**	**Sample**	**O**	**E**	**O/E**	**O**	**E**	**O/E**	**Dif'ce O/E**
1	5940440	127636	14	15.09	0.93	13	14.02	0.93	0
7	4951200	120184	10	9.58	1.04	10	9.56	1.05	0
1	4936750	118524	15	14.04	1.07	15	13.7	1.09	0.03
6	4927250	127718	8	8.74	0.92	7	8.23	0.85	−0.07

Table B-7. Results for the scenarios in which freeze date predictor variables were altered (continued)

			Baseline (original)			FST32AVE + 10			
Group	Site	Sample	O	E	O/E	O	E	O/E	Dif'ce O/E
1	5940440	127636	14	15.09	0.93	14	14.713	0.95	0.02
7	4951200	120184	10	9.58	1.04	10	9.6097	1.04	0
1	4936750	118524	15	14.04	1.07	15	13.797	1.09	0.02
6	4927250	127718	8	8.74	0.92	7	8.1843	0.86	−0.06
			Baseline (original)			LST32AVE − 10 and FST32AVE + 10			
Group	Site	Sample	O	E	O/E	O	E	O/E	Dif'ce O/E
1	5940440	127636	14	15.09	0.93	13	13.743	0.95	0.02
7	4951200	120184	10	9.58	1.04	10	9.6115	1.04	0
1	4936750	118524	15	14.04	1.07	15	13.532	1.11	0.04
6	4927250	127718	8	8.74	0.92	7	8.1706	0.86	−0.06
			Baseline (original)			LST32AVE − 15			
Group	Site	Sample	O	E	O/E	O	E	O/E	Dif'ce O/E
1	5940440	127636	14	15.09	0.93	13	13.945	0.93	0
7	4951200	120184	10	9.58	1.04	10	9.5818	1.04	0
1	4936750	118524	15	14.04	1.07	15	13.454	1.11	0.05
6	4927250	127718	8	8.74	0.92	7	8.2214	0.85	−0.06
			Baseline (original)			LST32AVE − 15 and FST32AVE + 15			
Group	Site	Sample	O	E	O/E	O	E	O/E	Dif'ce O/E
1	5940440	127636	14	15.09	0.93	13	13.415	0.97	0.04
7	4951200	120184	10	9.58	1.04	10	9.6052	1.04	0
1	4936750	118524	15	14.04	1.07	14	12.787	1.09	0.03
6	4927250	127718	8	8.74	0.92	7	8.1713	0.86	−0.06

Table B-8. Results for scenarios in which combinations of all climate-related predictor variables were altered simultaneously

			Baseline (original)			Changed by 1			
Group	**Site**	**Sample**	**O**	**E**	**O/E**	**O**	**E**	**O/E**	**Dif'ce O/E**
1	5940440	127636	14	15.09	0.93	13	14.04	0.93	0
7	4951200	120184	10	9.58	1.04	10	9.51	1.05	0.01
1	4936750	118524	15	14.04	1.07	15	14.03	1.07	0
6	4927250	127718	8	8.74	0.92	8	8.71	0.92	0
			Baseline (original)			**Changed by 2**			
Group	**Site**	**Sample**	**O**	**E**	**O/E**	**O**	**E**	**O/E**	**Dif'ce O/E**
1	5940440	127636	14	15.09	0.93	13	13.81	0.94	0.01
7	4951200	120184	10	9.58	1.04	10	9.49	1.05	0.01
1	4936750	118524	15	14.04	1.07	15	14.03	1.07	0
6	4927250	127718	8	8.74	0.92	7	8.23	0.85	−0.06

APPENDIX C

MAINE DECISION MODEL AND ANALYSES ON COMPONENT METRICS

C.1. OVERVIEW OF MAINE'S DEPARTMENT OF ENVIRONMENTAL PROTECTION (ME DEP) AQUATIC LIFE DECISION MODELS AND SAMPLE VARIABLES (PROVIDED BY MAINE DEP)

ME DEP's aquatic life decision models are four statistical models that use 30 variables of the macroinvertebrate community to determine the strength of association of a sample community to Maine's water quality classes. Each of the four linear discriminant models uses different variables, providing independent estimates of class membership. Association values are computed for each classification using one 4-way model and three 2-way models. The protocol is outlined in the ME DEP methods manual (Davies and Tsomides, 2002).

C.1.1. First-Stage Model and Variables

The first-stage model acts as a screen and gives the strength of association of the sample to each of the different water quality classes. This model provides four initial probabilities that a given site attains one of three classes (A, B, or C) or is in nonattainment (NA) of the minimum criteria for any class. These probabilities have a possible range from 0.0 to 1.0 and, after transformation, they are used as variables in each of the three subsequent second-stage or final decision models. See the section below on second-stage models.

The variables used in the first-stage model are variables important to the evaluation of all classes. Of the nine variables used in the first modeling stage, five measure abundance, two measure richness, and two variables are biotic indices involving tolerance to pollution and abundance. The **first-stage model** uses the following nine variables:

1. **Total Mean Abundance—**Total mean abundance (the mean number of individuals in a sample, usually based on 3 replicates) is a basic measure of community structure and is a strong predictor of both Class A and nonattainment. Total abundance values for the water quality classes appear to follow a curve shaped like the Odum et al. (1979) subsidy-stress gradient. Values for Class A are relatively low, due to low nutrients in natural Maine waters. Values for Class B and C communities tend to be high, indicating increased resources that might be available in a waterbody with increased loadings of materials from human alterations. Abundance values in nonattainment waters tend to be low but can also be highly variable.

2. **Generic Richness—**Richness (total number of taxa in a sample) is a good measure of water quality impact, declining as water quality declines. Low richness is a good predictor of nonattainment. Like abundance, richness follows the generalized subsidy-stress curve.

3. **Plecoptera Mean Abundance—**Plecoptera, or stoneflies, are very intolerant of even mild levels of pollution. Abundance is highest for Class A and declines with the classes to be nearly absent from the nonattainment class. The Maine water quality classification requires that Class A and B waters support all indigenous species, so it is expected that Plecoptera numbers will be maintained in those classes. Stoneflies function as predators and shredders.

4. **Ephemeroptera Mean Abundance—**Ephemeroptera, or mayflies, are intolerant of many pollutants, so abundances are distinctly lower for nonattainment samples than the other classes. Mayflies function as scrapers and collectors. Together with the stoneflies, these two groups represent highly sensitive orders that fulfill the major functional feeding roles in the community. These orders are important components of a Class A or B community.

5. **Shannon-Wiener Generic Diversity** (Shannon and Wiener, 1963)—Diversity is composed of a richness factor and an eveness factor. Richness distributes between the classes along a subsidy-stress curve. Diversity shows a decline in value from Class A to the nonattainment class as certain pollution-tolerant taxa gain advantages, due to increasing pollution load or other activities. As both diversity and richness decline, the stability of most natural communities usually declines.

6. **Hilsenhoff Biotic Index** (Hilsenhoff, 1987)—The biotic index provides a measure of the general tolerance level of the sample community toward organic (nutrient) enrichment. The index increases in value from Class A to the nonattainment class, indicating that increases in abundance may be attributable to increases among the tolerant taxa (a change allowed in Class B or C), or that there may be a decline in the taxa pool of intolerant organisms (a change allowed in Class C).

7. **Relative Chironomidae Abundance—**Chironomidae, a Family of flies in the Order Diptera that includes Nonbiting Midges and Midges, consist of a great number of taxa with wide-ranging tolerances and adaptations. Many tend to increase with increasing pollution load, probably as a response to reduced competition and predation, and to increased organic matter supply. Many have very short generation times and are, thus, capable of quickly colonizing areas where these conditions exist. The taxa that cause these increases are the collector types adapted to feeding on fine organic matter; some are primarily predators. These genera have been observed to increase in relative abundance presumably because of tolerance to reduced water quality, particularly the presence of some toxic substances, and the availability of other pollution tolerant prey.

8. **Relative Diptera Richness—**Many Diptera, or true flies, are pollution tolerant organisms. Relative Diptera richness increases from Class A to the nonattainment class. Increases in Diptera, particularly Chironomidae, have been observed with increasing pollution and sedimentation and loss of Ephemeroptera, Plecoptera, and Trichoptera.

9. ***Hydropsyche* Mean Abundance—**The genus *Hydropsyche*, one of the common net-spinning Caddisflies, provides some added discrimination to the model. Higher values for *Hydropsyche* abundance are found for Class B and are nearly absent from

nonattainment samples. *Hydropsyche* is a filter feeder and prospers under conditions of mild enrichment of suspended organic particles, conditions that might naturally be found below a lake outlet or might be found in Class B waters below a treatment plant outfall or in the presence of nutrient enrichment from nonpoint source pollution activities (e.g., agriculture). Relative to other genera of the Hydropsychidae family, *Hydropsyche* is usually less tolerant of low dissolved oxygen or toxic substances.

C.1.2. Second-Stage Models and Variables

The final decision models (the three, two-way models) are designed to distinguish between a given class and any higher classes as one group and any lower classes as another group (e.g., Classes A + B + C vs. NA; Classes A + B vs. Class C + NA; Class A vs. Classes B + C + NA). The equations for the final decision models use the predictor variables relevant to the class being tested. The process of determining attainment class using the association value is outlined in Appendix F of the ME DEP methods manual (Davies and Tsomides, 2002). Application of the three second-stage models or two-group tests is hierarchical:

"C or better" model: The first second-stage model determines the probability that an unknown sample belongs in the cluster of samples A + B + C versus the probability that it belongs in the cluster of nonattainment of Class C samples. This is referred to as the "C or better" model, which determines if the sample is at least a Class C, using the following variables:

1. **Probability (A + B + C)** from First-stage Model
2. ***Cheumatopsyche* Mean Abundance—**The abundance of *Cheumatopsyche*, one of the common net-spinning Caddisflies, generally increases with declining water quality and is usually the last of the Ephemeroptera-Plecoptera-Trichoptera genera found in abundance as water quality declines because *Cheumatopsyche* are generally found to be the most pollution tolerant genera within the family Hydropsychidae, among the order Trichoptera.
3. **Ephemeroptera, Plecoptera, Trichoptera (EPT)—Diptera Richness Ratio—**(uses all Diptera rather than just the Chironomidae.). Ephemeroptera-Plecoptera-Trichoptera are usually poorly represented in communities where water quality is poor. These orders provide considerable functional variety to aquatic communities, and when severely depleted, or replaced by Diptera, signal dysfunction of the community. Maine data show distinct separation of values for this variable between Class A, B, and C communities and the nonattainment communities.

4. **Relative Oligochaeta Abundance—**Proliferation of Oligochaeta, aquatic worms, has long been recognized as an indication of polluted waters, because many taxa are highly tolerant of low oxygen conditions and certain toxic substances, feed on fine organic particles and can colonize quickly in the absence of predators. Communities dominated by Oligochaeta are found when pollution loads are excessive. These organisms are usually the last to be eliminated by pollutant overloading and as the relative abundance of Oligochaeta increases, community structure, and function are usually diminished.

"B or better" model: The second two-way model is the "B or better" model, which determines if the unknown sample attains at least Class B standards. It discriminates between the cluster of A + B samples and the cluster of C + nonattainment of Class C samples. Family functional groups are important in this second two-way model. Changes in functional feeding group composition indicate the energy pathways through the aquatic ecosystem have been significantly altered. The major functional groups in the Maine data are as follows: collector-filterer, collector-gatherer, piercer, predator, scraper, and shredder. The "B or better" model uses the following variables:

1. **Probability (A + B)** from First-stage Model
2. **Perlidae Mean Abundance** (Family Functional Group)—Greater abundance of this family functional group is expected to occur in higher quality waters. This family of stoneflies encompasses large predators and usually occurs in waters of good quality. Generation time for some of these taxa is greater than 1 year; therefore, populations will persist only where water quality is consistently good for long periods of time.
3. **Tanypodinae Mean Abundance** (Family Functional Group)—This subfamily functional group is usually found in greater abundance in waters of lower quality. This Chironomidae subfamily is also a predator group, but these organisms are small in comparison to the Perlidae, and feed on small Oligochaeta and other Chironomidae that can also tolerate lower water quality.
4. **Chironomini Mean Abundance** (Family Functional Group)—Greater abundance of this Chironomidae subfamily group indicates increased availability of organic matter. Many taxa in this group are known to tolerate lower water quality. These organisms are collector-gatherers favoring fine, settled organic particles. Many of these taxa are multivoltine, capable of quickly colonizing favorable habitats and recolonizing after disturbances.
5. **Relative Ephemeroptera Abundance—**The Ephemeroptera, or mayflies, are generally an intolerant order and tend to be indicators of good to excellent water quality. While total Ephemeroptera abundance was used as a discriminating variable in the second-stage

discriminant model to separate the four classes, relative abundance is used to separate these two groups, particularly between the Class B and C waters. While Ephemeroptera abundance may not decline appreciably in Class C waters, there is an expectation for other non-Ephemeroptera taxa to increase.

6. **EPT Generic Richness—**EPT richness has been a common measure to identify waters of good quality. Of the three orders, Ephemeroptera and Plecoptera are considered the more intolerant. Many of the Trichoptera are also intolerant of low water quality. Collectively, these orders have a wide array of functional characteristics (feeding strategies and preferred resources, reproductive and life cycle strategies, habitat preferences). Higher values for EPT richness are indicative of a structurally and functionally diverse community. As EPT richness diminishes, it is presumed that this functional diversity also declines.

7. **Sum of Mean Abundances of *Dicrotendipes, Micropsectra, Parachironomus,* and *Helobdella*—**The sum of the abundance of four indicator taxa (three Chironomidae genera and one leech genera) is also used. All four are detritivores and generally occur in abundance only when water quality is diminished. A high abundance of this group is indicative of conditions of Class C or nonattainment.

"Class A" model: Class A is the highest quality water and is expected to be supportive of natural populations with the expectation that the community include many pollutant-intolerant organisms. The Class A decision model relies on the probability score from the second-stage linear discriminant function and many indicator taxa to ascertain Class A quality. The third two-way model is the "Class A" model and discriminates Class A samples from the cluster of samples in Classes B + C + Nonattainment of Class C using the following variables:

1. **Probability of Class A** from First-stage Model

2. **Relative Plecoptera Richness—**Plecoptera are well known as an intolerant order, showing great intolerance to a variety of pollutants. Their reproductive strategies render them slow to recolonize areas where they have been eliminated. Water quality, therefore, needs to be consistently good for the Plecoptera to be present. Relative richness of Plecoptera is expected to be greatest in the highest quality waters.

3. **Sum of Mean Abundance of *Cheumatopsyche*, *Cricotopus*, *Tanytarsus*, and *Ablabesmyia*—**These four taxa (a net-spinning Caddisfly and three Chironomidae genera) are considered pollution-tolerant and are not expected to occur in abundance in Class A waters. All four taxa occur most commonly in lower quality waters and may replace functions of less tolerant organisms when those populations decline.

4. **Sum of Mean Abundances of *Acroneuria* and *Stenonema***—*Acroneuria* (a stonefly genera of the Perlidae Family) and *Stenonema* (a mayfly genera) are two of the most common and abundant taxa in their respective orders and indicators of good water quality. The sum of their abundance provides a good discriminating variable.

5. **Ratio of Ephemeroptera and Plecoptera (EP) Generic Richness**—EPT richness is a good discriminating variable to identify Class A and B waters, but of this group, the Ephemeroptera and Plecoptera were usually the less tolerant taxa of the three orders. EPT richness is, thus, used as a variable for Class A waters.

6. **Ratio of Class A Indicator Taxa**—The number of Class A indicators divided by 7 (which is the total number possible). Seven indicator taxa were identified for Class A communities. Class A indicator taxa were present in 100% of Class A communities, <26% of Class B communities, <16% of Class C communities, and <1% of nonattainment communities. Class A indicator taxa were rarely found to be dominant taxa except in Class A communities. Values of zero for this variable (# of Class A indicator taxa among 5 most dominant taxa) were found in sample communities that were not determined to support Class A conditions. Class A communities had one or more indicator taxa among the five most dominant taxa for 54% of the samples. The Class A indicators are *Brachycentrus* (Trichoptera: Brachycentridae), *Serratella* (Ephemeroptera: Ephemerellidae), *Leucrocuta* (Ephemeroptera: Heptageniidae), *Glossosoma* (Trichoptera: Glossosomatidae), *Paragnetina* (Plecoptera: Perlidae), *Eurylophella* (Ephemeroptera: Ephemerellidae), and *Psilotreta* (Trichoptera: Odontoceridae).

Figure C-1 shows a flow chart that depicts Maine DEP's decision criteria. The protocol is also outlined in the Maine DEP methods manual (i.e., Davies and Tsomides, 2002).

Process for Determining Attainment Class Using Association Values

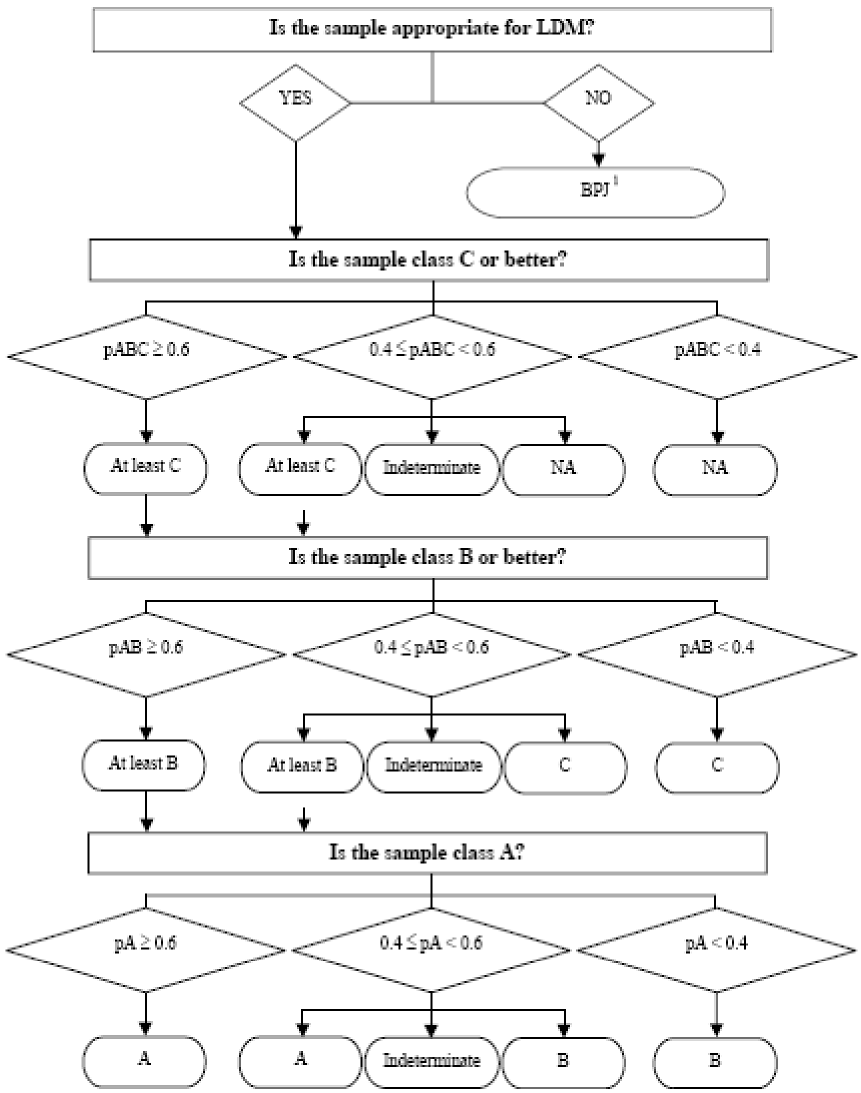

Figure C-1. Flow chart that outlines the process that Maine DEP uses for determining attainment class using association values from its four linear discriminant models (chart by Thomas J. Danielson, taken from ME DEP 2002 monitoring manual).

C.2. BOX PLOTS SHOWING THE DISTRIBUTIONS OF THE MODEL INPUT METRICS ACROSS THE DIFFERENT CLASSIFICATION GROUPS

Figures C-2 through C-24 show categorical box-and-whisker plots showing distributions of mean model input metric values across the classification groups based on a data set composed of rock-basket or rock-cone samples collected during Maine DEP's July−September index period.

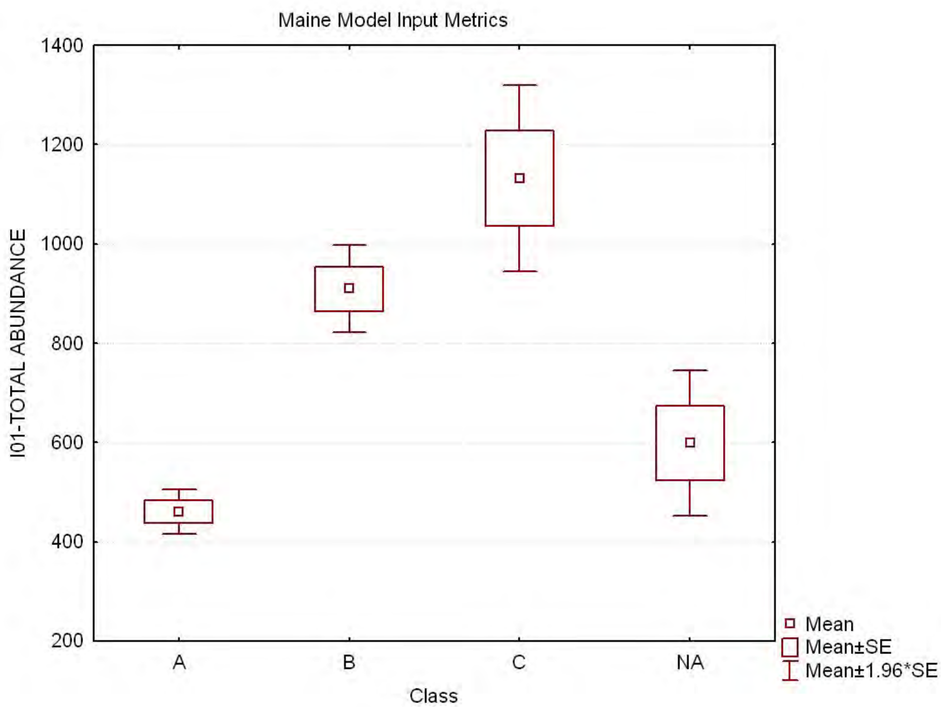

Figure C-2. Differences in total taxa abundance by class showing mean and standard error (SE).

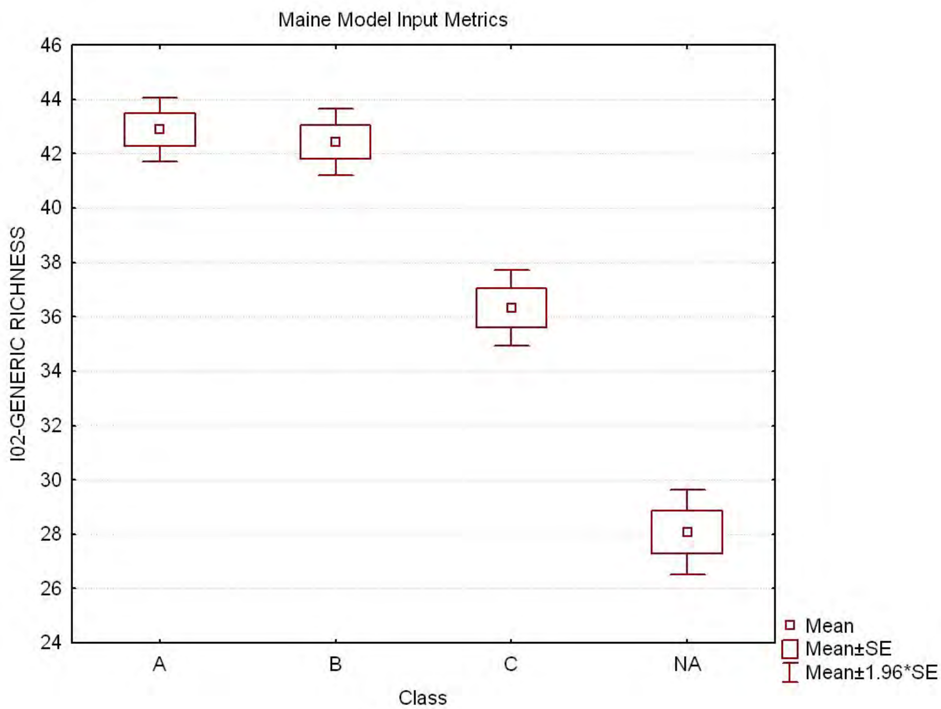

Figure C-3. Differences in richness of genera by class.

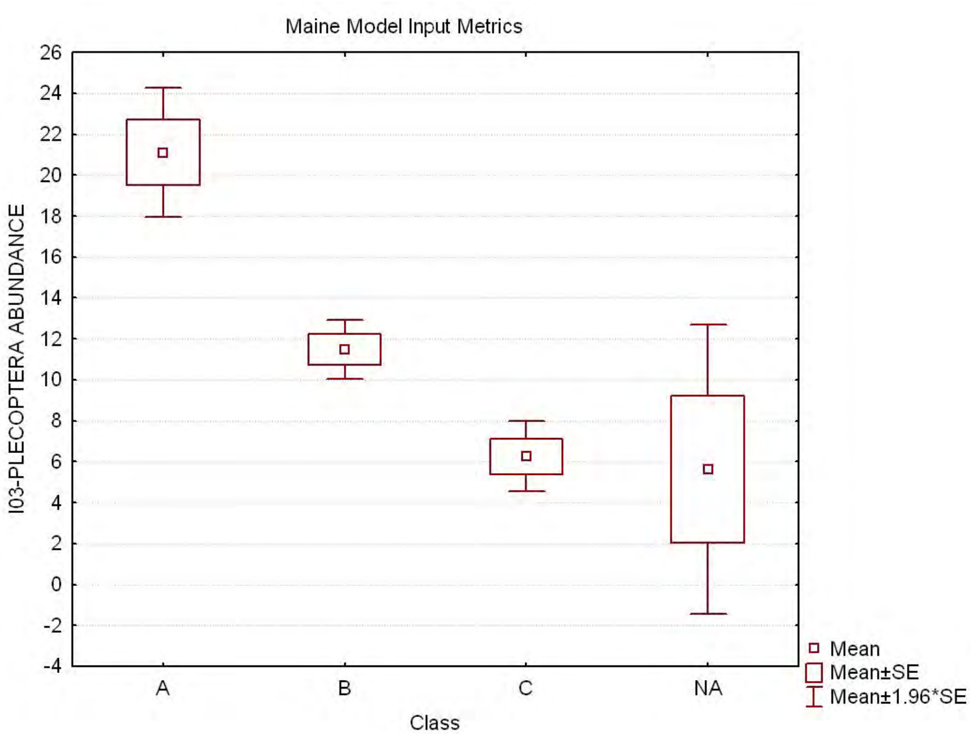

Figure C-4. Differences in Plecoptera abundance by class.

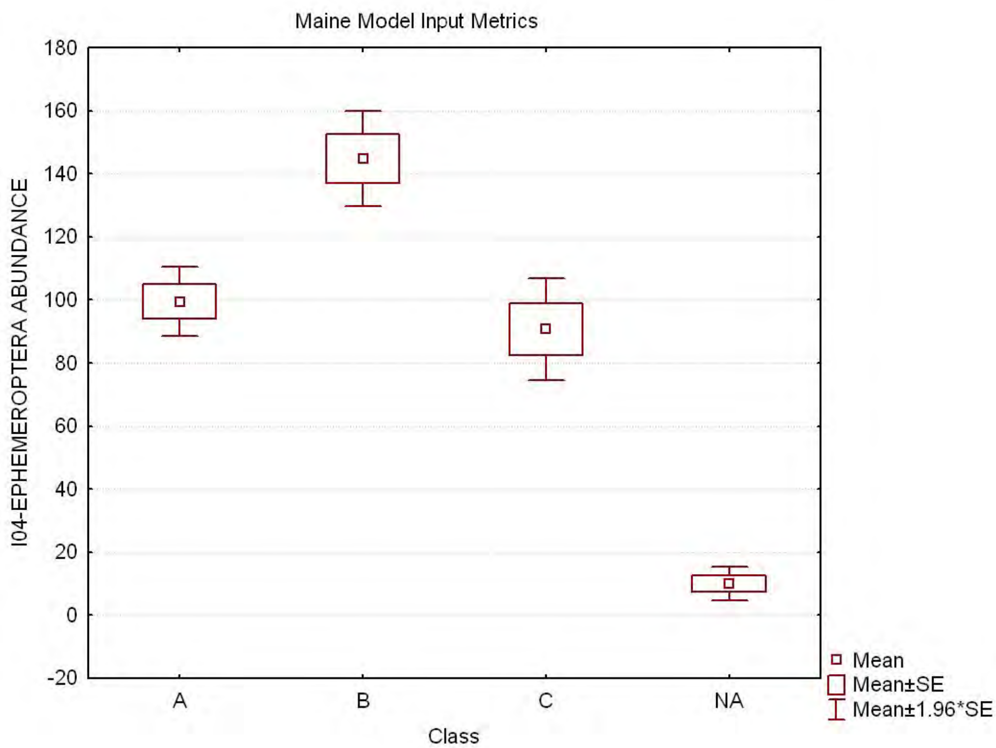

Figure C-5. Differences in Ephemeroptera abundance by class.

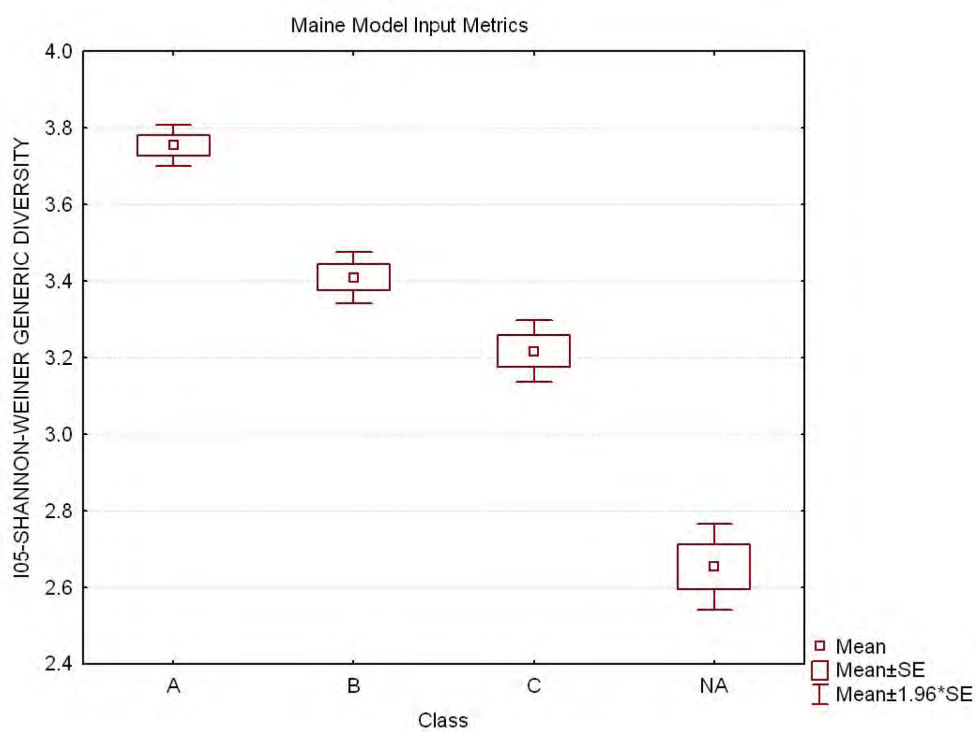

Figure C-6. Differences in Shannon-Wiener diversity of genera by class.

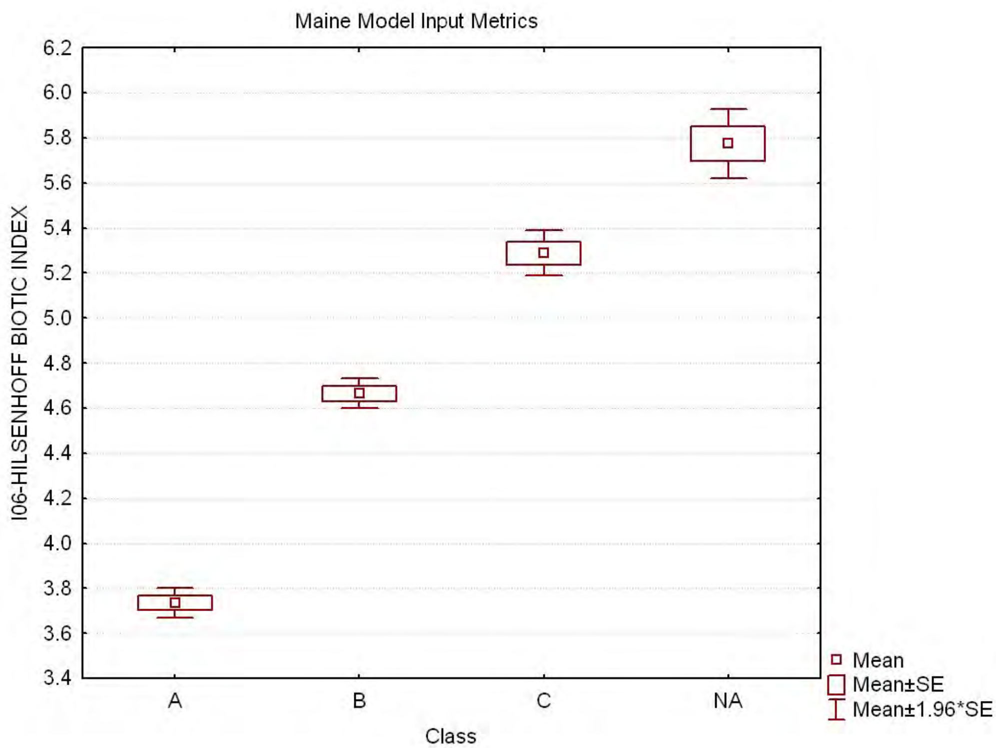

Figure C-7. Differences in Hilsenhoff Biotic Index by class.

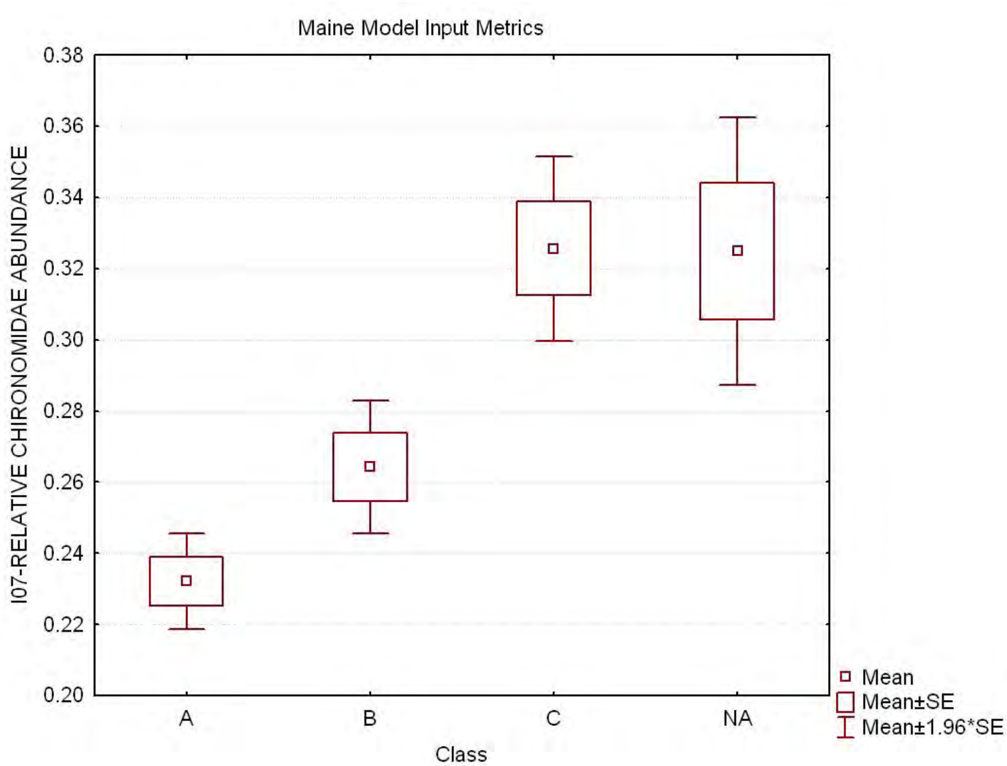

Figure C-8. Differences in relative Chironomid abundance by class.

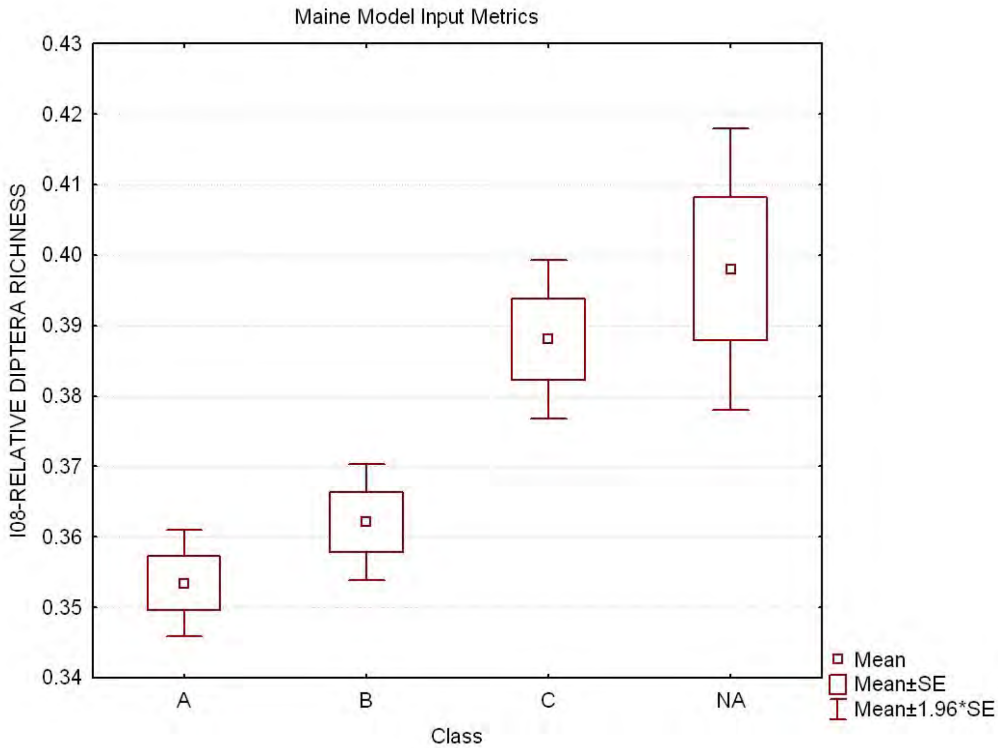

Figure C-9. Differences in relative Diptera richness by class.

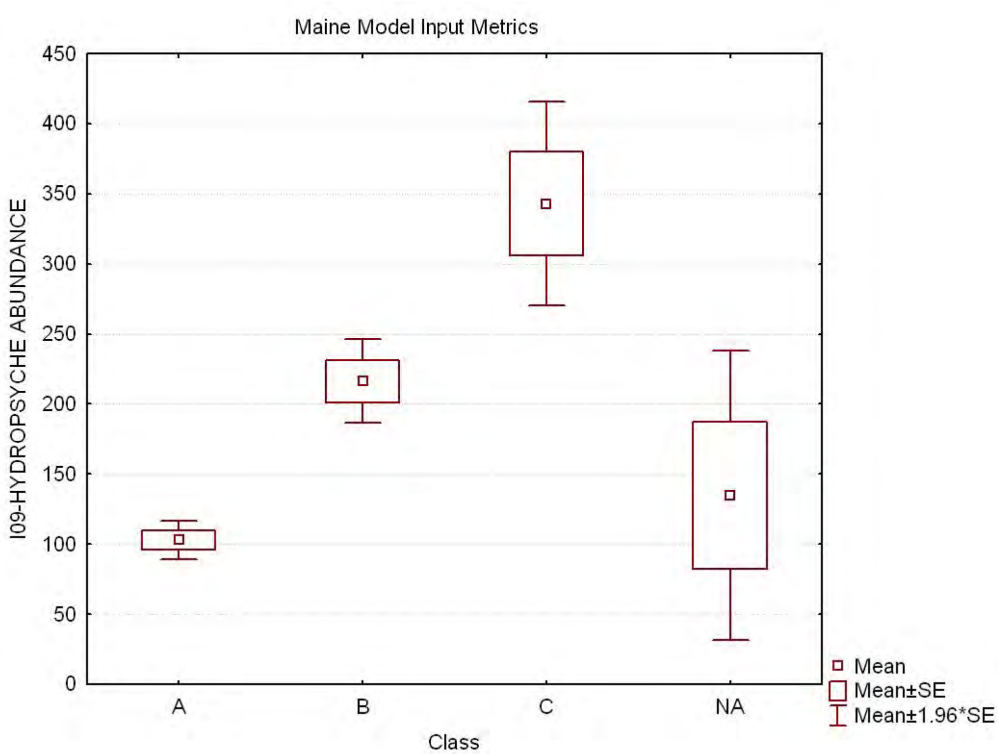

Figure C-10. Differences in *Hydropsyche* abundance by class.

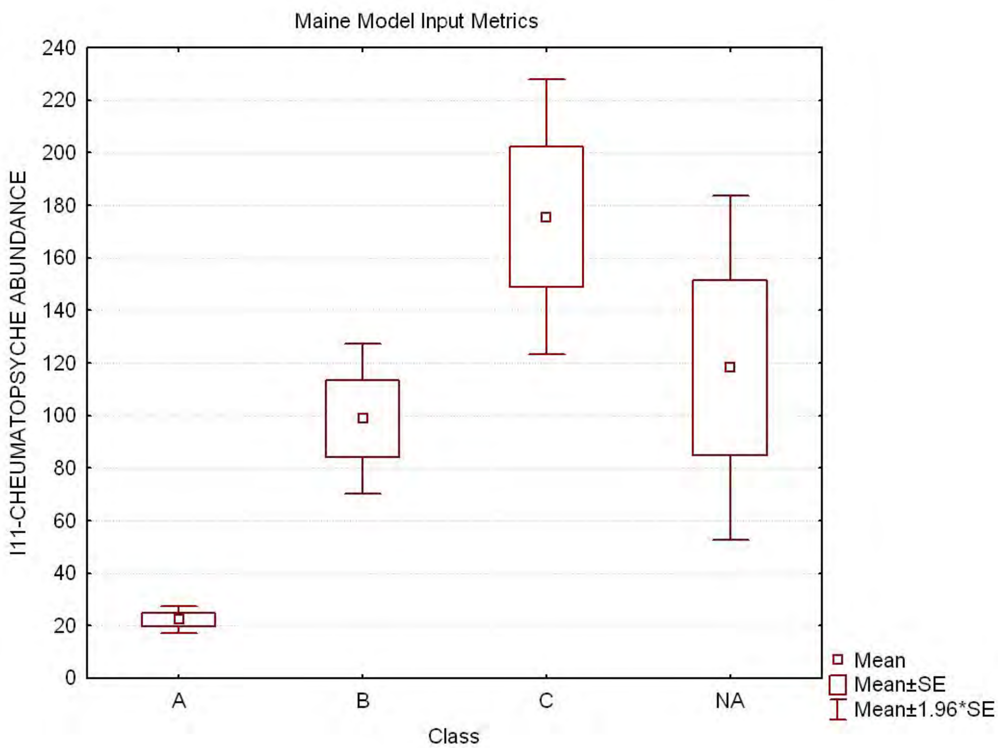

Figure C-11. Differences in *Cheumatopsyche* abundance by class.

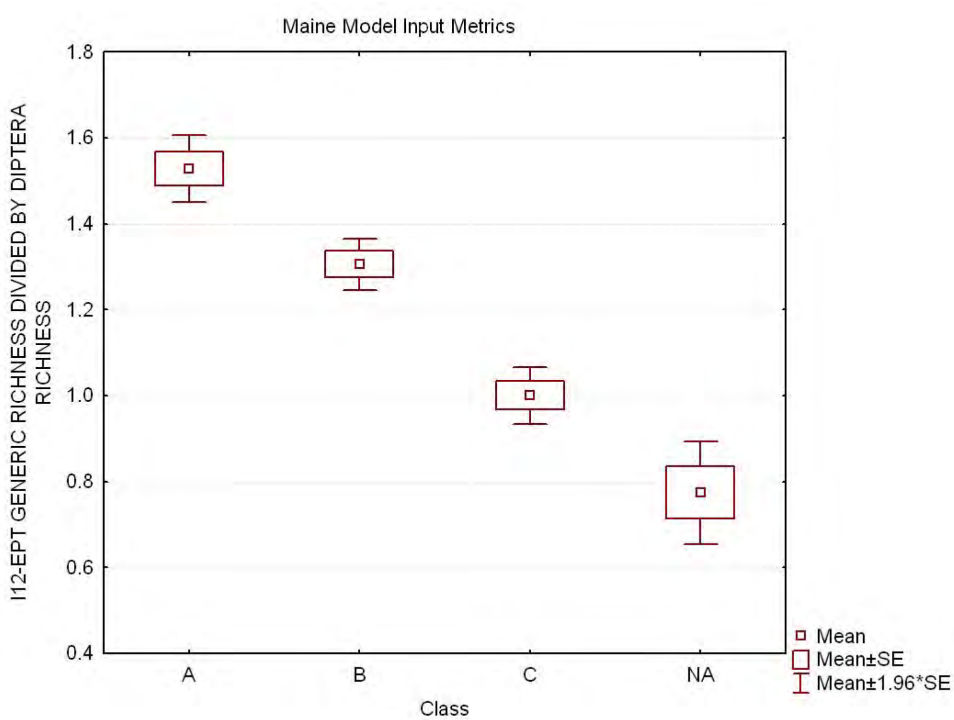

Figure C-12. Differences in EPT richness over diptera richness by class.

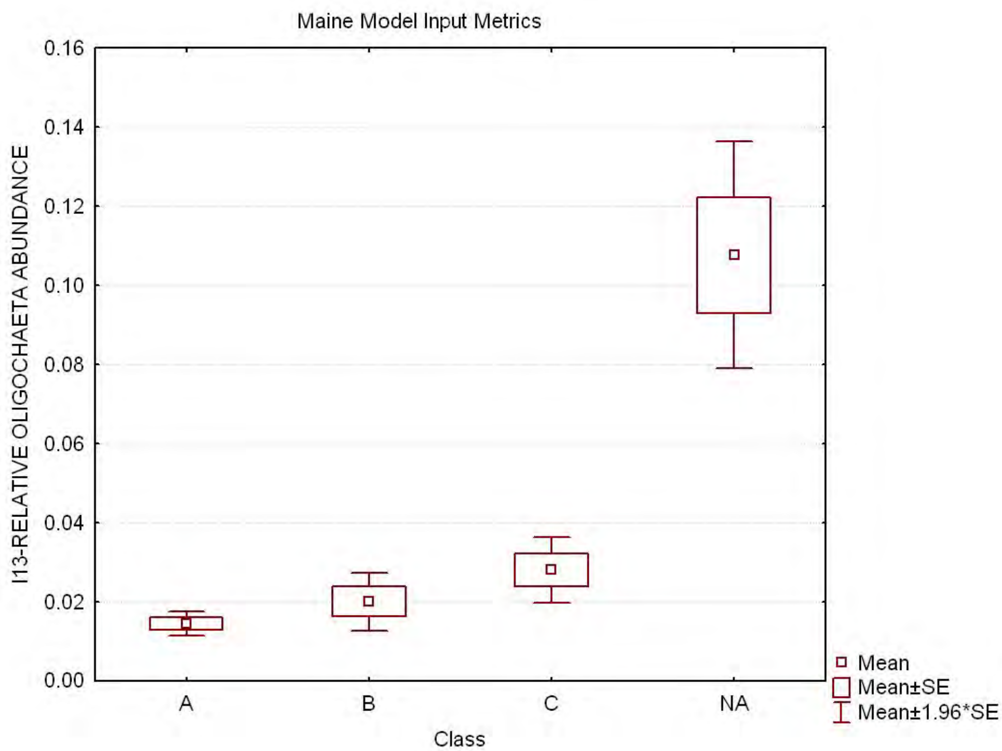

Figure C-13. Differences in relative Oligochete abundance by class.

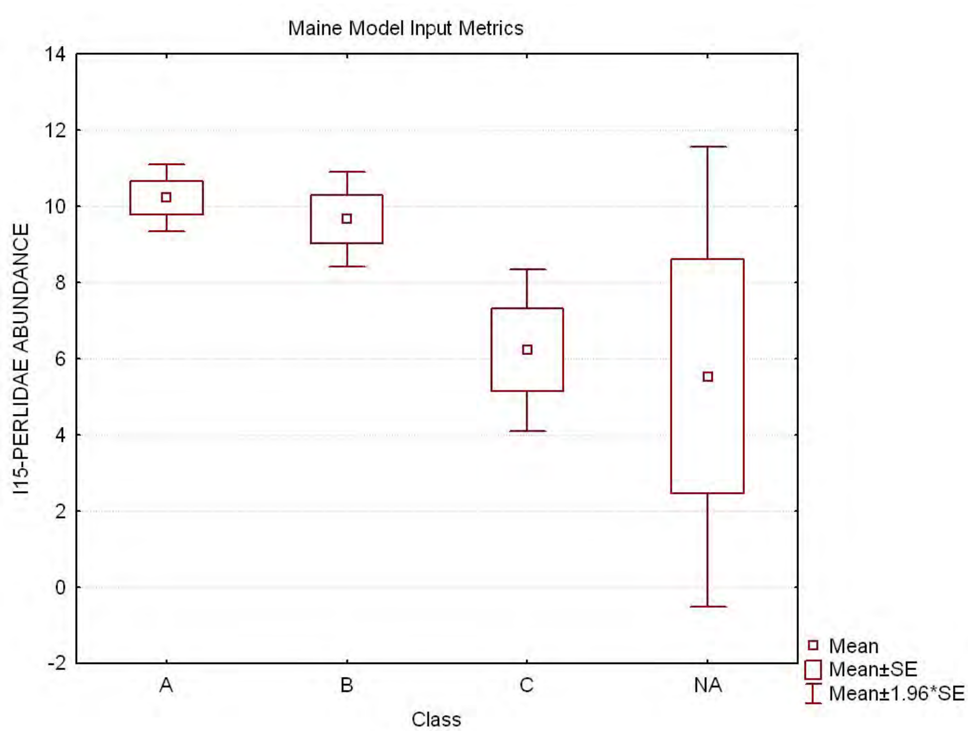

Figure C-14. Differences in Perlidae abundance by class.

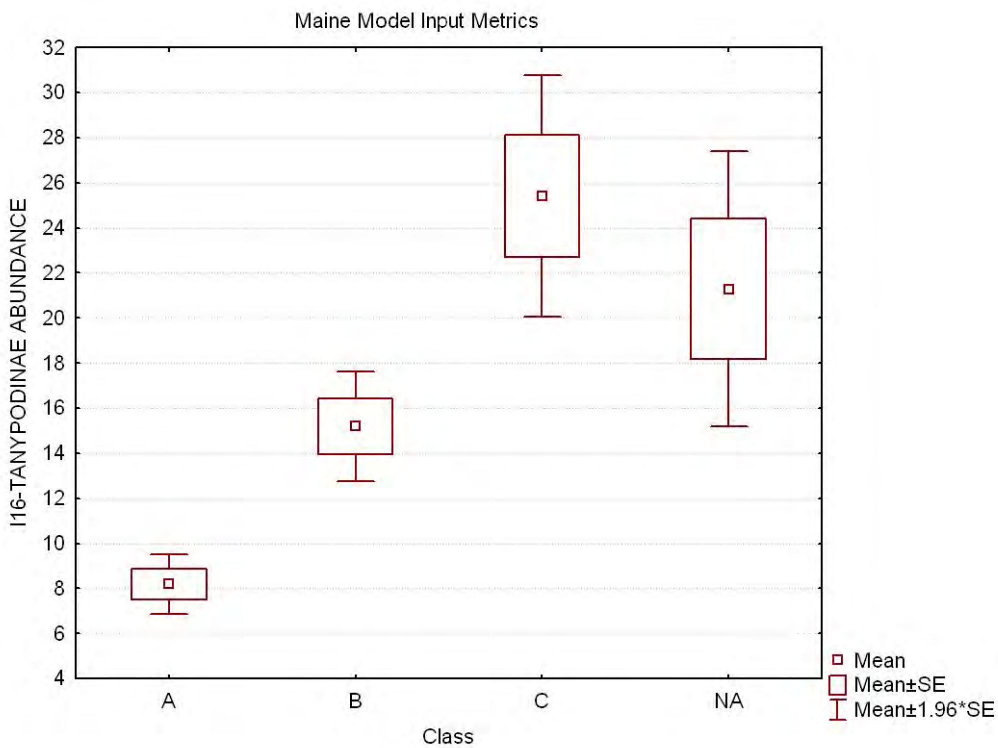

Figure C-15. Differences in Tanypodinae abundance by class.

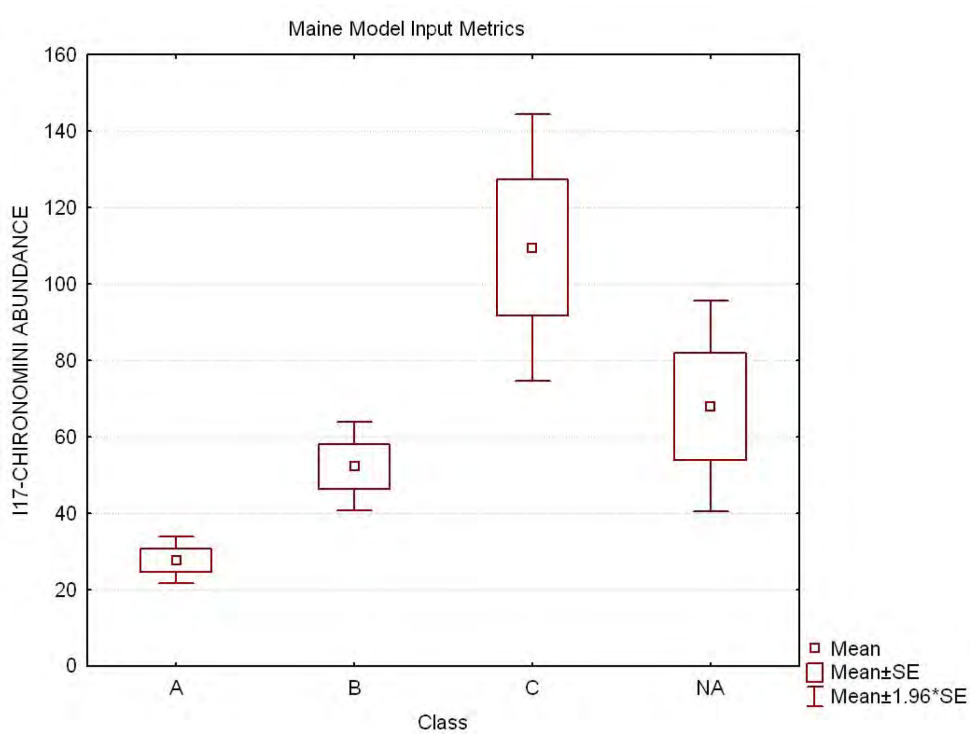

Figure C-16. Differences in Chironomid abundance by class.

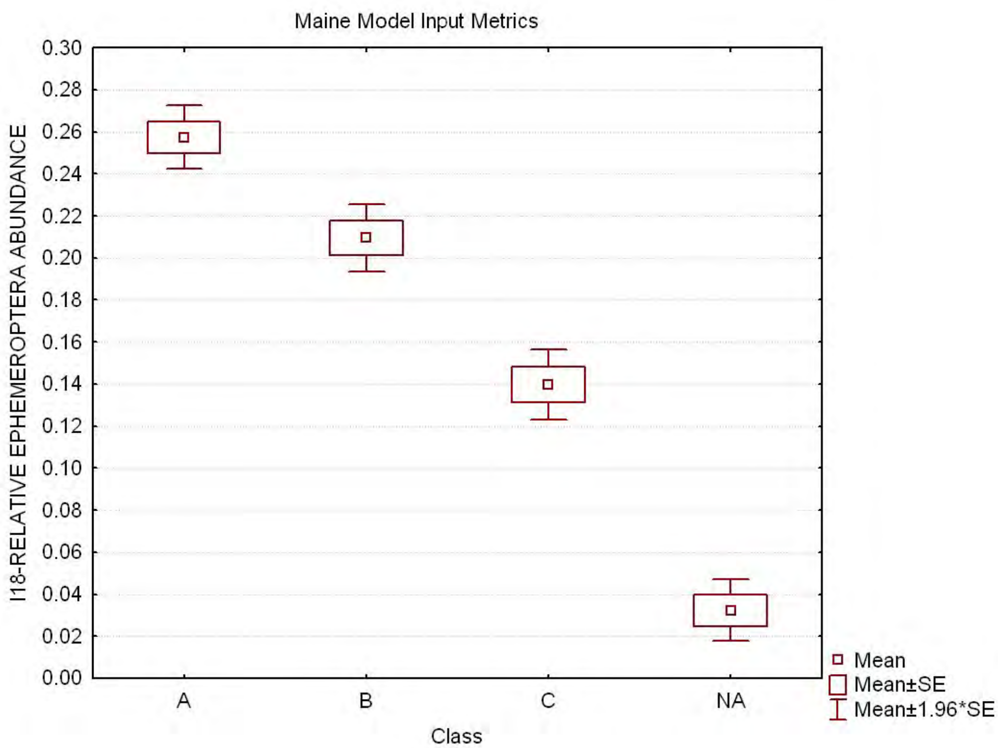

Figure C-17. Differences in relative Ephemeroptera abundance by class.

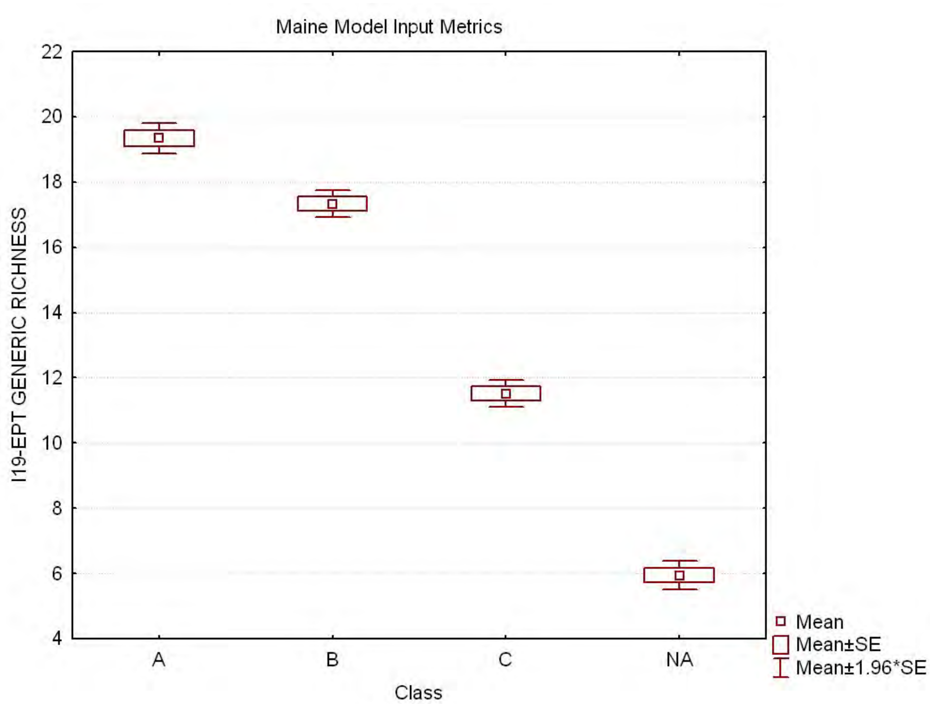

Figure C-18. Differences in EPT richness by class.

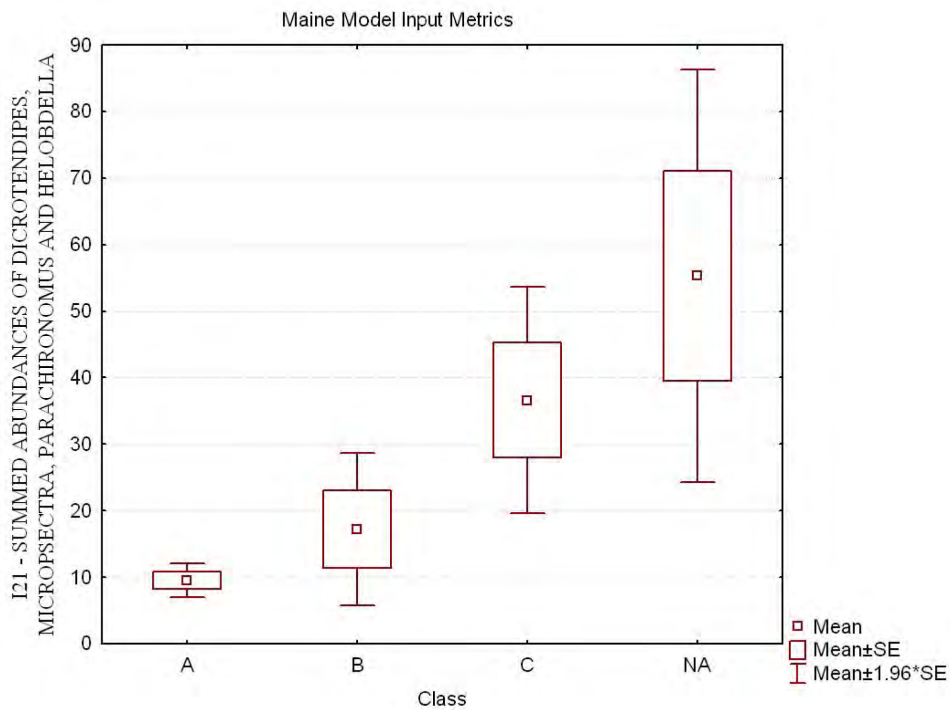

Figure C-19. Differences in total abundances of *Dicrotendipes*, *Micropsectra*, *Parachironomus*, and *Helobdella* by class.

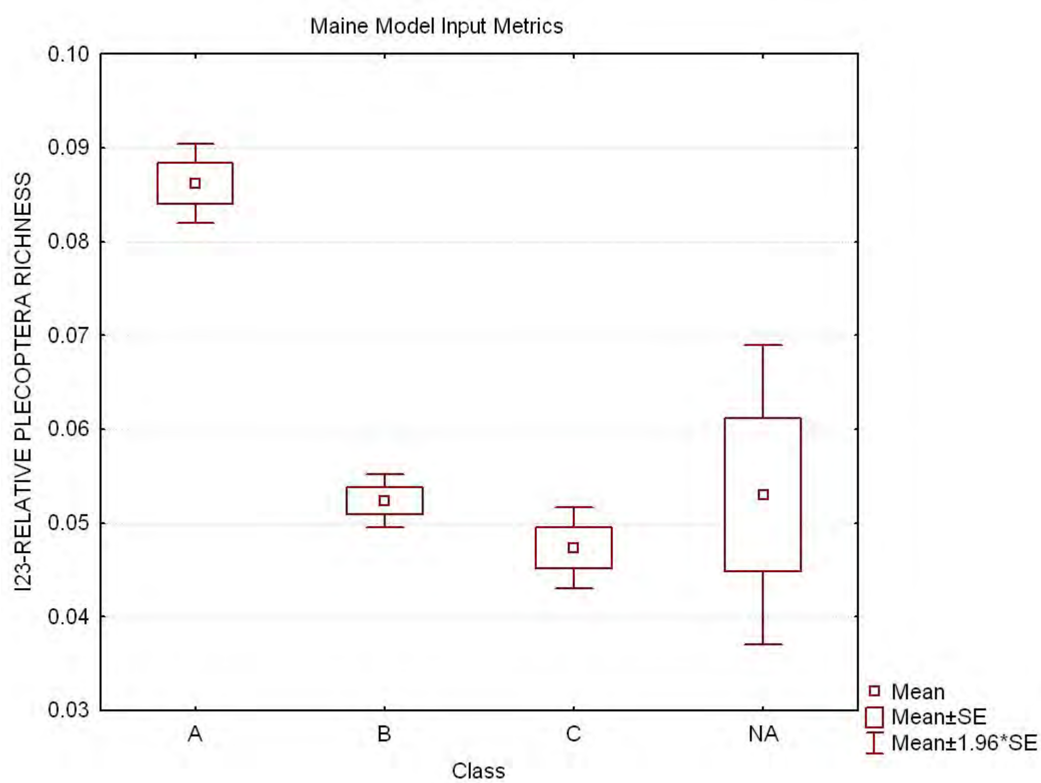

Figure C-20. Differences in relative Plecoptera richness by class.

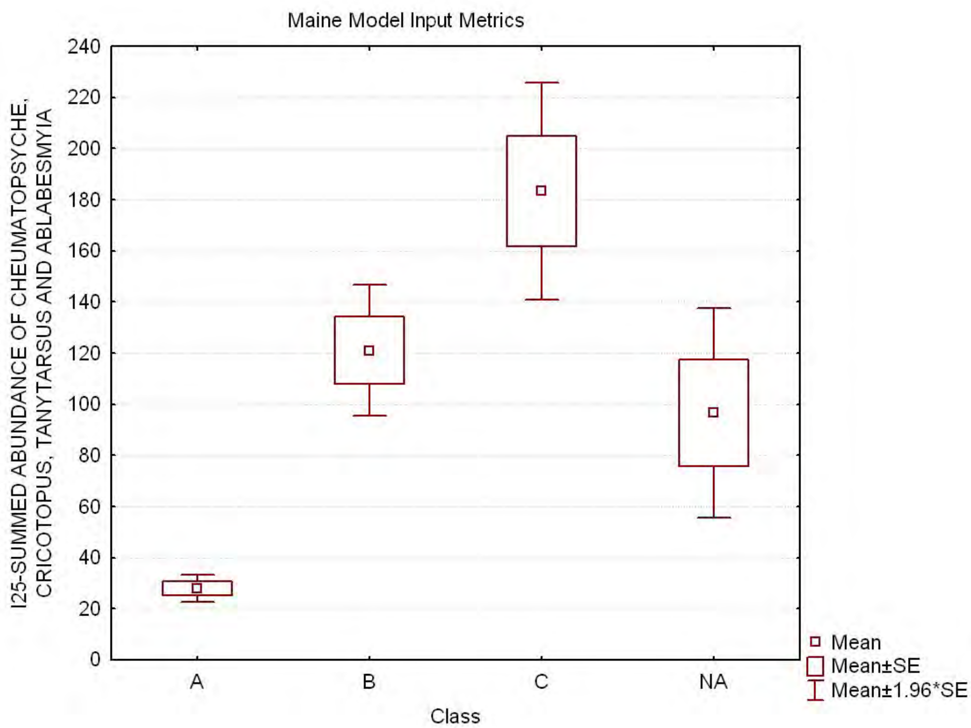

Figure C-21. Differences in total abundances of *Cheumatopsyche*, *Cricotopus*, *Tanytarsus,* and *Ablabesmyia* by class.

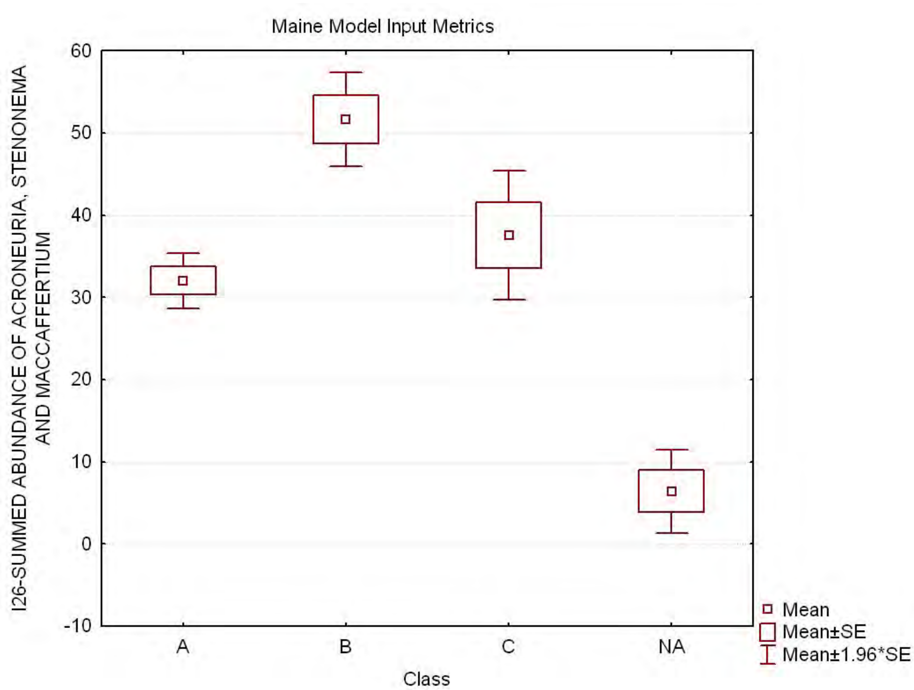

Figure C-22. Differences in total abundances of *Acroneuria*, *Stenonema*, and *Maccaffertium* by class.

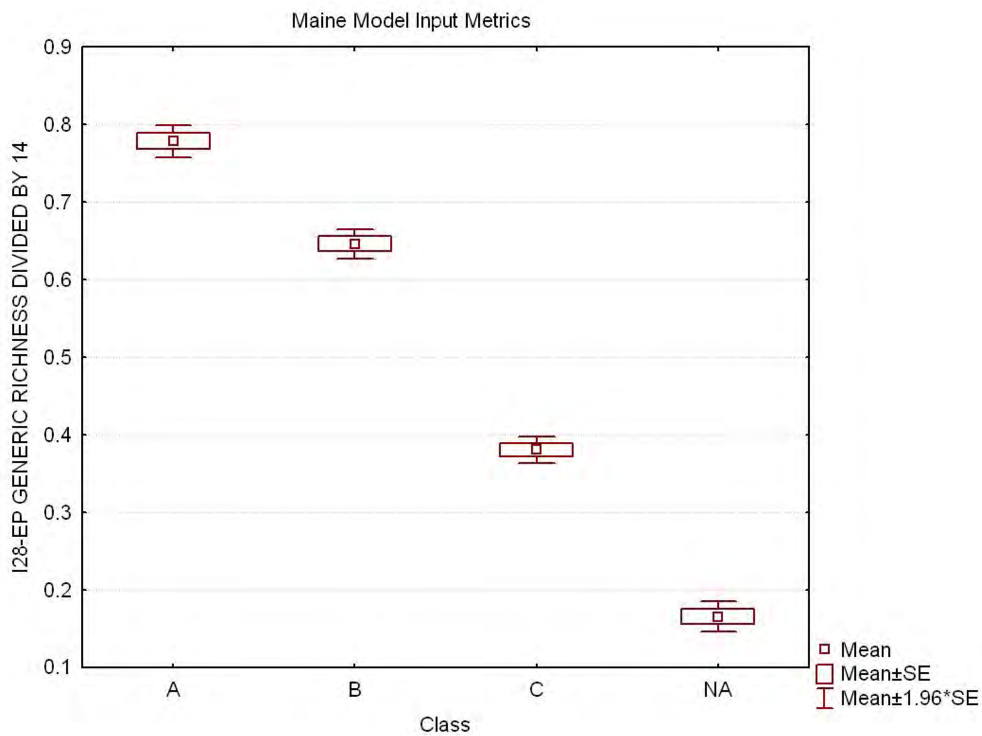

Figure C-23. Differences in EP richness by class.

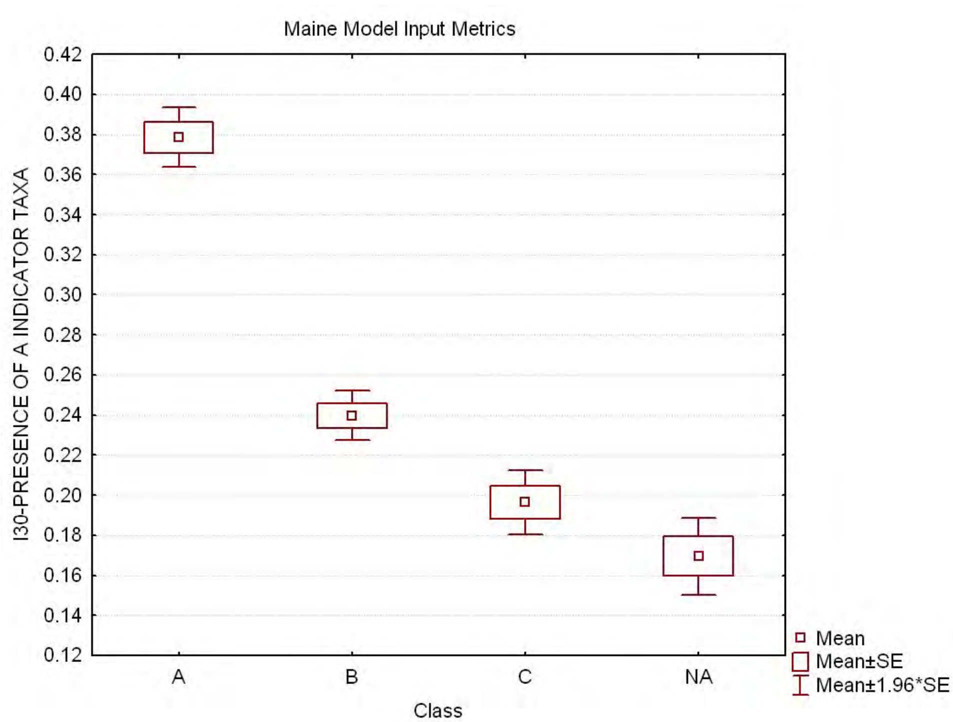

Figure C-24. Differences in presence of indicator taxa by class.

C.3. DISTRIBUTION OF INDICATOR TAXA BY YEARS GROUPED AS CLIMATE SURROGATES

Figure C-25 shows indicator taxa grouped by driest-, normal-, and wettest-year samples, while Figure C-26 shows indicator taxa grouped by lowest-, normal-, and highest-flow year samples.

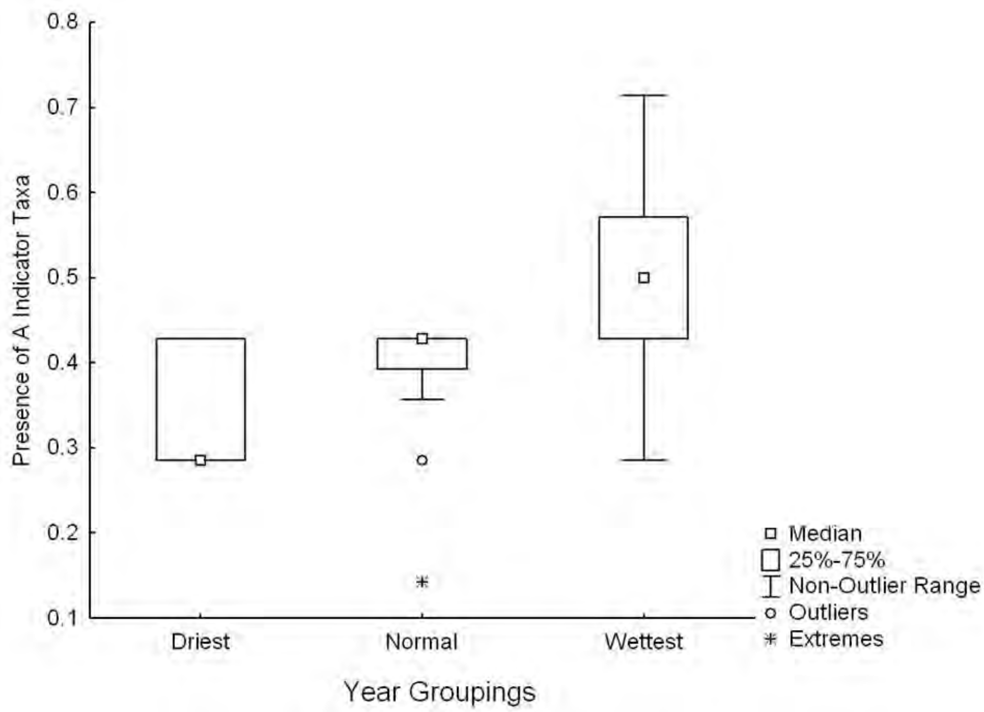

Figure C-25. Distributions of Class A indicator taxa metric values in driest-, normal-, and wettest-year samples at Maine site 56817 (Sheepscot). Year groupings are based on Parameter‑elevation Regressions on Independent Slopes Model (PRISM) mean annual precipitation from each site during time periods for which biological data were available. Data used in these analyses were limited to summer (July−September) rock-basket samples.

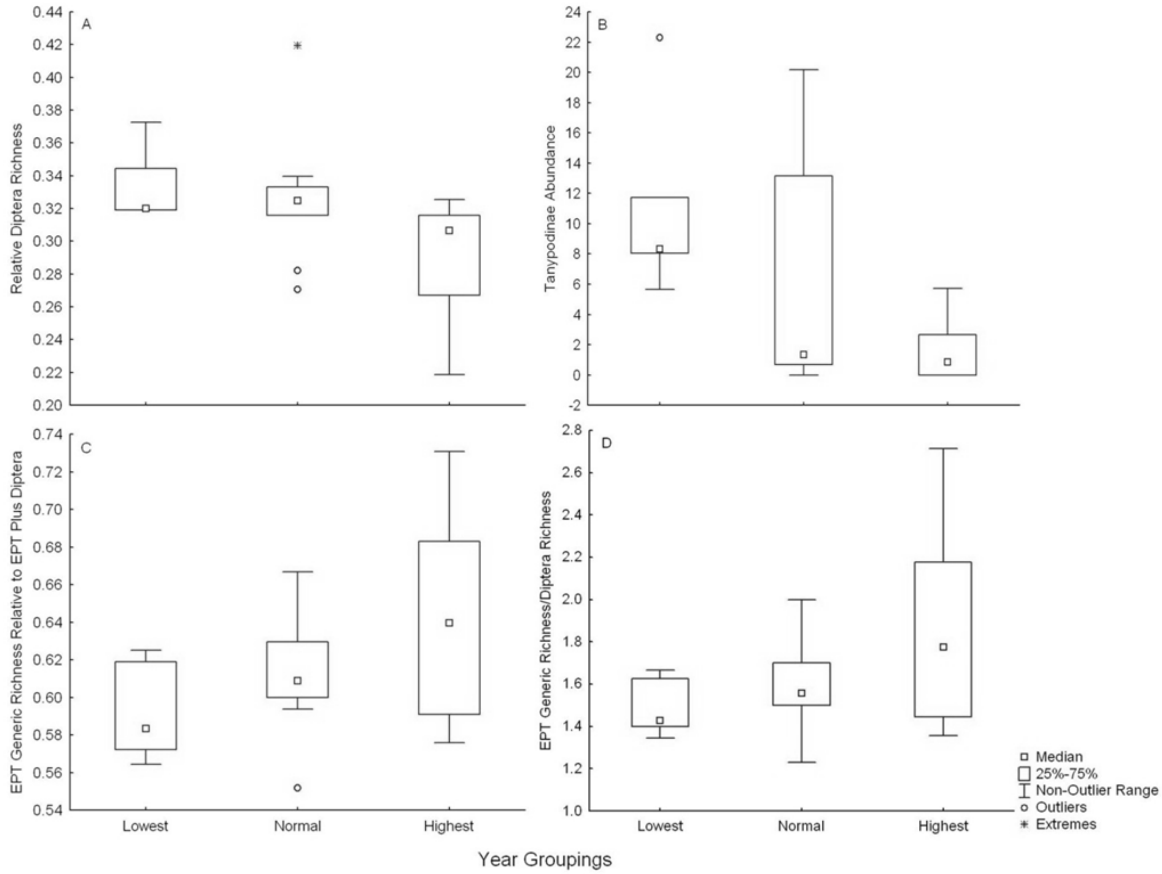

Figure C-26. Distributions of EPT and Dipteran-related metric values in lowest-, normal-, and highest-flow year samples at Maine site 56817 (Sheepscot). Plot (A) shows relative Diptera richness, (B) Tanypodinae abundance, (C) EPT generic richness relative to EPT plus Diptera, and (D) EPT generic richness/Diptera richness. Year groupings are based on IHA median monthly flows averaged across July−September. Data used in these analyses were limited to summer (July−September) rock-basket samples.

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