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GUIDELINES FOR THE EVALUATION OF AIR QUALITY TRENDS

U.S. ENVIRONMENTAL PROTECTION AGENCY

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GUIDELINE FOR THE EVALUATION OF AIR QUALITY TRENDS

U.S. ENVIRONMENTAL PROTECTION AGENCY
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TABLE OF CONTENTS

LIST OF FIGURES AND TABLES

PREFACE

The Monitoring and Data Analysis Division of the Office of Air Quality Planning and Standards has prepared this report entitled "Evaluation of Air Quality Trends" for use by the Regional Offices of the Environmental Protection Agency. The purpose of this report is to provide guidance information on current air quality trend evaluation techniques. Adherence to the guidance presented in the report will, hopefully, ensure mutually compatible ambient air quality trend evaluation by all States and Regions and will also facilitate trend interpretation. Further, any risks involved in policy decisions concerning National Ambient Air Quality Standards should be minimized. This report will serve on an interim basis until more specific and detailed guidance on this subject is presented.

TRENDS ANALYSIS GUIDELINE

1. INTRODUCTION

1.1. Purpose

The purpose of this guideline is to outline procedures that can be employed by the air pollution data analyst to evaluate trends in air quality. Trends will be generally considered as the broad long-term movement in the overall time sequence of historical air quality measurements. It will be examined in two ways. First will be in the form of a trend line or curve over time. Second will be a statistical categorization of the general direction of the movement over time, i.e., upward, downward, or no change. Associated with the second approach can be estimates of the rate of change of deterioration or improvement in the air quality. Most trend analysis can be performed upon aggregate measures of air quality estimates such as averages. For some pollutants, however, the behavior of the short-term air quality, such as maximum 1-hour concentrations, is important. The behavior of short-term air quality estimates do not necessarily lend themselves to the same kind of statistical treatment and as such, are treated using different techniques.

1.2. Usefulness

Evaluation of the long-term trend in a sequence of air quality parameters such as annual means is important in order to assess the relative effectiveness of control strategies and to determine the impact of emission growth or reduction on the air quality over time.

1.3. Limitations

The evaluation of air quality trends is largely a subjective procedure. Various statistical techniques are available to facilitate the evaluation, but insight and auxiliary knowledge are often necessary for the final determination. The methods of trends analysis presented in this guideline are primarily descriptive. They are designed to consider the trend in a single pollutant over time. They will be useful as a data reduction tool which will transform a collection of air quality measurements or summary statistics over time into a simpler form which can then be more easily interpreted. In this manner the complex problem of analyzing the long-term relationships among many different air pollutants monitored at various monitoring locations in a given area or Air Quality Control Region (AQCR) can be examined.

The classification of a long-term trend into a single category such as up or down is subject to certain constraints and assumptions. These include the time frame of interest, assumptions about the seasonal behavior of the pollutant and the type of statistical variability inherent in the measurements. The individual techniques presented depend on such considerations in varying degrees.

The techniques that are discussed are retrospective in nature, that is to say they describe the historical record of air quality measurements. No attempt will be made here to forecast or predict future air quality from past experienced air quality. Such techniques do exist, but for successful application, they should not be based on historical air quality measurements alone. A diffusion model or modified rollback procedure[1] may be used for air quality projections, thereby accounting for emissions, regulations, growth and meteorology.

2. DATA REQUIREMENTS AND SELECTION

2.1. Minimum Requirements

In order to analyze the trend in a pollutant, a time sequence of measurements or summary statistics over several years is required. Because of seasonal fluctuations, a trend should not be determined from one year's worth of measurements. The data can be in any aggregate form of air quality measurements (hourly, weekly, monthly, quarterly, or annual estimates). Ideally, the time series should not have any significant gaps in the continuity of the series although some gaps can be tolerated. Temporal balance is essential. For example, a single quarterly estimate may be omitted from the sequence of many quarterly estimates if there is not a pronounced seasonality. Missing data can introduce bias in the determination of the trend. This can be minimized with the availability of some prior knowledge of the data or some auxiliary information on meteorology and emissions. In any event such omissions should be clearly indicated. If the data satisfy the validity criteria as outlined in the Guideline for the Evaluation of Air Quality Data,[2] there should not be any problem. Appropriate procedures useful for analyzing trends when entire annual estimates are not available will be discussed in Section 4 on statistical techniques.

2.2. Form of the Data

An appropriate analysis can be based on several forms of the data. A preliminary analysis may be performed on the data at hand, usually available in air quality publications. For example, evaluation of the trend can be based on summary statistics such as annual/quarterly averages and percentiles. If a more detailed analysis is desired, the original raw data may have to be utilized. There is generally a trade off between the type of aggregate measure utilized because the larger the interval for the aggregate, the more precision and stability is contained in the estimate, but the fewer the number of time sequenced estimates are available for the trend analysis. It is sometimes advantageous to deal with certain estimates (such as daily or annual) in order to remove predictable factors such as diurnal and seasonal variation respectively.

2.3. Data Selection for Trends Analyses

When considering the analysis of the time series of measurements for a pollutant, certain precautions should be observed. In order to minimize the introduction of bias into the evaluation, the data should be a product of the same analytical (chemical and instrumental) methodology at the same sampling site location for the entire time period under consideration. A common instance of this problem is a minor instrument modification or movement. If one is willing to relax this rule in order to create the only possible complete record of data for the analysis, then one must be willing to accept the possibility of creating an apparent trend when none exists, or indicating no trend when one does exist.

Any change in the overall trend, especially an abrupt shift or alteration coincident with the modification, must be considered suspect. For completeness and maximum accuracy, all modifications to the placement or type of monitoring equipment should be investigated, recorded, and considered in the trend evaluation. The possibility of bias can be overlooked when the air monitoring specialist insures that there should not be any discontinuity in the data. However, it must be kept in mind that often the reason for instrument change was that something was wrong with the previous instrument or methodology.

3. CONTRIBUTING FACTORS TO TRENDS

There are both determinant and random factors which affect the trend of air quality measurements. The determinant factors include emissions, meteorological variables, and other factors having a predictable influence. Random factors are primarily sampling and analysis errors, transient meteorological phenomenon and random fluctuations in emissions. With appropriate auxiliary information on the environs of a monitoring site, the reliability of apparent trends can be appraised. For example, environmental change such as urban renewal in the vicinity of the sampling site can create the impression of an apparent trend caused by area wide deterioration. Moreover, in light of such localized change, the representativeness of that particular sampling site and its corresponding trend for an entire city or AQCR would have to be questioned.

An unusually cold winter may cause an annual average to be unusually high, possibly contributing to an apparent trend in the preliminary trend evaluation. In this case, auxiliary meteorological information on degree days, chill factor, etc., together with the original raw data would be necessary to confirm the suspicion.

4. STATISTICAL METHODOLOGY

4.1. General Discussion

Statistical techniques are desirable for an objective description and classification of the trend. They are necessary to sort out the real change in air quality that is distinguishable from the inherent random variability in air quality measurements. Although the statistical techniques are objective in the sense that they are reproducible and anyone applying them correctly will come up with the same result, they are nevertheless subject to error. These are the standard type I and type II errors of hypothesis testing discussed in texts on statistics. [3,4]

Statistical techniques can be descriptive or inferential. Descriptive statistics provide estimates of unknown parameters such as means, variances and rates of change. These are based on a set of empirical data drawn from the entire population of possible values. Inferences can be made about the population from which the data were sampled by judging the statistical significance. In general, this involves making certain assumptions about the population, such as the distribution being log-normal. Then the value of calculated test statistic, derived from the sample of data, is compared to a specific quantile of the assumed distribution of the test statistic. These are usually available in tabulated form. This quantile defines the significance or α level and specifies a critical value or pair of critical values of the test statistic.

The statistical significance can be utilized in more than one way. The traditional or classical approach is to preselect the α level and its corresponding quantile. Then a test of hypothesis is performed such as testing if no trend has occurred. If the test statistic falls in the predetermined critical region defined by the extremal values of the test statistic, the hypothesis is rejected. By implication, if the value of the statistic does not fall in the critical region, the hypothesis is accepted. For example, in trend analysis, the assumed underlying distribution of the test statistic of the air quality parameters corresponds to that of a random variable without trend, that is, the null hypothesis is there is not any trend. A rejection of the hypothesis is interpreted as the existence of a trend. Then the trend is or is not significant at the particular α level. Any other possible information in the test statistic is then usually ignored.

A second utilization of the statistical significance does not involve a preselected α level, per se. The statistical significance of the test statistic is defined by the significance level associated with the tabulated value equal to or just below the calculated statistic. Then the resultant significance level can be compared to a preselected level to classify the test parameter but in addition, can be used to judge the relative strength of the result compared with other cases.

Conventionally, preselected levels of 0.10, 0.05 or 0.01 are utilized. These would usually correspond to quantiles of 0.95, 0.975 and 0.995 respectively of a two sided statistical test for both upward or downward trends. The smaller the α or significance level, the less likely a trend would be declared erroneously. One might then say the trend is highly significant. Levels like 0.10 would be used as preliminary indicators of trend whereas smaller levels would be used to more vigorously test for significant trends at an individual site. The likelihood of correctly accepting a pattern as a non-trend is determined by the power of the individual statistical techniques.

4.2. Statistical Parameters

Air quality data may have different meanings when reviewed by different aggregate measures, although they frequently vary together. For example, a sequence of the average of maximum daily 8-hour or 1-hour concentrations can depict similar trends in direction but perhaps not similar in magnitude.

Nevertheless, it is useful to examine the trend in various aggregate measures, especially those relating to the air quality standards. In this manner the progress with respect to achieving each standard can be assessed. Such useful parameters are annual means and percent of observations exceeding the short-term standards. Once the parameter is selected, a statistical test is not always necessary because the trend may be obvious, but may be convenient for documentation purposes.

4.3. Time Periods

The time frame of the data under consideration can seriously affect the classification of the overall trend. For instance, if concentrations decreased sharply in the 4-years from 1960 to 1963 but remained level in the 8-years from 1964 to 1971, then the 12-year trend from 1960-1971 would probably be downward, whereas, the trend 8-years from 1964-1971 would result as no change. On the other hand, if concentrations experienced an increase from 1964-1971, its trend would be classified upward, whereas the overall trend from 1960-1971 might still be classified downward. Therefore, it can be seen that the classification of trend is clearly dependent on the time frame under consideration.

The time frame for evaluation should be selected in an objective manner. Usually the availability of data is the determining factor, but the interval can be preselected based on knowledge of the temporal pattern of emissions. It is desirable to perform the trend evaluation over several different time intervals in order to obtain a more complete description of the overall pattern and to avoid the aforementioned problems. In the first Annual Trends Report,[5] long-term trends were considered during the periods 1960-1967, 1964-1971, 1960-1971, and 1968-1971. It was not uncommon for the trend determined by evaluating the data in one time period to differ from the trend in another time period at a single location.

4.4. Specific Methods

There are some very sophisticated methods providing time series analysis of air quality data. These have been presented in some recent publications.[6,7] Although the methods can provide much information, they can be difficult to use and generally require assistance of a computer. Some of the simplier approaches utilized in the Federal trends reports[5] will be presented in this guideline. The techniques are oriented towards examining the concentration or frequency of occurrence of air quality measurements.

4.4.1. Graphical Analysis

When performing a trend analysis, it is extremely desirable to look at the data in graphic form. Usually plotting quarterly or annual statistics over time will be sufficient to depict the basic temporal pattern. At this point the determination of the trend may be intuitively clear. In order to facilitate the interpretation of the overall pattern, it can be helpful to determine an objective trend line for the data. This can be simply obtained by calculating a moving average of the observations. This will provide a smoother and simpler representation of the original data. For quarterly estimates, a moving annual average consisting of four quarterly estimates will eliminate the seasonal fluctuations and remove much of random variation as well. When considering annual estimates over several years, a three-year moving average will smooth out much of the year-to-year variation. In specific instances other averaging schemes may be considered. The selection of the appropriate moving average is subject to personal judgement. When employing the moving average, estimates of the trend line at the beginning and end of the data time series are usually omitted.

Other curve smoothing techniques such as the Whittaker-Henderson smoothing formula have previously been employed in the analysis of air quality trends, but they can be more difficult to apply since they generally require the use of a computer.

Example 1a: Figure 1 depicts a trend line for annual geometric Total Suspended Particulate (TSP) monitored at the NASN site in New Haven, Connecticut from 1960-1971. The curve was obtained by computing a 3-year moving average of the annual estimates and plotting each point at the middle year of each 3-year group. It characterizes the trend as reversing direction during the 12-year period.

Example 1b: Figure 2 depicts an analagous trend line for TSP at the Tucson, Arizona NASN site. In this instance, the trend line depicts a long-term downward trend which has stabilized in the latter years.

The trend lines thus formed provides a nice descriptive tool for the evaluation of the overall trend. Since subjective bias may creep into the interpretation of the trend, objective techniques are desirable to classify the overall pattern and quantify the amount of change. The following constitutes a variety of statistical techniques which have been useful for this purpose. Several techniques may be appropriate to analyze a given set of data. It may be desirable to employ more than one since occasionally they can produce different conclusions due to some of the different assumptions on which they are based. It is not uncommon, however, for several sets of assumptions to seem equally reasonable. It is at this point that subjective judgement of the auxiliary information contributes to assessing the various formal results. For convenience, Table 1 summarizes the typical usage of the particular statistical procedures. In each case, the procedure assumes at least that the observations or the air quality parameters could have occurred with equal likelihood.

4.4.2. Correlation Techniques

These techniques consider the statistical significance of the correlation of pollutant observations or summary statistics with the sequence in which they were observed. Since the time interval between observations is not considered, missing observations can be ignored.

TABLE 1 SUMMARY OF APPLICATION OF STATISTICAL PROCEDURES FOR CLASSIFYING TRENDS

Type of Analysis	Form of Data	Technique
Trend in short-term air quality	Specific quantiles or maximum value per year or of a given quarter/season	Spearman Correlation
	Percent observations greater than specific concentration between two time periods	Chi-Square
Trend in long-term air quality (averages)	Annual averages or average level for specific quarter/season over several years	Spearman Correlation or Parametric Correlation*
Estimation of rate of change in long-term air quality	Same as Above	Regression*

*Additional assumption required that observations are normally (log-normally) distributed.

FIGURE 1 - THREE YEAR RUNNING RAGES OF TOTAL SUSPENDED PARTICULATE

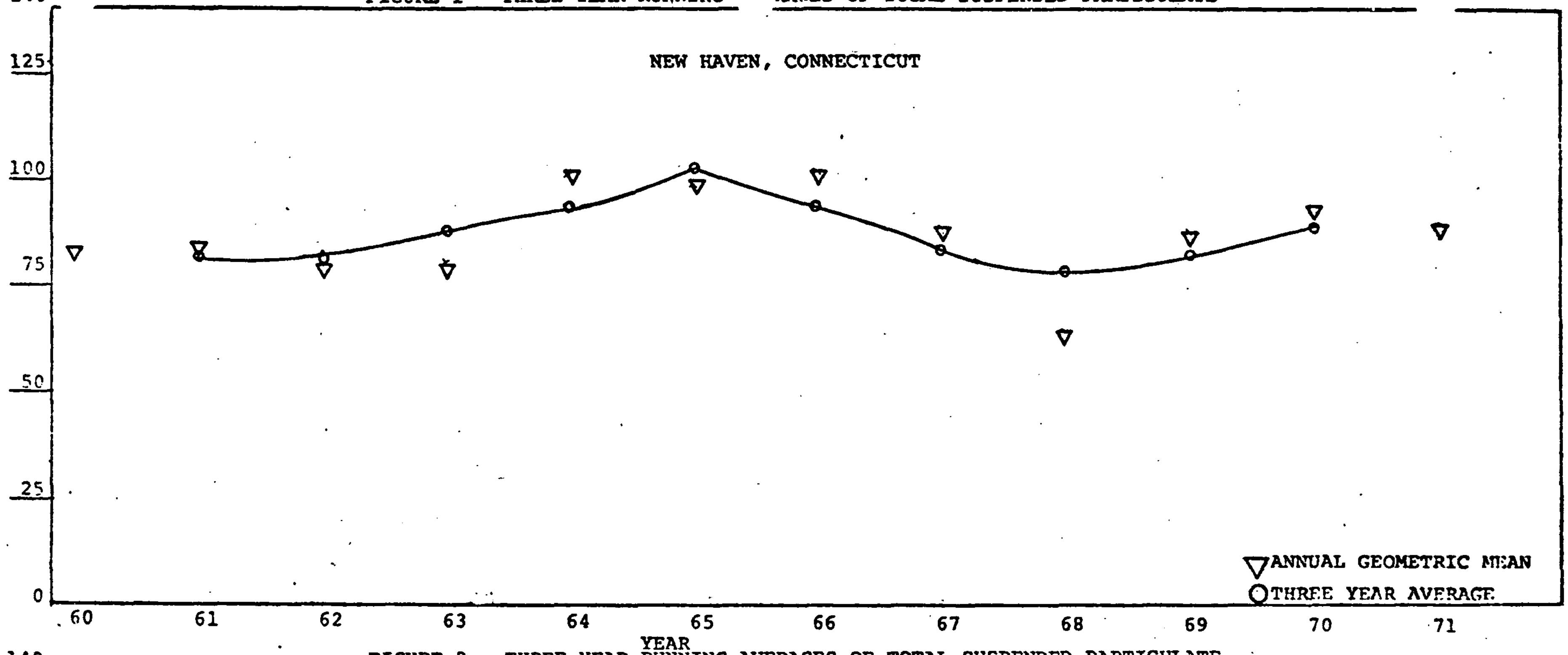
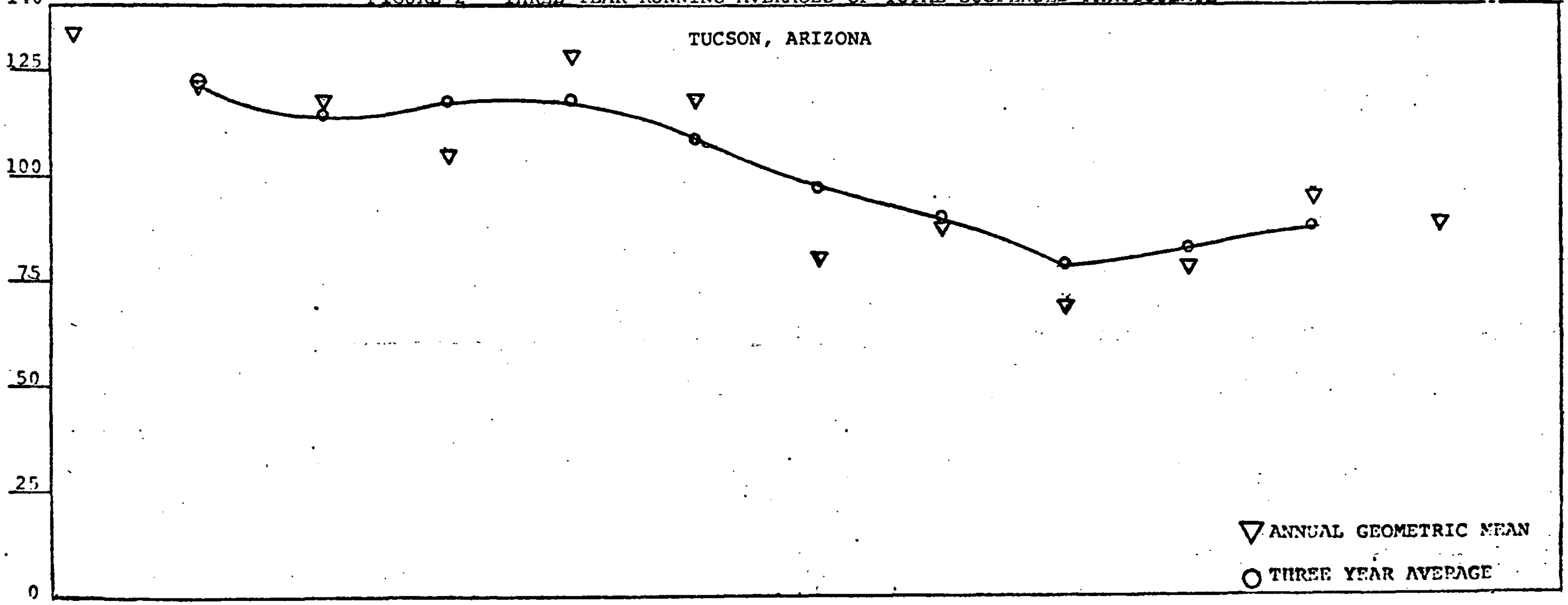


FIGURE 2 - THREE YEAR RUNNING AVERAGES OF TOTAL SUSPENDED PARTICULATE



They can be applied to any set of aggregate measure of pollutant values, subject to the assumption that they are equally likely and independent. Therefore, if seasonality is suspected, annual estimates should be used or individual seasonal estimates should be considered separately.

Two types of these procedures are presented. The first is nonparametric, meaning no further assumptions are necessary. It examines for a consistently changing series. The second is parametric, requiring the additional assumption, frequently encountered, that the data or their logarithms are normally distributed. It is sensitive to a constant absolute or percentage change.

4.4.2.1. Daniel's Test for Trend using the Spearman Rank Correlation

In order to utilize this procedure, at least four observations should be available. Given observations $X_1, \ldots, X_n$ and their corresponding relative ranks $R(X_1), \ldots, R(X_n)$, the test statistic is the Spearman Rank Correlation Coefficient:

$$\rho = 1 - \frac{6T}{n(n^2-1)}$$

where $T = \Sigma[R(X_i)-i]^2$, that is, the summed squares of the differences between each values rank and its sequential order, i, in the series of n observations. The absolute value of ρ is compared with a critical value w_p in Table 2, if $n < 30$, and with $w_p = X_p/\sqrt{n-1}$, if $n \geq 30$, where X_p is the p quantile of a standard normal random variable obtained from Table 3. If $|\rho| > w_p$ then a trend is declared significant at the $\alpha=2p$ significance level. A positive value of ρ indicates an upward trend while a negative value of ρ indicates a downward trend. It can be noted that the estimate of the Spearman rank correlation coefficient ρ is merely the usual product moment correlation of the ranks of the observations with the order in which the observations were taken.

Example 2a: Applications of Daniel's Test for Trend on Tucson TSP Data 1964-1971. The following table provides the annual geometric means, their relative values and the index over time.

X_i	128	118	80	89	70	78	96	88
$R(X_i)$	8	7	3	5	1	2	6	4
i	1	2	3	4	5	6	7	8

If ties had occurred, the ranks can be determined by averaging the ranks among the tied observations, or preferably utilizing the data estimates to the next available place, even if it is not a significant digit.

$$T = \Sigma\ (R(X_i)-i)^2$$

$$= (8-1)^2 + (7-2)^2 + (3-3)^2 + (5-4)^2 + (1-5)^2 + (2-6)^2 + (6-7)^2 + (4-8)^2$$

$$= 49 + 25 + 0 + 1 + 16 + 16 + 1 + 16$$

$$= 124$$

$$\rho = 1- \frac{6T}{n(n^2-1)}$$

$$= 0.476$$

The .90 quantile of the Spearman test statistic is .5000 for n=8. Therefore, apparent downward trend would not be accepted even at the α= 0.20 significance level.

Using the entire twelve year record of data, ρ=-0.769. This is greater than the .995 quantile for n=12. Therefore, the 12-year trend can clearly be classified downward.

The Spearman coefficient on the data from 1968-1971 is ρ=+0.80. This pattern is upward but is only significant at the 0.20 level. The technique is not very powerful at such small sample sizes.

The above technique is primarily useful for classifying the temporal pattern as upward or downward and indicating the consistency of the pattern by the statistical significance level.

4.4.2.2. Parametric Correlation Technique

Let X_i, i=1,n be a sequence of observations or their logarithms. The test statistic is

$$T = \frac{\sqrt{n-2}\ \sqrt{c}\ \hat{\beta}}{\sqrt{\sigma^2 - c\ \hat{\beta}^2}} \quad \text{where} \quad c = \frac{1}{12}(n^2-1)$$

$$\hat{\beta} = \frac{1}{nc} \Sigma \left(i - \frac{n+1}{2}\right) X_i$$

$$\sigma^2 = \frac{1}{n} \Sigma (X_i - \bar{X})^2$$

T is compared to the p quantile of Students t statistics with (n-2) degrees of freedom provided in Table 4. If $|T| > t$ then the trend is declared significant at the $\alpha=2(1-p)$ significance level. A positive value of T indicates an upward trend, while a negative value of T indicates a downward trend.

<u>Example 2b</u>: Application of Parametric Correlation Technique to Tucson, Arizona TSP Data 1964-1971.

$$T = \sqrt{n-2}\ \sqrt{c}\ \ \hat{\beta}/\sqrt{\sigma^2 - c\beta^2}$$

$$c = \frac{1}{12}(n^2-1) = \frac{1}{12}(64-1) = 5.25$$

$$\hat{\beta} = \frac{1}{nc} \Sigma \left(i - \frac{n+1}{2}\right) X_i$$

$$= \frac{1}{8(5.25)} \{ -3.5 \ln(128) - 2.5 \ln(118) - 1.5 \ln(80) - 0.5 \ln(89) + 0.5 \ln(70) + 1.5 \ln(78) + 2.5 \ln(96) + 3.5 \ln(88) \}$$

$$= -1.985/42 = -.047$$

$$\sigma^2 = \frac{1}{8} \Sigma (X_i - X)^2 = \frac{1}{8} \Sigma X_i^2 - \frac{(\Sigma X_i)}{8} = .03715$$

then $T = \sqrt{6}\ \ \sqrt{5.25}\ (-0.047/\sqrt{.037-5.25(.002)}$

$$= -1.65$$

This value lies between the .90 and .95 quantile of the students t statistic. Therefore, the trend can be considered significant at the 0.20 level but not the 0.10 level.

Both the Spearman and the parametric correlation techniques failed to detect a trend during 1964-1970 because of the year-to-year variability in the annual estimates.

Considering the entire 12-year period, the value of the test statistic T=-3.810. This is significant at the .01 level, and the trend can therefore be classified downward. The value of the corresponding test statistic for the 4-year interval 1968-1971 is T=+2.15. This is only significant at the 0.20 level. Note the similarity between these results and those obtained by using the simpler non-parametric analogue.

4.4.3. Regression Techniques

For this technique, the temporal distance between observations is considered. Its primary application is to produce estimates of the constant rate of absolute or percent change (growth or decay) over time.

4.4.3.1. Simple Linear Model

To estimate a constant absolute change, b, corresponding to the model X=a+bT,

$$\hat{b} = \frac{\Sigma(T_i-\bar{T})X_i}{\sqrt{\Sigma(T_i-T)^2}\sqrt{\Sigma(X_i-\bar{X})^2}}$$

where pollutant concentration, X_i exists at time T_i.

The estimate of "a" is $\hat{a} = \bar{X} - \hat{b}\bar{T}$.

The statistical significance of the estimate of b as compared with an assumed value b_o can be tested by computing

$$B = (\hat{b}-b_o)/\sqrt{s^2/\Sigma(T-\bar{T})^2}$$

where $s^2 = \{\Sigma(X-\bar{X})^2 - [\Sigma(T-\bar{T})X]^2/\Sigma(T-\bar{T})^2]\}/(n-2)$

and comparing B with the Student's t statistic, t, at the p quantile, with n-2 degrees of freedom. If $|B| > t$ then the rate of change is significantly different than b_o at the α=2p significance level.

In a similar manner, a confidence interval can be created about the estimate $\hat{b}$. The interval is defined as $\hat{b} \pm t \sqrt{s^2/\Sigma(T-\bar{T})^2}$. This interval contains the "true" rate of change, b, with Probability 1-α.

4.4.3.2. Exponential Model

To estimate the percent rate of change, r corresponding to the model $X=ar^T$, calculate and test significance of log (r) by substituting log (X_i) for X_i in the formulae of the previous section. The rate of change is usually presented as a change of (r-1) x 100% per unit of time.

Example 3: The above regression techniques are applied to the TSP data for New Haven, Connecticut.

The estimates of absolute and percentage rates of change are presented for the time intervals 1960-1971, 1964-1971, and 1968-1971.

Rates of Change

Absolute		Percent
0.26	1960-1971	+0.27
-2.24	1964-1971	-3.46
+7.00	1968-1971	+9.26

This again demonstrates that the choice of time interval can play an important role in the determination of an estimated rate of change.

4.4.4. Test for Trend in Proportion of Observations Above A Standard (Chi Square Analysis)

This technique is useful to test for a change in the extreme value or short-term statistics. It compares the percent of observations above a given threshold concentration, such as a 1-hour standard, between two time periods. It is desirable to consider independent observations. Therefore, for hourly data one should consider at most one observation per day, e.g., the maximum observation per day or the observation of a particular hour. In general, observations derived by intermittent sampling can be considered independent.

	No. Obs $\leq$ Standard	No. Obs > Standard	
TIME PERIOD I	a	b	n_1
TIME PERIOD II	c	d	n_2
			N

The test should only be used if there are at least five observations in each of the four cells.

Let $p_1=b/n_1$ be the proportion of observations in time period I that are above the standard. Similarly, $p_2=d/n_2$ for time period II.

One can test (i) for any change between the two time periods disregarding whether it is an increase or a decrease, e.e., $p_1=p_2$ or (ii) specific direction of change between the two time periods, say $p_1 \leq p_2$.

The test statistic T is defined as:

$$T= \frac{(n_1+n_2)(ad-bc)^2}{n_1 n_2 \ (a+c)(b+d)}$$

Consider a change to have occurred if T exceeds the Chi Square statistic of Table 5 at the 1-α quantile with 1 degree of freedom.

If only one direction of change is of interest, for example, has there been improvement, then consider improvement to have occurred if T exceeds the Chi Square statistic at the (1-2α) quantile. In either case the significance level is approximately α.

Example 4: The following table represents the number of days whose maximum 1-hour oxidant concentration exceeded the 1-hour standard at a particular location during 1964-1967 and 1968-1971.

	≤ standard	>standard	
1964-1967	662	154	n_1 = 816
1968-1971	714	111	n_2 = 825
TOTALS	1376	265	1641

$$T = \frac{(n_1+n_2)\ (ad-bc)^2}{n_1 n_2 (a+c)(b+d)}$$

$$= \frac{(1641)[(662)(111) - (154)(714)]^2}{(816)\ (825)\ (1376)\ (265)}$$

$$= 8.9$$

At the level of significance of .05, the calculated value of T exceeds the tabulated statistic at .90 quantile = 2.706. It can therefore be concluded that short-term oxidant levels have significantly decreased in recent years at the particular site.

5. ASSESSING REGIONAL TRENDS

Trends can be discussed in terms of measurements at a single location over time or collectively at a group of sites over time for the purpose of assessing national or regional trends. The collective analysis has been employed in the Federal Trends Reports[5].

In general, the assessment can be done in two ways. The recommended approach is to determine the trend at each individual site and then summarize the results for the group of sites. The trend at each individual site can be classified as upward, downward, or no change. This may be done over a variety of time periods, but it is important to separately consider the same time interval for each site. The summary would then be in the form of the number of upward trends, downward trends and no change. In order to consider trends at various concentration levels, the analysis may be considered for separate groups of sites with typically high or low concentrations.

An alternate approach is to consider a composite index of the data from all the sites at each point in time, such as a composite average over time. This composite form of the data lends itself to a convenient graphical summary, however, there are some limitations. In general, the composite can be dominated by a few individual sites. Say for example, the group of sites is diverse and constitute a wide range of concentration levels. Then a composite average can be dominated by the behavior of the sites with the highest concentration levels, thereby hiding the behavior at the sites with the lower concentration levels. Also, the rate of change of the composite may not represent the typical rate of change of the individual sites. A zero rate of change may in fact be a product of an equal number of increasing and decreasing patterns. Another source of error may be the non-independence or misrepresentation of the sampling stations. For example, within a particular AQCR the vast majority of the sampling locations can be concentrated within a single urban area, while the remaining sites are distributed throughout the remainder of the region. An equal weighing of the sampling information within the AQCR may actually favor certain well monitored districts and as such, misrepresent the entire AQCR. Moreover, many of the sites in that single urban area may provide equivalent or in a sense redundant information in terms of trends or concentration levels. A logical solution may be to form a weighted average of the sites within the AQCR according to spatial location or by combining information within separate homogeneous groupings such as business, industrial, residential, etc.

It can be seen it is imperative to investigate and consider the pollutant behavior and relative circumstances at individual sites in the evaluation of regional trends.

6. INTERPRETATION OF TRENDS

The classification of the trend of an air pollutant is a description of its historical behavior. This can be done by means of a fitted curve, an estimate of the rate of change or a qualitative description such as upward or downward. This classification is only a starting point. The reality of the so-called trend and the possible explanations depends on many factors, each of which must enter into the final analysis.

First of all, steps should be taken to ensure that the trend is not a product of changes in instrumentation, methodology, site location, etc. If these are the case, experience may dictate the relative effect of any of these factors.

Secondly, if the historical data record is only a partial sampling of the entire time period studied, perhaps derived by intermittent sampling, then the implication of the apparent trend must be considered. That is, is the historical record representative of the true air quality history or was it influenced by unrepresentative transient phenomenon? This evaluation may involve the investigation of the reality and representativeness of the extreme measurements which are causing the apparent change in air quality.

Thirdly, the representativeness of the trend at a particular site of a larger area must be considered. A site located in the central business district of an urban area may not be representative of the entire city nor its AQCR. This qualification applies to the sites of the National Air Surveillance Network.

Fourth, the trend is merely a representation of past air quality. Without accompanying data on meteorology and emission patterns, the trend should not be extrapolated to predict future concentration levels or continued direction of change.

TABLE 2 QUANTILES OF THE SPEARMAN TEST STATISTIC[a]

n	p = .900	.950	.975	.990	.995	.999
4	.8000	.8000				
5	.7000	.8000	.9000	.9000	–	
6	.6000	.7714	.8286	.8857	.9429	
7	.5357	.6786	.7450	.8571	.8929	.9643
8	.5000	.6190	.7143	.8095	.8571	.9286
9	.4667	.5833	.6833	.7667	.8167	.9000
10	.4424	.5515	.6364	.7333	.7818	.8667
11	.4182	.5273	.6091	.7000	.7455	.8364
12	.3986	.4965	.5804	.6713	.7273	.8182
13	.3791	.4780	.5549	.6429	.6978	.7912
14	.3626	.4593	.5341	.6220	.6747	.7670
15	.3500	.4429	.5179	.6000	.6536	.7464
16	.3382	.4265	.5000	.5824	.6324	.7265
17	.3260	.4118	.4853	.5637	.6152	.7083
18	.3148	.3994	.4716	.5480	.5975	.6904
19	.3070	.3895	.4579	.5333	.5825	.6737
20	.2977	.3789	.4451	.5203	.5684	.6586
21	.2909	.3688	.4351	.5078	.5545	.6455
22	.2829	.3597	.4241	.4963	.5426	.6318
23	.2767	.3518	.4150	.4852	.5306	.6186
24	.2704	.3435	.4061	.4748	.5200	.6070
25	.2646	.3362	.3977	.4654	.5100	.5962
26	.2588	.3299	.3894	.4564	.5002	.5856
27	.2540	.3236	.3822	.4481	.4915	.5757
28	.2490	.3175	.3749	.4401	.4828	.5660
29	.2443	.3113	.3685	.4320	.4744	.5567
30	.2400	.3059	.3620	.4251	.4665	.5479

For n greater than 30 the approximate quantiles of ρ may be obtained from

$$w_p \simeq \frac{x_p}{\sqrt{n-1}}$$

where x_p is the p quantile of a standard normal random variable obtained from Table 1.

SOURCE. Adapted from Glasser and Winter (1961), with corrections.

[a] The entries in this table are selected quantiles w_p of the Spearman rank correlation coefficient ρ when used as a test statistic. The lower quantiles may be obtained from the equation

$$w_p = -w_{1-p}$$

The critical region corresponds to values of ρ smaller than (or greater than) but not including the appropriate quantile. Note that the median of ρ is 0.

TABLE 3 NORMAL DISTRIBUTION[a]

w_p	p	w_p	p	w_p	p
−3.7190	.0001	−.4677	.32	.5244	.70
−3.2905	.0005	−.4399	.33	.5534	.71
−3.0902	.001	−.4125	.34	.5828	.72
−2.5758	.005	−.3853	.35	.6128	.73
−2.3263	.01	−.3585	.36	.6433	.74
−2.1701	.015	−.3319	.37	.6745	.75
−2.0537	.02	−.3055	.38	.7063	.76
−1.9600	.025	−.2793	.39	.7388	.77
−1.8808	.03	−.2533	.40	.7722	.78
−1.7507	.04	−.2275	.41	.8064	.79
−1.6449	.05	−.2019	.42	.8416	.80
−1.5548	.06	−.1764	.43	.8779	.81
−1.4758	.07	−.1510	.44	.9154	.82
−1.4395	.075	−.1257	.45	.9542	.83
−1.4051	.08	−.1004	.46	.9945	.84
−1.3408	.09	−.0753	.47	1.0364	.85
−1.2816	.10	−.0502	.48	1.0803	.86
−1.2265	.11	−.0251	.49	1.1264	.87
−1.1750	.12	.0000	.50	1.1750	.88
−1.1264	.13	.0251	.51	1.2265	.89
−1.0803	.14	.0502	.52	1.2816	.90
−1.0364	.15	.0753	.53	1.3408	.91
−.9945	.16	.1004	.54	1.4051	.92
−.9542	.17	.1257	.55	1.4395	.925
−.9154	.18	.1510	.56	1.4758	.93
−.8779	.19	.1764	.57	1.5548	.94
−.8416	.20	.2019	.58	1.6449	.95
−.8064	.21	.2275	.59	1.7507	.96
−.7722	.22	.2533	.60	1.8808	.97
−.7388	.23	.2793	.61	1.9600	.975
−.7063	.24	.3055	.62	2.0537	.98
−.6745	.25	.3319	.63	2.1701	.985
−.6433	.26	.3585	.64	2.3263	.99
−.6128	.27	.3853	.65	2.5758	.995
−.5828	.28	.4125	.66	3.0902	.999
−.5534	.29	.4399	.67	3.2905	.9995
−.5244	.30	.4677	.68	3.7190	.9999
−.4959	.31	.4959	.69		

SOURCE. Abridged from Tables 3 and 4, pp. 111–112, Pearson and Hartley (1962).

[a] The entries in this table are quantiles w_p of the standard normal random variable W, selected so $P(W \le w_p) = p$ and $P(W > w_p) = 1 - p$.

TABLE 4 PERCENTILES OF THE t DISTRIBUTION

df	$t_{.60}$	$t_{.70}$	$t_{.80}$	$t_{.90}$	$t_{.95}$	$t_{.975}$	$t_{.99}$	$t_{.995}$
1	.325	.727	1.376	3.078	6.314	12.706	31.821	63.657
2	.289	.617	1.061	1.886	2.920	4.303	6.965	9.925
3	.277	.584	.978	1.638	2.353	3.182	4.541	5.841
4	.271	.569	.941	1.533	2.132	2.776	3.747	4.604
5	.267	.559	.920	1.476	2.015	2.571	3.365	4.032
6	.265	.553	.906	1.440	1.943	2.447	3.143	3.707
7	.263	.549	.896	1.415	1.895	2.365	2.998	3.499
8	.262	.546	.889	1.397	1.860	2.306	2.896	3.355
9	.261	.543	.883	1.383	1.833	2.262	2.821	3.250
10	.260	.542	.879	1.372	1.812	2.228	2.764	3.169
11	.260	.540	.876	1.363	1.796	2.201	2.718	3.106
12	.259	.539	.873	1.356	1.782	2.179	2.681	3.055
13	.259	.538	.870	1.350	1.771	2.160	2.650	3.012
14	.258	.537	.868	1.345	1.761	2.145	2.624	2.977
15	.258	.536	.866	1.341	1.753	2.131	2.602	2.947
16	.258	.535	.865	1.337	1.746	2.120	2.583	2.921
17	.257	.534	.863	1.333	1.740	2.110	2.567	2.898
18	.257	.534	.862	1.330	1.734	2.101	2.552	2.878
19	.257	.533	.861	1.328	1.729	2.093	2.539	2.861
20	.257	.533	.860	1.325	1.725	2.086	2.528	2.845
21	.257	.532	.859	1.323	1.721	2.080	2.518	2.831
22	.256	.532	.858	1.321	1.717	2.074	2.508	2.819
23	.256	.532	.858	1.319	1.714	2.069	2.500	2.807
24	.256	.531	.857	1.318	1.711	2.064	2.492	2.797
25	.256	.531	.856	1.316	1.708	2.060	2.485	2.787
26	.256	.531	.856	1.315	1.706	2.056	2.479	2.779
27	.256	.531	.855	1.314	1.703	2.052	2.473	2.771
28	.256	.530	.855	1.313	1.701	2.048	2.467	2.763
29	.256	.530	.854	1.311	1.699	2.045	2.462	2.756
30	.256	.530	.854	1.310	1.697	2.042	2.457	2.750
40	.255	.529	.851	1.303	1.684	2.021	2.423	2.704
60	.254	.527	.848	1.296	1.671	2.000	2.390	2.660
120	.254	.526	.845	1.289	1.658	1.980	2.358	2.617
∞	.253	.524	.842	1.282	1.645	1.960	2.326	2.576

TABLE 5 QUANTILES OF A CHI SQUARE RANDOM VARIABLE WITH ONE DEGREE OF FREEDOM

Quantile, p	w_p
.750	1.323
.900	2.706
.950	3.841
.975	5.024
.990	6.635
.995	7.879
.999	10.830

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