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Agricultural Sector Benefits Analysis For Ozone: Methods Evaluation and Demonstration

AGRICULTURAL SECTOR BENEFITS ANALYSIS FOR OZONE: METHODS EVALUATION AND DEMONSTRATION

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EXECUTIVE SUMMARY

The U.S. Environmental Protection Agency (EPA) is currently beginning work on the Regulatory Impact Analysis (RIA) for the reconsideration of the ozone National Ambient Air Quality Standard (NAAQS). The RIA provides background information that includes benefits, costs and other information for alternative standard specifications.

In preparation for the RIA, EPA required an applied model that could use agricultural sector biological dose response information, agricultural cost of production data and air quality information to estimate changes in producer and consumer welfare due to changes in ozone exposures for agriculture. The air quality information and exposure response information which will be used in the RIA are not yet available; therefore, preliminary air quality information is used. Also, exposure yield functions were estimated from information contained in summary National Crop Loss Assessment Network (NCLAN) reports. The exposure yield data in these NCLAN summary reports is aggregated while the data which will be used by NCLAN to develop the dose response information for the RIA is more detailed.

The research described in this report is an attempt to incorporate the dose-response information obtained from NCLAN into an economic model of agricultural production. The result of this work is an assessment model capable of describing the change in societal welfare emanating from the agricultural production of soybeans, wheat, corn, cotton, peanuts, sorghum and barley in response to changes in rural ambient ozone concentrations.

The economic assessment model discussed in this report exploits a very important hypothesized biological relationship between ozone and crop production, namely, ozone neutrality. This term implies that the optimal ratio of factors of production is invariant with respect to ozone concentrations. This means that an agricultural production function shifts in a way that does not influence the optimal mix of productive factors. The assumption of a neutral production function shift is implicit in the design of NCLAN ozone experiments where the experimental focus is on crop yield.

The assessment model has the ability to calculate a measure of the change in societal welfare which is equal to the change in the sum of consumer and producer surplus evaluated at current 1978 ambient and alternative ozone concentrations. Throughout the text of this report, this measure of the change in societal welfare (either positive or negative) due to alternative ozone exposures is termed net consumer and producer surplus.[1] The term net does not imply that the costs of the regulatory action have been considered -- indeed they explicitly have not.

The simple diagram below illustrates the calculation of net consumer and producer surplus as executed by the assessment model. The curve D represents the demand for a particular crop and the curve S_0 the crop's supply curve conditioned on a given ozone concentration. Equilibrium price and quantity are P_0 and Q_0 respectively. Consumer surplus is the area A and producer surplus is the area B + C. If ozone concentrations fall the supply curve shifts to S_1 and the new equilibrium price and quantity become P_1 and Q_1 respectively. The new consumer surplus is equal to the area A + B + E + F

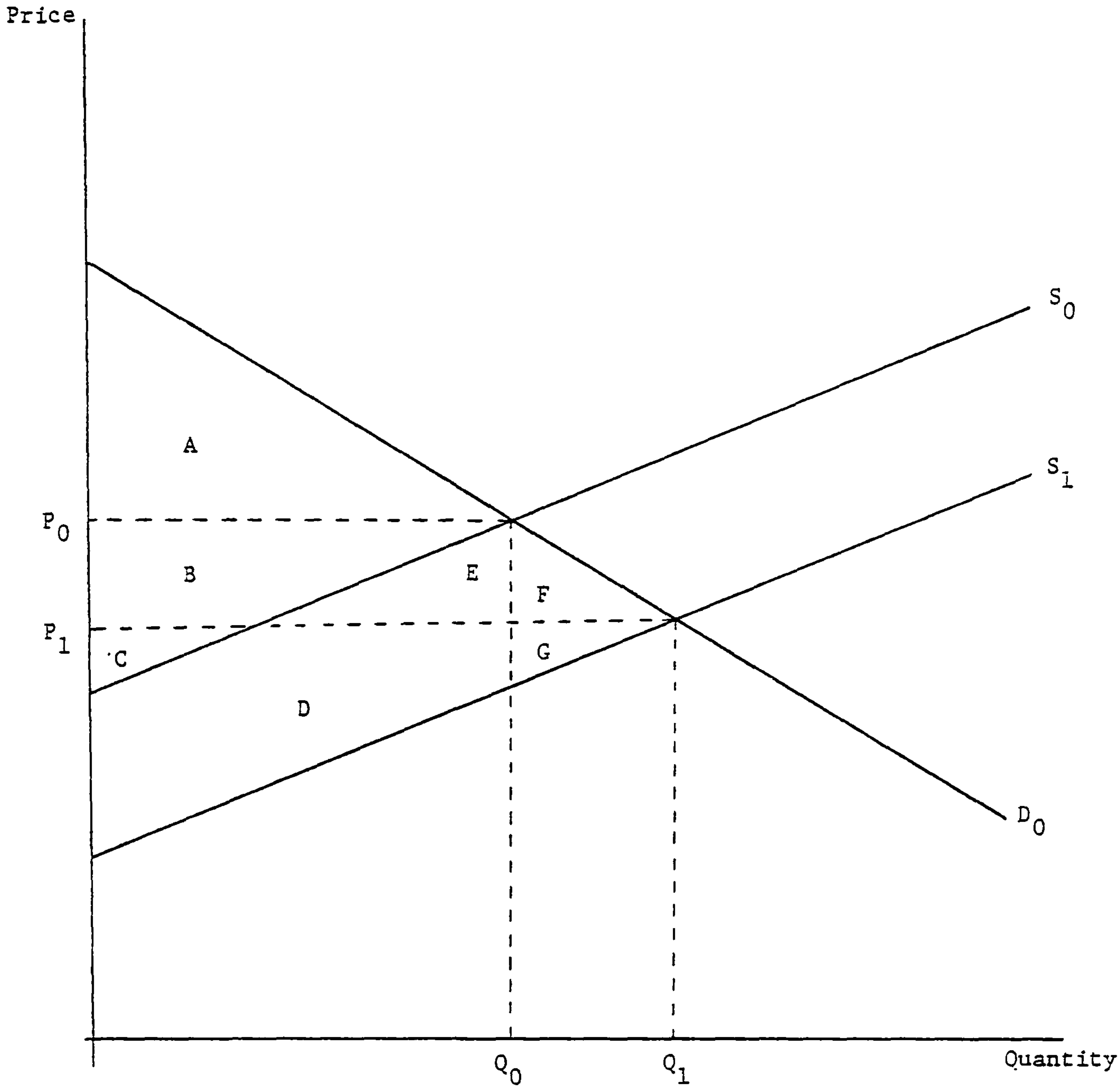


Figure 1. Net Consumer and Producer Surplus Calculation

A = Consumer Surplus for Demand Curve D_0 and Supply Curve S_0

B+C = Producer Surplus for Demand Curve D_0 and Supply Curve S_0

P_0 = Equilibrium Price for S_0 and D_0; P_1 = Equilibrium Price for D_0 and S_1

Q_0 = Equilibrium Quantity for S_0 and D_0; Q_1 = Equilibrium Quantity for D_0 and S_1

A+B+E+F = Consumer Surplus for Supply Curve S_1 and Demand Curve D_0

C+D+G = Producer Surplus for Supply Curve S_1 and Demand Curve D_0

and producer surplus is equal to C + D + G. The change in societal welfare is equal to the net gain in consumer plus producer surplus which is equal to the area D + E + F + G.

To calculate the change in welfare the assessment model must determine the shape and placement of the demand curve D, the shape and placement of the original supply curve S_0 and the manner in which S_0 shifts in response to ozone changes. The demand information is borrowed from the United States Department of Agriculture (USDA) estimates and is discussed in Chapter 8. The shape of the supply curve S_0 is obtained from a model developed solely for this purpose, while information describing the shift in the supply curves comes from aggregate experimental data collected by NCLAN, and from NCLAN dose-response equations published in Heck et al. (1984a, 1984b).

The economic model generating the supply functions for particular crops is named the Regional Model Farm (RMF) which reflects the regional nature of the data base providing the prime informational input to the model. The RMF is designed around the biological hypothesis of ozone neutrality. Ozone neutrality has the desirable property that all factor demand intensities (ratios of factor inputs) are invariant with respect to changing ozone concentrations. Since ozone neutrality does not induce factor substitution, and holding factor prices constant during the analysis, we are able to treat the production function underlying our supply function as Leontief.

The informational component of the RMF is derived from the Firm Enterprise Data System (FEDS). Operated by USDA, FEDS provides agricultural analysts with sample operating budgets which describe the entire cost structure for producing an acre of a particular crop in a specific region of the continental U.S.. The budget is representative of the average agricultural practice in that specific region and is verified with a battery of farm level surveys. A single budget for the production of soybeans in southeastern North Carolina, for example, may include cost information on as many as 200 inputs to agricultural production, the average yield per acre to be expected and the total number of acres planted in the region.

For each of the FEDS producing areas we assume that the FEDS budget for a particular crop type represents both the cost and yield existing for that budget year, for given prices of inputs, outputs, and ambient ozone concentrations. Since the FEDS budgets are on a per acre basis we assume constant returns to scale in order to aggregate across all of the planted acres covered by a single budget. Further, we assume that during the analysis input prices do not change.

With these assumptions in place the construction of aggregate supply functions for particular crops is straightforward. First, given constant returns to scale, marginal cost is equal to average cost. For a particular crop/region budget we divide the total cost of producing an acre of the crop by the yield per acre and thus generate an estimate of the marginal cost per crop unit. Repeating this calculation for all regions growing the same crop produces an array of marginal costs of production across the entire continental U.S.. When the marginal cost of production in each region is mapped against the output of that region we have a region specific supply curve for each crop. Ranking these regional supply curves by marginal cost from lowest to highest and then aggregating across regions yields the aggregate supply function for the specific crop. This aggregation produces a stepped supply curve such as that depicted in Figure 2.

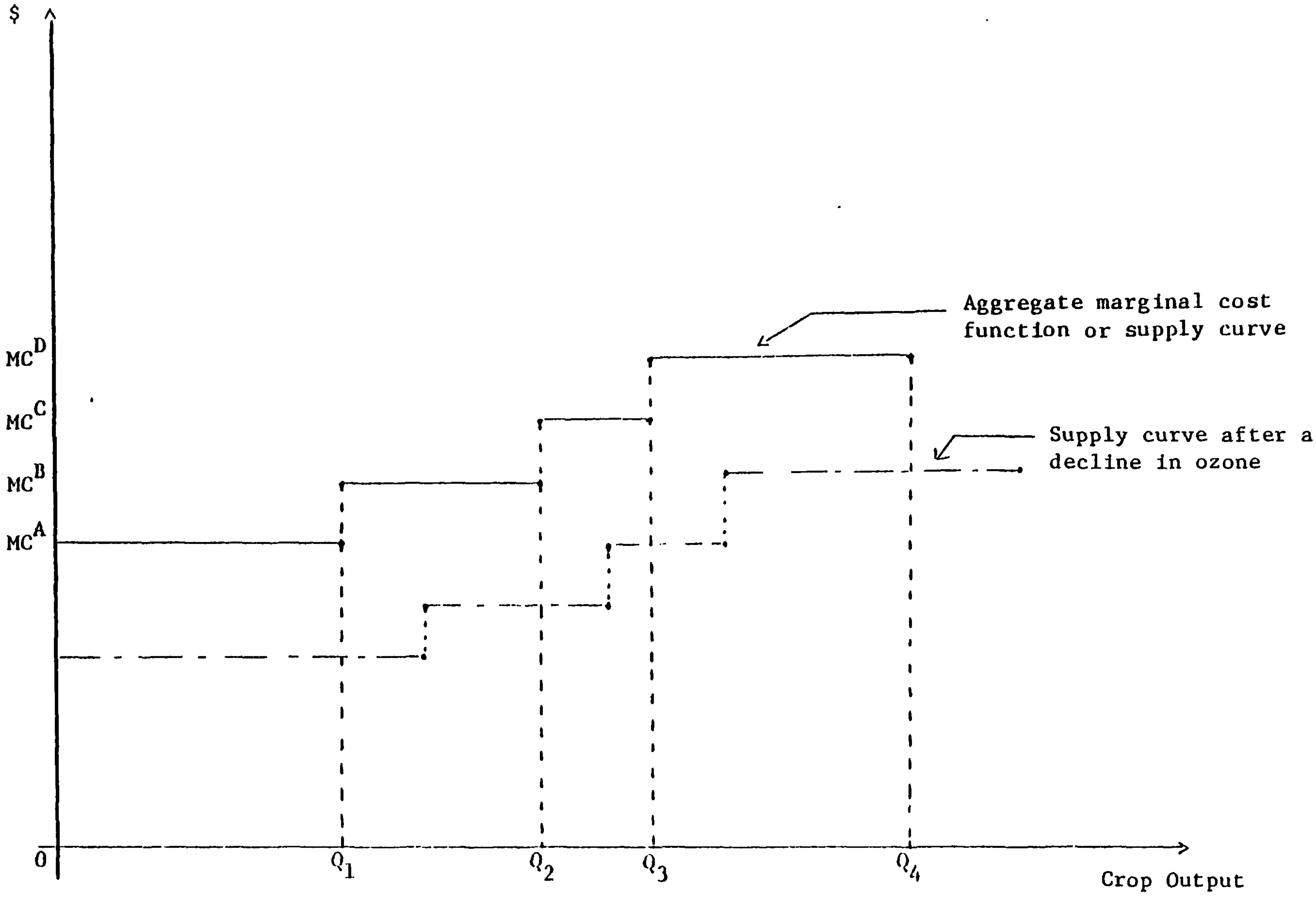


Figure 2. Aggregate supply curve for regions A, B, C, D for crop Q.

The stepped supply curve generated by the RMF is analogous to S_0 on Figure 1. To obtain S_1 we employ the NCLAN experimental evidence. Essentially NCLAN is a network of research sites that among other research tasks performs controlled experiments designed to identify the dose-response relationship between ambient ozone concentrations and the yield of particular crops. Using the data generated by these experiments we have estimated dose-response functions that explain a measure of crop yield as a function of ozone. The functional specification we utilize permits the estimated dose-response relationship to be linear or take on a wide variety of nonlinear forms. Using these dose-response functions it is possible to explain the shift in the crop supply functions when ozone concentrations change and thus determine the new supply function analogous to S_1 in Figure 1. To examine the sensitivity of our welfare calculations to the functional specification of our estimated dose-response functions we have performed a parallel analysis using functions recently made available by NCLAN in Heck et al. (1984a and 1984b).

The accuracy of any welfare estimates generated by the assessment model is linked to: (1) the accuracy of the RMF in defining the baseline crop specific supply curves; (2) assumed characteristics of the demand side of the market, specifically elasticity of demand;[2] (3) the biological dose-response functions defining the shift in the supply curves, and (4) the reliability of county level ozone concentration estimates. By the time the RIA for ozone is undertaken, NCLAN will have extensively studied the dose-response functions and EPA will have prepared final estimates of the county level ozone concentrations. In this report we analyze, through the use of sensitivity analysis, assumptions which underlie the cost structure of agricultural production as perceived by the RMF, the implicit assumptions regarding the demand elasticities utilized in the welfare calculations, and alternative specifications of the dose-response equations.

On the basis of model results presented in Chapters 7 and 8 and the sensitivity analysis presented in Chapter 9, the RMF approach to the calculation of agricultural benefits for ozone seems far superior to the vast majority of competing approaches discussed in Chapter 3. As the sensitivity analysis suggests, the RMF welfare calculations are robust with respect to demand elasticity assumptions and will benefit from the continuous refinement of the NCLAN dose-response information and EPA ambient air quality data.

The majority of the results presented in this report were completed and transmitted to OAQPS in a final report dated September 30, 1983. Those results were based on a set of five dose-response equations estimated by RFF staff using published, aggregate NCLAN experimental data for five crops: soybeans, corn, wheat, cotton and peanuts. In May of 1984 NCLAN released dose-response functions estimated from the original, unpublished, disaggregate experimental data using a flexible functional specification (WYBUL) for several crops. As part of the Regulatory Impact Analysis for the ozone NAAQS RFF staff examined the sensitivity of the results presented in the original September 1983 report to the use of the RFF estimated dose-response functions by recalculating several welfare estimates employing the new NCLAN functions. The use of the NCLAN functions provided for broader crop coverage and permitted the inclusion of sorghum and barley in addition to the original five crops.

FOOTNOTES

1. Consumer surplus is the difference between what a consumer would be willing to pay for each unit of a good rather than do without it and what the consumer actually pays for each unit of the good. Producer surplus is the difference between what each producer is paid for each unit of the good and what he would accept rather than foregoing sale of the good.

2. Demand elasticity is a measure of how responsive quantity demanded is to a change in the price of a good. It is defined as the percentage in quantity demanded divided by the percentage change in price.

CHAPTER 1

INTRODUCTION

In preparation for an eventual ozone Regulatory Impact Assessment (RIA), EPA required an applied model that could use agricultural sector, biological dose-yield information and air quality information to estimate changes in producer and consumer well-being. In other words, the changes in economic surplus due to changes in ozone exposure for agriculture. This report presents a preliminary version of such a model. The air quality information and exposure response information which will be used in the RIA are not yet available.

The research described in this report is an attempt to incorporate the natural science information obtained from NCLAN research into an economic model of agricultural production. The result of our work is an economic assessment model of agricultural cost and production designed to examine the impact of ground level ozone concentrations on the production of seven field crops: soybeans, wheat, corn, cotton, peanuts, sorghum and barley. The model draws its economic information from the Firm Enterprise Data System (FEDS), developed by the United States Department of Agriculture (USDA), and thus contains the information necessary to assess ozone impacts at a fine level of regional disaggregation.

The economic assessment model discussed in this report exploits a very important hypothesized property of the biological relationship between ozone and crop production, namely, "neutral factor productivity enhancement" (NFPE). This term implies that the optimal mix of factors of production is invariant with respect to ozone concentrations. This can be understood by visualizing an agricultural production function which shifts neutrally with changes in ozone concentrations. The assumption of a neutral production function shift is implicit in the design of NCLAN ozone experiments since the major focus of the experiments is on yield. If one were to believe that ozone differentially impacts productive factors implying a nonneutral production function shift then one would design experiments which systematically varied input quantities in addition to ozone and would lead to dose-input functions as well as dose-yield functions.

For the purposes of our present study we maintain a partial NFPE hypothesis. That is, we assume that all preharvest factors of production have their productivities affected equally by changes in ozone concentration. However, we find little evidence to support a similar view regarding factors of production involved in harvesting activities. Therefore, in our model we admit the possibility that the productivity of harvest production factors may not be affected by changes in ozone concentrations. For example, an increase in yield associated with a decrease in ozone will result in productivity enhancement for preharvest factors of production but may not enhance harvest factors. Therefore marginal harvest cost might be unchanged and total harvest cost increased.

It is not reasonable to assume that all environmental pollutants will shift agricultural production functions neutrally. For example, some preliminary greenhouse evidence suggests that acid precipitation has the effect of reducing fungicide retention on plant surfaces, thus requiring more frequent applications. Reductions in the acidity of precipitation would thus result in "biased factor productivity enhancement" (BFPE) and would imply a nonneutrally shifting production function.

The above example highlights the importance of recognizing that the biological relationship between environmental factors and crop production has a great deal to do with economic model construction, if that model is designed to incorporate natural science information in an economically meaningful fashion. A biological relationship which results in BFPE requires an exceedingly more complex economic model than a relationship characterized by NFPE. For a more detailed discussion of these concepts see Kopp and Vaughan (1983).

One serious limitation of any economic model which requires biological dose-response functions is the nature of the available functions themselves. Since they are particular to the conditions at the individual site where the experiments were conducted, and the *ceteris paribus* controls of the experiments, their results are not easily generalizable to any particular crop grown over broad geographic regions of the country. This is indeed a serious problem because complete dose-response *surfaces* for plant species and cultivars which reflect variations in soil type, weather, and farming practices are not available. Even ignoring variations in operating practice, plant response to ozone is potentially a function of soil and climatic conditions (light quality and intensity, temperature, relative humidity, wind, and the concentrations of pollutants other than ozone at the field level) and other complicating factors such as pests and plant disease (Leung *et al.*, 1978). Although field experiments continue, an expert panel concluded in 1977 that:

> A complete understanding of the many factors that affect the response of vegetation to oxidant pollutants is probably impossible. An understanding of the individual factors is possible, however, and much is already known; but the interactions between some of these many factors are unclear (NAS, 1977, p. 513).

As we shall discover below, the lack of completely and exhaustively specified dose-response functions by species and cultivar adds uncertainty to the economic evaluation of the gains or losses to agriculture of alternative ozone standards because the economic models have to be driven by imperfect versions of such functions. A possible alternative outside the scope of this study is to rely instead on microtheoretic models of farm production, estimated from real world data. Here, ozone concentrations would be included with other pollutants and weather conditions as explanatory variables, along with the usual economic variables. This approach is briefly discussed in Chapter 3 but we caution this approach would require very detailed ozone information.

However, no matter which approach to quantitative economic modeling is undertaken, they all include estimation of the firms' (and the aggregate) supply function by crop in order to generate welfare impacts. Before the modeling methods for doing so are discussed, we present in Chapter 2, in a purely descriptive way, an overview of the agricultural production system. Next, we briefly outline some of the approaches available to quantitatively model this system, and tie each of them to the particular benefit measures of ozone control each is able to produce. Having established the frame of reference we describe in greater detail several of the modeling alternatives which, in our opinion, are reasonable and might be pursued in this project.

Chapter 3 discusses the various empirical methods for assessing the impacts of photochemical oxidants on agricultural production activities, while Chapter 4 provides a brief review of the economic concepts of consumer and producer surplus as used in the analysis of public policy. Chapter 5 presents a detailed discussion of the economic assessment model constructed for the analysis of ozone impacts. Chapter 6 provides a lengthy but necessary discussion of the biological dose-response functions imbedded in the economic assessment model. Using a set of EPA specified ozone concentration scenarios, changes in yield for the five crops considered in this study are reported in Chapter 7. The results of sensitivity studies on crucial model parameters are reported in Chapter 8. Again using the EPA ozone scenarios, the impacts of alternative concentrations on agricultural cost and production by crop are discussed in Chapter 9. Chapter 10 contains suggestions for future research.

CHAPTER 2

AN OVERVIEW OF AGRICULTURAL PRODUCTION

Agricultural production processes can be distinguished from conventional theoretical constructs of single product manufacturing processes on two general grounds. First, agricultural processes typically result in multiple outputs being produced by a single firm (Mittelhammer _et al._, 1981) and, second, agricultural production is affected by inputs from the natural system (weather) outside of the control of the producer (Weaver, 1980). Ozone, which may adversely affect plant yield, is only one element in the set of potentially important variables affecting agricultural production processes.

There are four broad types of agricultural production activities:

(1) crop production

(2) animal raising

(3) dairy farming

(4) combined operations (for 1, 2 and 3 above)

A generalized schematic is given in Figure 2-1 which shows that purchased and natural (precipitation, sunlight, etc.) factor inputs are transformed by production processes into desired product outputs, along with nonmarketed outputs discharged to the environment as residuals. A specific representation of crop production activities appears in Figure 2-2 which illustrates the types of choices regarding technology and output mix the profit maximizing farmer must make.

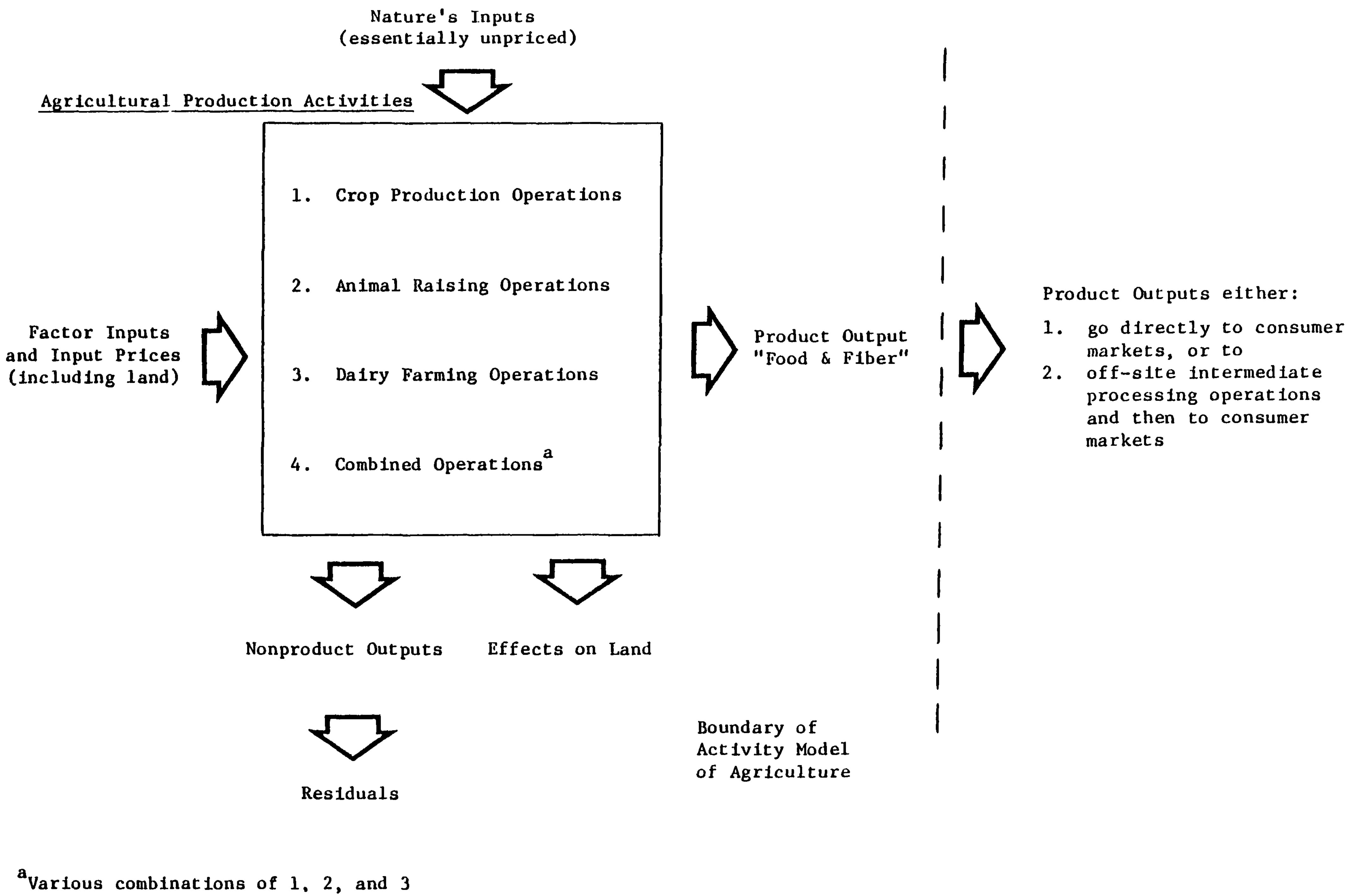


Figure 2-1. Representation of a "generalized" model of agricultural activities.

Nature's Inputs

Sunlight, length of growing season, precipitation, ground water, and other climatic factors (e.g., wind)

Factor Inputs and Prices

Seeds, bulbs, plants

Machinery and equipment, i.e., automobiles, trucks, tractors, cornpickers, balers, combines

Fertilizers, i.e., commercial fertilizers, lime

Pesticides, i.e., defoliants, insecticides, herbicides

Energy, i.e., kwh, gasoline, diesel fuel

Labor, i.e., farm labor, contract labor, machine labor

Water

Building materials

Land - soil and topographic characteristics

Crop Production Operations

Unit Operations/Other Production Variables:

1. Crop Mix, i.e., field corn, barley vegetables
2. Crop Rotation Pattern and Schedule, i.e., continuous corn, corn-corn-alpha-corn
3. Tillage Method, i.e., minimum tillage, no tillage, shallow plow, harrow, disk
4. Plowing Practices, i.e., contouring, grading rows, ridge planting
5. Fertilization Practices - mix of fertilizers; application rates, methods, and schedules
6. Pesticide Practices - mix of pesticides; application rates, methods, and schedules
7. Irrigation Methods/Systems - if any, i.e., sprinklers, line canals
8. Harvesting Technology
9. On-site Crop Processing, i.e., washing and packing
10. Other

Product Output

- Crops harvested
  - Field corn for all purposes, i.e., for grain, for silage
  - Soybeans for all purposes, i.e., for seed grain, silage
  - Wheat for grain
  - Other small grains
  - Soybeans
  - Hay
  - Peanuts
  - Tobacco
  - Potatoes
  - Vegetables
  - Orchard crops
  - Greenhouse products
  - Other crops

Product Outputs either

1. go directly to consumer markets, or to
2. off-site intermediate processing operations. i.e., canning, vegetable oil processing & refining, etc. (these operations are considered separate activities and analyzed accordingly)

Figure 2-2. Representation of agricultural crop producing activities.

Crop producing operations involve the planting, growing and harvesting of crops. There are three general types of cropping operations: nonirrigated -- where all water inputs are from natural precipitation; irrigated -- where the majority of water inputs are transported to and applied on cropland by man; and orchard growing operations (tree fruits and grapes) which can be either irrigated or nonirrigated. The production function for each type of cropping activity is also different. Each activity uses different combinations of factor inputs (types and amounts) and unit operations to produce different product outputs.

The basic forces which determine crop production possibilities on any farm are soil and climate characteristics since they specify the range of crops for which production is technically feasible. Given these feasibility constraints the farmer selects the input menus, crop mixes and rotation patterns that, based on factor prices and output market values, maximize his profits (Heady and Jensen, 1954). Multiproduct outputs from a single farm may be observed in any given year either because the farmer has elected to reduce his risk by diversification or because he has chosen to grow a combination of crops in a rotation sequence rather than a single crop continuously over time, or because his farm includes different soil types -- or even different microclimates.

Modeling such a complex system is a major undertaking which cannot generally be performed either within a short time frame or at modest expense, as we shall discover from the discussion to follow.

CHAPTER 3

EMPIRICAL METHODS OF ASSESSING THE IMPACTS OF CHANGES ON AGRICULTURAL PRODUCTION DUE TO PHOTOCHEMICAL OXIDANTS

3.1. ALTERNATIVE APPROACHES

Ozone concentrations potentially affect the firm's production function -- the technically feasible quantity of output producible from any specified input set -- and, by implication, its cost function. Hence the problem of estimating the dollar impacts of a policy which lowers (raises) ambient ozone concentrations ultimately becomes a problem of agricultural supply analysis, given that one has some knowledge of the demand side, or can make plausible assumptions about demand response (elasticity).

In agricultural economics there exists a long, and intellectually rich tradition of efforts to quantitatively represent various aspects of the agricultural production system described briefly in the preceding pages. (For a review, see Judge, et al., 1977).

In fact, several of the alternative approaches to empirical agricultural supply analysis were well understood more than twenty years ago (Nerlove and Bachman, 1960). However, in the decade of the sixties significant advances were made in operationalizing optimization models of farm behavior (Hall, Heady and Plessner, 1968). In the seventies duality theorems have been successfully utilized in facilitating the applied econometric analysis of farm profits within the context of the neoclassical model of the competitive firm (Yotopoulos and Lau, 1979). Duality theory has expanded the frontiers of applied econometric analysis of firm behavior beyond the production function approach to show that cost or profit functions are equally adequate representations of the firm's technology. Further, hypotheses concerning homogeneity and separability of the multiproduct firm's cost function (see below for definitions) can be statistically tested under the cost function approach using flexible functional forms (Brown, Caves and Christensen, 1979), as is also the case for the profit function (Lau, 1972).

Yet curiously a quite recent catalogue of methods available to place economic values on crop yield changes attributable to atmospheric pollution, Leung _et al_. (1978), ignored these advances entirely. Their use has only recently been suggested by Crocker _et al_. (1981) and no empirical applications of the cost or profit function approaches have yet been undertaken to analyze the welfare impacts of ozone on agricultural production. The small set of econometric production function studies which have been done to analyze the ozone problem all simplistically impose nonjointness on the production function, omit or improperly measure inputs, and ignore the simultaneous equation bias problem -- caveats mentioned in the literature over twenty years ago (Plaxico, 1955; Griliches, 1957; Hildebrand, 1960; Walters, 1963; Hoch, 1958; Hoch, 1976).

Our own review of the literature on this subject suggests at least six feasible routes of applied analysis. All of the methods outlined below differ in terms of data requirements, complexity, and the extent to which they are firmly grounded in economic theory:

I. Rule-of-Thumb Models

1. Biologists "Valuation"

II. Economic Optimization Models

1. Linear Programming Models of Crop/ Livestock Production
2. Quadratic Programming Models of Crop/ Livestock Production and Output Demand

III. Econometric Models

1. Models Utilizing Experimentally Derived Dose-Response Functions

    a. Aggregate Econometric Agricultural Supply and Demand Models
    b. Microtheoretic Econometric Agricultural Supply and Demand Models

2. Models Utilizing Statistically Derived Associations Between Pollutant Concentrations and Production Activity Variables

    a. Microtheoretic Econometric Agricultural Supply and Demand Models with Pollutant Arguments

In brief, the <u>Biologists Valuation</u> model simply makes output a function of ozone concentrations via a dose-response function, and values changes in output due to changes in ozone concentrations at the reigning output price crop-by-crop.

The <u>linear programming</u> (LP) model of crop production selects the cost minimizing set of production activities subject to a specified bill of goods to be produced and constraints on the availability of certain critical inputs like land. Biological dose-response functions are used to alter the quantity of output producible from the set of inputs required for each production activity to mimic the effect of varying ozone concentrations. <u>Quadratic programming</u> (QP) models of agriculture use a production activity matrix just like that of the linear programming problem. The principal difference is that (linear) demand functions for product outputs are an integral part of the model, so output quantities and prices are endogenous. The criterion function is a quadratic function which represents either (a) the maximization of producers' plus consumers' surplus or (b) the maximization of producer profits. (Although the linear programming problem can be set up as one of profit maximization, the criterion function is linear because output prices are exogenously fixed, not endogenously solved for as in the Q-P model.)

The Aggregate Econometric supply and demand model involves the econometric estimation of price response functions for producers and demand functions for buyers from aggregate historical data. The link between economic theory and the specification of the models is generally somewhat loose. On the supply side, assumptions about optimizing behavior (cost minimization or profit maximization) need not be made in order to estimate the equations of the system. Experimentally derived dose-response functions supply exogenous information in order to shift the intercepts of the crop supply curves to reflect alternative ozone standards. In contrast the Microtheoretic Econometric models specify an objective function for the firm and derive the models to be estimated from this specification under perfectly competitive conditions. The parameters of the estimated microtheoretic models are made functions of pollutant concentrations and thus changes in the concentrations alter the model parameters and serve to shift relevant supply functions. Experimentally derived dose-response functions may be employed as estimates of the true but unknown functions embedded in the model.

The last modeling approach builds directly upon the microtheoretic econometric model discussed above but estimates the parameters of the pollutant induced supply shift jointly with the supply parameters themselves. Such models are securely grounded in economic theory and can be structured such that ozone concentrations are embodied as arguments in the functional specification. Hence, there is no need for independent information on biological dose response, given such influences are already contained in the real world data from which the function is estimated.

General properties of each of these six approaches are catalogued in Table 3-1. The first category, normative versus positive, is meant to distinguish normative models which indicate what "ought to be" from positive models describing "what is." Although this distinction is a simplification (Friedman, 1935) for our purpose we can say that normative models produce solutions which describe the way the world should behave given our assumptions. Particularly, the optimizing models (LP, QP) often produce prescriptive solutions for competitive equilibrium prices, input quantities demanded, output quantities produced, and the spatial allocation of production. Sometimes such solutions are at odds with observed reality. One can never be sure if discrepencies between the model solutions and reality are a result of the incorrect or inaccurate modeling of production activities, improper constraints, or just the fact that the real world operates suboptimally due to market interference or distortions (Oury, 1971).

In contrast, the econometric models reflect by the very nature of the data employed to develop them, historical reality over space and time. Thus they cannot perfectly capture the effects of new technologies developed outside of the time (or space) span of the data, nor can they tell us much about the effect on the production technology of changes in institutional rearrangements which are not translated into changes in market prices. They take the institutional setting as a given (Yotopoulos and Lau, 1979).

Table 3-1. ALTERNATIVE BENEFIT ESTIMATION MODELS FOR AGRICULTURE

	Normative or positive model	Economic theory of the firm	Averting behavior to ozone	Biological dose-response functions	Output demand conditions	Benefit measure
I. Rule-of-thumb models						
a. Biologists' valuation	?	None	None allowed	Required as initial condition	Exogenously fixed prices	Producers' surplus
II. Optimization models						
a. Linear programming	Normative	Cost minimization or profit maximization subject to constraints	Generally not allowed	Required as initial condition	Exogenously fixed quantities (cost min) or exogenously fixed prices (profit max)	Net producers' and consumers' surplus
b. Quadratic programming	Normative	Net social benefit maximization (producers' plus consumers' surplus) subject to constraints	Generally not allowed	Required as initial condition	Endogenous equilibrium price/quantity determination - demand functions incorporated in the model	Net producers' and consumers' surplus
III. Econometric models						
a. Aggregate supply/demand	Positive	Some recognition or symmetry restrictions on cross-price terms	Generally not allowed	Required as initial condition	Endogenous equilibrium price/quantity determination	Net producers' and consumers' surplus
b. Microtheoretic supply/demand	Positive	Fully consistent with optimization via duality theorems	Generally not allowed	Required as initial condition	Endogenous equilibrium price/quantity determination	Net producers' and consumers' surplus
c. Neoclassical econometric production, cost, or profit function	Positive	Fully consistent with optimization via duality theorems	Reflected in the data	Not required—reflected in producer choices	Endogenous equilibrium price/quantity determination	Net producers' and consumers' surplus

The second property in Table 3-1, economic theory of the firm, depicts the extent to which the approaches are consistent with and grounded in that theory. The Biologists Valuation method is devoid of theoretical content. Both Programming methods are theoretically grounded but assume on the production side that there are constant returns to scale, infinitely elastic supplies of variable input; divisibility of production processes; additivity of two or more processes; and a finite set of process alternatives. Further, the QP model assumes linear demand functions for product outputs (Naylor and Vernon, 1969).

The Aggregate Econometric method requires little in the way of theory, except for some general specification of the variables affecting supply and demand price and a conceptualization of the aggregate system as either simultaneous or recursive in the estimation step. All Microtheoretic approaches are, as previously mentioned, fully consistent with the theory of the firm (Varian, 1978, Chapters 1 and 4).

The third and fourth properties in Table 3-1, averting behavior and biological dose response, are intimately connected. Any economic model which requires as input an experimentally generated biological dose-response function based on a few varieties of a single species as input necessarily precludes the possibility of producer substitution among varietal seed or plant inputs in response to changes in ozone concentrations. Suppose, for example, that the dose-response function for a single crop is based on a single variety, labelled V_1 in Figure 3-1. Also, assume there are other varieties which are more resistant to ozone (V_2, V_3) for which experimental dose-response functions are unavailable but are familiar to the farmer. If all varieties require exactly the same amounts of cooperant inputs per unit

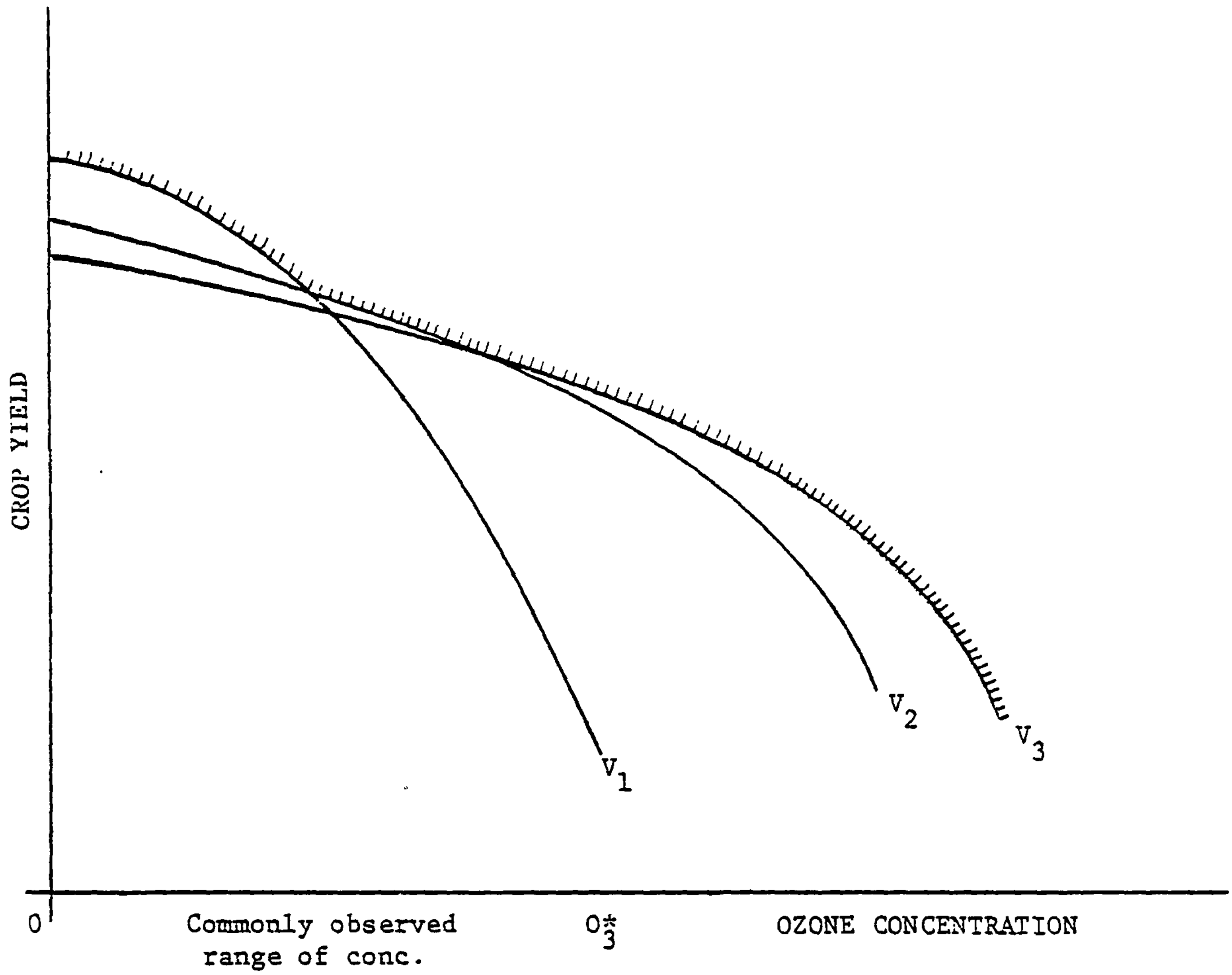


Figure 3-1. Dose-Response Functions for Varietals of a Given Crop

V_1 = Variety 1

V_2 = Variety 2

V_3 = Variety 3

output we would observe almost no "damage" due to ozone over the policy range $0\text{-}O_3^*$ in the real world, since costs would be relatively unaffected by ozone concentrations except for extreme changes. (The heavily shaded envelope yield function in the figure). However, if V_1 drives our economic model, the benefits of ozone reductions will be falsely, and perhaps vastly, overstated. This is a potential pitfall of all economic models requiring experimentally generated single-variety biological dose-response functions. Only the last, fully statistical, microtheoretic approach is free of this problem. But, it does require accurate farm level ozone measures which, unfortunately, do not exist.

The final two properties included in Table 3-1, output demand conditions and benefit measures are also linked. To fully understand the implications of each modeling route in these areas, a lengthier treatment is required. We devote Chapter 4 to such considerations.

The remainder of this chapter contains an in-depth discussion of what we have termed the microtheoretic approach. On several grounds the microtheoretic approach is to be preferred to all others. It has the ability to incorporate biological information (see Kopp and Vaughan (1983)) or to estimate the parameters of biological functions directly from observed producer behavior. Moreover, since the economic assessment model we will present in Chapter 5 is a member of the general microtheoretic family structure we feel the lengthy discussion is valuable.

The microtheoretic approach provides the analyst with a set of extremely powerful research tools since the approach captures both the physical-engineering aspects of production and the behavior of economic agents who manage the production activity. The neoclassical theory of the firm provides the theoretical foundations and a set of organizing principles which insure the internal consistency of any analysis of production activity conducted using the microtheoretic (M-T) methodology.

Before we begin our discussion one point must be well understood. Utilization of the M-T approach dictates strict adherence to economic theory. Any deviation from the theory can cast the entire analysis in doubt. This implies that model construction and estimation be devoid of *ad hoc* appendages or generalizations and that each step in the empirical analysis comply first with theoretical strictures before any subsequent steps are undertaken or policy conclusions drawn. We raise this caveat to emphasize the observation that much applied work masquerading under the guise of neoclassical-econometrics is inconsistent with underlying economic theory and thus the results cannot claim to possess the explanatory power which the theory provides. Since theoretical consistency is vitally important to the confidence one can place in empirical results our presentation of the M-T approach shall be fairly formal. This formality is necessary so that the subtleties of the theoretical dictates can be identified and their importance in the construction of economic models revealed.

During our preliminary discussion of the M-T approach we will draw no distinction between agricultural production and any other type of production activity. We do this to simplify the presentation and to focus on the more general elements of the approach. In subsequent discussion we shall focus on the specific modeling of agricultural production in an environment containing airborne pollutants.

3.2. THEORETICAL REVIEW OF PRODUCTION DUALITY MODELS

The bulk of the theoretical results presented in this section are drawn in whole or part from three survey papers: Diewert (1974), (1978) and Rosse (1970). All proofs are omitted and only the major empirical properties of various functions are presented. For more theoretical detail the interested reader is directed to the extensive bibliography found in Diewert (1978).

We begin our theoretical discussion by identifying the production unit as a firm which combines n factors of production to produce m kinds of output, utilizing a given technology, which specifies the physical transformation of inputs to outputs. The multiple output nature of technology complicates the analysis; however, since most agricultural production units produce more than one output it would be pointless to present theoretical models based on a single output assumption. We take as given the primal technology set T which identifies all feasible input-output combinations. The set T is formally defined as:

$$T = \{(x,y) \mid (x,y) \text{ is a feasible production choice}\} \tag{1}$$

where x is an n x 1 vector of inputs and y an m x 1 vector of outputs.

T has the following properties:

T.1 T is a closed set

T.2 T is convex

T.3 T exhibits free disposability of inputs

Clearly, the technology set T is of fundamental importance since any physical effect on production, attributable to an environmental variable (air pollutants for example) must impact production through an alteration in the technology set T.

Given the technology set T we may express the firm's production possibilities as the maximum of output y_i the firm can produce given that it produces fixed quantities of the remaining m - 1 outputs and fixed inputs. We define the maximal output rate for output i as:

$$g_i(x^0, {}^i y^0) = \max\{y_i \mid (x,y) \in T,\ x \leqq x^0,\ {}^i y \geqq {}^i y^0\} \tag{2}$$

where ${}^i y = (y_1, y_2, \ldots, y_{i-1}, y_{i+1}, \ldots, y_m)$

(x^0, y^0) specifies a point in T

The transformation function may now be defined as

$$G(x,y) = \begin{cases} -y_i + g_i(x, {}^i y) & \text{if } (x,y) \in T \\ \leqq 0 & \text{Otherwise} \end{cases} \tag{3}$$

The transformation function G indicates the distance in output space between a specified input-output set (x,y) and the closest efficient output vector producible by the same input vector. If $G(x,y) = 0$ then the transformation function defines all those technically efficient input-output combinations. If for any (x^0,y^0), $g(x^0,y^0) > 0$ the (x^0,y^0) is a technically inefficient input-output combination and thus G can serve as a measure of its technical inefficiency -- smaller positive values of G indicating greater efficiency. For any $G(x^0,y^0) < 0$, (x^0,y^0) is an infeasible production choice, i.e., outside the technology set T and beyond the frontier of the transformation function G. The ability of G to serve as a measure of efficiency will be discussed in later portions of this section when we discuss the actual modeling of ozone's impact on agricultural production. In the case of a single output the transformation function reduces to the familiar single output production function notion.

The transformation function has the following properties:

G.1 G is continuous

G.2 G is monotonic, i.e., G is nondecreasing in x and nonincreasing in y

G.3 G is quasi concave in every convex subset of X cross Y

Given properties G.1-G.3, Rosse (1970) and Diewert (1974) have demonstrated that technology set T may be retrieved (defined) in terms of the transformation function G as shown below.

$$T = \{(x,y) \in G(x,y) \geqq 0\} \tag{4}$$

Thus, a duality exists between the primal notion of a technology set and the notion of a transformation function. This duality insures that the production possibilities of a firm facing a multiple input, multiple output technology can be fully described by a transformation function; and further, that any impact realized upon the technology set T due to the effect of an environmental set of variables will be mirrored in the transformation function.

We now introduce the minimum cost function which can be defined equivalently by (5) or (6).

$$C(p,y) = \min\{p'x \mid (x,y) \in T\} \tag{5}$$

or

$$C(p,y) = \min\{p'x \mid G(x,y) \geq 0\} \tag{6}$$

where p is an n x 1 vector of input prices

"'" indicates vector transposition

The cost minimization problem models the firm's decision making process as the firm chooses optimal quantities of the variable factors of production while facing given rates of output and fixed factor prices. At a cost minimum the optimal factor demands are consistent with a firm which is both technically and allocatively efficient, i.e., a situation in which the firm is operating on the transformation function frontier $(G(x,y) = 0)$ and is employing factors of production in the correct factor intensities (allocative efficiency).

The minimum cost function has the following properties:

C.1 C is continuous

C.2 C is monotonic, nondecreasing in y

C.3 positive linear homogeneous (PLH) in p

C.4 strictly quasi concave

Given properties C.1-C.4 of the cost function, the frontier transformation function (i.e., $G(x,y) = 0$) and the efficient input-output combinations of the technology set T may be retrieved from knowledge of the cost function alone. Once again this duality implies that impacts on the technology set may be perceived and examined through the cost function.

If C satisfies C.1-C.4 and is differentiable then the following result due to Shephard (1953) holds.

$$\frac{\partial C(p,y)}{\partial P_i} = x_i^*(p,y) \tag{7}$$

where $x_i^*(p,y)$ is the cost minimizing quantity of i^{th} input needed to produce the vector y with given input prices p. Thus one may find the optimal factor demand equations by simple differentiation (Shephard's lemma) or as the solution to the following optimization problem.

$$x_i^*(p,y) = \min\{p'x | G(x,y) \geq 0\}$$

In the latter case one would posit a functional expression for the transformation function G and solve the minimization problem in terms of x. Unfortunately, unless simple (i.e., restrictive) functional forms for G are chosen the solution vector is often not analytically derivable. On the other hand, if one chooses the cost function approach one need only postulate an expression for the cost function and simply apply Shephard's lemma.

If the cost function satisfies C.1-C.4 then impacts on the technology set T are transmitted to the optimal factor demands (7). Since the optimal demands are a direct reflection of resource usage the demand equations provide a convenient vehicle for assessing resource gains or losses associated with impacts on the technology set T.

Differentiation of the cost function with respect to each y_i produces a set of interdependent marginal cost functions. Given perfect competition assumptions, these marginal cost functions can be used to characterize the supply responses of individual production units and thus provide another vehicle for benefit calculation purposes.

We now wish to extend the generality of our discussion to permit a subset of our input vector x to be composed of quasi-fixed stocks of inputs (capital is the usual example) and to examine models which are capable of explaining both the firm's input and output choices. That is, we are interested in deriving models capable of producing short-run factor demand and output supply equations.

To begin our analysis we require some additional notation. Partition the input vector x into two exhaustive and mutually exclusive subsets $x^v(x_1, \ldots, x_s)$ and $x^f(x_{s+1}, \ldots, x_n)$ where x^v are the freely variable inputs and x^f the quasi-fixed stocks. Let p^v stand for the s x 1 vector of variable input prices and p^* the m x 1 vector of output prices. Now define variable profit as $\pi = p^{*'}y - p^{v'}x^v$. Finally, we amend the properties of our technology set T by adding T.4 (constant returns to scale).

We now introduce the variable profit function defined as:

$$\pi(p^v,p^*,x^f) = \max\{p^{*'}y - p^{v'}x^v \mid (x^v,x^f,y) \in T\} \tag{8}$$

The variable profit function models the firm's decision making process as it seeks to maximize total variable profits by choosing cost minimizing quantities of variable inputs and profit maximizing levels of output all conditional on levels of quasi-fixed stocks and subject to the constraints of the technology set.

The variable profit function has the following properties:

P.1 π is PLH in p^v and p^*

P.2 π is convex in p^v and p^* for every x^f

P.3 π is PLH in x^f

P.4 π is nondecreasing in x^f for every p^v, p^*

P.5 π is concave in x^f for every p^v, p^*

P.6 π is increasing in p^* and decreasing in p^v

Given properties P.1-P.6 of the variable profit function and properties T.1-T.4 of the technology set there exists a duality between the profit function and the technology set (see Diewert (1974), pp. 137) which permits characteristics of the technology set to be perceived via the profit function. Further, if π is differentiable an analog to Shephard's lemma, known as Hotelling's lemma, applies to variable profit functions. Specifically, differentiation of the profit function with respect to input and output prices generates optimal factor demand and output supply equations respectively.

$$\frac{\partial \pi(p^v, p^*, x^f)}{\partial p_i^v} = x_i^{v*}(p^v, p^*, x^f) \text{ : optimal factor demands} \qquad (9)$$

$$\frac{\partial \pi(p^v, p^*, x^f)}{\partial p_j^*} = y_j^*(p^v, p^*, x^f) \text{ : optimal output supplies} \qquad (10)$$

The profit function is an extremely powerful tool for the analysis of firm behavior since it provides both factor demand and output supply equations. Moreover, given its duality with the technology set, impacts on the technology set are immediately transmitted to the supply equations permitting straightforward consumer surplus calculations.

Summarizing briefly, we have demonstrated how the results of duality theory are capable of linking models of producer behavior to characteristics of the underlying physical relations between inputs and outputs; and similarly, how alterations in those physical relations are transmitted to observable economic relations in the form of demand and supply equations. We hope that this theoretical development emphasizes a remark we made in the introduction to this section regarding theoretical consistency. For example, the power of the variable profit function to define optimal demands and supplies rests on the stated properties P.1-P.6 of the function. If an empirically estimated profit function violates even one of the properties, Hotelling's lemma produces nonsense rather than economically defensible and useful functions. When examining the results of empirical studies employing dual relationships one must always begin with the uninteresting examination of the theoretical consistency of the estimated functions in terms of their required properties. Only if these properties are met should one give any attention to subsequent empirical results.

The preceding discussion has demonstrated that there exist several possible models of production which could conceivably be employed to examine the impacts of exogenous factors (e.g., airborne pollutants) on the engineering features of production technologies. Utilizing the results from duality theory one may construct transformation, cost or profit function models through which one can perceive the manifestation of these exogenous factors on input demand and output supply functions. Having quantified these perceptions it is a straightforward, albeit time consuming, task to calculate social benefits.

If one reflects for a moment on the assumed properties of the technology set T one realizes how extraordinarily general these assumptions are. We make no assumptions regarding the associations between groups of inputs, groups of outputs or groups of inputs and outputs. We assume nothing about substitution possibilities or the aggregation of inputs and outputs. Unfortunately, this high degree of generality is compromised as soon as we attempt to empirically implement the theoretical models since we must choose functional structure (i.e., specific function specifications) for the transformation, cost or profit functions. As soon as one imposes structure on these functions one begins to make a priori statements regarding the engineering features of the underlying technology. Since these a priori statements can impact the qualitative and quantitative manifestations of exogenous factors impacting the underlying technology, we want to set out clearly the relationships between functional structure and resulting a priori statements.

We shall limit our discussion of functional structure primarily to the concept of separability. Essentially, separability concerns the decomposition of a function into groups of subfunctions. If a function can be so decomposed the function is said to be separable. The impact of separability is to impose additional structure on the function which one can perceive by an examination of the function's derivatives (we shall assume that the functions we are concerned with are twice differentiable).

To formally define separability we introduce a simple function F of N arguments $x_1, \ldots, x_n$.

$$F(x) = F(x_1, \ldots, x_n) \tag{11}$$

The variable indices of x form the set I = [1, ..., n]. Partition I into m exhaustive and mutually exclusive subsets. $\hat{I} = [I^1, \ldots, I^m]$. The partition $\hat{I}$ forms m subsets of the arguments of F(x). If F(x) can be written

$$F(x) = \hat{F}(g^1(x^1), g^2(x^2), \ldots, g^m(x^m)) \tag{12}$$

then F(x) is said to be weakly separable in the partition $\hat{I}$. If F(x) can be written

$$F(x) = F^*(g^1(x^1) + g^2(x^2), \ldots, g^m(x^m)) \tag{13}$$

then $F(x)$ is said to be strongly separable in the partition $\hat{I}$. If $F(x)$ is strongly or weakly separable then the g functions maybe interpreted as aggregator functions which permit consistent aggregation of the arguments in each subset of the partition $\hat{I}$. Thus we have the first important result -- consistent aggregation of subsets of the arguments of a function requires separability.

The impact of separability on the associations among arguments of the function can be clearly seen by an examination of functional derivatives. If the function $F(x)$ is weakly separable with respect to the partition $\hat{I}$ then the ratio of the partial derivatives of F with respect to two arguments within a single subset is independent of the magnitude of arguments outside that subset; i.e.,

$$\frac{\partial}{\partial x_k}\left(\frac{F_i}{F_j}\right) = 0 \quad \text{for all } i,j \in I^r,\ k \notin I^r \tag{14}$$

where $F_i, F_j = \partial F/\partial x_i,\ \partial F/\partial x_j$ respectively.

If the function $F(x)$ is strongly separable with respect to the partition $\hat{I}$ then the ratio of partial derivatives of F with respect to two arguments each within different subsets is independent of the magnitude of arguments outside of either subset; i.e.,

$$\frac{\partial}{\partial x_k}\left(\frac{F_i}{F_j}\right) = 0 \quad \text{for all } i \in I^r,\ j \in I^s,\ k \notin I^r \cup I^s \tag{15}$$

To realize the economic importance of separability one need only think of F(x) as a production function. First, only if F is separable is it possible to aggregate inputs in such a fashion that the value of each aggregate is invariant with respect to the levels of inputs outside the aggregate. Thus, without separability no aggregation is possible. Second, if F is weakly separable in the partition $\hat{I}$ then the marginal rate of substitution between any two inputs within a single subset is independent of the level of any input outside that subset. Third, if F is strongly separable in the partition $\hat{I}$ then the marginal product of any input in a subset is independent of any input outside that subset. The second and third results imply two more. Fourth, if F is weakly separable in the partition $\hat{I}$ then the Allen partial elasticities of substitution between two elements of one subset and an element outside that subset are equal, i.e.,

$$\sigma_{ik} = \sigma_{jk} \quad \text{for } i,j \in I^r \text{ and } k \notin I^r \tag{16}$$

This implies for example that if all energy inputs to a production process formed one subset and all capital inputs another, then for example, the elasticity of substitution between electricity and factory equipment is exactly equal to the substitution between coal, natural gas or fuel oil and factory equipment. Finally, if F(x) is strongly separable in $\hat{I}$ then Allen partial elasticities of substitution between any two inputs in different subsets and a third input not in either subset are equal, i.e.

$$\sigma_{ik} = \sigma_{jk} \quad \text{for } i \in I^r,\ j \in I^s,\ k \notin I^r \cup I^s \tag{17}$$

If each input formed its own subset then all Allen elasticities of substitution would be equal. This result is characteristic for example of the multifactor CES and the Cobb-Douglas production functions.

It is readily apparent that separability can constrain the associations among economic variables; thus in choosing a functional structure for our economic models one will want to constantly be aware of the ramifications of the chosen structure. We outline briefly below the consequences of differing types of separability on the transformation G.

Input to Output Separability

If the minimum cost function can be written as a multiplicatively separable function in a two subset partition, one subset containing all input prices and the other all output variables then the transformation function is said to be separable, i.e., if the cost function can be written

$$C(p^V, y) = \phi(p^V)\psi(y) \tag{18}$$

The transformation function can be written

$$G(x,y) = -F(x) + H(y) = 0 \tag{19}$$

Input-output separability implies that consistent aggregates of inputs and output can be formed. This in turn implies and is implied by the result that the marginal rate of technical substitution between any two inputs is independent of the level of any particular output and that the marginal rate of output transformation is independent of the level of any particular input. To determine whether the underlying technology set was indeed input-output separable one would test econometrically the parametric restrictions which would be implied by multiplicative separability.

Again if the transformation function is separable then the profit function can be written in a multiplicatively separable form, i.e.

$$\pi(p^{v},p^{*}) = \theta(p^{v})\tau(p^{*}) \tag{20}$$

and a test for transformation function separability could be carried out by testing parametric restrictions on the profit function which would yield multiplicative separability.

Nonjointness of Production

The transformation function is said to be nonjoint in inputs if there exists individual production functions for each output, i.e.

$$G(x,y) = 0 \quad \text{is nonjoint in inputs if} \quad y_i = f_i(x_{i1}, \ldots, x_{in}) \tag{21}$$

$$i < 1, \ldots, m$$

and $G(x,y) = 0$ is nonjoint in outputs if there exists individual factor requirements functions, i.e.

$$G(x,y) = 0 \text{ is nonjoint in outputs if } x_i = g_i(y_{i1}, \ldots, y_{im}) \quad i = 1, \ldots, n \tag{22}$$

If G is nonjoint in inputs and outputs then $C(y,p^v)$ may be written

$$C(p^v,y) = y_1\phi^1(p^v) + y_2\phi^2(p^v), \ldots, + y_m\phi^m(p^v) \tag{23}$$

implying that the cost of producing all outputs is the cost of producing each output separately. The corresponding profit function is,

$$\pi(p^v,p^*) = \sum_{i=1}^{m} \sum_{j=1}^{n} \alpha_{ij}p_j^v/p_i^* \tag{24}$$

which implies that all production functions are identical up to a multiplicative constant.

Clearly, if the transformation is nonjoint the modeling of the technology is greatly simplified since the multiple output nature of the production activity can be decomposed into a set of individual output production processes. It would be difficult to imagine that such nonjointness exists in agriculture and even input-output separability may not exist. Assuming such separable structures when indeed they do not exist causes econometric specification error which can seriously distort the empirical results. As a rule of thumb one would assume as little separability as possible.

Separability of the Input and Output Subsets

If G is input-output separable, and the input subset is weakly separable in the partition I_x containing r subsets while the output subset is weakly separable in the partition I_y containing s subsets then G may be written

$$G(x,y) = -F^*(f^1(x^1),\ f^2(x^2),\ \ldots,\ f^r(x^r)) \tag{25}$$

$$+\ H(h^1(y^1),\ h^2(y^2),\ \ldots,\ h^s(y^s))$$

and the corresponding cost function, partitioned in a similar fashion, may be written

$$C(p^v y) = [\phi^*(\phi^1(p^{v1}),\ \phi^2(p^{v2}),\ \ldots,\ \phi^r(p^{vr}))] \tag{26}$$

$$[\psi^*(\psi^1(y^1).\ \psi^2(y^2),\ \ldots,\ \psi^s(y^s))]$$

And finally the corresponding profit function

$$\pi(p^v p^*) = [\theta^*(\theta^1(p^{v1}),\ \theta^2(p^{v2}),\ \ldots,\ \theta^r(p^{vr}))] \tag{27}$$

$$[\tau^*(\tau^1(p^{*1}),\ \tau^2(p^{*2}),\ \ldots,\ \tau^s(p^{*s}))]$$

The properties of weakly separable functions discussed in the opening paragraphs of this section may now be applied to interpret the ramifications of separability on the input and output subsets. Strong separability for all three functions merely imposes additivity on all the subfunction components $f(\cdot)$, $h(\cdot)$, $\phi(\cdot)$, $\psi(\cdot)$, $\theta(\cdot)$, $\tau(\cdot)$. Again implications of strong separability may be deduced from our previous discussion.

The importance of separability cannot be overemphasized since it imposes a priori restrictions on the associations among inputs, outputs and between inputs and outputs. To keep these restrictions as minimal as possible we will want to choose functional structure for our econometric models with an eye toward separability considerations as well as empirical tractability.

3.3. MODELING THE IMPACT OF ENVIRONMENTAL VARIABLES ON AGRICULTURAL PRODUCTION

Conceptually, there are only two substantive differences between the microtheoretic modeling of an agricultural production activity and a manufacturing activity. First, since land is immobile and varies in degree of productivity, the land input into an agricultural production activity is necessarily nonhomogeneous. Thus, in modeling agricultural production the heterogeneity of the land input must be taken into consideration. Second, unlike the majority of modern manufacturing processes, agriculture is highly susceptible to the influence of nonmarket factors, e.g., climate variations, biological infestation and natural and man-made atmospheric pollutants, to suggest a few. Since these are nonmarket factors, they cannot be treated symmetrically with the marketable inputs to agricultural production; however, they are not totally beyond the control of the economic agents organizing agricultural production. Variation in annual rainfalls can be combated with market inputs such as irrigation capital, biological infestations with varieties of fungicides, herbicides and pesticides, and atmospheric pollutants with resistant varietals.

Dealing with the heterogeneity of the land input requires an index of land productivity or regionally specific production models where land homogeneity may be claimed. Land quality indexes have been constructed for many years and thus this requirement does not pose an insurmountable problem. Given such an index δ_i, where i counts the types of land employed, e.g., land used for grazing versus land used for cash crop production, one merely employs a factor augmentation perception of the technology set T where each land component of the input vector is scaled by the appropriate δ_i. Clearly, the number of land types must be less than the number of observations on agricultural production. If land were a variable factor in the long run, assuming reasonably competitive markets, then a cost or profit function approach would not require the δ_i index since the varying productivities would be capitalized into the service price of the land.

Modeling the nonmarket forces affecting agriculture poses a more difficult problem. For simplicity, let us consider only environmental influences and designate the vector of such influences E. For any given vector E, the technology set is determined by the physical and biological relations of agriculture. Thus, as E varies so does the technology set T, and therefore the set T is a function of the vector of environmental influences. This causality between E and T implies a transformation function of the form where E impacts the manner in which x is transformed into y.

$$G(x,y,E) = 0 \tag{28}$$

Our empirical problem is essentially one of quantifying the impact which E has on the transformation of x into y. As we shall demonstrate, there exist at least two possible approaches to this problem. The first would be an econometric procedure where the impact of E on the x,y transformation is estimated from observed nonexperimental data. The second approach, and the one we employ in this study is to use experimental natural science information to form the link between E and the x,y transformation.

The manner in which E affects the x,y transformation determines how it should be modeled within the G function. The simplest impact E could have would impose function separability such that G is written

$$G(x,y,E) = G^{*}(H(x,y) + (E)) = 0 \tag{29}$$

This form of direct separability of G implies that the frontier transformation function is neutrally displaced inward and outward as the components of E change. This direct separability of G implies cost and profit functions of the form

$$C(p^{v},y,E) = (C^{*}(p^{v},y) + (E)) \tag{30}$$

and

$$\pi(p^V, p^*, E) = (\pi^*(p^V, p^*) + (E)) \tag{31}$$

The economic assessment model we shall present in Chapter 5 is based on a slightly simplified form of the cost function in Equation 30. Specifically, the cost function is limited to a single output such that vector y has only a single element. We are justified in utilizing 30 due to the hypothesized neutral impact which ambient ozone has on the productivity of production factors. In the economic jargon of Chapter 1 we term this neutral factor productivity enhancement.

It is, of course, quite possible that E has a nonneutral effect on inputs but neutral on outputs or a neutral effect on inputs and a nonneutral effect on outputs. In these two cases the transformation would have to be input-to-output separable and appear as

$$G(x,y,E) = -F(x,E) + G(y) = 0 \quad \text{input nonneutral} \tag{32}$$

or

$$G(x,y,E) = -F(x) + G(y,E) = 0 \quad \text{output nonneutral} \tag{33}$$

The corresponding cost and profit functions are written

$$C(p^V,y,E) = \phi(p^V,E)\psi(y) \quad \text{input nonneutral} \tag{34}$$

and

$$\pi(p^V,p^*,E) = \theta(p^V,E)\tau(p^*) \quad \text{input nonneutral} \tag{35}$$

or

$$C(p^V,y,E) = \phi^*(p^V)\psi(p^*,E) \quad \text{output nonneutral} \tag{36}$$

and

$$\pi(p^V,p^*,E) = \phi(p^V)\tau(p^*,E) \quad \text{output nonneutral} \tag{37}$$

Finally, if E affects both inputs and output nonneutrally then G must be input to output nonseparable and we are back to the fully nonseparable forms of the transformation, cost and profit functions. As we choose functional structure for G, C and we restrict the paths along which the impact of E on the technology set can be perceived; thus, we restrict E's impact on input demand and output supply functions and in turn restrict E's impact on social benefit calculations.

Let us now consider modeling the impact of E on agricultural production via the microtheoretic econometric approach using a minimum cost function in which we embed a vector of environmental variables. For ease of exposition let all inputs be variable. Then X is an n x 1 vector of variable inputs, Y an m x 1 vector of outputs, and E an s x 1 vector of environmental variables, which the economic agents operating the agricultural technology take as constant. The agents also know how the vector E affects their technology set T. Finally, to make the analysis nontrivial we assume E varies across agricultural production units.

If we do not impose separability of any type on the transformation function then the joint output minimum cost function may be written

$$TC = C(P,Y,E) \tag{38}$$

where TC = minimum total cost

and the factor demand equations are

$$\frac{\partial C(P,Y,E)}{\partial P_i} = x_i^*(P,Y,E) \qquad i = 1, \ldots, n \tag{39}$$

To estimate the factor demand equations and thereby estimate the effect of E on the resource cost of agricultural production, we must specify a functional form for C(P,Y,E). To maintain as much generality as possible we choose the multiple output transcendental logarithmic cost function (translog). The translog has the exceedingly desirable property that it can be interpreted as a second order local approximation to any underlying cost function. In addition, the translog can be expressed as a fully nonseparable function.

Using the notation above we write the nonseparable translog as

$$\ln TC = \alpha_0 + \sum_i^m \alpha_i \ln Y_i + \sum_j^n \beta_j \ln P_j + \sum_k^s \delta_k \ln E_k \tag{40}$$

$$+ 1/2 \sum\sum_{ij}^{mm} \rho_{ij} \ln Y_i \ln Y_j + 1/2 \sum\sum_{ij}^{nn} \gamma_{ij} \ln P_i \ln P_j + 1/2 \sum\sum_{ij}^{ss} \phi_{ij} \ln E_i E_j$$

$$+ \sum\sum_{ij}^{mn} \theta_{ij} \ln Y_i \ln P_j + \sum\sum_{ij}^{ms} \psi_{ij} \ln Y_i \ln E_j + \sum\sum_{ij}^{ns} \tau_{ij} \ln P_i \ln E_j$$

For each factor input a share equation can be formed

$$m_i = \beta_i + \sum^n \gamma_{ij} \ln P_j + \sum^m \theta_{ij} \ln Y_j + \sum^s \tau_{ij} \ln E_j \tag{41}$$

Joint estimation of (40) and the system of share equations (41) by maximum likelihood techniques provides an estimate of the joint marginal cost functions and thus the just output supply equations as given by (42).

$$MC_i = \frac{TC}{Y_i} [\alpha_i + \sum_j^m P_i \ln Y_j + \sum_j^n \theta_{ij} \ln P_j + \sum_j^s \psi_{ij} \ln E_j] \tag{42}$$

Conceptually, the above model is extremely appealing and straightforward. However, there are several empirical issues which often prohibit its adoption. First, the ability to identify the relationship between E and marginal cost is contingent on the ability to statistically control for all other variables which can affect cost. In the marginal cost equation (42) these variables are factor prices, output and our other environmental influence variables such as weather. In this context statistical control is different from experimental control. We simply cannot hold the values of these variables constant as we can in a laboratory experiment; therefore, we must provide the statistical model with quantitative measurements of all relevant variables. This greatly complicates the model, adds large numbers of parameters and increases problems of collinearity among the independent variables.

Second, in the physical world some variables move with one another due to social or physical relations existing between them. If E and some set of other variables which explain cost move with another then the statistical model will be incapable of distinguishing their individual impacts. In laboratory controlled experiments, we can force orthogonality between these variables but when we must rely on natural experiments we are subject to the whim of man and nature.

Finally, there must be some variation in the variables of interest. If we are concerned with the impact of a change in E on the agricultural supply function we must observe variation in E. In the case of air pollutants this is a serious problem. Given, the regulated nature of pollutants, their concentrations can be very uniform over large areas. In the case of ozone, for example, a pollutant with an experimentally proven impact on crops, its concentration across much of the rural corn belt is probably so uniform that it is doubtful any meaningful statistical association could be identified.

For the above reasons and several other more subtle and technical issues, the identification of the physical dose-response mechanism with a microtheoretic econometric model can be difficult. Moreover, even if accomplished model verification is largely impossible -- one simply cannot observe the predicted welfare changes. Since the welfare estimates are directly linked to the dose-response relation more confidence can be obtained if this relationship is identified and empirically quantified under controlled experimental conditions.

The NCLAN experimental studies have focused on the effect of various air pollutants on crop yields. The potential differential impact which these pollutants might have on inputs to the agricultural production activity has not yet been studied by NCLAN. This is consistent with the belief that ozone (the prime pollutant of interest) has a neutral effect on all nonharvest production inputs (NFPE). To examine this issue briefly consider a simple single output production function for preharvest activities as given below.

$$Y = f(x_1, \ldots, x_n, E) \tag{43}$$

If E does indeed affect all inputs neutrally then one may write (43) as

$$Y = \phi(E)\ F(x_1, \ldots, x_n)\ , \tag{44}$$

where given a fixed vector of $x, \phi(E)$ can be interpreted as a dose-response function and dose-response functions developed by NCLAN $\hat{\phi}(E)$ used as proxies to the true function $\phi(E)$.

For concreteness let us assume (43) is a Cobb-Douglas and replace $\phi(E)$ with its NCLAN proxy $\hat{\phi}(E)$.

$$Y = \hat{\phi}(E)\prod_{i}^{n} x_i^{\alpha_i} \qquad (45)$$

The production function (45) has a dual representation as the minimum cost function

$$C = r\hat{\phi}(E)^{-1/r} \left(\prod_{i}^{n} \alpha_i^{\alpha_i}\right)^{-1/r} \left(\prod_{i}^{n} P_i^{\alpha_i}/r\right) Y^{1/r} \qquad (46)$$

and a corresponding marginal cost function

$$\frac{\partial C}{\partial Y} = \hat{\phi}(E)^{-1/r} \left(\prod_{i}^{n} \alpha_i^{\alpha_i}\right)^{-1/r} \left(\prod_{i}^{n} P_i^{\alpha_i}/r\right) Y^{1/r-1} \qquad (47)$$

Thus using $\phi(E)$ changes in E can be theoretically transformed into appropriate shifts in the agricultural supply functions thus permitting welfare calculations. This method of employing NCLAN biological relations embedded in microtheoretic cost functions underlies our economic assessment model.

CHAPTER 4

WELFARE GAINS (LOSSES) FROM DECREASED (INCREASED) OZONE CONCENTRATIONS: A REVIEW OF CONSUMER AND PRODUCER SURPLUS

Suppose we have a single agricultural crop produced by a number of farms under perfectly competitive market conditions. For this crop, decreases in ozone concentrations shift each farm's isoquants in input space toward the origin and increases have the opposite effect. The result in price-quantity space of a decrease in ozone concentration is then a shift in individual marginal cost curves downward; and vice versa for an increase in ozone concentration. A similar effect will be observed in the aggregate supply curve, which is the horizontal sum of the individual marginal cost curves under a given ozone regime.

Now, there are four alternative sets of assumptions about demand and supply elasticities under which the benefits of changes in ozone concentrations are customarily measured. These are developed in Table 4-1 below.

Case I is the most restrictive and embodies a peculiar set of assumptions -- namely that marginal cost is zero up to some point, Q_i, proportional to ozone concentration, and infinite thereafter; while aggregate demand is perfectly elastic at the reigning market price. This is what is implied when one applies dose-response relationships to existing quantities produced and values the quantity changes at the reigning market price. This procedure has been employed by Heck _et al_., n.d., and several earlier studies

TABLE 4-1. ALTERNATIVE ASSUMPTIONS ABOUT SUPPLY (E_s) AND DEMAND (E_d) ELASTICITIES USED TO OBTAIN WELFARE EFFECTS OF ALTERNATIVE OZONE STANDARDS

	Case I (Biologists' Valuation)	Case II	Case III	Case IV
Aggregate Supply	$Q < Q_i : E_s = \infty$ at zero price $Q > Q_i : E_s = 0$ $Q_i = f$ (ozone)	$E_s > 0$	$E_s > 0$	$E_s > 0$
Aggregate Demand	$E_d = \infty$	$E_d = \infty$	$E_d = 0$	$0 < E_d < \infty$

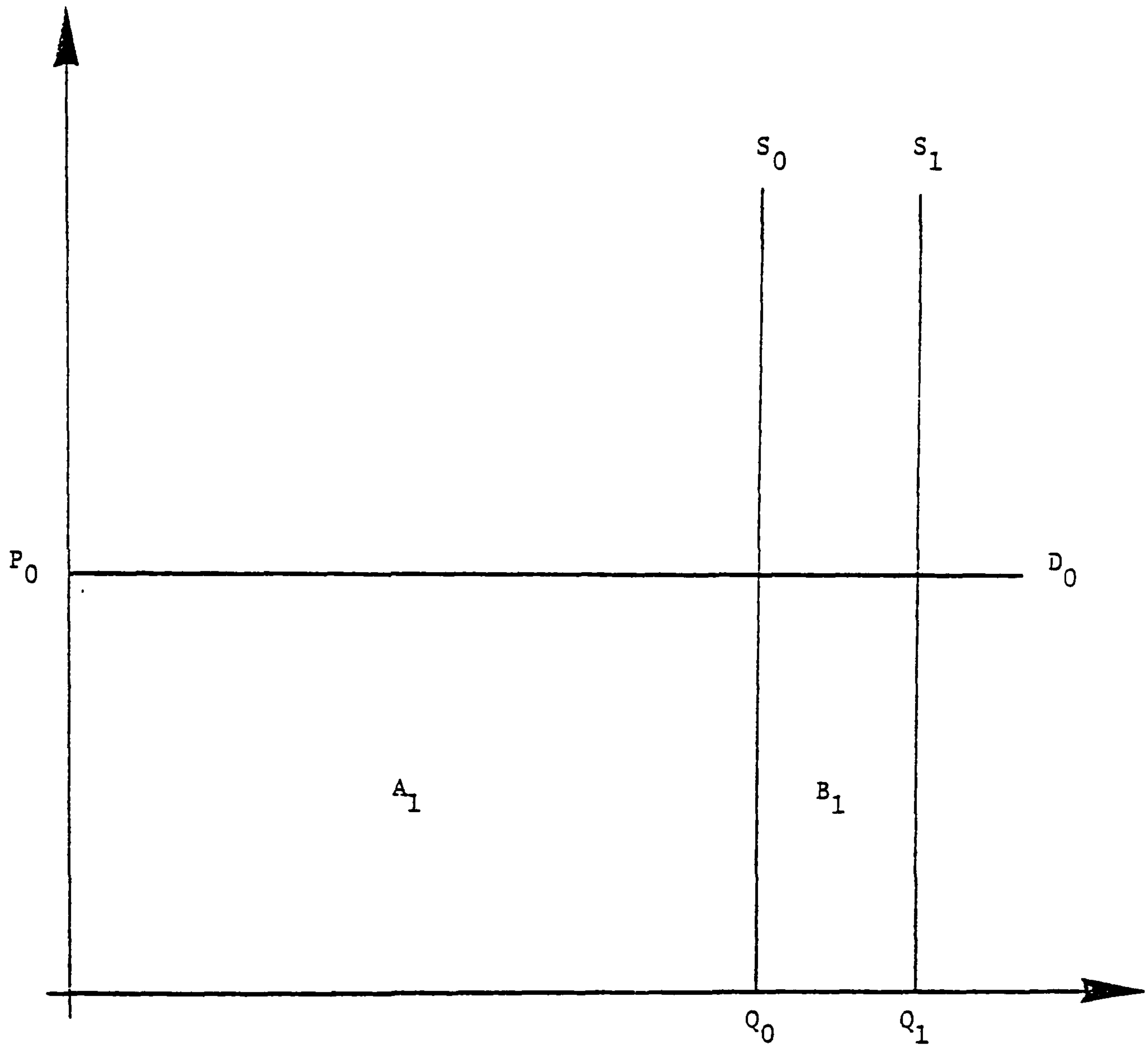


Figure 4-1. Case I.

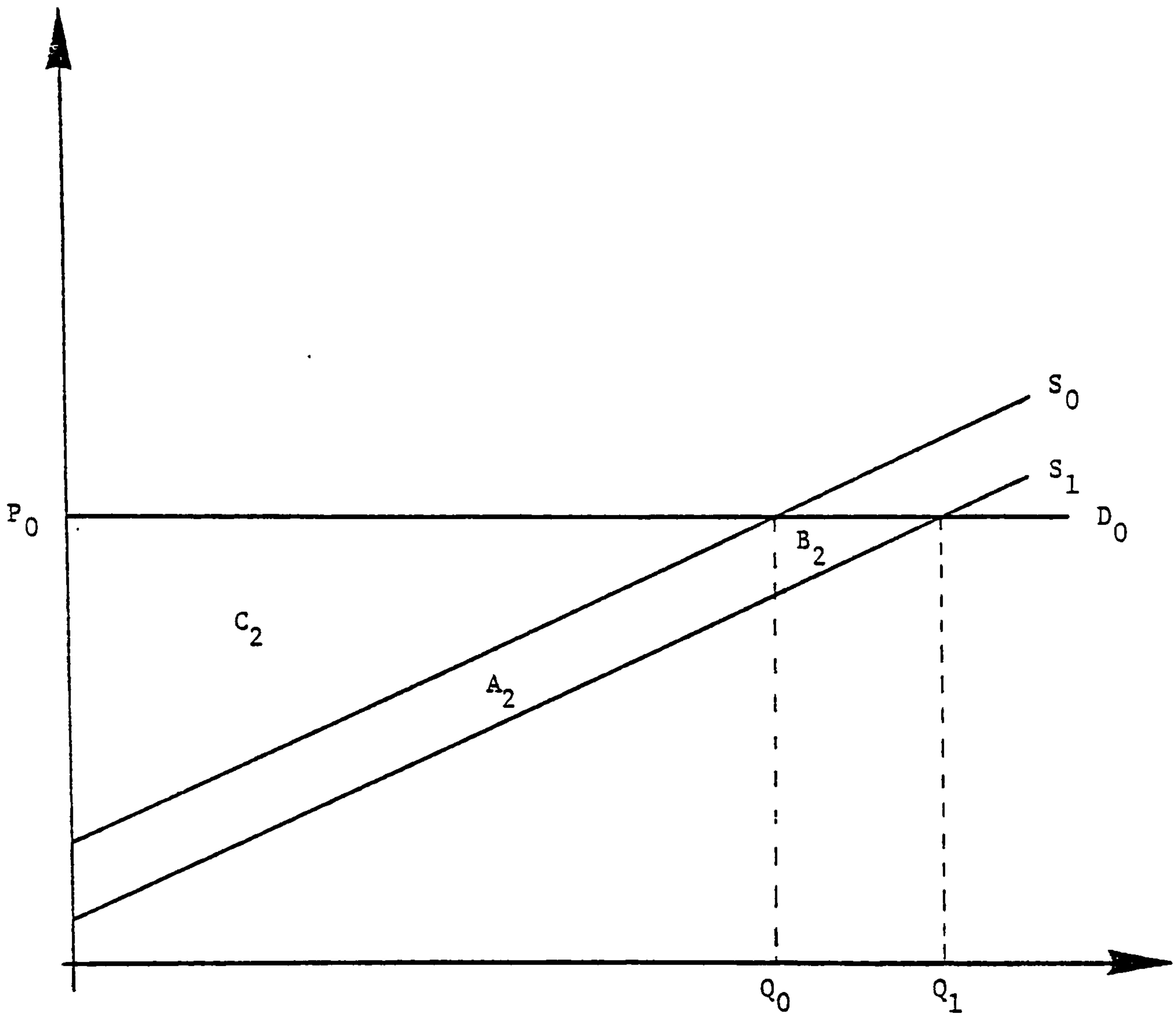


Figure 4-2. Case II.

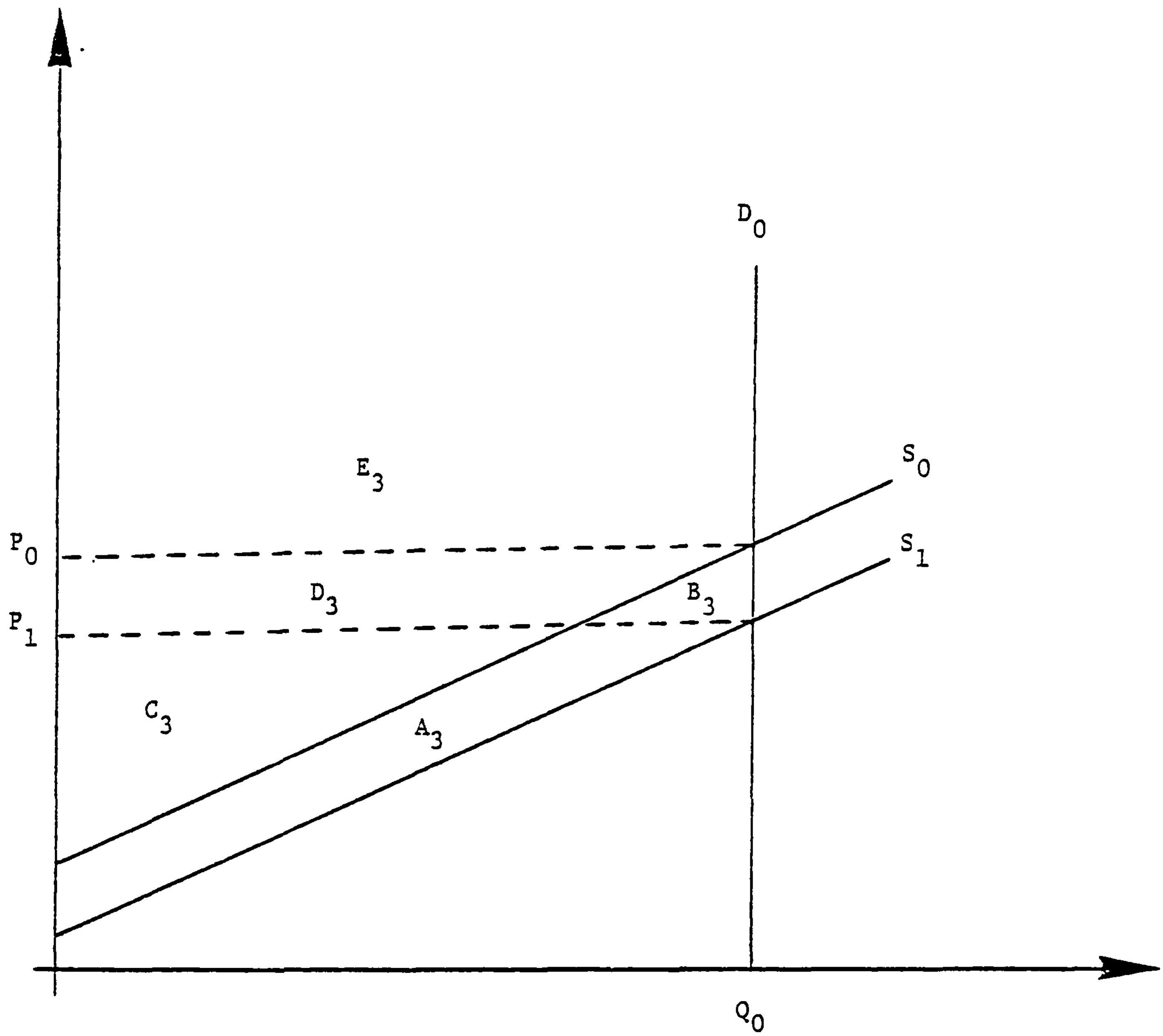


Figure 4-3. Case III.

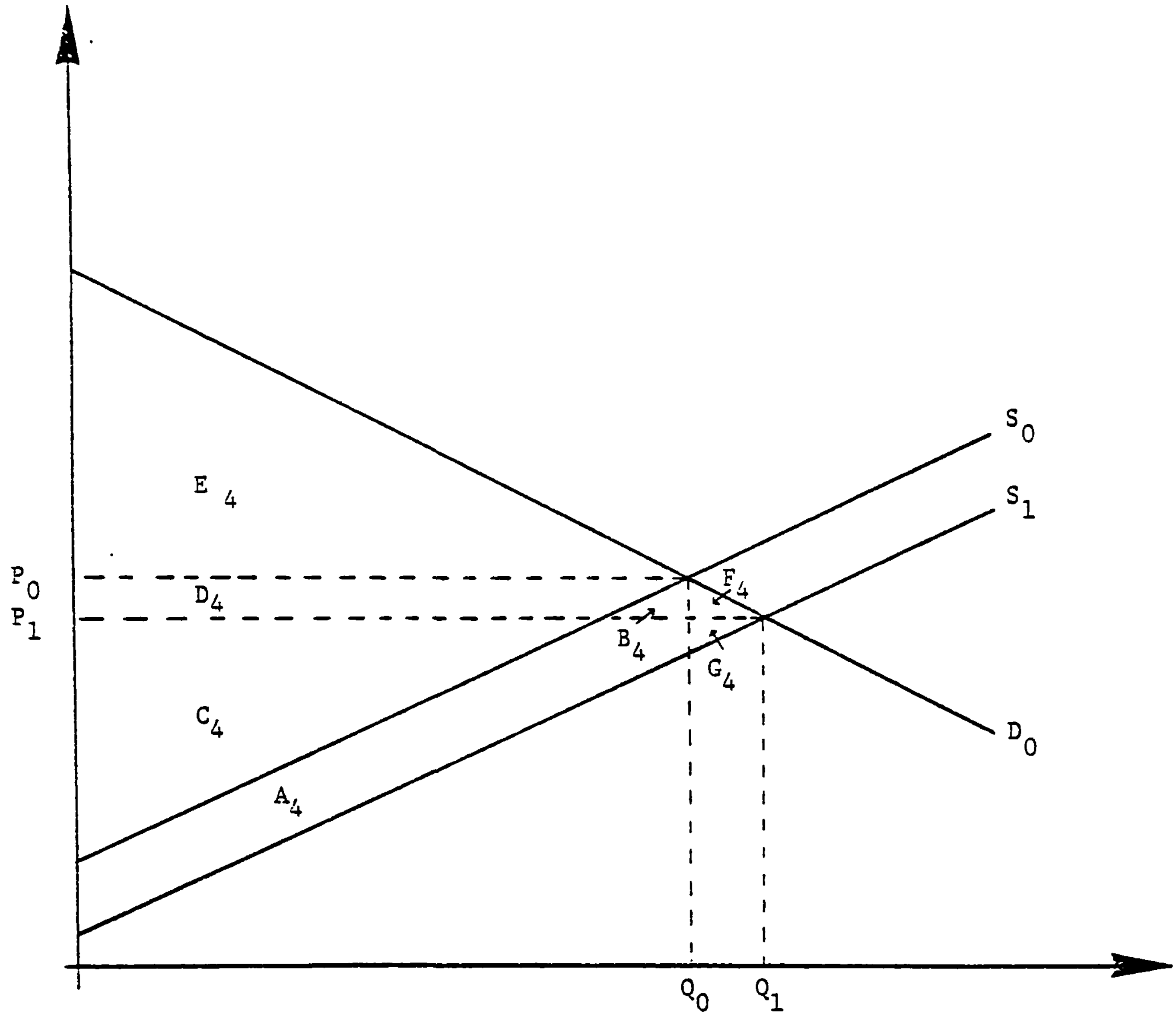


Figure 4-4. Case IV.

criticized for it by Adams _et al._, 1982. Case I is what we have previously labeled _Biologists Valuation_. This calculation may be justified as a first order approximation to the change in _consumers' surplus_ arising from a policy change, and hence is not totally devoid of economic content. (See Deaton and Muellbauer, 1980, p. 185, and Varian, 1978, p. 221).

Graphically, Case I is displayed in Figure 4-1 where we assume a _decrease_ in ozone concentrations and linear supply and demand curves. In this case the discontinuous supply curve is perfectly elastic up to Q_0 and inelastic thereafter. Lowering ozone concentrations shifts the point of discontinuity out to Q_1. Producers' surplus (rents accruing to owners of factors of production) before the change is represented by area A_1. After the change is area $A_1 + B_1$, so the welfare gain, area B_1, accrues entirely to producers.

While Case I relies entirely on the biological dose-response function and existing market prices and quantities for outputs, Cases II and III attempt to quantitatively model the behavior of producers to achieve an aggregate representation of the supply function. The methods of so doing encompass the Mathematical Programming and Microtheoretic routes discussed previously. Whatever the route, the aggregate demand side is ignored. Two extreme simplifying assumptions can be made about demand, once the supply function has been estimated.

The first is that demand is perfectly elastic at some reigning output price, $P = P_0$. In this case, shown in Figure 4-2, there is no consumers' surplus, either before or after the change. Prior to the change, Q_0 is demanded and produçers' surplus is area C_2. After the change, Q_1 is demanded and producers' surplus is area $C_2 + A_2 + B_2$. The net gain, $A_2 + B_2$, accrues wholly to producers. It also represents the decrement in resource costs required to produce the prepolicy level of output (area A_2), plus the producers' surplus on the output increment ($Q_1 - Q_0$), or area B_2.

Case III, shown in Figure 4-3 is perhaps a more realistic one for agricultural commodities, since it posits perfectly inelastic demand. Before the policy consumers' surplus is the (infinite) area E_3 and producers' surplus is area $D_3 + C_3$. After the policy, consumers' surplus is area $E_3 + D_3 + B_3$ and producers' surplus is area $C_3 + A_3$. The net gain, therefore, is area $A_3 + B_3$, which also represents the resource cost savings in production of Q_0 occasioned by the policy. This savings is distributed between consumers and producers, where consumers gain $D_3 + B_3$ and producers gain $-D_3 + A_3$ -- i.e., area D_3 is a transfer from producers to consumers. Note also that the entire area $A_3 + B_3$ in Case III is equivalent to area A_2 in Case II, the discrepancy between the total benefits in the two instances being the area B_2 in Panel 2.

Figure 4-3 depicts the most general case, one which would be represented, say, by an aggregate quadratic programming model of market equilibrium for agriculture. In this type of model, a Linear Programming representation of production activities is linked to a linear aggregate demand function, with the objective of maximizing the sum of producer and consumer surpluses (Takayama and Judge, 1964).

With our assumption of a single product, the total surplus before the ozone reduction is area $E_4 + D_4 + C_4$, of which E_4 is consumers' surplus and $D_4 + C_4$ is producers' surplus. Afterwards, the total surplus expands to $E_4 + D_4 + B_4 + F_4 + G_4 + C_4 + A_4$, of which $E_4 + D_4 + B_4 + F_4$ is consumers' surplus and $C_4 + A_4 + G_4$ is producers' surplus. The net gain of ozone reduction is therefore $A_4 + B_4 + F_4 + G_4$. This net gain is allocated between consumers as a gain of $D_4 + B_4 + F_4$ and producers as a gain of $-D_4 + A_4 + G_4$ where, again, D_4 is a transfer from producers to consumers.

Note that the area $A_4 + B_4$ is identical to $A_3 + B_3$ which itself equals A_2. Therefore, the only difference between the estimate from Case IV and that from Case III is the welfare triangle $F_4 + G_4$ in Figure 4-4. Further, the area $F_4 + G_4$ is encompassed in (i.e., less than) the area B_2 in Figure 4-2. Thus, for the single product case we can unambiguously rank the estimates of welfare gain across Cases II through IV, assuming equal welfare weights apply to the affected producer and consumer groups (Just _et_ _al_., 1982, Ch. 8): Case III $\leq$ Case IV $\leq$ Case II. Thus, for a single product, the linear programming solutions may be adequate representations of benefits vis-a-vis the more complex quadratic programming solution. But we can say nothing very useful about Case I relative to the other three cases.

If we move to the multiple output case the conclusions drawn above still hold if: (1) supply functions for each crop are independent of the level of output of the other crops in the multiproduct system (production exhibits nonjointness) and (2) demand functions for each crop are independent of the prices of other market crops. The same thing is true if (1) above holds and, instead of (2) we have a multiple price change situation which produces an estimate of consumers' surplus gain which is _independent of the path of integration_, money income held constant. (Silberberg, 1978; Just _et_ _al_., 1982).

More specifically, assume we have a set of Marshallian money income demand curves of an n good system of the sort $x_i = x_i^M (P_1, \ldots, P_n, M)$. The sum of consumer surpluses due to changes in prices with money income, M, held constant is the line integral:

$$CS^M = - \Sigma\int x_i^M dP_i = - \int\Sigma x_i^M dP_i$$

This is the area under all of the (linear) demand curves over the relevant limits of integration. It will not be independent of the path of price changes unless the partial derivatives of the uncompensated demand functions across commodity pairs, x_i^M, x_j^M with respect to prices P_j and P_i are equal, that is $\partial x_i^M/\partial P_j = \partial x_j^M/\partial P_i$. By definition this is a property of compensated Hicksian demand functions. But, for the integral of a set of Marshallian demand functions to be path independent the special case of a homothetic utility function is required. This implies that the income elasticities of demand for all goods in the system are equal to unity (for a proof, see Silberberg, 1978).

In general, then, equality of cross-price terms is not a general property of Marshallian demand functions, so the Marshallian surplus measure associated with multiple price changes will not be unique in the sense that it is independent of the assumed sequence of those changes. There are two more exact surplus measures, equivalent variation (EV) and compensating variation (CV) which can be obtained as the integrals under a set of Hicksian (not Marshallian) demand curves.

Compensating variation is the minimum amount a consumer would have to be compensated after a price change (i.e., from initial price vector P^0 to terminal price vector P^1) and be as well off as he was before the change (i.e., remain at initial utility level μ_0. Equivalent variation is the amount of income, given the original price vector P^0, that would leave the consumer as well off as he would be with the price vector P^1 and its attendant utility level μ^1. In terms of money expenditure, e, itself a function of prices and reference utility levels:

$$CV = e(P^1, \mu^0) - e(P^0, \mu^0)$$

$$EV = e(P^1, \mu^1) - e(P^0, \mu^1)$$

Note that the difference between the two concepts is the reference utility level (μ^0 or μ^1 respectively), and that either can be positive or negative, depending on the way prices change (see Varian, 1978, Ch. 7).

If Hicksian demand curves could be parameterized (which they generally cannot be) either CV or EV could be obtained from the areas under such curves. In general, CV is independent of the price path, but EV is not (Silberberg, 1972; Mohring, 1971). In any case, it can be shown (Willeg, 1976) that under reasonable assumptions, Marshallian surpluses provide a good approximation to CV and EV.

When we move toward a less restrictive set of assumptions the practical estimation of welfare changes becomes much less tractable. If we allow marginal costs of production for any crop to be a function of its output level, the output levels of other crops, and input prices, and at the same time are faced with a set of path dependent Marshallian demand functions, there is no uniquely defined net social product maximum (i.e., sum of producer and consumer surplus across all final commodity outputs). Therefore, in this situation there is no way to estimate the "benefits" of an air quality scenario since, if total pre and post scenario benefits are undefined so is the change in them occasioned by the scenario. (For a proof in the Q-P context, see Yaron et al., 1965.) In the model we present in Chapter 5 we assume path independence and nonjointness of production.

CHAPTER 5

THE REGIONAL MODEL FARM

5.1. INTRODUCTION

Recalling from Chapter 3 the practical problems posed by explicit incorporation of ozone variables in the econometric functions and the availability of off-the-shelf biological information from NCLAN (National Crop Loss Assessment Network), it was decided that the use of a biologically driven microtheoretic assessment model was the most appropriate vehicle for analyzing ozone impacts on agriculture. This model was named the Regional Model Farm (a name that reflects the model's data base more than anything else).

Reconsider for the moment the simple agricultural production function for a single crop developed in Chapter 3. Denote the output of this crop Y and let the 1 x n vector x represent inputs

$$Y = f(x) \tag{1}$$

Employing the notation of Chapter 3, where E is a vector of environmental variables, which we shall reduce to a scalar measuring ozone concentrations, and $\phi(E)$ a function of E, we rewrite (1) to permit E to affect the production of Y

$$Y = f(x, \phi(E)) \tag{2}$$

If E neutrally affects the production function then (2) can be written as

$$Y = f(x)\phi(E) \tag{3}$$

and the corresponding cost function is written as

$$C = (C(P_x,Y)\phi(E)) \tag{4}$$

where P_x is a vector of input prices.

Assuming f(x) is characterized by constant returns to scale we may draw a two input unit isoquant for f(x) at two ozone concentrations E_0 and E_1, where $E_0 > E_1$, as shown in Figure 5-1. The lines PP and P'P' are isocost lines at constant input prices and the points A^0 and A^1 depict the cost minimizing equilibrium quantities of x_1 and x_2 under the two ozone regimes. From the figure one can see that neutral shifts in the production function, due to changes in ozone concentrations, imply in the case of ozone reductions, proportional decreases in all inputs while leaving the mix of inputs unchanged.

This hypothesized ozone neutrality (NFPE) has the desirable property that with constant factor prices all factor demand equilibriums lie on a ray from the origin and that ray may be determined from a single observed factor demand equilibrium. Since the neutrality of ozone will not induce any factor substitution, and if we hold factor prices constant, we may treat the production and cost functions (3) and (4) as if they were generated from a Leontief production process. This is precisely what we do in the construction of the RMF.

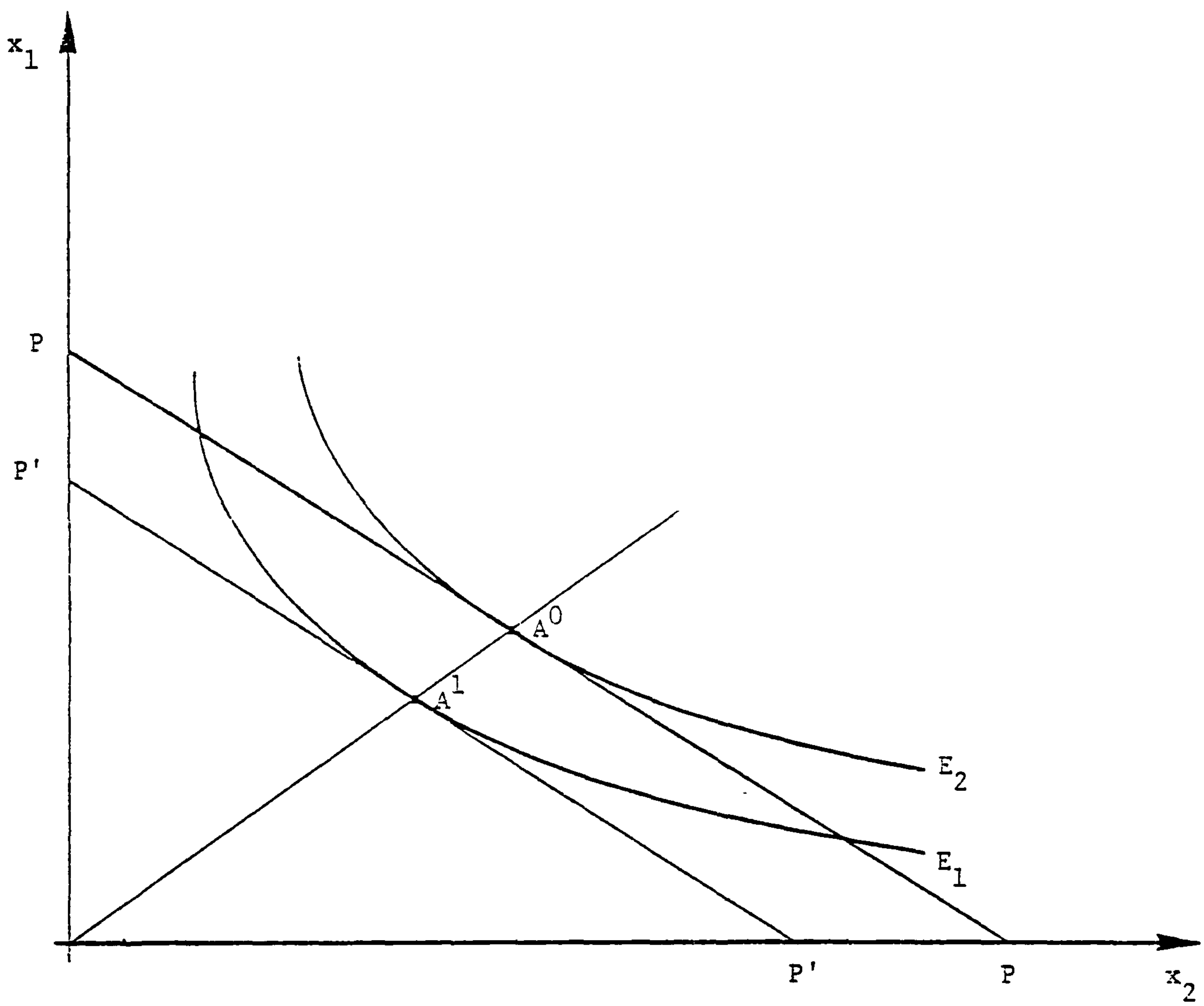


Figure 5-1. A Neutral Shift in the Production Function Due to Change in Ozone Exposure

5.2. SIMPLE HEURISTICS OF THE REGIONAL MODEL FARM (RMF)

The estimation of social welfare gains from agricultural activity occasioned by a reduction in ambient ozone concentrations using the RMF requires three distinct pieces of information. First, the physical (biological) relationship between ambient ozone concentrations and the growing characteristics of crop types must be known and expressed as a functional relationship. Such relationships are generally known as dose-response functions and in their simplist form relate a measure of crop yield to a given ozone concentration. In their most sophisticated form they are implicit functions of a set of growing characteristics which include not only yield but such things as insecticide and fungicide retention and a host of causal variables which include all relevant pollutants, indexes of insect infestation, moisture availability, pathogen concentrations, etc..[1]

The second piece of required information is a characterization of the cost structure of agricultural production. Since resources are limited the welfare of society increases when the same level of a particular output can be produced with a decreased level of resources. If these resources exchange in regular markets then a measure of the resource costs of production necessary to supply a given level at output will permit us to measure resource savings.[2] If resource savings are to be appropriately measured at the firm level one must capture the value of all resources purchased in the market by the firm and then these resources must be aggregated to scalar value. Finally, the value of the resources required to produce an additional unit of output must be derived. This per unit resource cost is termed the marginal cost of production and when expressed as function of output becomes the output supply function of a perfectly competitive firm. As we shall demonstrate, the supply function provides the necessary information on resource savings to estimate social welfare gains.

The final piece of information required by the welfare analysis concerns the demand for agricultural products. Under the restrictive assumptions regarding demand, such as perfectly elastic or inelastic demand relations, explicit knowledge of the demand function is not required. However, if demand has any elasticity greater than zero in absolute value and less than infinity some knowledge of the demand relationship is required for accurate benefit estimation. In this study we will use USDA estimates of demand elasticity. Since these are national estimates they abstract from transportation cost. Indeed our study assumes that transportation cost has a minimal effect on the welfare calculations and we therefore ignore it.

The structure of the RMF is derived from its underlying data base identified as the Firm Enterprise Data System (FEDS). Operated by the U.S. Department of Agriculture, FEDS provides agricultural analysts with sample operating budgets which describe the entire cost structure for producing an acre of a particular crop in a specific region of the continental U.S.. The budget is representative of the average agricultural practice in that specific region and is verified with a battery of farm level surveys every two years. A single budget for the production of soybeans in southeastern North Carolina, for example, may include cost information on as many as 200 inputs to agricultural production, the average yield per acre to be expected and the total number of acres planted in the region. The FEDS divides the U.S. into over 200 producing areas; thus when we examine the cost of producing wheat, for example, we will be considering the variation in production cost for over 160 wheat producing areas of the U.S.. This extremely fine disaggregation of the cost structure of production by region and crop is one of the major strengths of the RMF since it will permit calculation of benefits for each region. These regional benefit calculations will not be subject to regional aggregation biases and can permit a detailed analysis of how the social welfare gains will be regionally distributed.

For each of the FEDS producing areas we assume that the FEDS budget for a particular crop type represents both the cost and yield existing for that budget year, for given prices of inputs, outputs, and ambient ozone concentrations. Since the FEDS budgets are on a per acre basis we assume constant returns to scale in order to aggregate across all of the planted acres covered by a single budget. Further, we assume in the analysis that input prices do not change in reaction to a change in ozone concentrations.

With these assumptions in place the construction of aggregate supply functions for particular crops is straightforward. First, given constant returns to scale marginal cost is equal to average cost and equal to a constant. For a particular crop/region budget we divide the total cost of producing an acre of the crop by the yield per acre and thus generate an estimate of the marginal cost per crop unit. Repeating this calculation for all regions producing the same crop produces an array of marginal costs of production across the entire continental U.S.. When the marginal cost of production in each region is mapped against the output of that region we have a region specific supply curve for each crop. Ranking these regional supply curves by marginal cost from lowest to highest and then aggregating across regions yields the aggregate supply function for the specific crop. This aggregation produces a stepped supply curve such as that depicted in Figure 5-2.

Consider for a moment Figure 5-2. Output level Q_4 represents the total quantity of crop Q produced by regions A through D. Region A is the lowest cost producer with a marginal cost of MC^A and a production rate of Q_1. Region B is the next least cost producer with a marginal cost of MC^B and an output rate of $Q_2 - Q_1$. The integral of the marginal cost function from 0 to Q_4 is the total cost of producing Q_4. If the yield per acre in each region increases, due to say a decline in ozone concentrations, then the step function shifts downward as illustrated by the dashed function in Figure 5-1. Once again the integral of the dashed function from 0 - Q_4 is the total cost of producing Q_4. The difference between these two integrals is the saving in resources occasioned by the reduction in ozone concentrations. The actual resource saving calculations made by the RMF are somewhat more complex than this simple description conveys but the technique is essentially the same.

5.3. ANALYTICS OF THE REGIONAL MODEL FARM AND WELFARE CALCULATIONS

Analytics

The most straightforward way to think of the RMF is in terms of a Leontief production function for each region/crop combination. The Leontief production function is given below.

$$Q = \min(x_1/a_1,\ x_2/a_2,\ \ldots,\ x_n/a_n) \tag{5}$$

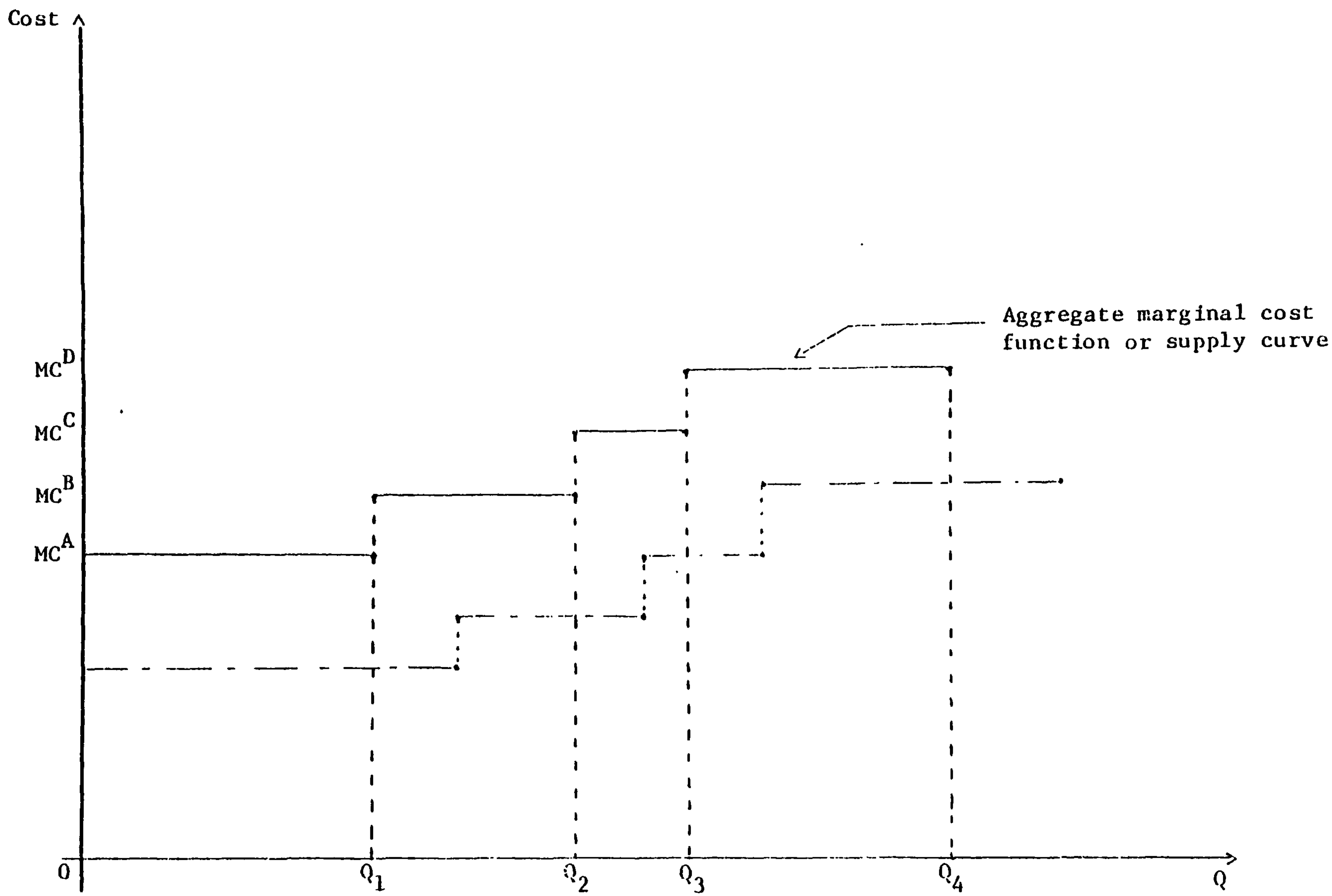


Figure 5-2. Aggregate supply curve for regions A, B, C, D for crop Q.

where: x_i are the physical quantities of the n factors of production

a_i are technological constants conditioned on a set of variables (e.g., climatic conditions, soil characteristics, ozone concentrations, etc.)

Q is the output rate of a single crop in a single area

The objective of our analysis is to derive the marginal cost function associated with this production function. Assuming the economic agents controlling production seek to minimize cost, they face the following optimization problem which specifies the minimum cost of producing Q subject to the Leontief technology.

$$\text{min:} \quad \sum_i P_i x_i \tag{6}$$

$$\text{ST:} \quad Q = \min(x_1/a_1,\ x_2/a_2,\ \ldots,\ x_n/a_n)$$

The solution to the above problem implies

$$x_1/a_1 = x_2/a_2 = \ldots = x_n/a_n = Q \tag{7}$$

The optimal factor demands then are

$$x_i = a_i Q \tag{8}$$

Inserting the optimal demands in the objective function leads to the cost function below.

$$C = Q(\sum_i P_i a_i) \tag{9}$$

Differentiating (9) with respect to output leads to the marginal cost function

$$MC = \partial/\partial Q = \sum_i P_i a_i \tag{10}$$

The graphs of Equations 9 and 10 are displayed as Figures 5-3 and 5-4.

For any particular producing region in FEDS there is an upper bound on acreage planted, thus one of the factor inputs is constrained by an upper limit. The competitive profit maximizing farm operator confronted by a land constraint will first attempt to obtain the maximum output possible from the limited amount of land available and choose combinations of factor inputs in such a fashion that the cost of producing the maximum output is minimized. We can examine these sequential decisions in a two stage optimization framework. Let us first assume that all inputs have upper bounds, then we first seek to maximize output subject to these constraints.

$$\text{max:} \quad Q = \min(x_1/a_1,\ x_2/a_2,\ \ldots,\ x_n/a_n) \tag{11}$$

$$\text{ST:} \quad x_i \leq \bar{x}_i$$

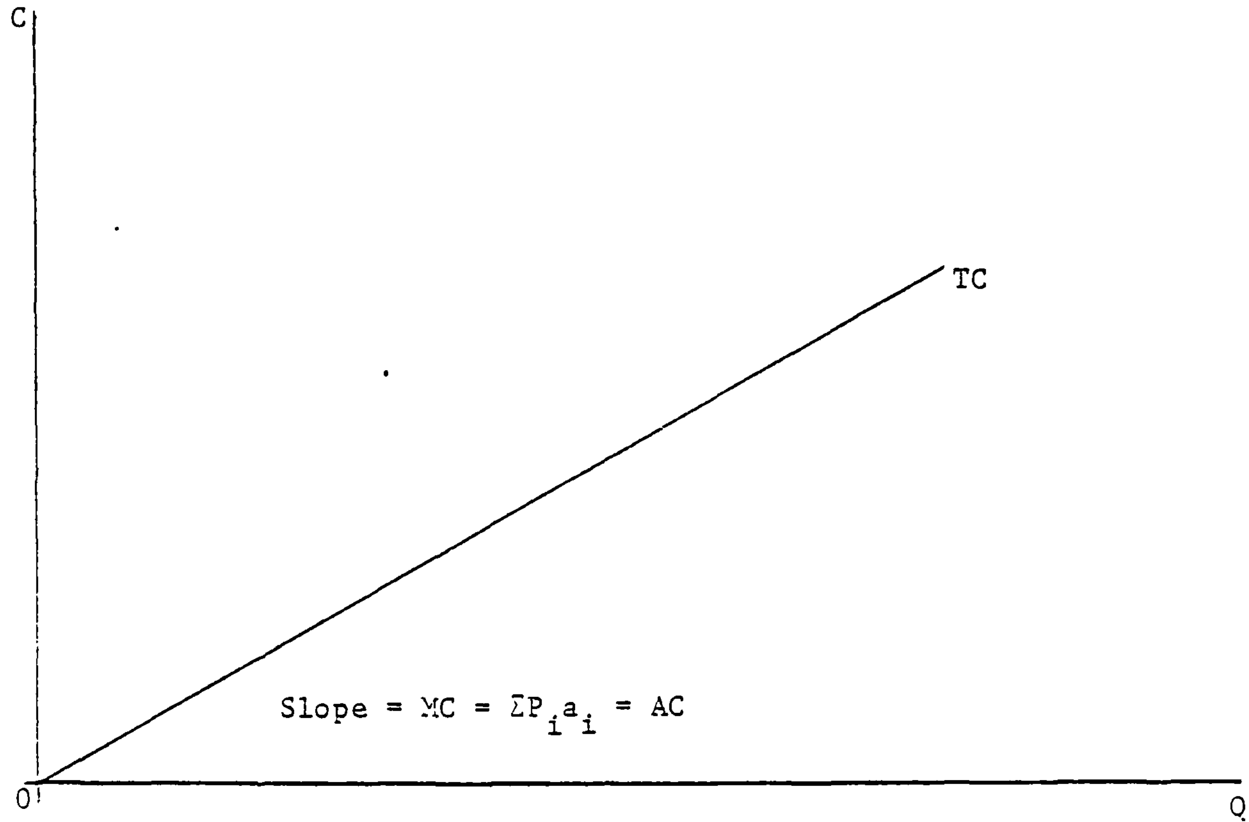


Figure 5-3. Total cost function.

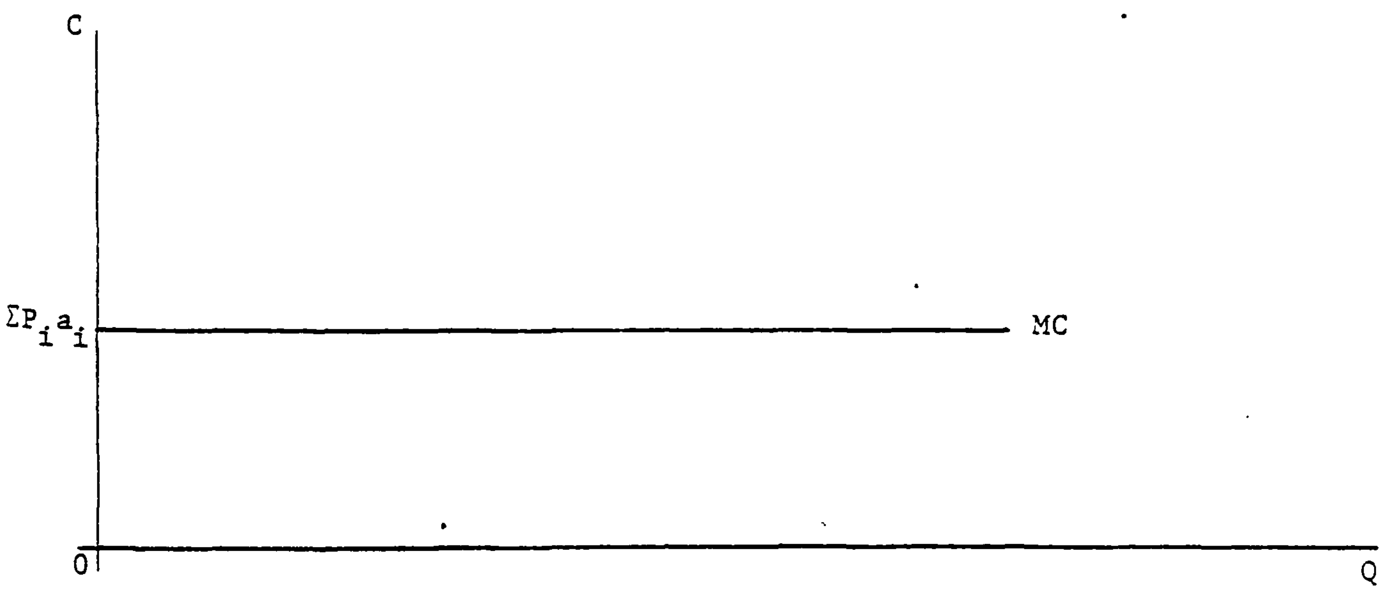


Figure 5-4. Marginal cost function.

where: the upper bounds on the n inputs are denoted by $\overline{x}_i$.

The solution to this problem yields a max Q^* equal to the smallest $\overline{x}_i/a_i$. We next minimize the cost of producing Q^*.

$$\min: \quad \sum_i P_i x_i \tag{12}$$

$$ST: \quad Q^* = \min(x_1/a_1,\ x_2/a_2,\ \ldots,\ x_n/a_n)$$

The optimal factor demands are

$$x_i^* = a_i Q^* \tag{13}$$

Then the dual cost function is

$$C = \begin{cases} Q(\sum_i P_i a_i) & \text{iff} \quad Q \leq Q^* \\ \infty & \text{otherwise} \end{cases} \tag{14}$$

and the associated marginal cost function is

$$MC = \begin{cases} \sum P_i a_i & \text{iff} \quad Q \leq Q^* \\ \infty & \text{otherwise} \end{cases} \tag{15}$$

The graphs of Equations 14 and 15 are displayed as Figures 5-5 and 5-6.

In the realistic case of agricultural production land is the only input subject to binding constraints. If we denote land as x_s and its maximum upper bound by $\overline{x}_s$, then from optimization problem (11) maximum output is equal to

$$Q^* = \overline{x}_s/a_s \tag{16}$$

and the factor demands are

$$x_i^* = a_i Q^* = a_i(\overline{x}/a_s) \tag{17}$$

The shapes of the total cost and marginal cost functions in case of a single constrained input will appear as Figures 5-5 and 5-6 respectively.

Next let us assume that a change in the set of conditioning variables occurs, due to say a decrease in ambient ozone concentrations. This change in ozone has the effect of increasing the productivity of some or all inputs to the production activity. Analytically, this is captured by a reduction in the technology constants a_i. For the present, let us assume that the productivity of all inputs is enhanced equally. We represent this enhancement by a term such that

$$\hat{a}_i = \delta a_i, \text{ for all } i, \text{ where } 0 \leq \delta \leq 1 \tag{18}$$

Using the results contained in (16) and (17) we now have

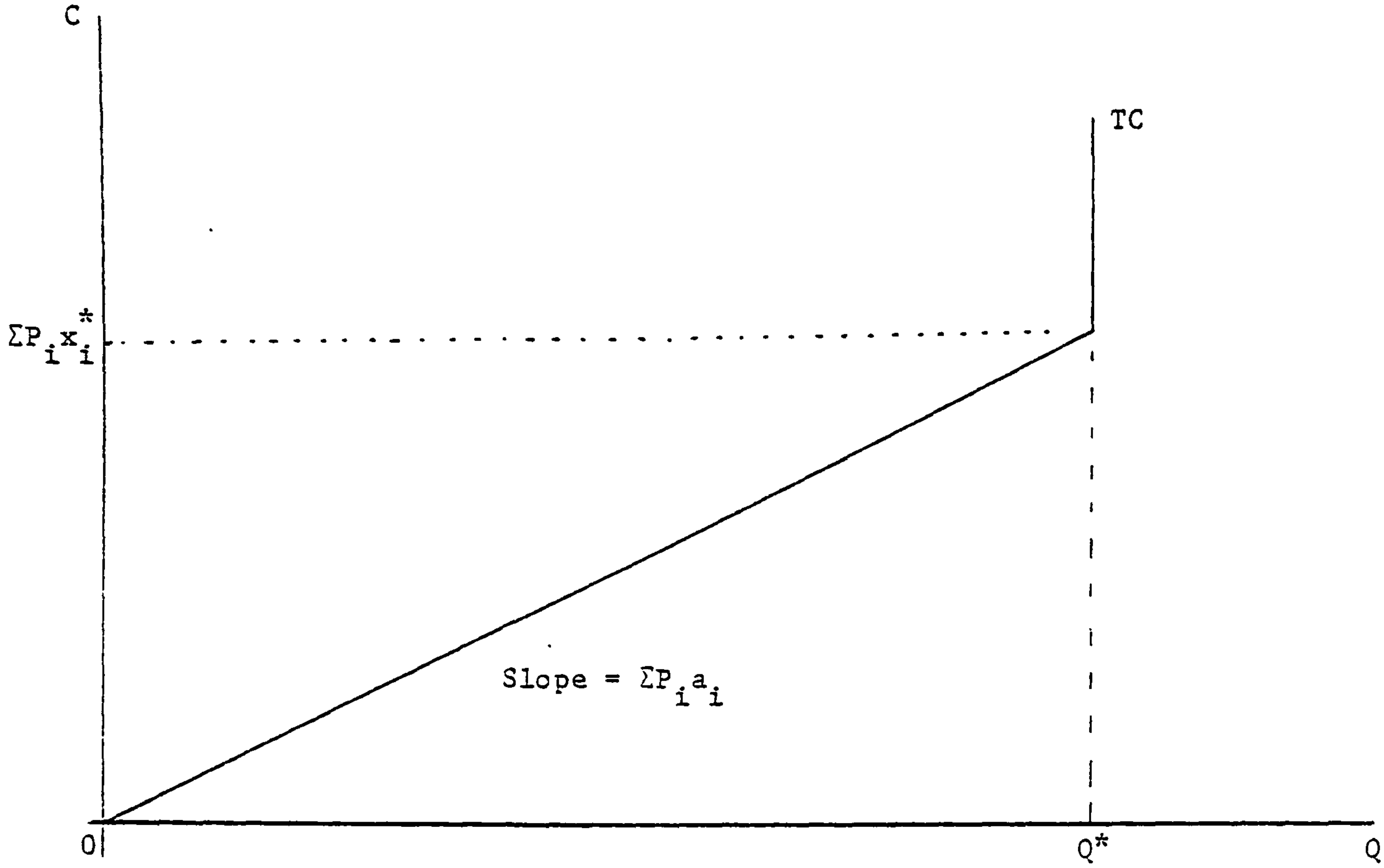


Figure 5-5. Total cost function.

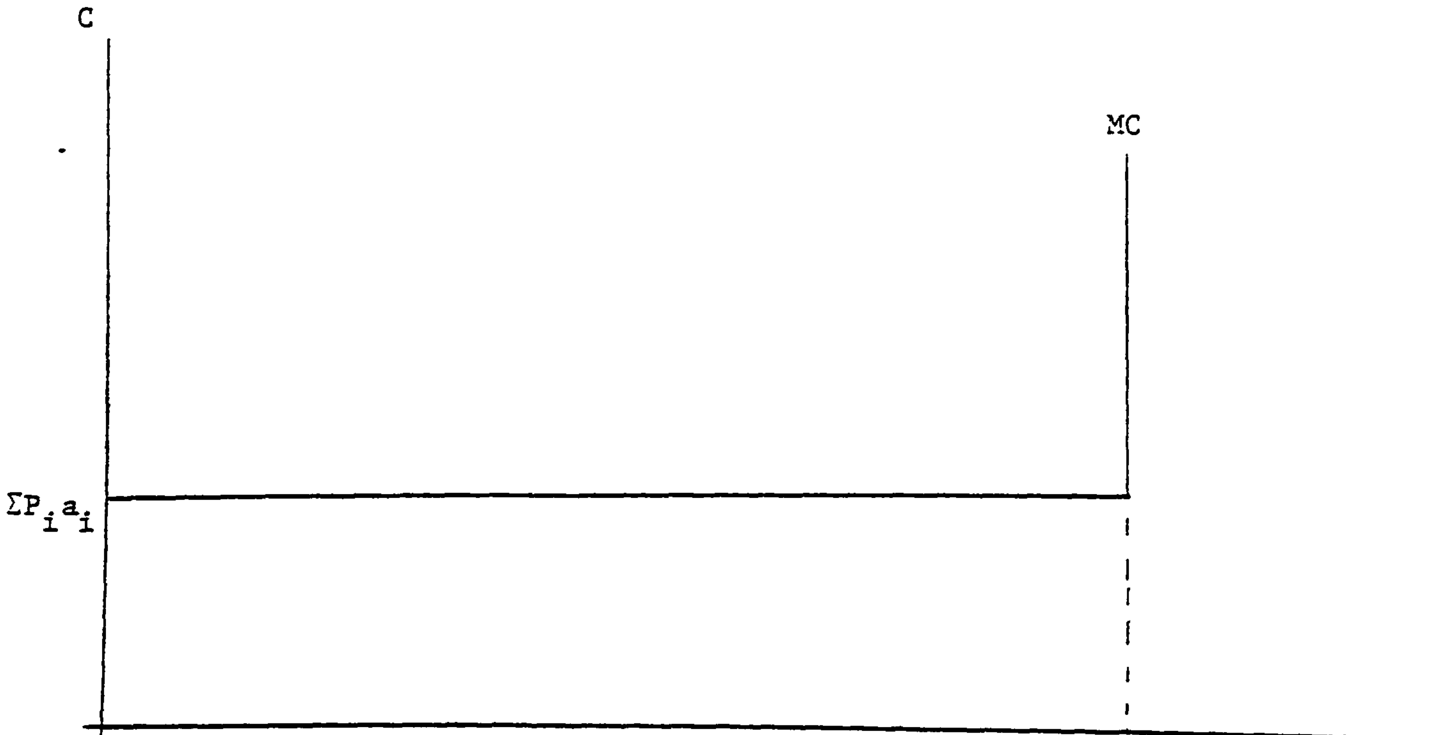


Figure 5-6. Marginal cost function.

$$\text{maximum} \quad Q = \hat{Q} = \overline{x}_s/\delta a_s \tag{19}$$

$$\text{optimal factor demands } \hat{x}_i = \hat{a}_i\hat{Q} = \hat{a}_i(\overline{x}_s/\delta a_s) \tag{20}$$

Since

$$\hat{Q} = (1/\delta)Q^* \Rightarrow \hat{x}_i = x_i^* \tag{21}$$

total cost of producing the larger output ($\hat{Q} \geq Q^*$) is identical to the cost of producing Q^*. The graphs of the total cost and marginal cost functions before and after a change in conditioning variables are given by Figures 5-7 and 5-8 respectively. Recalling from the previous section, the resource saving resulting from the hypothesized decrease in ozone concentrations is equal to[3]

$$\Delta W = \int_0^{Q^*} MC^*(Q) - \int_0^{Q^*} \hat{MC}(Q) \tag{22}$$

In the analysis above we made the simplifying assumption that the productivity of all preharvest inputs will be affected equally by a change in ozone concentrations. Certainly this is not the case for harvest inputs. If declines in ozone concentrations increase yields per acre it is difficult to see how harvest costs per acre would not rise. Thus preharvest cost per bushel can fall while harvest cost per bushel remains unaffected.

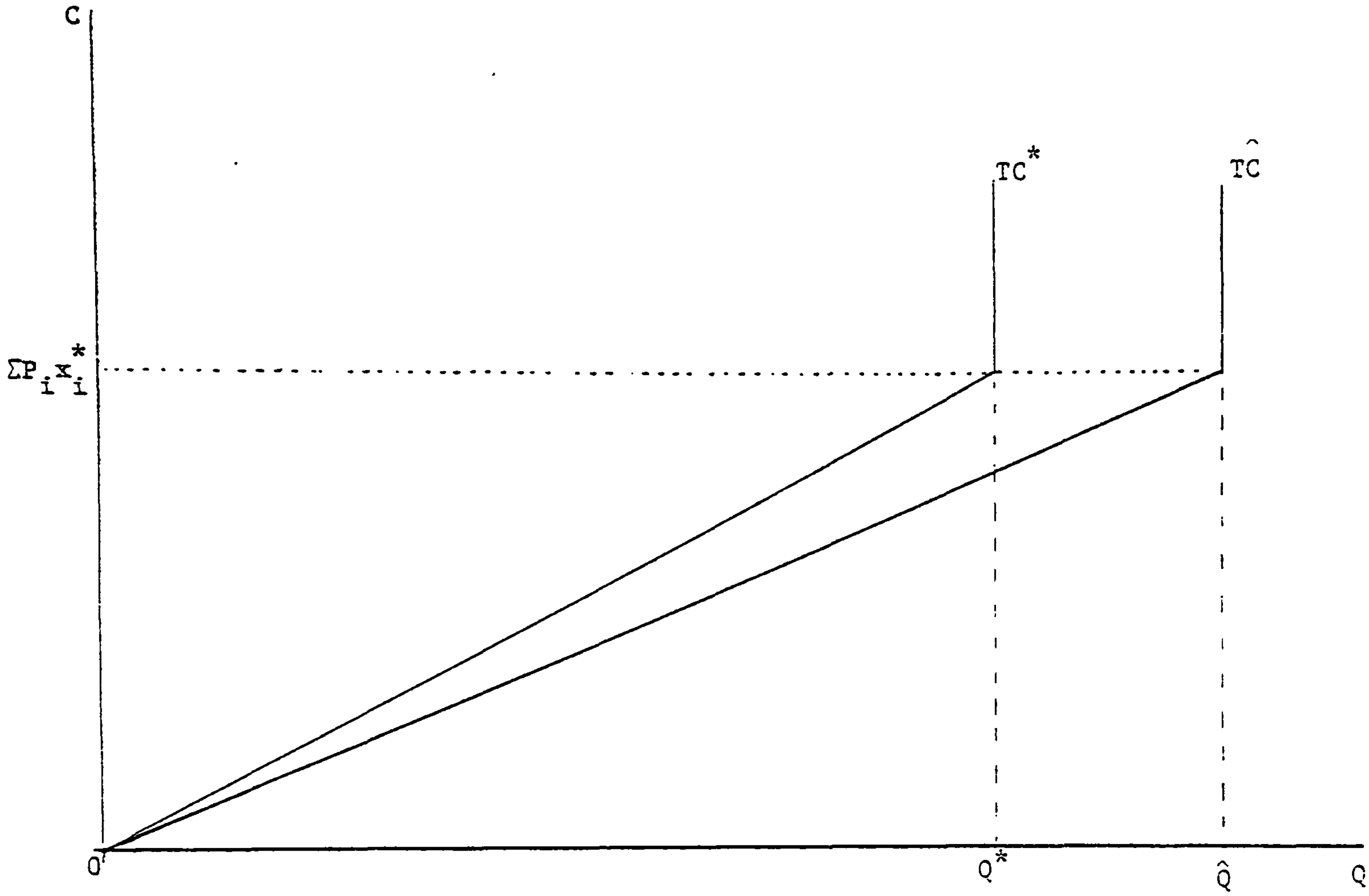


Figure 5-7. Total cost function.

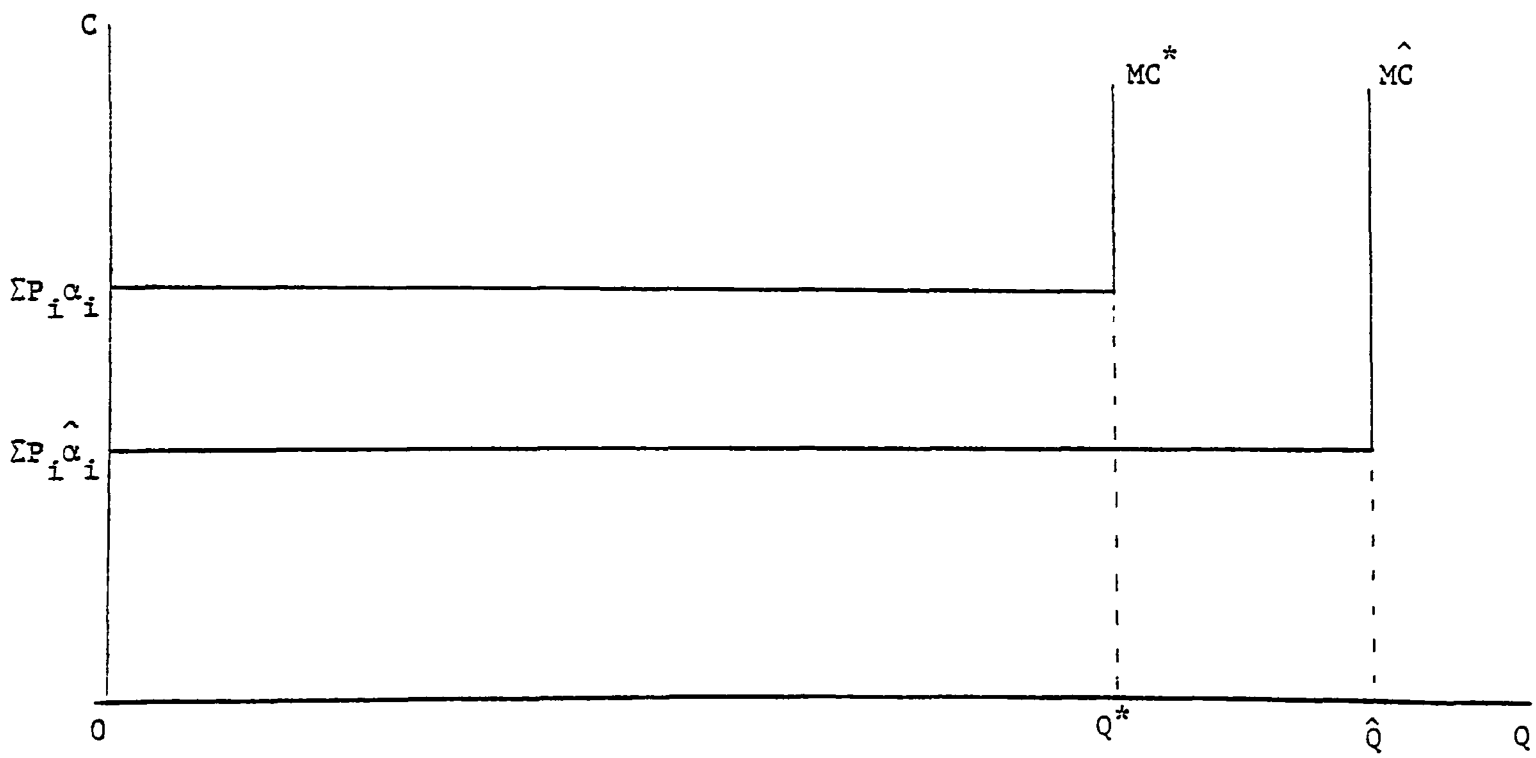


Figure 5-8. Marginal cost function.

Let us assume that the change in conditioning variables (ozone concentrations) affects only a single input x_r, where input x_s is still the constrained input.

Let maximum output from (16) be

$$Q^* = \min(x_1/a_1,\ x_2/a_2,\ \ldots,\ x_n/a_n) = \overline{x}_s/a_s \tag{23}$$

Then, given the stated conditions above, max output $\hat{\hat{Q}}$ will vary depending on the relation between x_r and x_s and the value of δ. These variations are displayed below.

$$\text{If } r = s \quad \text{then} \quad \hat{\hat{Q}} = \overline{x}_r/\delta a_r = \hat{Q} \tag{24}$$

In this case the constrained input is the same input experiencing the productivity increase, thus the new output level $\hat{\hat{Q}}$ will be the same output level as that attained if all inputs experienced an equal productivity increase. However, we will see later that the structure of cost will be different.

$$\text{If } r \neq s \quad \text{then} \quad \hat{\hat{Q}} = \overline{x}_s/a_s = Q^* \tag{25}$$

In this instance the productivity of the constrained input is not affected by the ozone change thus no increase in agricultural output will be forthcoming; however, costs of production will be lessened due to the enhanced productivity of x_r.

$$\text{If } \delta = 1 \quad \text{then} \quad \hat{\hat{Q}} = \overline{x}_s/a_s = Q^* \tag{26}$$

Naturally if there is no productivity enhancement for any of the productive factors output remains unchanged.

To examine the cost of production we must now consider the optimal factor demands under each output scenario (24)-(26). Under (24) we have

$$\text{optimal demands} \quad \hat{\hat{x}}_i = a_i\hat{Q} \quad \text{for } i \neq r,s \tag{27}$$

$$\hat{\hat{x}}_r = \delta a_r\hat{Q} \quad \text{for } r = s \tag{28}$$

which implies that total cost is equal to

$$TC = \Sigma P_i(a_i\hat{Q}) + P_r(\delta a_r\hat{Q}) \tag{29}$$

$$i \neq r,\ s$$

In this scenario the maximum output obtainable is the same as that which would result if the productivity of all inputs was enhanced as in the case in Equation 20. However the cost given by (29) exceeds that calculated from (20) since all inputs x_i, $i \neq r,s$ are unaffected by productivity enhancement. Graphically, the total cost function derived from (20) is plotted on Figure 5-9 and labeled TC(20) while the total cost function for (29) is plotted and labeled TC(29).

Let us now examine scenario (25) where the productivity enhancement does not affect the constrained input. In this case output does not expand beyond Q* and the optimal demands are

$$\hat{\hat{x}}_i = a_i Q^* \quad \text{for } i \neq r \tag{30}$$

$$\hat{\hat{x}}_r = \delta a_r Q^* \quad \text{for } r \neq s \tag{31}$$

which implies that the total cost is equal to

$$TC = \sum_{i \neq r} P_i(a_i Q^*) + P_r(\delta a_r Q^*) \tag{32}$$

The total cost function is plotted on Figure 5-9 and labeled TC(32).

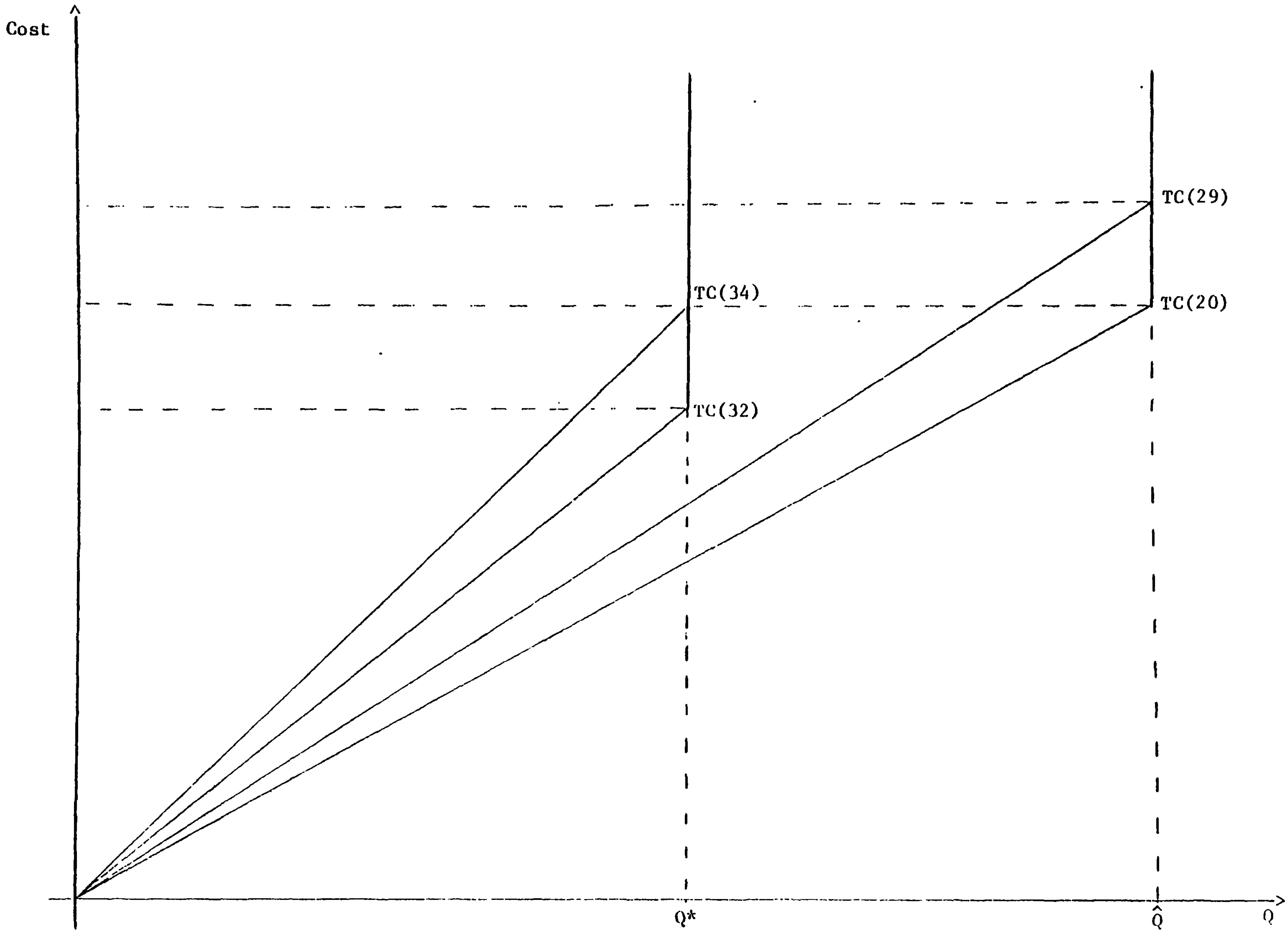
Finally, if we consider scenario (26) where no productivity enhancement takes place then output does not increase beyond Q* and the optimal factor demands are

$$\hat{\hat{x}}_i = a_i Q^* \quad \textit{for all } i \tag{33}$$

and therefore the implied total cost function is

$$TC = \Sigma P_i(a_i Q^*) \tag{34}$$

and is graphed on Figure 5-9 and labeled TC(34).


Cost
TC(29)
TC(34)
TC(20)
TC(32)
Q*
Q̂
Q

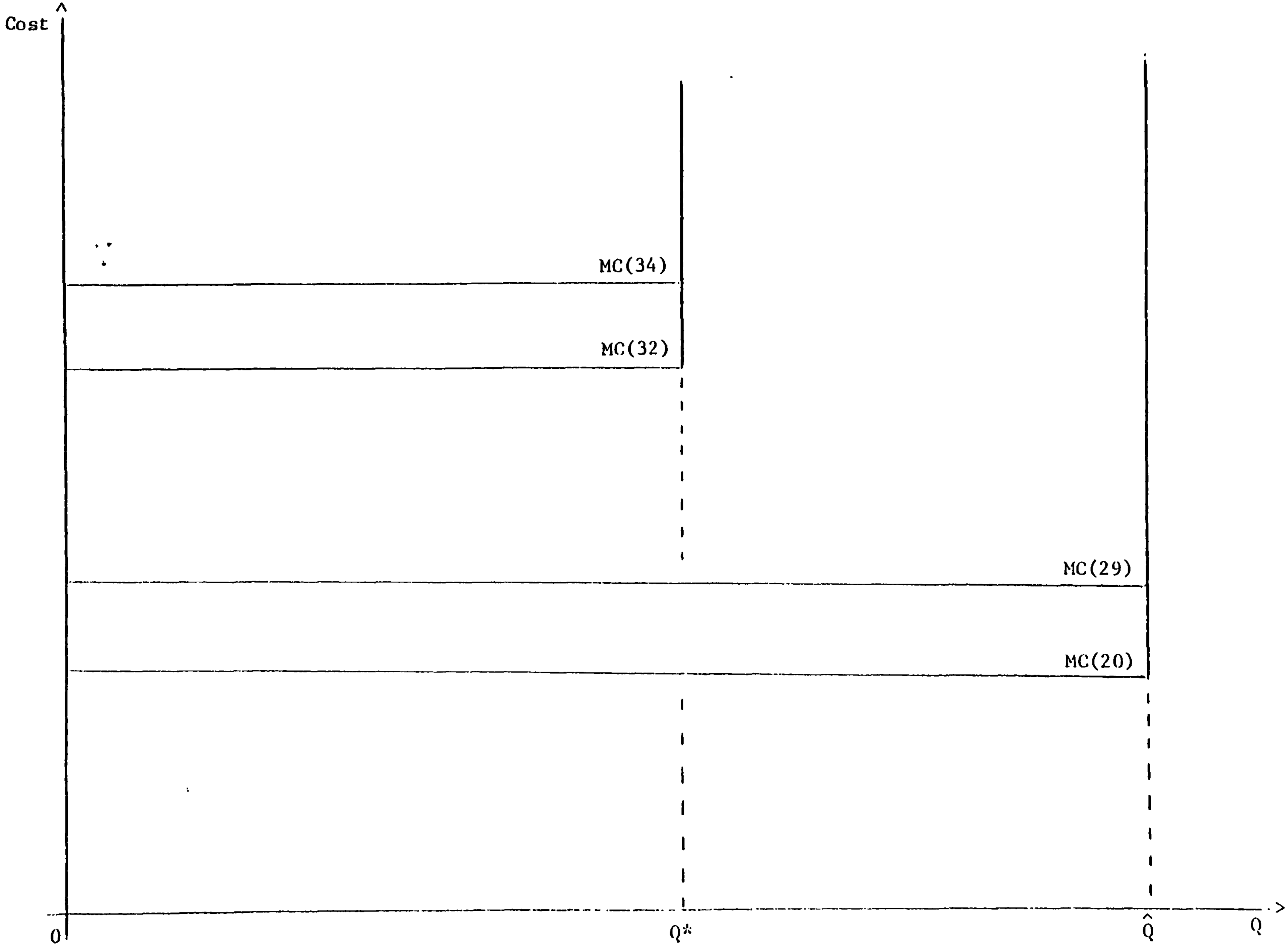


Figure 5-10. Marginal cost functions under alternative scenarios regarding the differential impact of ozone concentration changes on factors of production

Each marginal cost function corresponding to the four total cost functions are displayed on Figure 5-10 and labeled in a manner analogous to Figure 5-9. Since we will be integrating under these marginal cost functions to obtain welfare estimates, the importance of differential productivity enhancements embodied in the cost curves is fairly important.

It is reasonable to assume that land is a quasi-fixed factor in agriculture (a constraining input in the terminology of our analysis above) and all other inputs freely variable. Thus, we shall be concerned with a model similar to the total and marginal cost functions described by Equations 14 and 15. Further, NCLAN biological evidence suggest that yields are inversely related to ozone concentrations and therefore lower concentrations will elicit higher per acre yields. If we believe that it costs more to harvest a bumper crop than a normal crop then we would be inclined to adopt a model of cost similar to the total cost function (29). In such a model a distinction is made between harvest and nonharvest cost and the productivity of factors allocated to the two categories is permitted to be differentially impacted by changes in ambient ozone concentrations. This dichotomized cost model forms the basis for the RMF welfare calculations.

5.4. WELFARE CALCULATIONS

Before we discuss the specifics of the RMF welfare calculations we briefly review the interplay between production supply and consumer demand functions in the calculation of welfare changes. As we have previously stated the aggregate supply functions derived from the RMF will be upward sloping step functions. For ease of exposition let us consider them linear functions with positive slopes. In this instance all we will be concerned with is the elasticity of linear demand functions. Perfectly elastic demand functions will not be considered since the assumption is totally untenable given the huge inventory of unsold agricultural products that currently exists.

In the case of perfectly inelastic demand welfare estimates are based only on the resource cost savings obtained in production. Thus, the impact of governmental price support programs will not affect these welfare calculations. When a less than perfectly inelastic demand is assumed an unknown effect may be present.

We first consider a perfectly inelastic demand relation as depicted in Figure 5-11. Before a reduction in ozone the producer supply curve is given by S_0 and the market clearing price is P_0. Consumer surplus is the infinite area E and producer surplus is the area C + D. After a reduction in ozone the producer supply curve shifts to S_1 and market price falls to P_1. Consumer surplus now expands to E + D + B and producer surplus is C + A. The net gain in consumer and producer surplus is therefore A + B which is equal to the resource savings concept discussed previously.

If we now consider a demand function which is not perfectly inelastic such as that depicted in Figure 5-12 the benefit calculation is somewhat different. Before the ozone change the producer supply curve is S_0, market price is P_0, quantity demanded and supplied is Q_0, consumer surplus is E and producer surplus is D + C. After a reduction in ozone the producer supply curve shifts to S_1, market price falls to P_1, quantity expands to Q_1, consumer surplus is E + D + B + F and the producer surplus is equal to C + A + G. The net gain in consumer and producer surplus is A + B + F + G where A + B is the resources savings and G + F is the value of the difference between

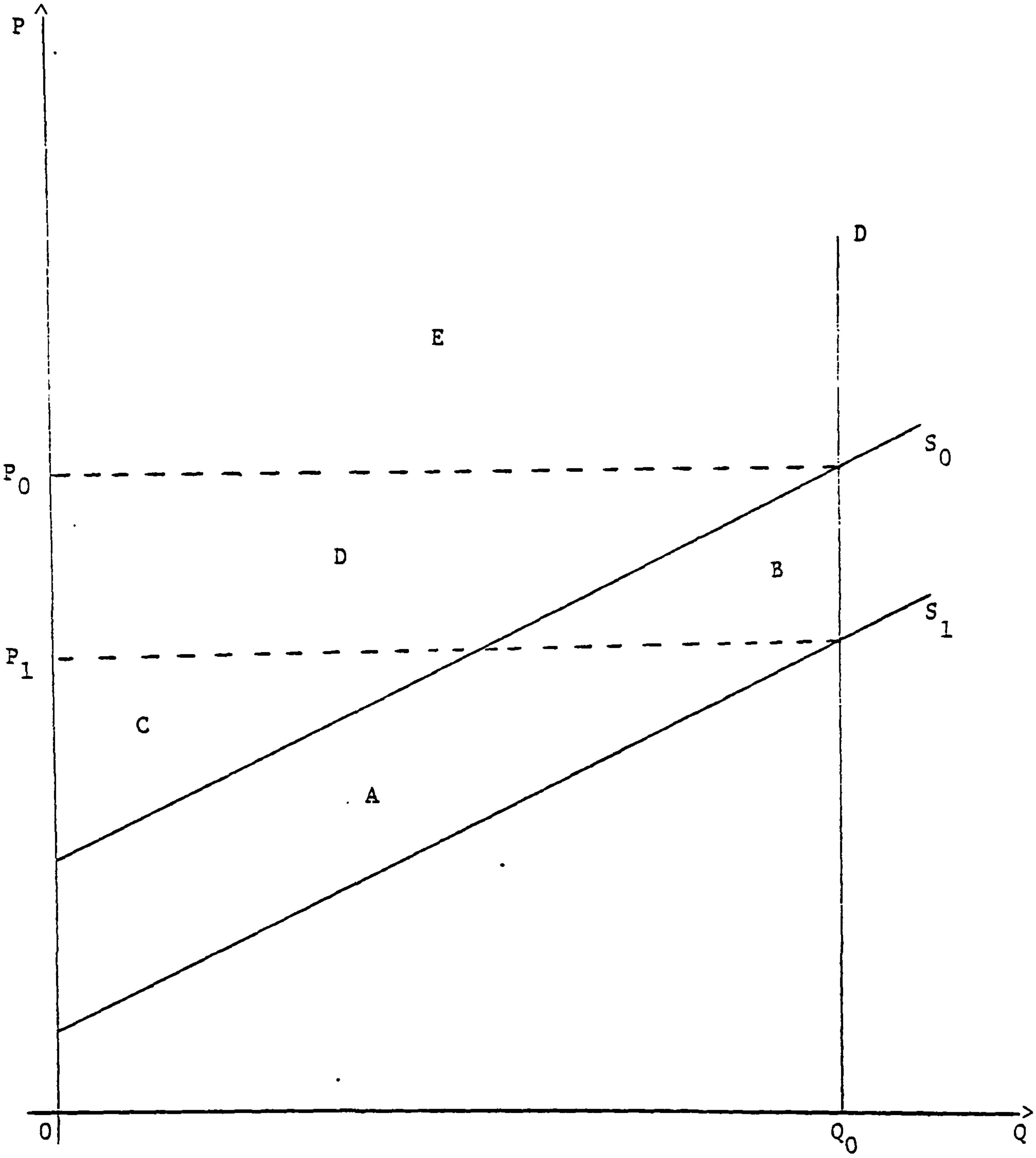


Figure 5-11. Perfectly inelastic demand.

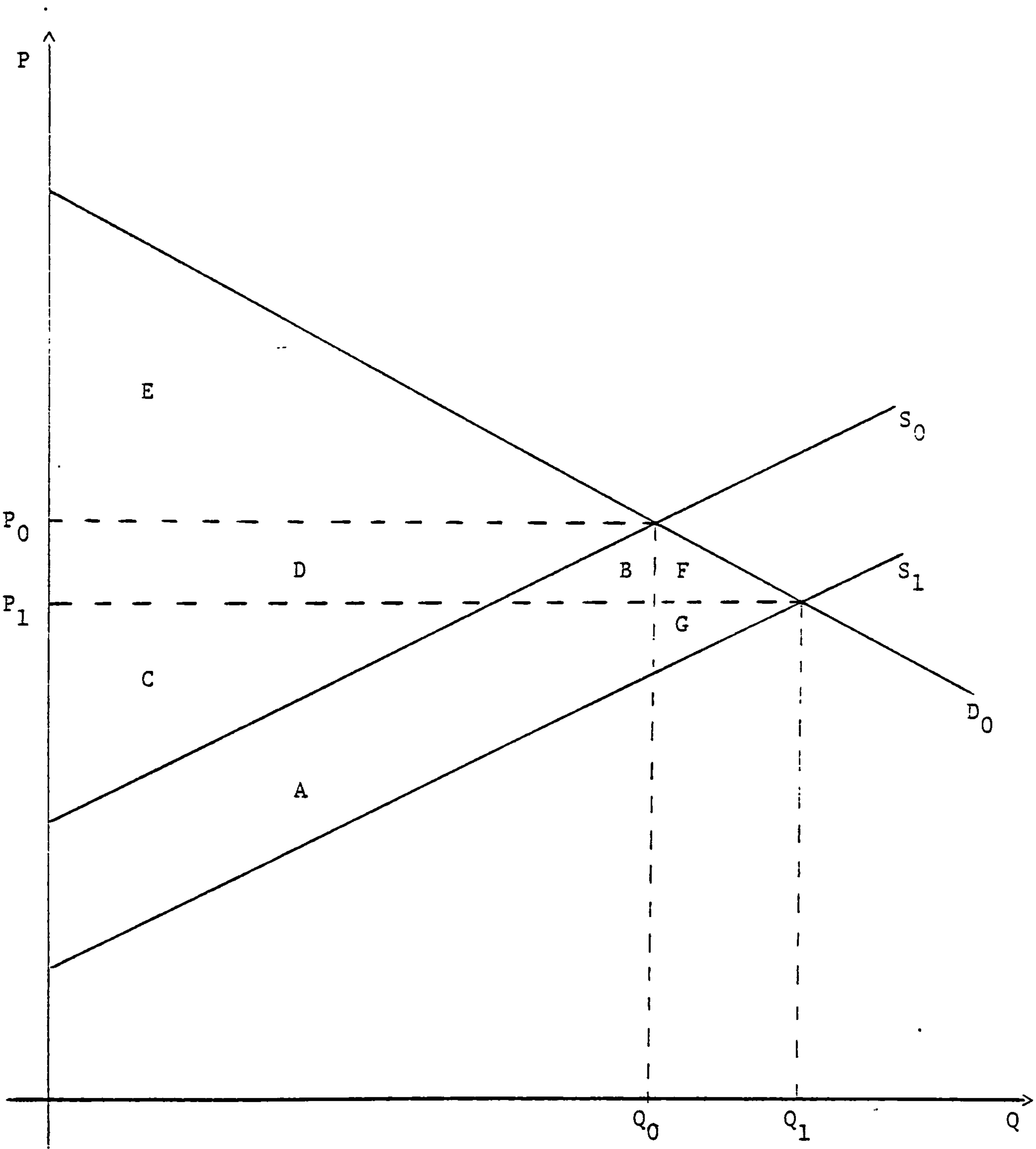


Figure 5-12. Demand Not perfectly inelastic.

the marginal benefit of consumption and the marginal cost of production for the extra quantity $Q_1 - Q_0$. While A + B + G + F is the total welfare gain the division of this gain between consumers and producers is dependent upon the elasticities of supply and demand.

The difference between the two welfare calculations described above is the area G + F. The more elastic the demand curve the greater this area. Without explicit knowledge of regional demand functions by crop and by region directly calculating the area G + F is impossible. To ascertain the potential magnitude of G + F we intend to construct a linear demand curve for a particular crop and assign it alternative arc elasticities. We then calculate the area G + F under these elasticity alternatives as part of a benefit calculation sensitivity study.

5.5. OPERATIONALIZING THE WELFARE CALCULATION

We describe below the steps necessary to perform the actual welfare calculations. Bear in mind the NCLAN experimental work provides the basis for the biological dose-response functions, the FEDS provides the cost structure of the RMF and assumptions regarding demand elasticity are employed to calculate the value of additional output.

The first step in the process is to determine the intersection of crop types for which NCLAN dose-response functions and FEDS budgets exist. At the time the research described in the report was being conducted NCLAN had published a limited number of dose-response functions. For the most part these functions were linear or quadratic and in our opinion required further refinement. The decision was made to employ published NCLAN experimental results and reestimate the dose-response equations using a flexible functional specification. The published data limited our efforts to five crops: soybeans, corn, wheat, cotton and peanuts; thus, the majority of the discussions in this report concerns these five crops and is based upon the dose-response equations estimated by the authors. Recently, NCLAN has published a new set of dose-response equations based upon a flexible functional specification. These new equations are available for the five crops referenced above plus sorghum and barley. In Chapter 9 we examine the impact which these new NCLAN equations have had on the welfare calculations and also supply welfare estimates for sorghum and barley based on these new functions.

We next examine the NCLAN data for a particular crop and define the period over which the dose-response function is calculated (specifics of the actual dose-response function estimation are contained in Chapter 6). We then proceed to the EPA supplied data base containing county level concentrations of ozone for the year 1978. For each county this data set contains monthly averages of seven hour daily maximums for the months April-October. In the case of soybeans we select the data for July, August and September and average it to a three-month value consistent with the experimental data.

The third step is to select from the FEDS file those budgets for a particular crop, in this present example soybeans. For each budget we determine the counties contained in the budget's region and once again average the three-month county ozone data to the level of the appropriate FEDS area.

The fourth step is to match relevant NCLAN dose-response functions to the appropriate FEDS area. To do this we first map all FEDS areas into the specified NCLAN regions. Then, if there are three dose-response functions for soybeans, each derived from a different NCLAN lab, we apply the individual dose-response functions to those FEDS areas contained in the NCLAN region which developed the function. If a soybean producing area does not lie in a NCLAN region that has a soybean dose-response function we use the function from the geographically closest NCLAN region. Naturally, if we have only one dose-response function it is applied to all producing regions. When multiple dose-response functions exist for alternative crop varietals we employ the method of Frontier Tidwell discussed in Chapter 6, section 6.7.

Once we have identified the appropriate dose-response function we pass to it the area-wide ozone concentration, before any regulatory change in the standard, and calculate the value of the yield variable. Using scenarios supplied by EPA we next pass to the function post regulation values for the area-wide ozone levels and recompute the yield variable. Using the formula below we compute the increase in yield to be expected in the FEDS area.

$$\Delta YIELD = \frac{Y^{*}-Y}{Y} \tag{35}$$

where: Y is the yield before regulatory action

Y* is the yield after regulatory action

Having selected the budgets for a particular crop, we order these budgets by their marginal costs of production and assemble the aggregate supply functions as displayed on Figure 5-2. To calculate the marginal cost of production after the regulated change we recast Equation 35 as below.

$$\delta = 1/(1+ \Delta YIELD) \tag{36}$$

where δ is the same as that employed in the analytical discussions above. After calculating δ, which varies by FEDS area, we are in a position to construct the new aggregate supply function.

To capture the differential impacts of ozone changes on nonharvest and harvest cost we aggregate all factors of production for each region into these two components of total cost and employ the following formula to compute the marginal cost for a specific area.

$$MC = (1/(1+\Delta YIELD))(MARNONHRV) + (1/(1+\gamma\Delta YIELD))(MARHRV) \qquad (37)$$

where: MARNONHRV = marginal nonharvest cost

γ = differential harvest effects $0 \leq \gamma \leq 1$

MARHRV = marginal harvest cost

If $\gamma = 1$ then the productivity of factors of production employed in harvesting is enhanced by an amount equal to the nonharvest factors. If $\gamma = 0$ then harvest factors are unaffected. Varying γ between 0 and 1 allows for a range of impacts.

We are now in a position to calculate the welfare changes under the assumption of perfectly inelastic demand. We first integrate under the preregulation supply function from zero to the aggregate output level contained in the FEDS. We then integrate under the post regulation supply curve from zero again to the FEDS output figure. The difference between the value of these two integrals is the net consumer and producer welfare gains. When the demand elasticity is not equal to zero the calculation is somewhat more complex.

The procedures outlined above are repeated for each of the five crops we shall be considering in this analysis. The sum of the welfare gains for each crop represents the total social welfare gain occasioned by regulatory action.

5.6. CONCLUSION

The regional model farm approach to agricultural benefits estimation is admittedly simplistic. A particular weakness of the RMF is its static nature and therefore its inability to capture the adjustment decisions of farm managers and to present a dynamic perception of agricultural responses to changes in pollutant levels. On the positive side of the ledger the RMF easily incorporates experimental data in a consistent fashion; and most importantly, provides the ability to calculate regional benefits at a high level of resolution. This regional disaggregation of the RMF is depicted on Maps 1-10 where the ten production regions of the RMF are displayed. If we consider for the moment Region 01 "Northeast" we can see that it is composed of some 20 subregions. The total agricultural benefits occurring to the northeast will be sum of the subregion benefits. Thus we will be able to determine, for example, how the benefits will be distributed between upstate New York and Western New York.

Regional distribution of benefits and the associated equity considerations have been highlighted as crucial issues in the latest NCLAN 1981 Annual Report. Since the sensitivity of crop types to ozone varies across crops and since these crops are planted in geographically distinct areas, some farmers will stand to gain more than others if ozone concentrations are reduced.

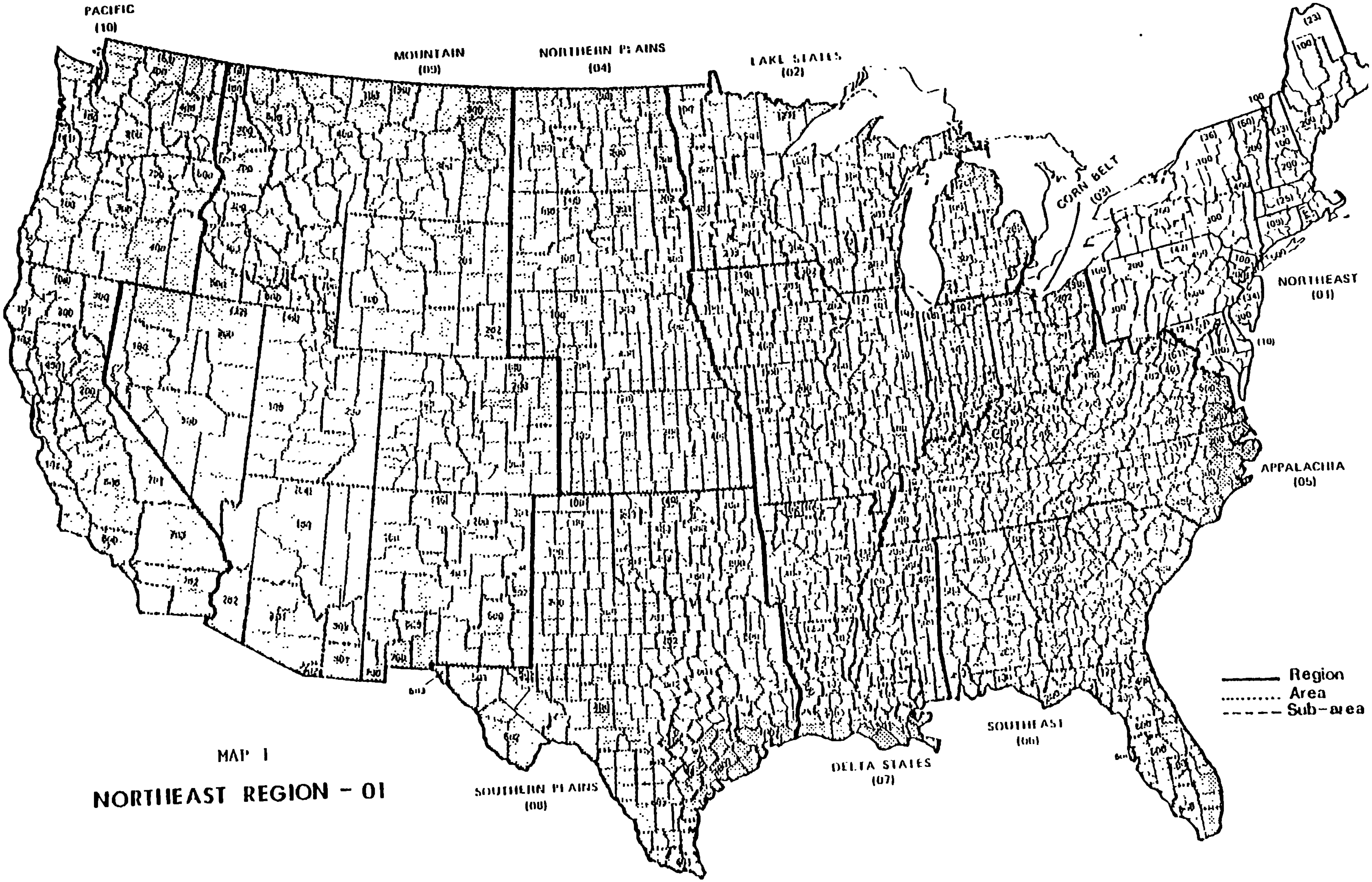
Moreover, even for the same crop grown in a contiguous geographic area, ambient ozone concentrations differ. Even in the unlikely event that a change in the regulatory standard changes ozone concentrations by a constant proportional amount in all areas, the differences in the absolute level will imply different yield effects when the biological dose-response mechanism is nonlinear.

FOOTNOTES FOR CHAPTER 5

1. In personal conversations with Boyce Thompson Institute Staff it has become apparent that a focus on yield alone may not be adequate to characterize effects of environmental pollution. In the case of acid-rain, for example, yield is apparently unaffected but the insecticide retention capability of various plant species is greatly lessened. Given the high cost of insecticide, welfare gains can be expected if acid rain is abated even though yields may not increase.

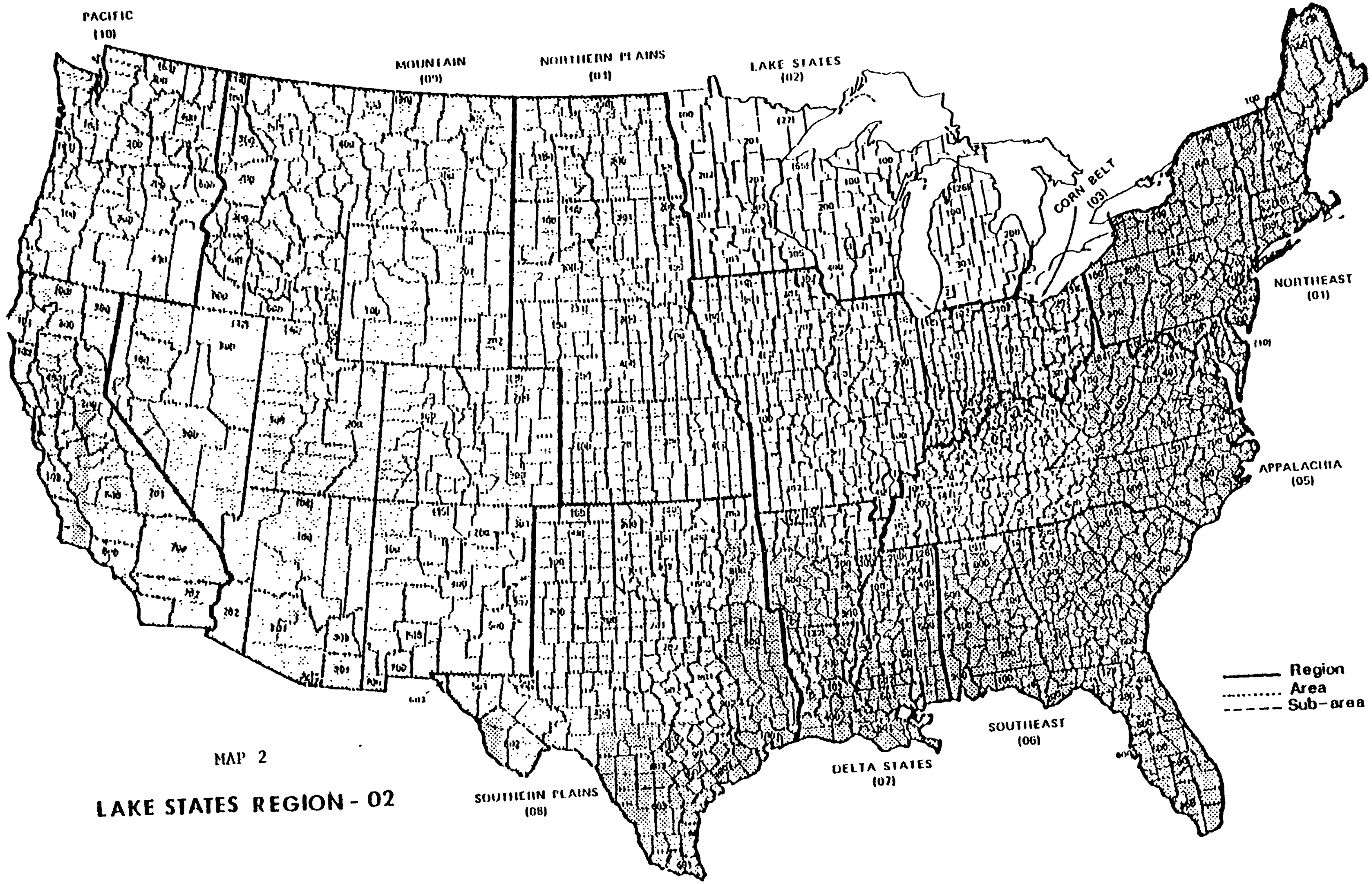
2. The concept of resource savings is analogous to the notion of technical efficiency developed by Farrell (1957) and the coefficient of resource utilization introduced by Debreu (1951).

3. Note the resource savings results from the production of the same quantity Q* with fewer inputs due to the decline in ozone concentrations and thus increase in productivity of factor inputs.



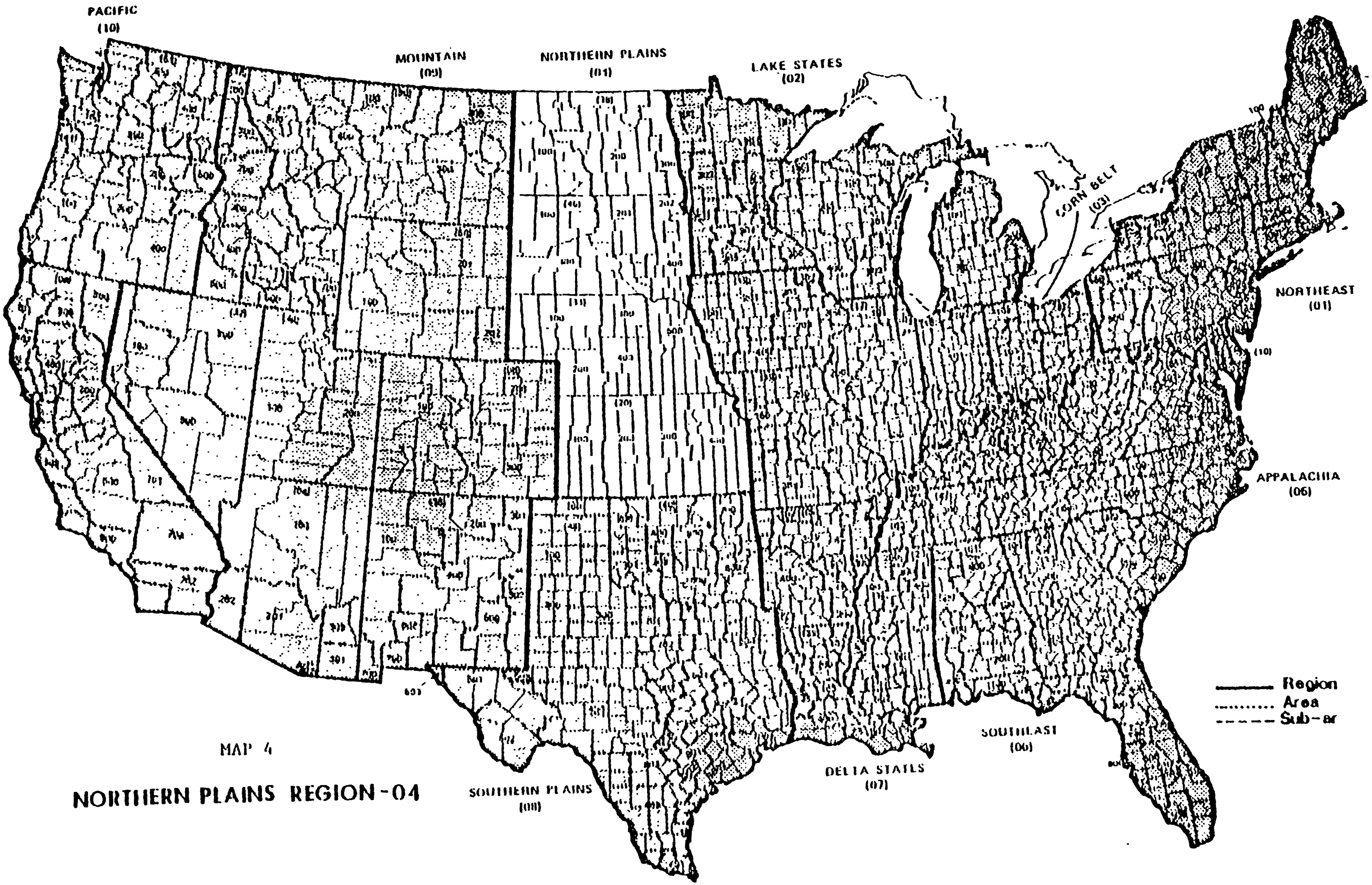
MAP 1

NORTHEAST REGION - 01



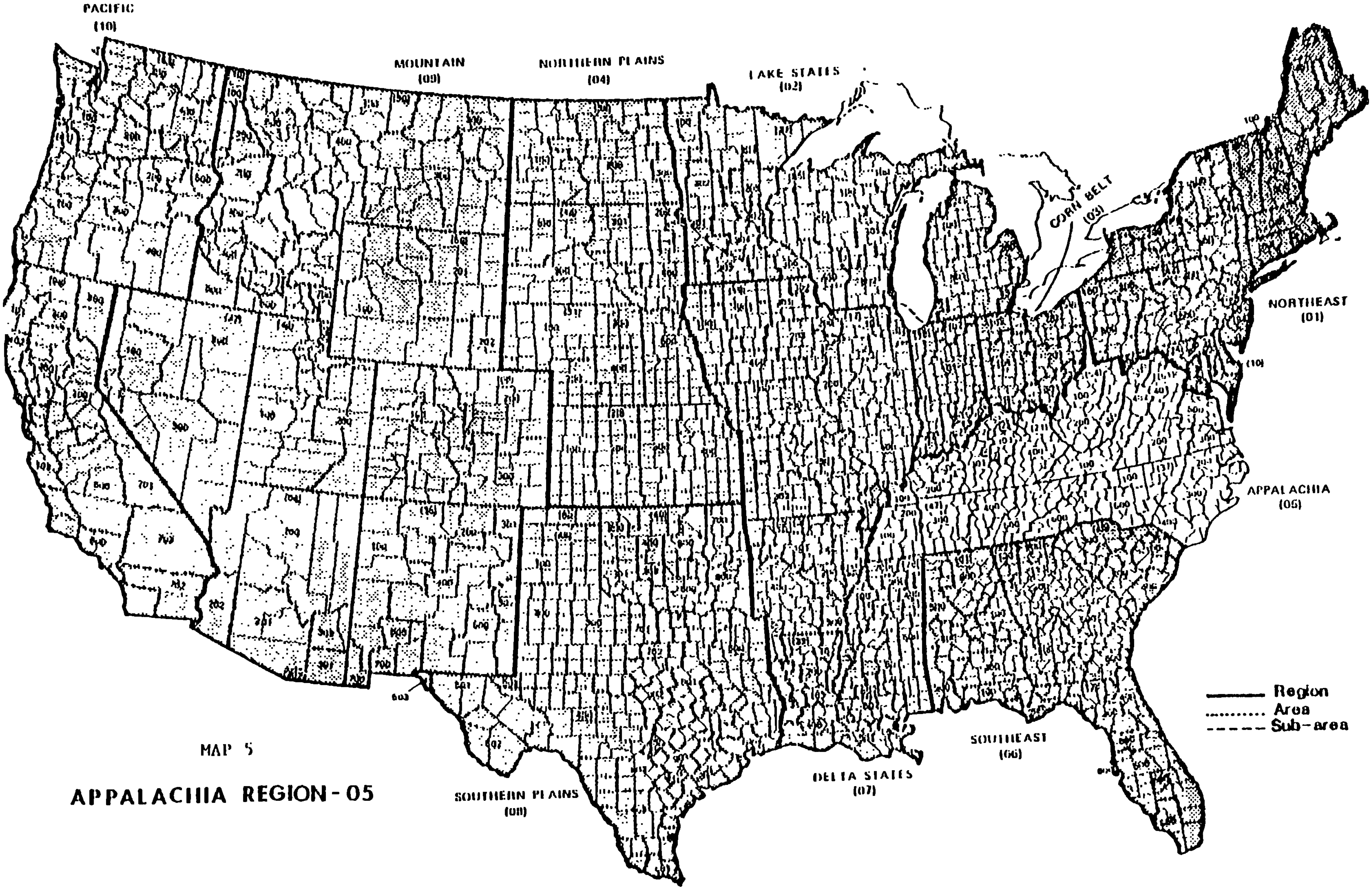
MAP 2

LAKE STATES REGION - 02



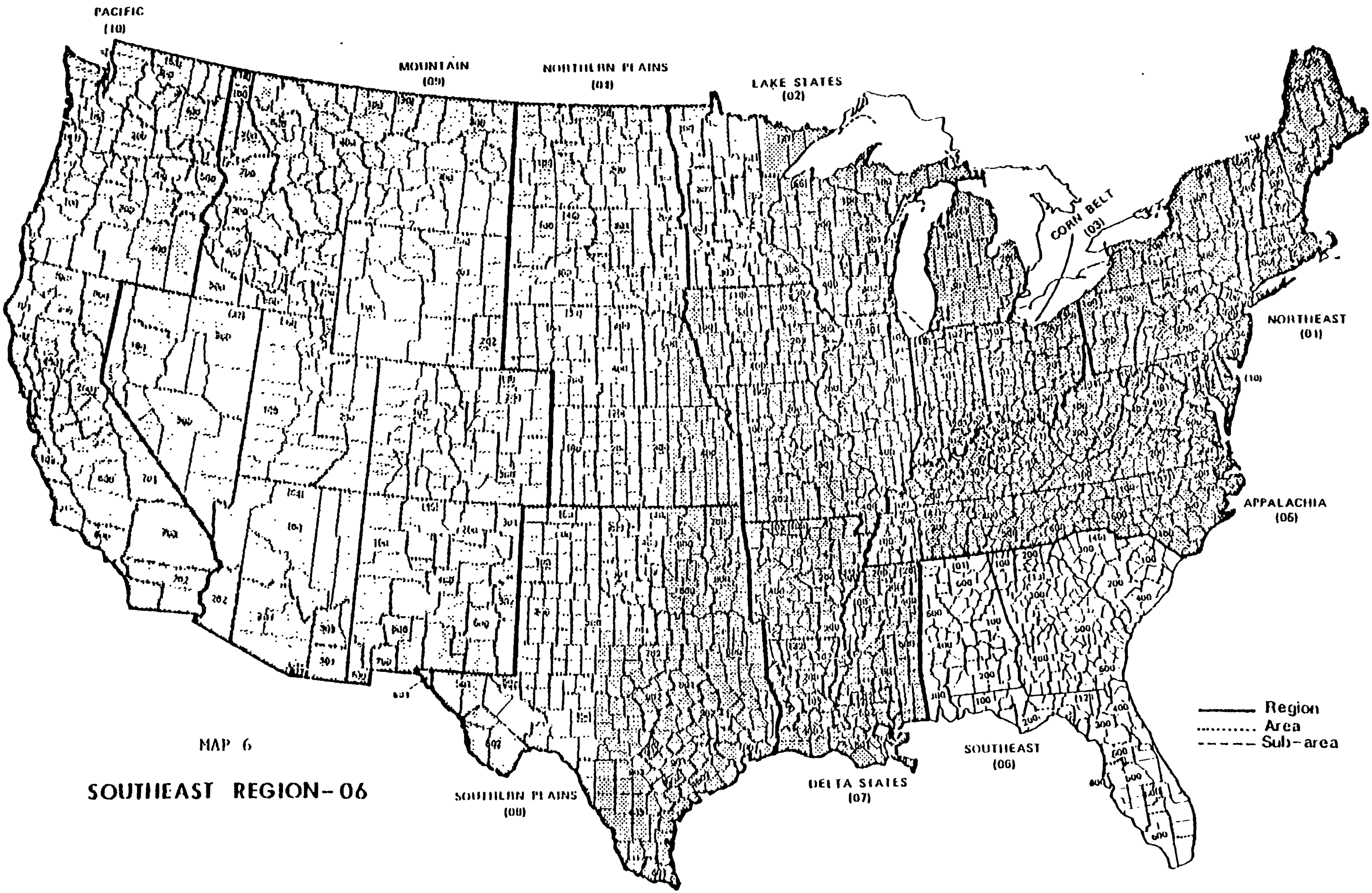
MAP 4

NORTHERN PLAINS REGION-04



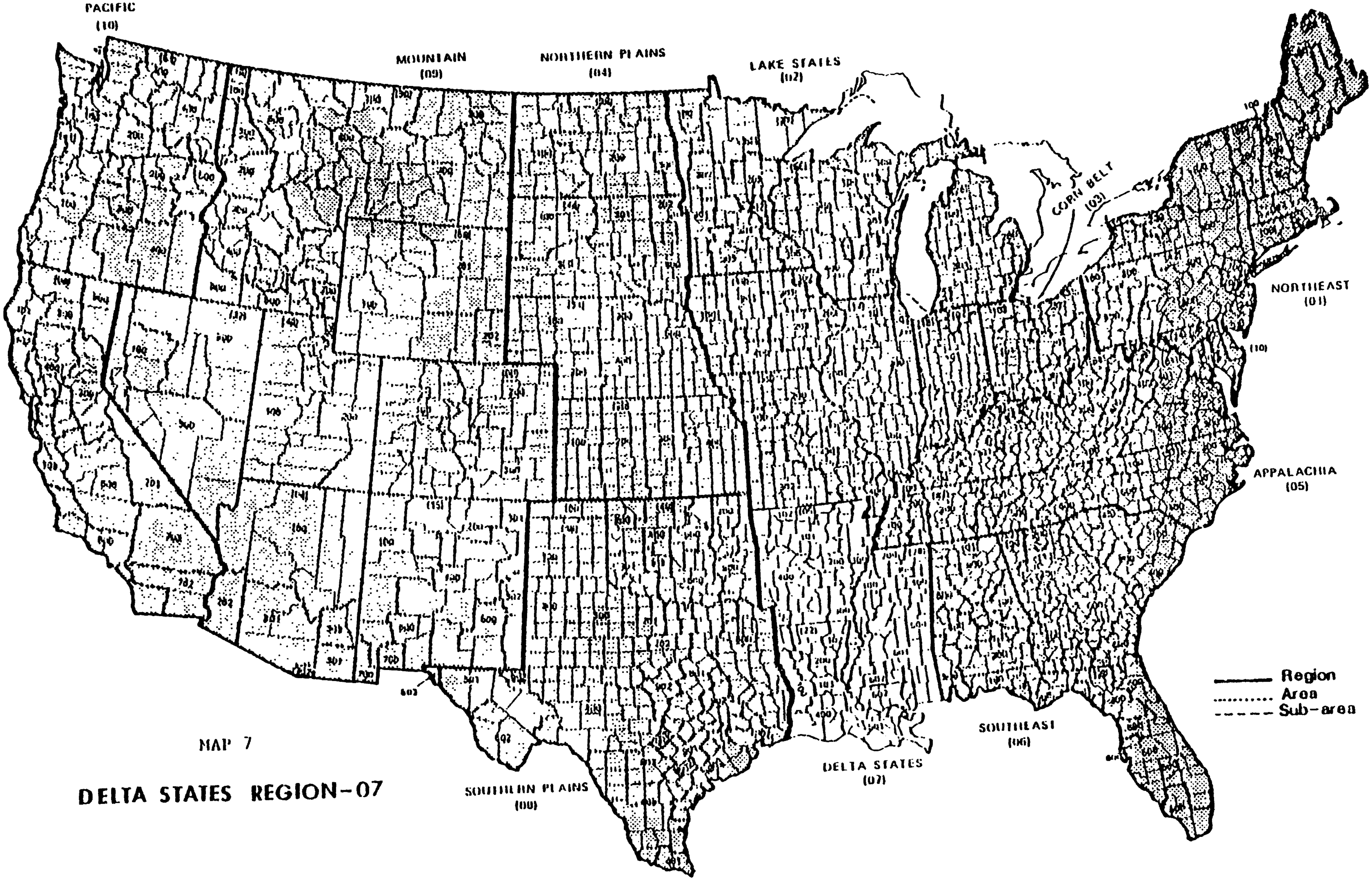
MAP 5

APPALACHIA REGION - 05



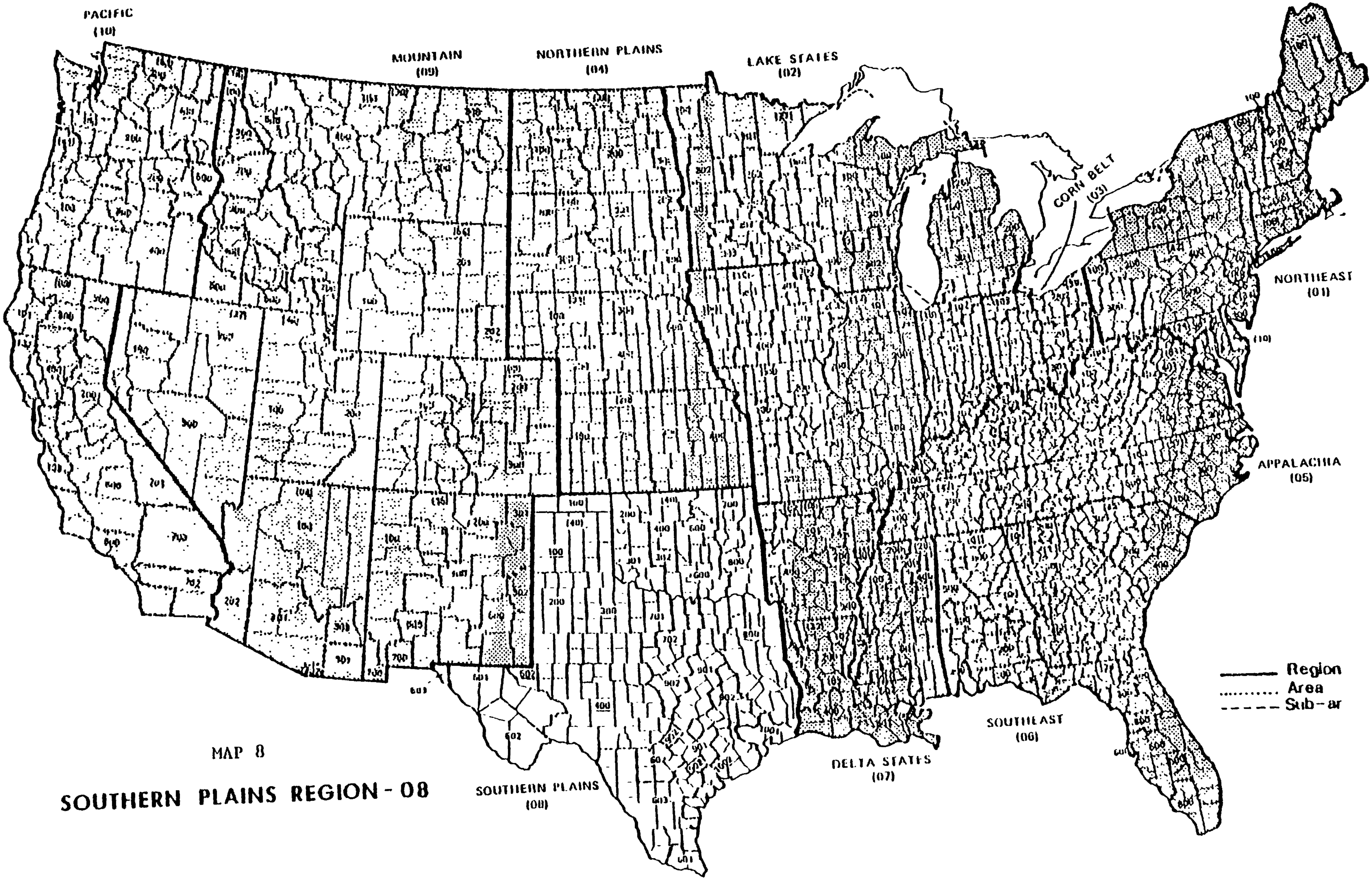
MAP 6

SOUTHEAST REGION-06



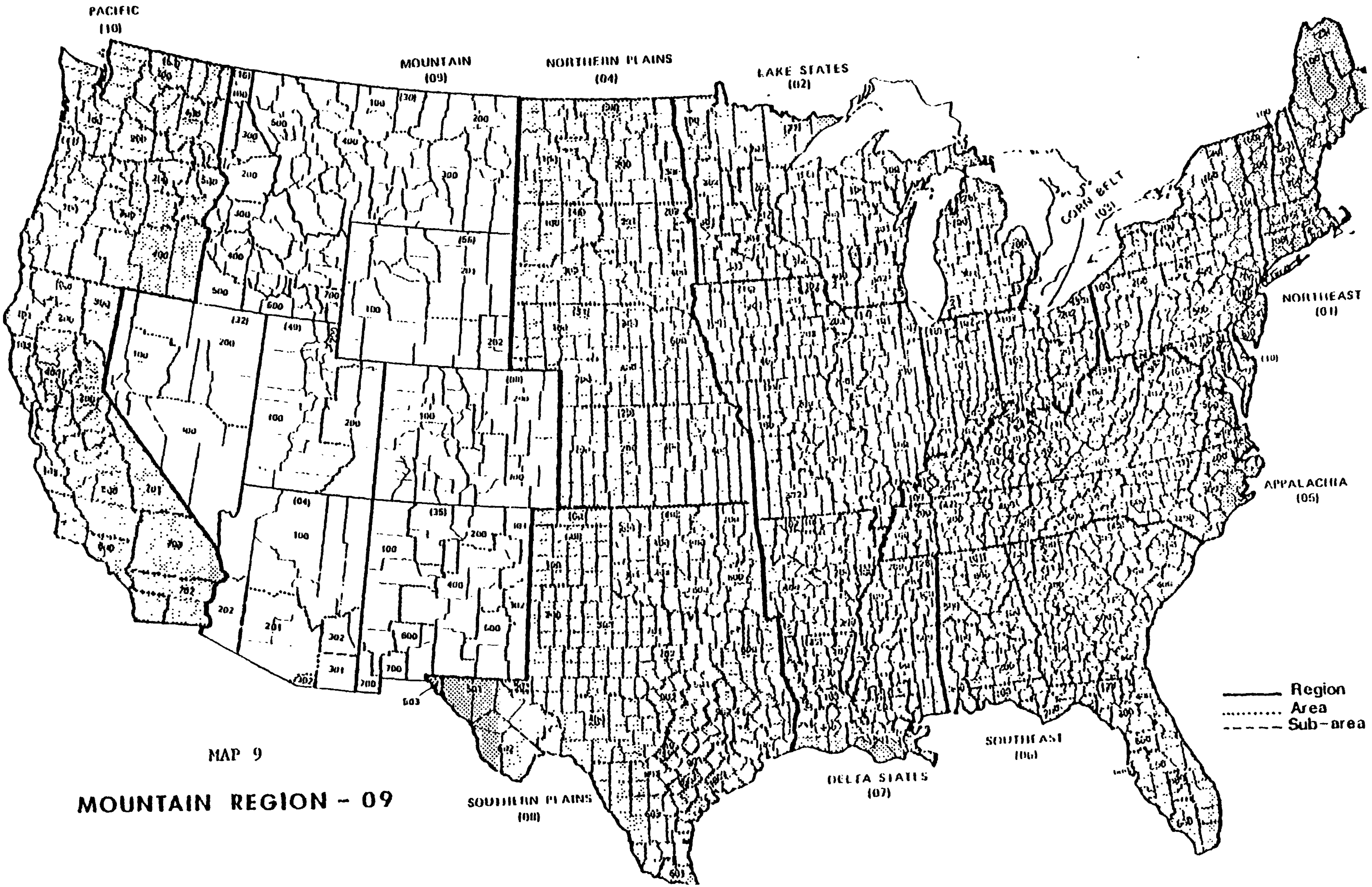
MAP 7

DELTA STATES REGION-07



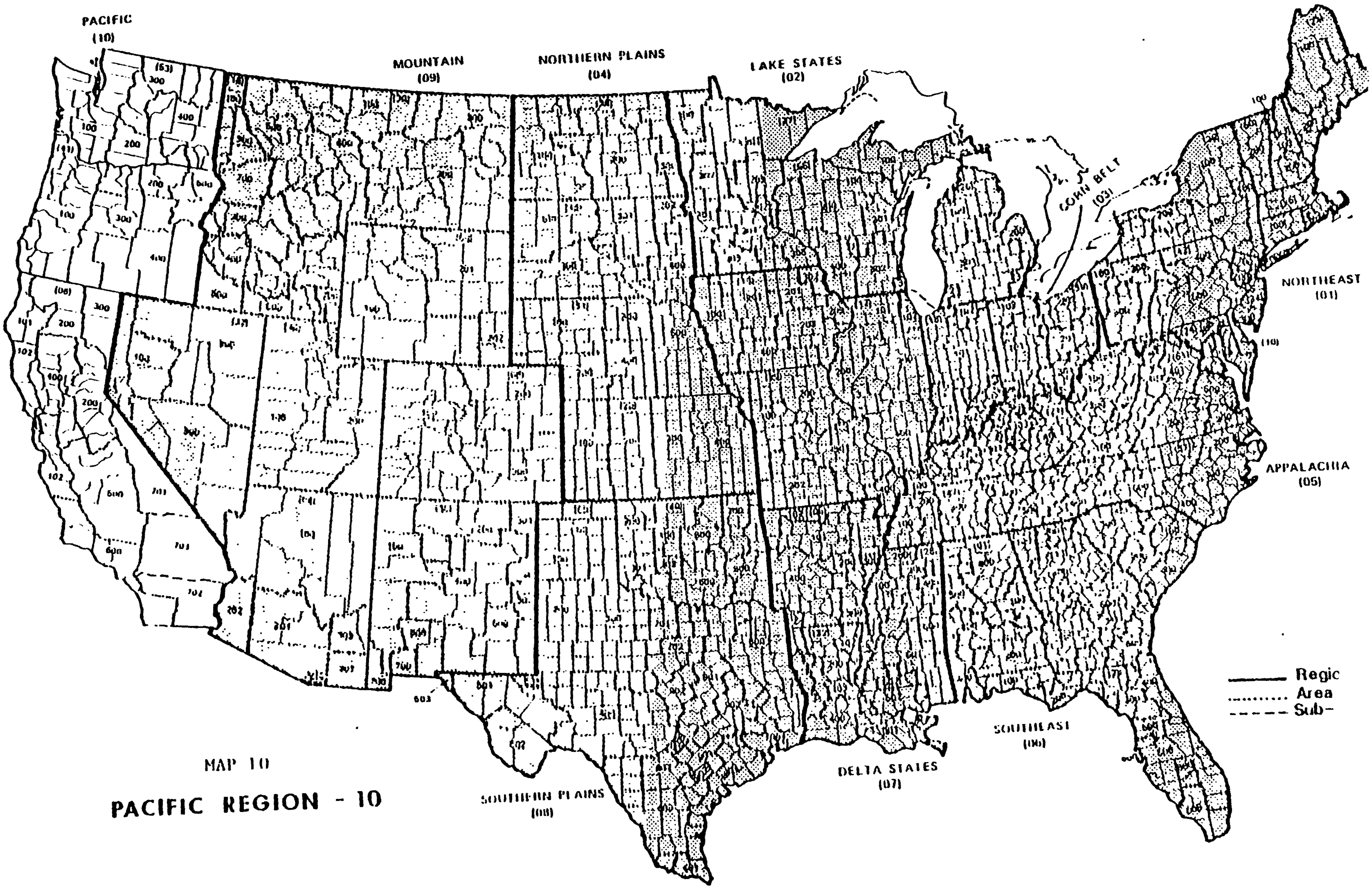
MAP 8

SOUTHERN PLAINS REGION - 08



MAP 9

MOUNTAIN REGION - 09



MAP 10

PACIFIC REGION - 10

CHAPTER 6

THE ESTIMATION OF DOSE-RESPONSE FUNCTIONS

6.1. INTRODUCTION

The purpose of this chapter is to discuss the empirical dose-response functions estimated from published NCLAN experimental results. Very recent NCLAN estimated dose-response functions are discussed in Chapter 9. The RMF requires four types of information to estimate the welfare loss/gain which may accrue to society in the event of a rise/decline in ambient ozone concentrations. The major informational component of the RMF is a detailed account of the cost structure for the production of specific agricultural commodities for specific areas of the continental U.S.. The second component is an estimate of county level ozone concentrations for rural agricultural areas while the third component is an estimate of the demand elasticity for specific agricultural commodities. The final component is a mathematical expression which relates a measure of a particular crop/variety yield in a specific region to a measure of ambient ozone concentration. This functional expression is employed in the RMF to adjust the marginal costs of crop/region specific agricultural production to changes in ambient ozone.

Conceptually, there are two approaches to the identification of the relationship between ambient ozone and crop specific yield. The first is statistical in nature and employs actual measures of ozone concentration, measures of yield and measures of all the variables relevant to yield. Such an approach might involve the estimation of an agricultural yield equation over regional subareas where ozone concentrations are known to differ. Alternatively, one might estimate a crop specific cost function over the same subareas with ozone as an argument in the function (see Chapter 3 for a discussion of the microtheoretic econometric approach). Regardless of the method employed, primal or dual, the reliability of the estimated relationship between ozone and yield or cost is dependent upon the accuracy of the ozone data, the variation in ozone, yield and cost data across the sample, and the ability to control for all factors other than ozone which may affect yield or cost.

The second approach to the dose-response problem is experimental and involves subjecting particular crop varieties to alternative levels of ozone under conditions of experimental control. The variation in yield resulting from these experiments can then be directly linked to ozone concentrations and a simple two variable equation (yield and ozone) estimated to describe the relationship. This experimental approach is pursued by NCLAN (National Crop Loss Assessment Network).

The reliability of the experimental approach is a function of several factors. First, crops in farmers' fields must respond to ozone in the same manner as those in the controlled experimental plots. Second, for the large part, experimental control is maintained by holding all factors other than ozone constant. If factors such as pathogen concentrations affect the relationship between ozone and yield and cannot be controlled for in the experiment, then the simple two variable dose-response equation is inadequate. Third, identical crops grown on different plots must respond identically to ozone concentrations. This is, of course, necessary if one intends to generalize the experimental results to a regional basis as NCLAN intends. Finally, the correct mathematical specification of the dose-response relationship must be specified in the estimation. Choosing a quadratic or plateau linear form when the true relation is logistic can result in serious distortions to the relationship.

After reviewing the statistical and experimental approaches we have decided to utilize the NCLAN experimental results for the following reasons. First, given the limited budget of this project, using available experimental results is very cost effective and therefore attractive. Second, it is not at all clear that the detailed agricultural, climatological and soil data at sufficient level of regional disaggregation can be obtained in order to statistically control for all factors affecting yield. Third, the database containing county level ozone concentrations is generated by an interpolation technique using monitoring sites in primarily urban areas to estimate ozone concentrations in rural counties. The accuracy of this data is unknown. Finally, county level concentrations of other pollutants such as SO_2 do not currently exist and thus the effects of SO_2 on yield could not be adequately controlled for in a statistical sense. At the present time we believe it is advisable to use the experimentally derived results in preference to an estimated statistical function.

The design of the NCLAN experiments and their execution are well documented in Heck et al. (1981) and (1982) and will not be discussed in this chapter. In Section 6.2 we present a fairly detailed investigation of the problems involved in the estimation of a dose-response relationship from experimental data. Since it is not at all clear that yield changes calculated from an estimated dose-response relation are robust with respect to functional form and estimation technique, Section 6.2 begins an investigation of these problems. Section 6.3 presents the published NCLAN dose-response functions for the crops included in the RMF (soybeans, wheat, cotton, corn and peanuts). Section 6.4 discusses the Box-Tidwell functional specification and the estimation procedure used to re-estimate the NCLAN dose-response functions. Section 6.4 also presents the data employed in the estimates drawn from Heck et al. (1981), (1982) and Heagle (1979). Section 6.5 presents the RFF estimates of Box-Tidwell dose-response functions for soybeans, wheat, cotton, corn and peanuts. Section 6.6 discusses the method of frontier Box-Tidwell employed to handle the variety averting behavior problem. Finally, Section 6.7 presents some concluding remarks.

6.2. STATISTICAL CONSIDERATIONS IN FITTING DOSE-RESPONSE FUNCTIONS

Response Surfaces

The reported results of the NCLAN experiments to date have involved the estimation of linear dose-response functions based on experimental data. The scope of the experiments does not yet allow the empirical study of the crop yield response surface; that is, the empirical modeling of the nature and strength of all of the disparate influences on yield, including weather, soil type, and farming practice, along with the concentration of all influential pollutants, including but not limited to ozone.[1]

Response surface methodology (Box et al., 1978, Ch. 15; Biles and Swain, 1980, Ch. 3) can answer a number of interesting questions:

> How is a yield response affected by a given set of explanatory variables (rainfall, temperature, ozone, sulfur dioxide, etc.) over some specified region of interest?

What combination of levels, if any, of the explanatory variables will produce maximum (local or global) yields, and what does the response surface look like around the maximum (or maxima)?

Up to now, data to fit a crop yield response surface have been lacking. Such data may be forthcoming from the work of NCLAN. But, at present, data limitations have important implications for the transferability of single equation dose-response models estimated from any particular site where the data generating experiments were conducted to any other producing area. As we know, weather conditions, soil type, and farming practices can vary widely across the country and even between two adjacent farms. So, empirical ozone dose-yield response models of the narrow sort based on local experiments require certain assumptions to be consistently applied elsewhere. Specifically, the partial derivatives of the log of the true yield response surface (which is unknown) with respect to ozone concentrations must be independent of the levels of each and every other important variable affecting yield in the model. If this is not the case, response surfaces are needed.

6.3. CROP YIELD-OZONE DOSE MODEL SPECIFICATION: THE SINGLE VARIABLE CASE

Lack of experimental information necessary to estimate a response surface confines us to very simple empirical models for estimating the influence of ozone concentrations over the growing season on crop yield, all else having been held constant in the design of the NCLAN experiments. The fact that published NCLAN data for any particular experiment represent average yields over a number of plots does not help, for such averaging reduces the amount of information in the data, inflates measures of goodness of model fit, and introduces the possibility of heteroskedasticity in the error term

(Kmenta, 1971, pp. 322-336; Haitovsky 1973). Assuming away the potential for heteroskedasticity by assuming an equal number of observations (plants) per plot whence the averages came still leaves the problem of very few observations (generally 7-10) per experiment. This in turn means any models to be estimated using the averaged NCLAN data must be parsimonious in terms of parameters.

Even so, the appropriate mathematical form of the dose-response relationship in the single explanatory variable model must be determined. Two approaches are open.

The first, and certainly the most convenient approach is to be able to say with some certainty on a priori theoretical grounds (plant pathology in this case) that one particular functional form is best. Ex post, the reliability of the theoretical model could be exposed to statistical specification error tests (Ramsey, 1969, 1974; Thursby and Schmidt, 1977; Thursby, 1979; Harvey, 1981).[2] If these tests reveal a serious problem, a rethinking of the prior nonsample information forming the basis of the unreliable model would be in order.[3]

Plant pathologists, if anyone, may be in a position to advocate one particular form over all others. But unfortunately there seems to be no consensus on functional form among the experts, based on a Delphi survey conducted by General Research Corporation (Carriere et al. 1982).[4] A review of the literature shows that a preponderance of biologists have in practice fitted linear functions to experimental data, whatever their theoretical preconceptions (Heck et al., 1982). Thus the extant dose-response literature gives us a menu of functional forms, without recommending any particular selection.

The second avenue is wider and much less well defined but basically it involves letting the data indicate which form is best. Here "best" takes on a wide range of meanings, each with a different level of sophistication, ranging from eyeball inspection of data plots, R^2 comparisons across alternative forms where the yield data is measured commensurately in the regressions, power transforms evaluated in the maximum likelihood context, to tests of nonnested hypotheses. Some of these approaches are briefly reviewed below.

Ordinary Least Squares: Piecewise Linear Approximations, Polynomial Approximations and Simple Tests for Nonlinearity

One simple way to handle potential nonlinearity in an ordinary least squares (OLS) context is to approximate a nonlinear function with linear line segments. In the dose-response literature, one example of this approach is the plateau linear model. (Heck *et al.*, 1982, for an example; Kmenta, 1971, p. 469, and Judge *et al.*, 1980, p. 388, for a discussion of the more general case).

In the single variable case, a sample plateau model could be written as:[5]

$$Y_i = b_0 + b_1(D(X_i^* - X)) + \varepsilon_i$$

where b_0, b_1 are parameters to be estimated and the usual assumptions of the classical normal linear regression model are presumed to be satisfied. Here, Y_i represents yield over the $i = 1, \ldots, n$ observations, X_i represents ozone dose, D represents a dummy variable which takes on a value of one if dose is equal to or greater than some known critical level, X* and ε_i is $N(0,\sigma^2)$.

In this model, b_0 represents a constant yield between $X_i = 0$ and the break point defined by X*. Thereafter, the yield function has an augmented intercept and the change in yield per unit change in X is given by b_1 for all doses greater than X*. The null hypothesis of a linear relationship of constant slope and intercept across all values of X in this simple case (i.e., $Y_i = b_0' + b_1'X_i + \varepsilon_i$) can be tested by an F test (Kmenta, 1971, p. 469). The problem with this approach is that we usually do not know, a priori, the best way to approximate the nonlinear function with linear segments -- i.e., where to place the break point (or points) X*. Said otherwise, we do not know how to best break up the overall sample into separate subsamples, each of which behaves according to its own (approximately linear) regime. Positing a number of break points where slopes and intercepts change can quickly exhaust degrees of freedom.[6]

Another legitimate method which can be wasteful of degrees of freedom is the fitting of an approximating polynomial to a nonlinear function based on the Taylor's series expansion of any function f(X) around some arbitrary point (Kmenta, pp. 452-454). Essentially this method involves estimating a function in the powers of X. Linearity can be tested via the F test of the null hypothesis that the parameters attached to the higher order terms are zero.

A practical problem with this second approach is that the columns of the matrix of explanatory variables X, X^2, X^3, etc. tend to be highly correlated, leading to inflated estimated variances of the parameter estimates.

A theoretical objection to both of the tests for linearity mentioned above is that such tests lead to pretest estimators which can have undesirable sampling properties if the null hypothesis is incorrect (Judge et al., 1980, Ch. 3). This objection can almost always be made, however, whatever course of model selection is pursued.

Ordinary Least Squares: Linearizing Transformations

There are any number of models which are nonlinear with respect to the variables but linear with respect to the parameters to be estimated. After appropriate transformation of the independent and/or dependent variables, such functional forms can be estimated by ordinary least squares (OLS). For example, in the one explanatory variable case, where ε_i is $N(0,\sigma^2)$, we can write:

Untransformed Model	Transformed Model
$Y_i = b_0 X_i^{b_1} e^{\varepsilon_i}$	$\ln Y_i = b_0' + b_1' \ln X_i + \varepsilon_i$
$Y_i = b_0 e^{b_1 X_i + \varepsilon_i}$	$\ln Y_i = b_0' + b_1' X_i + \varepsilon_i$
$Y_i = \frac{1}{b_0 + b_1 X_i + \varepsilon_i}$	$\frac{1}{Y_i} = b_0 + b_1 X_i + \varepsilon_i$

There are many examples of such implicitly linear forms in standard econometrics texts -- Daniel and Wood (1980), for example, present a large selection. The problem with this approach is that, a priori, we often do not know which nonlinear model is appropriate -- unless theoretical considerations lead us to one particular model. (Biles and Swain, pp. 156-57). The procedure of preselecting one convenient nonlinear form that is implicitly linear can, in practice, be rather ad hoc.

Further, if we are interested in a family of such candidates there may be no simple way to choose among them using standard OLS regression packages. This is particularly the case if the alternative models are nonnested in the sense that one model cannot be obtained from the other as a limiting process (for example, $Y_i = b_0 X_i^{b_1} e^{\varepsilon_i}$ versus $Y_i = 1/(b_0 + b_1 e^{X_i + \varepsilon_i})$ or $Y_i = b_0 + b_1 X_i^2 + \varepsilon_i$ versus $Y_i = b_0 + b_1 X_i^3 + \varepsilon_i$). In many instances we read applied work stating that one functional form was chosen over all others because it "fit the data better", was "more satisfactory". What is usually meant in these cases is that the specification with the smallest residual variance (or highest R^2) was selected as best, a criterion suggested by Theil (1971, p. 543).

Theil claims that on average, the residual-variance estimator of the incorrect specification will exceed that of the correct specification given that one of the alternative models is indeed the "true" model. So, some practitioners using OLS compare alternative models (when the dependent variable is measured the same way in each) on the basis of goodness of fit (R^2, or $\bar{R}^2$) or, if the dependent variable is not measured the same way (e.g., lnY, 1/Y and Y) on the basis of "pseudo" R^2 or pseudo mean square error measures based on transformed residuals. This is a rather unpersuasive procedure which has been criticized by Pesaran (1974). If used with two models where the dependent variable is measured differently, Theil's residual variance criterion may give contradictory results. Suppose a linear and a log linear model are fitted to the data using OLS. Then, we have four mean square error measures to compare. The two actual measures (MSE_{lin} for the linear model and MSE_{log} for the double log) are based on the residuals from the fitted models. The pseudo measures are based on the sum of the squared differences between the log of the actual dependent variable minus the log of the linear model's predictions ($PMSE_{lin}$) or the sum of the squared differences between the actual dependent variable minus the antilog of the log model's predictions ($PMSE_{log}$). We compare $MSE_{lin} \gtrless PMSE_{log}$ and $PMSE_{lin} \gtrless MSE_{log}$. But, there is no reason to expect these two comparisons to give consistent results; that is both comparisons favoring one of the forms over the other.

Nonlinear Modeling: Sophisticated Methods

The preselection of a set of transformations to permit ordinary least squares analysis has become less common with the advent of efficient nonlinear modeling programs which permit the direct estimation of the transforming parameters, either by nonlinear least squares or maximum likelihood.

One example is the Box-Cox (1964) class of transformations on the dependent and independent variables. The general model for the single independent variable case is of the form

$$Y_i^{(\lambda_1)} = b_0 + b_1 X_i^{(\lambda_2)} + \varepsilon_i$$

where $Y_i^{(\lambda_1)} = (Y_i^{\lambda_1} - 1)/\lambda_1$, and $X_i^{(\lambda_2)} = (X_i^{\lambda_2} - 1)/\lambda_2$, λ_1 need not equal λ_2, and $\varepsilon_i \approx N(0,\sigma^2)$. It is assumed the transformed dependent variable is normally distributed, homoskedastic and has an expectation linear in b_0, b_1. The model is intrinsically nonlinear. The functional form resultant from the Box-Cox transformation depends on the values of the λ_i, which are estimated along with the b's (See Spitzer, 1982, for a complete discussion of the maximum-likelihood, nonlinear least squares and iterated OLS methods for estimating the parameters of the Box-Cox transformation.)

With the Box-Cox transformation, if $\lambda_1 = 0$ and $\lambda_2 = 1$ the model is semi-log; if $\lambda_1 = \lambda_2 = 0$ the model is double-log; and if $\lambda_1 = \lambda_2 = 1$ the model is linear. Other intermediate cases are, of course, possible.

The Box-Cox procedure is an attractive way to allow the data to dictate functional form, and linearity can easily be tested by a likelihood ratio test. But there are at least three problems with the method. The first is that the true model may not be included in the general form, so the inadequacy of a false maintained hypothesis cannot be tested (Aneuryn-Evans and Deaton, 1980). The second difficulty is that the conventional Box-Cox maximum likelihood estimator does not, as usually performed, separate out the decision of whether Y (and hence the error term) should be treated as homoskedastic or heteroskedastic from the decision regarding the correct functional form. Specifically, there is bias in estimating λ_1 toward a transformation of Y which reduces heteroskedasticity (Zarembka, 1974; Judge et al., 1980). This problem might be remedied by using Lahiri and Egy's (1981) amended version of the Box-Cox maximum likelihood estimator, but even so another more critical problem remains. This third problem is that the transformed dependent variable -- and hence the error term -- will be truncated for all values other than $\lambda_1 = 0$. With Y assumed to be greater than or equal to zero, $(Y^{\lambda_1} - 1)\lambda_1$ will be greater than or equal to $-1/\lambda_1$ for λ_1 greater than or equal to zero, and conversely for λ_1 less than or equal to zero (Amemiya and Powell, 1982). Thus the transformed variable $Y^{(\lambda_1)}$ cannot strictly be normally distributed unless $\lambda = 0$. This leads Amemiya and Powell to note that the Box-Cox maximum likelihood estimator is not, strictly speaking, a statistical model. It is merely a method of estimating the parameters which potentially can produce inconsistent parameter estimates. Amemiya and Powell propose a nonlinear two-stage least squares estimator (NL2S) of the Box-Cox model, instead of the customary methods outlined in Spitzer (1982).

In our application, the data simply do not merit the expense and difficulty of constructing a program to implement the NL2S Box-Cox estimator. We follow a simpler but not unsophisticated course, which is explained in detail in subsequent discussions. The following discussion presumes nonlinear estimation procedures are employed for all models discussed.

Fitting Logistic and Box-Tidwell Functions

Briefly, with sufficient data the essence of our approach would be to posit a theoretically appealing model -- the logit function -- and compare it with a variable transformation model of the Box-Tidwell (1962) type. The method of comparison could be based on Sargan's unmodified likelihood ratio for model discrimination. Ideally, such a comparison should also involve tests of nonnested hypotheses. The Davidson-MacKinnon (1981) "C" and "P" tests are attractive candidates, but unfortunately cannot be used with much confidence in the face of very small samples. Yet because future dose-response research might profit from the application of such tests, their outlines are sketched in a subsequent section. But first the form of the models which could be estimated from the available NCLAN data is explained.

The inherently nonlinear logistic model in three parameters (Maddala, 1977, p. 7) is given by:

$$Y_i = \frac{b_0}{1+b_1 e^{b_2 X_i}} + \varepsilon_i\,, \qquad b_0,\ b_1,\ b_2 \geq 0, \quad \varepsilon \sim N(0,\sigma^2)$$

The logistic takes on the value $b_0/(1 + b_1)$ when X is zero and as X goes to infinity the value of Y approaches zero.[8] Physical considerations based on threshold values provide a common sense justification for using a logistic model to represent the dose-response relationship (Cox, 1970). The logistic model has been extensively used in biological work, and in the case of crop yield it makes sense (see Carriere _et al._, 1982). Negative predicted yields are impossible however high the ozone dose, and the logistic model reflects this aspect of physical reality that a simple linear model does not.

An even more general logistic with a lower threshold equal to some positive constant greater than zero is the four parameter model:

$$Y_i = b_0 + \frac{b_1}{1+b_2 e^{b_3 X_i}} + \varepsilon_i$$

As X approaches infinity, Y approaches b_0. Parameter restrictions on this general model produce other logistic models often seen in the literature such as:

$$Y_i = b_0 + \frac{1}{1+b_2 e^{b_3 X_i}} + \varepsilon_i\,, \qquad b_1 = 1$$

$$Y_i = b_0 + \frac{b_1}{1+e^{b_3 X_i}} + \varepsilon_i , \qquad b_2 = 1$$

However, biologists may not be satisfied with any of the above logistic representations, so an alternative is to let the data dictate functional form.

So, in contrast to choosing a theoretical model a priori, we can write a nonlinear model and consider estimating a transforming parameter in the explanatory variable dose as part of a nonlinear estimation procedure. The Box-Tidwell (1962) method is based on such an approximating transformation.

The Box-Tidwell transformation is just a special case of the generalized Box-Cox transformation. Its advantage is that since no transformation of the dependent variable is involved, neither of the two problems mentioned in connection with the Box-Cox transform (heteroskedasticity, truncated error) arises.

With one explanatory variable, the Box-Tidwell model requires three parameters to be estimated, b_0, b_1, and λ:

$$Y_i = b_0 + b_1 X_i^{\lambda} + \varepsilon_i , \qquad \varepsilon_i \sim N(0,\sigma^2)$$

where X_i^{λ} is exponentiated to the λ power and is not equal to the transformation of the X variable on page 108.

In the positive quadrant, the sign of the second derivative of the Box-Tidwell function cannot change. Therefore, it has no inflection points, which means that the model is more restrictive than the logistic, which does have an inflection point (i.e., the first derivative of the function has an extreme value). Said simply, the Box-Tidwell model permits no change in curvature (i.e., from convex to concave) while the logistic model does.[9] Obviously, since both of these models (logistic, Box-Tidwell) are intrinsically nonlinear, nonlinear least squares estimation is required (see Draper and Smith, 1966; Judge <u>et</u> <u>al.</u>, 1980).

Practically speaking, the Box-Tidwell model is just a "graduating" function which is expected to represent the true function over a <u>limited region of the X space</u> reasonably well. It cannot capture the "S" shape of the logistic. But, the data may not show a logistic pattern simply because the complete domain of dose was not represented in the experiments, and thus the point of inflection not revealed. If it were revealed, the logistic model should better represent the data, where the criterion of better is given by the class of nonnested hypothesis tests mentioned above.

To illustrate, Figure 6-1 shows three extreme possibilities assuming the true dose-response function is logistic. In panel A the full shape of the logistic is revealed by the data, with the point of inflection (X*) positioned near the mean of the observed dose data. In panel B, the logistic's inflection point is positioned near a dose of zero, giving the function the appearance of being convex to the origin over the observed range of dose. In panel C the inflection point shows up near the uppermost dose measurement giving the impression of a concave function in the positive quadrant.

Because it has no inflection point, the Box-Tidwell approximation to the true logistic is visibly better for the cases represented in panels B and C of Figure 6-1 than it is for the situation shown in panel A. In the two former situations (B,C) it may in fact be difficult to statistically distinguish between the true logistic and the Box-Tidwell approximation in small to moderate sized samples. Of course, this discussion assumes that the logistic function is in fact the true model. But, a less restrictive point of view would admit that either, both, or neither of the posited models could have generated the observed data.

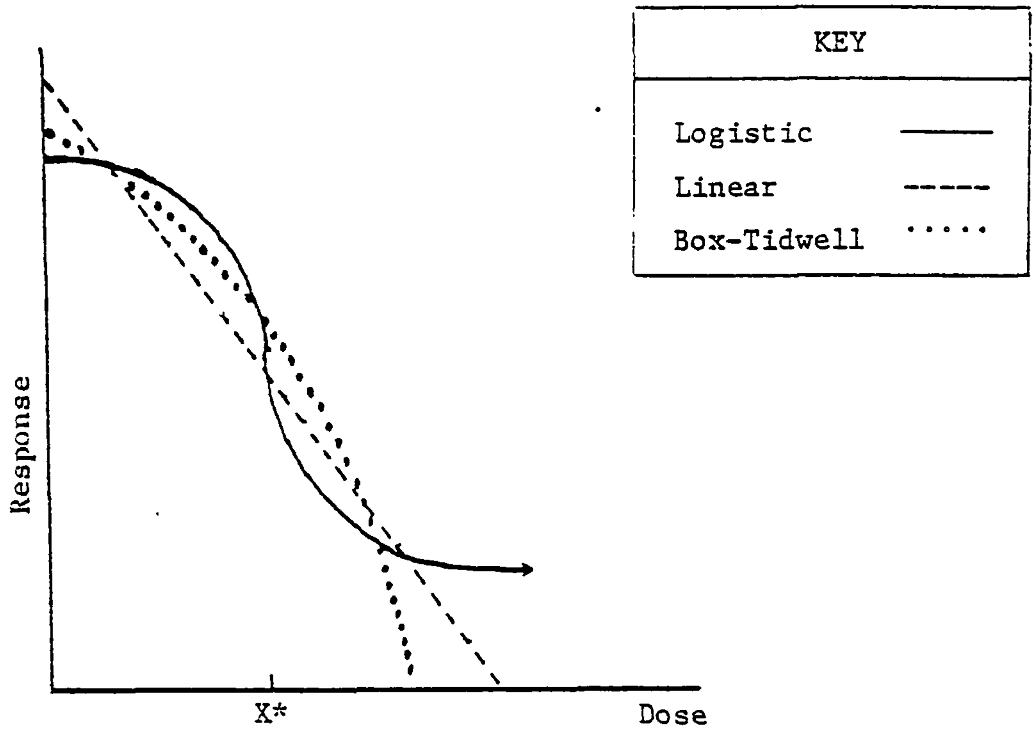
Model Discrimination, Nested and Nonnested Hypothesis Tests

When testing nested hypotheses, it is not possible to simultaneously reject the null and alternative hypotheses and conclude that neither is correct.

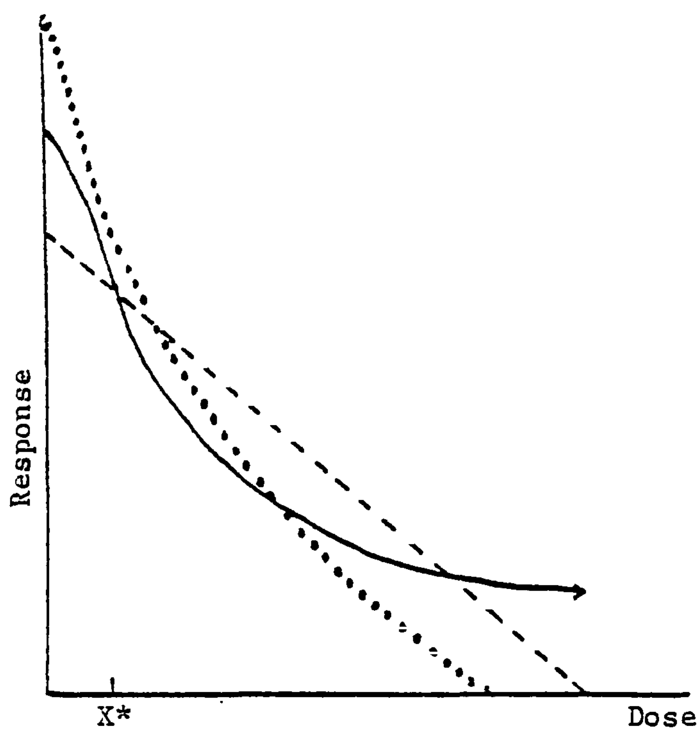
For example, the linear model is just a special (nested) case of the Box-Tidwell model with the restriction that $\lambda = 1$. Thus it is simple to test for linearity (a test of the null hypothesis that $\lambda = 1$) by constructing a confidence interval around $\hat{\lambda}$ at the chosen level of type one error to see if it encompasses the value of one given by the null hypothesis of linearity. But of course, neither model may be correct.

Distinguishing between two intrinsically nonlinear functions such as the logistic and Box-Tidwell is not so straightforward. Properly speaking, nonnested hypothesis tests should be used, since the models are nonnested (Pesaran and Deaton, 1978; Aneuryn-Evans and Deaton, 1980; Davidson and MacKinnon, 1981).

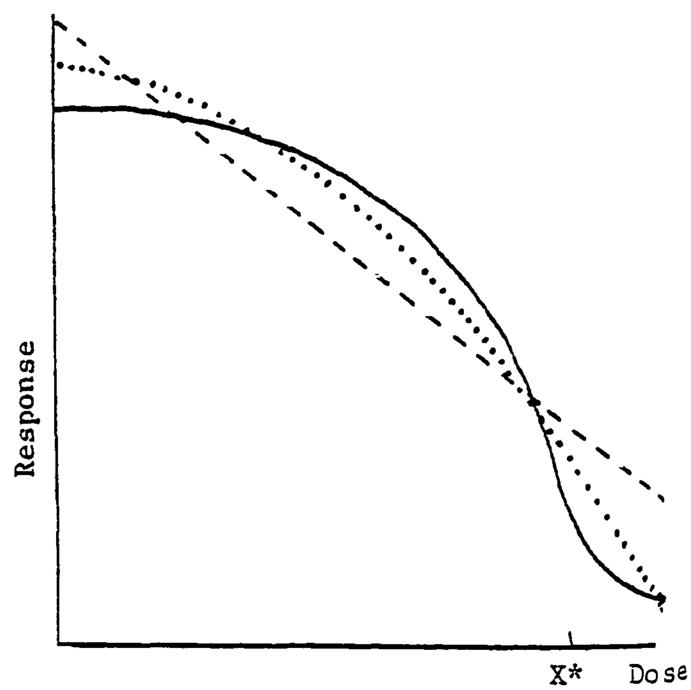
In lieu of such tests, there is the simpler alternative of the unmodified likelihood ratio. This model discrimination criterion is the nonlinear estimation analogue of Theil's R^2 criterion in OLS. Like Theil's criterion, the likelihood ratio (variously labelled the Sargan test or Akaike's Information Criterion) is not really a statistical test with known statistical



Panel A: Full Logistic with Concave and Convex Regions



Panel B: Logistic Principally Convex to Origin



Panel C: Logistic Principally Concave to Origin

Figure 6-1. Alternative locations of the observed point of inflection, X* of the logistic function, with linear and Box-Tidwell approximations.

properties. Instead it is just a method of model discrimination which is easy to calculate and should be successful "on average" presuming one of the models in the comparison set is the true model. No significance level can be set for such a comparison: one just chooses the model with the higher likelihood (Aneuryn-Evans and Deaton, 1980; Harvey, 1981).

Specifically, suppose the null hypothesis H_0 is represented by the three parameter logistic function with parameter vector θ. The alternative hypothesis H_1 is represented by the three parameter Box-Tidwell approximation function with parameter vector β.

In general matrix notation we can write the models compactly as:

Logistic

$$H_0 : Y = f(X,\theta) + \varepsilon_0$$

Box-Tidwell

$$H_1 : Y = g(X,\beta) + \varepsilon_1$$

where Y is an n x 1 column vector of observations, X is an n x k matrix of explanatory variables, ε_0, ε_1 are n x 1 column vectors of disturbances, and f,g represent the logistic and Box-Tidwell functions respectively with parameter vectors θ and β.

With the assumption of normally distributed errors the two log likelihood functions (log $\dot{L}$) in the three parameter case can be written, with the observation index i = 1, ..., n, as:

Logistic

$$\log L(\theta,\sigma_0^2) = -(n/2) \log 2\pi - (n/2) \log \sigma_0^2 - \Sigma\varepsilon_{0i}^2/2\sigma_0^2$$

where from our earlier notation:

$$\varepsilon_{0i} = (Y_i - (b_0/1 + b_1 \exp b_2X_i))$$

or, in matrix notation:

$$\Sigma\varepsilon_{0i}^2 = (Y - f(X,\theta))'(Y - f(X,\theta))$$

Box-Tidwell

$$\log L(\beta,\sigma_1^2) = -(n/2) \log 2\pi - (n/2) \log \sigma_1^2 - \Sigma\varepsilon_{1i}^2/2\sigma_1^2$$

where from our earlier notation:

$$\varepsilon_{1i} = (Y_i - (b_0 + b_1X_i^{\lambda}))$$

or, in matrix notation:

$$\Sigma\varepsilon_{1i}^2 = (Y - g(X,\beta))'(Y - g(X,\beta))$$

The ratio of the likelihoods under H_0 and H_1, LR, is the difference between $\log L(\theta,\sigma_0^2)$ and $\log L(\beta,\sigma_1^2)$.[10] Since we must estimate σ_0 and σ_1, the last terms on the rhs of both log likelihood functions are equal to n/2. Therefore, the estimate of the difference between the two log likelihood functions, $\hat{LR}$, simplifies to:

$$\hat{LR} = (-n/2\ln\hat{\sigma}_0^2) - (-n/2\ln\hat{\sigma}_1^2)$$

or

$$\hat{LR} = n/2\ln(\hat{\sigma}_1^2/\hat{\sigma}_0^2)$$

All this means is that if $\hat{LR}$ is positive, accept the model specification of H_0, otherwise accept H_1. Even more simply, when the intrinsically nonlinear models are estimated by either nonlinear least squares or maximum likelihood techniques (and no transformation of the dependent variable is undertaken) the criterion tells us to accept the model with the lesser mean square error (or higher R^2). This is just Theil's model discrimination criterion applied to intrinsically nonlinear models.

The Monte Carlo evidence presented in Aneuryn-Evans and Deaton (1980) suggests the unmodified likelihood ratio (which they call the Sargan test but is also known as the Akaike Information Criterion (AIC)) is a useful discriminator between two alternative models provided one can be certain in advance that either H_0 or H_1 is in fact true.[11] When both H_0 and H_1 are false the likelihood ratio discriminator is misleading for it forces a decision when in fact indecision is possible -- both models should be rejected.

The advantage of the Sargan method is computational simplicity, a feature not shared with the Cox-Pesaran type nonnested test procedures for functional form specification set out in Pesaran and Deaton (1978) and Aneuryn-Evans and Deaton (1980). Fortunately, a family of nonnested hypothesis testing procedures has recently been developed by Davidson and MacKinnon (1981)(DM) which are simple to compute -- the C and P tests.

With a sufficiently large sample, the idea of the class of DM tests would be to test the logistic model H_0 against the Box-Tidwell model H_1, conditional on the truth of H_0. Reversing roles, the Box-Tidwell model, H_0, would be tested against the logistic model, conditional on the truth of the new H_0. Obviously, the following outcomes are all possible under the nonnested hypothesis testing scheme:

<u>Logistic</u>	$H_0 : Y = f(X,\theta)$	Accept	Reject
<u>Box-Tidwell</u>	$H_0 : Y = g(X,\beta)$	Accept	Reject

The possibility of rejecting both models with these tests is rather unsettling. Such a nihilistic outcome would not satisfy an investigator seeking an immediate solution to a problem, since it can only elicit the familiar call for more research. But, in dismissing the idea that relative superiority of model fit is a useful way to compare models Pesaran and Deaton (1978, p. 678) state their position quite strongly:

> It is important that notions of the absolute fit or performance play no part in the analysis. Indeed it should be clear ... that, apart from the nested case, we regard such indicators as meaningless. In considering whether an alternative hypothesis, together with the

> data contains sufficient information to reject the currently maintained hypothesis, the question of whether that alternative 'fits' well or badly, even if meaningful, is certainly irrelevant. An hypothesis, which one would not wish to consider seriously in its own right, can be a perfectly effective tool for disproving an alternative, even if that alternative may in some respects seem much more promising. *It is thus important that tests between nonnested hypotheses or models should encompass the possibility of rejecting both, as does the Cox procedure.* [Italics added]

This position may involve a bit of intentional overstatement, since later in the same paper the authors merely suggest that their tests be used as a supplement to, but not a replacement for, "current practices", which reasonably could be taken to mean model discrimination on the basis of fit.

Such issues aside, the set-up for the family of Davidson-MacKinnon tests is quite simple.[12] These tests are closely related but not identical to the Pesaran-Deaton (1978) tests. As before, we have the two competing (nonnested) nonlinear models:

$$H_0 : Y = f(X,\theta) + \varepsilon_0$$

$$H_1 : Y = g(X,\beta) + \varepsilon_1$$

Both error terms are assumed to be normally independently distributed with zero mean and respective variances σ_0^2 and σ_1^2.

Define the maximum likelihood predictions (*) of each observation of the Y vector given the maximum likelihood (ML) estimates of θ and β as:

$$f_i^* = f_i(X_i,\theta_{ML})$$

$$g_i^* = g_i(X_i, \beta_{ML})$$

The C (conditional) test of the truth of H_0 involves a linear regression to estimate the test parameter α, conditional on the β_{ML} vector:

$$Y_i = (1 - \alpha)f_i^* + \alpha g_i^* + \varepsilon_i$$

or

$$Y_i - f_i^* = \alpha(f_i^* - g_i^*) + \varepsilon_i$$

The validity of H_0 can be tested by using a conventional t test of the null hypothesis that α^*, the estimate of α, equals zero. However, the t statistic for α^* is not distributed asymptotically as $N(0,1)$ if H_0 is true. Rather, the estimate of the variance of the distribution of the t statistic for the C test is asymptotically biased below 1 when H_0 is true. Practically speaking, this means that the nominal level of significance chosen for the test will overstate the true asymptotic level of significance, or otherwise said, the true probability of Type I error (probability of rejecting a true H_0) will be less than the nominal level chosen. The C test is therefore conservative in the sense that it is less likely to reject a true H_0 than one wishes it to be.

To produce a test statistic which is asymptotically distributed as $N(0,1)$ the authors suggest the J (joint) test which estimates α and β jointly in the nonlinear regression:

$$Y_i = (1 - \alpha)f_i(X,\beta) + g_i^* + \varepsilon_i$$

However, a simpler computational test procedure when H_0 is nonlinear, which shares the same asymptotic properties of the J test, is the P test. The P test involves a linearization of the J test, around the β_{ML}^* vector:

$$Y_i - f_i^* = \alpha(g_i^* - f_i^*) + b_i f_1' \ldots + b_k f_k' + \varepsilon_i$$

where f denotes $\partial f/\partial\beta_k|\beta_{kML}$ for k = 1, ..., K parameters in the nonlinear model under H_0 and b_1, ..., b_k are parameters to be estimated along with α in the P regression. To complete either the C or P procedures, the roles of H_0 and H_1 are reversed and the tests repeated. It should also be noted that several models can be simultaneously compared using an extension of the J or P procedures.

Unfortunately for our purposes, the aggregate data contained in the NCLAN annual reports are not sufficiently large to merit the indulgence in such sophisticated hypothesis testing as that described above. The small sample performance of these tests is largely unknown, but their application to samples of even twenty observations would appear unwise (Pesaran, 1982; Davidson and MacKinnon, 1982).

In fact, the aggregate data sets available in the annual reports are so small as to preclude statistical tests of functional form. Yet differences in functional form of the dose-response relationship obviously could have significant impacts on the economic benefits produced by models relying upon them. In the same vein, it does not seem unreasonable to presume that natural-world relationships are likely to be nonlinear. It is germane to raise this question, although our logit and Box-Tidwell approximating functions are poor answers to it, given the data at hand.

6.4. NCLAN REPORTED DOSE-RESPONSE FUNCTIONS

The Firm Enterprise Data System (FEDS) contains production cost information on twenty-nine major crops grown in the continental U.S.. At the time the research described in this report was conducted the intersection of FEDS crops and NCLAN experimental information contained soybeans, wheat, corn, cotton, and peanuts. Since the FEDS data underlies the Regional Model Farm benefit estimation method, we are constrained by FEDS in the crops that can be examined. This constraint makes it impossible to employ information on crops such as tomatoes and beans.

We note at the outset and caution the reader that in all of the RFF estimates dose-response functions the ambient air plots were included in the estimation data base. This was done to increase the number of observations in our data sets but may impart some bias to our results if these ambient air plots lead to a systematic bias in crop yields.

In the 1980 NCLAN annual report (Heck et al. (1981)) dose-response functions are reported for the Corsoy variety of soybeans and NC-6 peanuts, with the experiments conducted at Argonne National Laboratory and North Carolina State University respectively. Both experiments were of the open-top-chamber variety. Linear functions were used to describe the experimental results and related a measure of yield to an experimentally maintained level of ozone over the 7 hr. period 0900-1600. In the case of soybeans the ozone fumigation began on August 6 and ended on October 9, while for peanuts the period of fumigation extended from June 16 to October 6.

Table 6-1. NCLAN ESTIMATED DOSE-RESPONSE FUNCTIONS DEVELOPED IN 1980 AND PUBLISHED IN THE 1980 NCLAN ANNUAL REPORT

Crop: SOYBEAN (CORSOY)

NCLAN Region: Central States (ARGONNE)

Interactions: NONE

$$Y^* = 23.14 - 123.20(\text{Ozone})$$

Crop: PEANUTS (NC-6)

NCLAN Region: Southeast (N.C. STATE)

Interactions: NONE

$$Y^{**} = 173.20 - 1045.6(\text{Ozone})$$

Notes: Y* = seed weight per plant, Y** = weight of pods. Ozone is measured in part per million. Corsoy and NC-6 are varieties of soybeans and peanuts respectively. Ozone concentrations were added during the same 7-hour period each day: 0900-1600 hr std time.

The NCLAN estimated dose-response functions for soybeans and peanuts are presented in Table 6-1. The measures of yield incorporated in the functions are seed weight per plant for soybeans and weight of pods for peanuts.

In the case of soybeans it is not clear from Heck et al. (1980) whether other functional specifications were estimated. While not stated, apparently twenty or more observations were available for use in the estimation permitting more complex association between yield and ozone than that portrayed by the linear function. As outsiders to NCLAN with access to only the summarized NCLAN results, it is impossible for us to make an objective assessment of the statistical reliability of the estimated dose-response functions. Based on the preliminary NCLAN reports any conclusions we might draw would be of dubious value and unfair to the NCLAN researchers. Therefore, we merely present the remainder of the published NCLAN dose-response functions without comment.

In Heck et al. (1982) (the 1981 NCLAN Annual Report) dose-response functions are reported for corn, soybeans, and cotton. In the case of soybeans and corn alternative varieties were examined. This variety analysis provides us with dose-response functions for two major corn varieties, and four types of soybeans, Hodgson, Davis, Williams, and Essex. Only a single variety of cotton was examined, Acala SJ2. For the two corn varieties stepped linear functions (termed "plateau linear" by NCLAN) were estimated. The soybean functions are predominantly quadratic with two exceptions which are linear and the cotton functions are linear. All of the dose-response functions published in the 1981 NCLAN Annual Report are displayed on Table 6-2.

TABLE 6-2. NCLAN ESTIMATED DOSE-RESPONSE FUNCTIONS DEVELOPED IN 1981 AND PUBLISHED IN THE 1981 NCLAN ANNUAL REPORT

Crop: CORN (PIONEER 3780)

NCLAN Region: Central States (ARGONNE)

Interactions: NONE

$$Y = 10836 + D(-78993(OZONE - 0.071))$$

where: $D = 0$ if $OZONE < 0.071$

$D = 1$ otherwise

Crop: CORN (PAG 397)

NCLAN Region: Central States (ARGONNE)

Interactions: NONE

$$Y = 12221 + D(-105751(OZONE - 0.090))$$

where: $D = 0$ if $OZONE < 0.090$

$D = 1$ otherwise

Crop: SOYBEAN (HODGSON)

NCLAN Region: Northeast (BOYCE-THOMPSON)

Interactions: NONE

$$Y = 2628 - 9875(OZONE)$$

Table 6-2 (continued)

Crop: SOYBEAN (DAVIS)

NCLAN Region: Southeast (N.C. STATE)

Interactions: NONE

$$Y = 5345 - 39886(\text{OZONE}) + 109600(\text{OZONE})^2$$

Crop: SOYBEAN (WILLIAMS)

NCLAN Region: Southeast (BELTSVILLE)

Interactions: NONE

$$Y = 4426 - 110429(\text{OZONE})$$

Crop: SOYBEAN (ESSEX)

NCLAN Region: Southeast (BELTSVILLE)

Interactions: NONE

$$Y = 3901 - 5038(\text{OZONE})$$

Crop: COTTON (ACALA SJ2)

NCLAN Region: Southwest (SHAFTER)

Interactions: MOISTURE (NORMAL)

$$Y = 2036 - 6884(\text{OZONE})$$

Crop: COTTON (ACALA SJ2)

NCLAN Region: Southwest (SHAFTER)

Interactions: MOISTURE (STRESSED)

$$Y = 1301 - 2784(\text{OZONE})$$

Table 6-2 (continued)

Crop: SOYBEAN (DAVIS)

NCLAN Region: Southeast (N.C. STATE)

Interactions: $SO_2(SO_2 = 0.026$ ppm)

$$Y = 5220 - 39194(OZONE) + 109600(OZONE)^2$$

Crop: SOYBEAN (DAVIS)

NCLAN Region: Southeast (N.C. STATE)

Interactions: $SO_2(SO_2 = 0.085$ ppm)

$$Y = 4937 - 37624(OZONE) + 109600(OZONE)^2$$

Crop: SOYBEAN (DAVIS)

NCLAN Region: Southeast (N.C. STATE)

Interactions: $SO_2(SO_2 = 0.367$ ppm)

$$Y = 3585 - 30120(OZONE) + 109600(OZONE)^2$$

Crop: SOYBEAN (WILLIAMS and ESSEX)

NCLAN Region: Southeast (BELTSVILLE)

Interactions: $SO_2(SO_2 = 0.071$ ppm)

$$Y = 4503 - 37798(OZONE) + 164897(OZONE)^2$$

Crop: SOYBEAN (WILLIAMS and ESSEX)

NCLAN Region: Southeast (BELTSVILLE)

Interactions: $SO_2(SO_2 = 0.148$ ppm)

$$Y = 4212 - 25322(OZONE) + 103541(OZONE)^2$$

Table 6-2 (continued)

Crop: SOYBEAN (WILLIAMS and ESSEX)

NCLAN Region: Southeast (BELTSVILLE)

Interactions: SO_2(SO_2 = 0.334 ppm)

$$Y = 3863 - 26153(OZONE) + 92033(OZONE)^2$$

Notes: All yields are in KG/HA, ozone is measured in parts per million of 7 hr average concentrations. Names in parentheses following crop identifications are variety identifiers. Ozone concentrations were added during the same 7-hour period each day: 0900-1600 hr std time.

6.5. RE-ESTIMATING THE NCLAN DOSE-RESPONSE FUNCTIONS

In Section 6.2 of this report we discussed the merits of a logistic specification but conclude, given the range of ozone concentrations employed in the experiments, that a Box-Tidwell form is more appropriate. All of the dose-response functions reported in Table 6-1, 6-2 and several additional functions were estimated with a common Box-Tidwell specification. In the following subsection we discuss in detail the estimation procedure and present the computer estimation code.

Estimating the Box-Tidwell Dose Response Function

Recall that the Box-Tidwell (BT) model can be written as

$$Y = b_0 + b_1 X^{\lambda} + \varepsilon \tag{1}$$

where Y, X, and ε are nx1 and b_0, b_1, and λ are scalar parameters. The objective is estimation of the parameters b_0, b_1, and λ.

Several approaches are possible. If one were to assume that ε was a normally distributed random vector, with $E(\varepsilon)=0$ and $Var(\varepsilon)=\sigma^2 I$, i.e. the ε were i.i.d. normal, then the two most appealing approaches -- maximum likelihood estimation (MLE) and nonlinear least squares (NLLS) -- are identical. The problem with the normality assumption is that it admits the possibility of negative yields. This, in fact, is a weakness of any BT specification which allows both for $E(\varepsilon)=0$ and nondegenerate variances.

Without making an explicit assumption about the distribution of the ε, save that $E(\varepsilon)=0$, (1) can be estimated by NLLS. Given certain regularity conditions, which may in fact be violated here, the asymptotic distribution of the NLLS estimator for $\delta = [b_0, b_1, \lambda]$ is

$$n^{.5}(\hat{\delta}_{NLLS}-\delta) \dashrightarrow N(0,\sigma^2 \text{ plim}(n^{-1}F(\delta)'F(\delta))^{-1})$$

where $F(\delta)$ is nxk and $F_{ij}= (\partial f_i/\partial \delta_j)$, where i indexes observations and j indexes parameters, and $f=b_0 + b_1X^{\lambda} + \varepsilon$. $F(\delta)$ and σ^2 are typically estimated at the NLLS estimates with σ^2 estimated as $(n-k)^{-1}$SSR (see Judge, et al., p. 723 for a more detailed discussion of this asymptotic distribution and its derivation).

Nonlinear regression algorithms converge most quickly to the optimal parameter estimates when provided with parameter starting values "close" to those that satisfy the criterion function, in this case, the minimum of the sum of squared residuals. Indeed, without proximate starting values, it is possible that the solution algorithms will take quite a long time to converge even if the second-order conditions for unique minima are satisfied. There is thus a premium to be put on obtaining good starting values.

Box and Tidwell suggest an iterative method for obtaining the parameter starting values. Their method will approximately converge to the first moment of the NLLS parameter estimates if the relevant second order conditions are satisfied.

Box and Tidwell proceed as follows. Considering only the univariate model specified in (1), and given observations on y_u and x_u, $u=1,\ldots,n$, assume $E(y_u)= \eta_u$ and $E(y_u-\eta_u)(y_v-\eta_u)=\sigma^2$ for u=v and =0 for u≠v. Further, it is assumed that $\eta=f(\xi,\beta)$ where ξ is a vector of the transformed X vector such that $\xi = g(X,\lambda)$, λ being, in general, a parameter vector of the transformation, but in the case of (1) a scalar parameter. Thus, the BT formulation is

$$y_u = f(g(x_u,\lambda),\beta) + \varepsilon \tag{2}$$

For present purposes, it is the BT treatment of the power transformation that is of moment. Here, define for the i^{th} round transformation (i.e. the transformation made on the i^{th} iteration) ξ_i such that

$$\xi_{iu} = x_u \quad \text{for } \lambda_i \neq 0$$

$$= \ln(x_u) \text{ for } \lambda_i = 0$$

Of interest, of course, is the estimation of the parameters λ and β of (2). Assume 1 as a starting value for λ, i.e. $\lambda_1 = 1$. Expanding $f(\xi,\beta)$ around $\lambda_1 = 1$ in a Taylor series gives:

$$f(\xi_u,\beta) = f(x_u,\beta) + (\lambda-1)(\partial f(\xi_u,\beta)/\partial\lambda) + R \tag{3}$$

Evaluating $(\partial f(\cdot)/\partial\lambda)$ at $\lambda_1 = 1$ gives

$$f(\xi_u,\beta) \approx f(x_u,\beta) + (\lambda-1)(\partial f(x_u,\beta)/\partial x_u)(x_u \ln(x_u)) \tag{4}$$

A first round estimate of $(\partial f(x_u,\beta)/\partial x_u)$ can be produced from the estimated slope coefficient of a linear regression of Y on a constant term and X. Denote this slope estimate as $\hat{Y}_1$. Using this, fit the OLS equation

$$y_u = f(x_u,\beta) + (\lambda-1)\hat{\gamma}_1 x_u \ln(x_u) \qquad (5)$$

or

$$y_u = f(x_u,\beta) + \theta_1 x_u \ln(x_u) \qquad (6)$$

From the estimate of θ_1, $\hat{\theta}_1$, obtained in (6), one can back out a second-round estimate of λ as $\lambda_2 = (\hat{\theta}_1/\hat{\gamma}_1) + 1$. Using this, one retransforms the X vector as $\xi_2 = X^{\lambda_2}$, regresses Y on a constant term and X^{λ_2}, obtains the slope coefficient $\hat{\gamma}_2$, and fits the equation

$$y_u = f(x_u,\beta) + (\lambda-1)\hat{\gamma}_2 x_u \ln(x_u) \qquad (5')$$

or

$$y_u = f(x_u,\beta) + \theta_2 x_u \ln(x_u) \qquad (6')$$

From this, the third-round estimate of λ, λ_3, is derived as $\lambda_3 = (\hat{\theta}_2/\hat{\gamma}_2) + 1$, and the process continues until convergence.

The reason that the BT parameter estimates obtained from the iterative OLS method must be treated as starting values for a NLLS algorithm rather than as the parameter estimates themselves is that the estimates of the moments of b_0 and b_1 at any iteration are conditional on the value of λ. At each iteration, λ is treated parametrically, with optimization carried out only with respect to b_0 and b_1. Because of this, there will be no estimate of the standard error of λ and the OLS estimates of the variances and covar - ances of b_0 and b_1 will be biased. However, by using the BT values as starting values in a NLLS algorithm, one avoids this problem because λ, b_0, and b_1 are treated as parameters to be estimated simultaneously.

The attached SAS program documents the method used to obtain the BT starting values. Initial values for λ, b_0, and b_1 are obtained, respectively, as the value of L1 and the parameter estimates for the intercept and slope of the regression of Y on XNORM in the final iteration. Four to six iterations are all that are typically required to obtain "correct" starting values. Using these values, the SAS PROCs MODEL, SYSNLIN, and NLIN are used to calculate the parameter estimates of the dose-response functions and their standard errors.

The Experimental Data

The data which underlie our re-estimation of the NCLAN dose-response functions are drawn from three sources: Heck *et al.* (1981), (1982) and Heagle *et al.* (1979). All data reported in these documents were derived from experiments conducted in approximate accordance with NCLAN protocols. The experiments are of the open-top-chamber and zonal types and thus exclude all closed control chamber and green house studies. With the exception of a set of experiments conducted on four red winter wheat varieties (Heagle (1979)) all experiments and resulting data are described in NCLAN annual reports.

The lack of availability of the disaggregate experimental data, that is, data pertaining to each chamber of a multi-chamber experimental design, significantly limits our estimation of dose reponse form. Rather, we employ average information across all chambers which were intended to receive

TABLE 6-3. INDEX OF DOSE-RESPONSE VARIABLES DRAWN FROM 1980 NCLAN ANNUAL REPORT

SOYBEAN (CORSOY), Central States NCLAN Region	
OZ3MO	Ozone conc. (PPM) 7/1 - 9/30
OZ2MO	Ozone Conc. (PPM) 8/6 - 9/30
NS	Number of Seeds
SW	Seed Weight
SWP	Seed Weight per Plant
SWHP	Seed Weight per Healthy Plant
WS	Weight per Seed
OIL	Percentage Oil
PROT	Percentage Protein
PEANUTS (NC-6), Southeast NCLAN Region	
OZ5MO	Ozone Conc. 6/17 - 10/6
SHTW	Fresh Shoot Weight
RTW	Fresh Root Weight
PODW	Total Pod Weight
MPODW	Marketable Pod Weight
MPODN	Marketable Pod Number

TABLE 6-4. RAW EXPERIMENTAL DATA
SOYBEAN (CORSOY), NCLAN Central States Region

OZ3MO	OZ2MO	NS	SW	SWP	SWHP	WS	OIL	PROT
.037	.022	718	108	13.9	20.4	.149	19.5	38.9
.050	.042	742	105	13.8	19.0	.141	19.2	38.9
.050	.042	784	112	14.1	18.4	.143	19.2	38.3
.064	.064	694	95	11.5	14.9	.137	18.9	39.6
.079	.089	612	77	9.4	11.7	.125	19.0	39.5
.094	.115	508	58	7.0	9.4	.115	18.2	40.7

TABLE 6-5. RAW EXPERIMENTAL DATA
PEANUTS (NC-6), NCLAN Southeast Region

OZ5MO	SHTW	RTW	PODW	MPODW	MPODN
.056	893	20	204	158	77
.025	1008	21	187	142	70
.056	761	16	145	122	58
.076	483	12	110	92	45
.101	402	9	77	69	34
.125	219	5	43	40	22

TABLE 6-6. INDEX OF DOSE-RESPONSE VARIABLES DRAWN FROM 1981 NCLAN ANNUAL REPORT

CORN (2 Varieties), NCLAN Central States Region	
OZ4MO	Ozone Conc. 6/20 - 9/10
KGHAPI	Yield KG/HA - PIONEER 3780
SDWPI	Weight of 100 Seeds - PIONEER 3780
PTKPI	Percent Kerneled - PIONEER 3780
KGHAPA	Yield KG/HA - PAG 397
SDWPA	Weight of 100 seeds - PAG 397
PTKPA	Percent Kerneled - PAG 397
SOYBEAN (HODGSON), NCLAN Northeast Region	
OZ3MO	Ozone Conc. 7/23 - 9/30
NOS	Number of Seeds
SDW	Seed Weight
SOYBEAN (DAVIS O_3 AND SO_2), NCLAN Southeast Region	
OZ	Ozone Conc.
SO2	SO_2 Conc.
SD100	Weight of 100 Seeds
SDW	Weight of Seeds per Meter of Row

Table 6-6 (continued)

SOYBEAN (ESSEX and WILLIAMS, O_3 and SO_2), NCLAN Southeast Region	
OZFM	Ozone Conc. During Fumigation
OZSEA	Ozone Conc. During Season
PLTSE	Plants/M Row ESSEX
PLTSW	Plants/M Row WILLIAMS
YIELDE	Yield G/M Row ESSEX
YIELDW	Yield G/M Row WILLIAMS
SDSIZE	Seed Size ESSEX
SDSIZW	Seed Size WILLIAMS
SEEDSE	Seed Numbers ESSEX
SEEDSW	Seed Numbers WILLIAMS
COTTON (ACALA SJ2), NCLAN Southwest Region	
OZ	Ozone conc.
LD	Percent Leaf Damage
YLD	Mean Gross Yield

TABLE 6-7. RAW EXPERIMENTAL DATA
CORN (2 VARIETIES), NCLAN Central States Region

OZ4MO	KGHAPI	SDWPI	PTKPI	KGHAPA	SDWPA	PTKPA
.044	10474	24.2	89.5	11387	23.7	91.0
.015	10991	25.7	88.3	11832	25.8	89.8
.044	10743	24.3	87.4	12911	25.6	93.0
.073	10909	24.7	88.2	11461	25.3	89.4
.100	8237	20.0	87.5	11044	24.0	91.0
.129	6101	17.6	88.5	8319	18.6	89.0
.156	4232	15.4	82.1	5040	15.9	84.2

TABLE 6-8. RAW EXPERIMENTAL DATA
SOYBEAN (HODGSON), NCLAN Northeast Region

OZ3MO	NOS	SDW
.017	76.3	12.1
.035	73.5	11.5
.035	73.3	11.1
.060	69.3	9.7
.084	66.7	8.4
.122	60.6	7.1

TABLE 6-9. RAW EXPERIMENTAL DATA
SOYBEAN (DAVIS), NCLAN Southeast Region

OZ	SO2	SD100	SDW
.0245	0	17.6	412
.0553	0	17.0	381
.0687	0	15.9	318
.0858	0	14.2	273
.1058	0	13.4	246
.1247	0	13.3	222
.0531	0	16.0	379
.0245	.026	18.2	438
.0553	.026	15.9	318
.0687	.026	15.0	313
.0858	.026	13.3	238
.1058	.026	13.3	250
.1247	.026	13.2	190
.0531	.026		
.0245	.085	18.1	426
.0553	.085	15.4	329
.0687	.085	13.6	294
.0858	.085	13.7	233
.1058	.085	13.2	198
.1247	.085	12.3	193
.0531	.085		
.0245	.367	15.3	286

Table 6-9 (continued)

OZ	SO2	SD100	SDW
.0553	.367	14.2	237
.0687	.367	13.3	192
.0858	.367	13.1	189
.1058	.367	13.0	154
.1247	.367	12.8	164
.0531	.367		

TABLE 6-10. RAW EXPERIMENTAL DATA
SOYBEAN (ESSEX AND WILLIAMS), NCLAN Southeast Region

OZFM	OZSEA	PLTSE	PLTSW	YIELDE	YIELDW	SDSIZE	SDSIZW	SEEDSE	SEEDSW
.014	.014	18.7	20.6	343	363	13.6	19.1	2553	1805
.039	.039	19.4	19.4	289	340	13.0	17.7	2235	1970
.071	.060	18.9	19.5	259	268	12.2	16.7	2219	1656
.096	.077	20.1	20.2	242	262	12.0	16.1	1959	1579

Note: The yield variables were averaged across alternative sulfur dioxide concentrations.

TABLE 6-11. COTTON (ACALA SJ2), NCLAN Southwest Region

OZ	LD	YLD
.018	0	1423.8
.045	0	1356.0
.071	6	1109.3
.111	29	859.5
.143	55	864.3
.185	61	592.5
.077	5	1194.0

TABLE 6-12. INDEX OF DOSE-RESPONSE VARIABLES
DRAWN FROM HEAGLE ET AL. (CANADIAN JOURNAL OF BOTANY)

WHEAT (4 Varieties RED WINTER), Experiments conducted in Southeastern U.S.

OZ2MO	Ozone Conc. 4/9 - 5/31
SDWBB	Seed Weight per Plant - BLUEBOY II
SDWCOK	Seed Weight per Plant - COKE, 47-27
SDWHOL	Seed Weight per Plant - HOLLY
SDWOA	Seed Weight per Plant - OASIS

Note: Experiments conducted prior to NCLAN formation.

TABLE 6-13. RAW EXPERIMENTAL DATA
WHEAT (4 VARIETIES RED WINTER), Southeast U.S.

OZ2MO	SDWBB	SDWCOK	SDWHOL	SDWOA
.06	4.79	4.01	4.16	4.06
.03	5.84	5.09	4.95	4.45
.06	5.74	4.55	4.91	4.41
.10	4.97	3.82	4.43	3.89
.13	4.02	2.91	3.30	3.28

Note: Experiments conducted prior to NCLAN formation.

the same ozone concentrations. The result of this averaging is a reduction in the degrees of freedom (number of observations) available for our re-estimation of the dose-response functions.

Table 6-3 presents the variable index for the data sets drawn from the 1980 NCLAN Annual Report. Tables 6-4 and 6-5 display the accompanying raw data used in our estimation programs. It is readily apparent from an examination of Tables 6-4 and 6-5 that only six observations exist for the estimation of the soybean and peanut functions.

Table 6-6 displays the variable index for data sets drawn from the 1981 NCLAN Annual Report while Tables 6-7 - 6-11 display the associated raw data sets. Finally, Tables 6-12 and 6-13 display the variable index and raw data pertaining to the wheat experiments reported in Heagle et al. (1979).

6.6. RFF BOX-TIDWELL DOSE-RESPONSE FUNCTION ESTIMATES

In the following sequence of tables we present our estimates of dose-response functions based upon the data sets displayed in subsection 6.4. Each estimated function is based on common specification which we have termed a Box-Tidwell in recognition of its developers. Recall the form of the Box-Tidwell as given below in the case of single independent variable x.

$$Y = b_0 + b_1 X^{\lambda} + \varepsilon \qquad (7)$$

where b_0 is an intercept term, b_1 a slope parameter and λ a curvature parameter. In the event that $\lambda = 1$ the expression (7) reduces to a linear function of x. If $\lambda > 1$ then (7) becomes a concave function and if $\lambda < 1$ (7) is a convex function. Thus, for example, if the true relationship underlying the estimation of the Corsoy soybean dose-response function (Table 6-1) is indeed linear, as suggested by the NCLAN choice of functional form, then we would expect λ to be very close to unity. Similarly, if the plateau function employed in the case of Pioneer 3780 corn (Table 6-2) is a reasonable approximation to the true relation we will expect λ to be greater than unity.

In the tables to follow we present estimated functions for specific crop/varieties which vary by choice of yield variable and in some instances by ozone averaging times.

We note that all the data points presented in Tables 4-2, 4-3 and 4-5 - 4-12 were used in the estimation. These data points include control plots exposed to ambient air without chambers. If a chamber bias exists in the experiments then our estimated functions will be impacted by the inclusion of the control plot.

Table 6-14 displays the functions estimated for Corsoy soybeans. These functions are comparable to the NCLAN relationship depicted in Table 6-1. The equations displayed in Table 6-14 range over five alternative yield variables and two averaging times. The NCLAN function depicts seed weight per healthy plant as a function of a two month averaging time. Our curvature parameter suggests that the linear form employed by NCLAN is a reasonable approximation to the data.

It is not the purpose of this report to evaluate each of our functions with respect to their NCLAN counterparts. The purpose of the above discussion is merely to highlight the sensitivity of the relationship to the choice of functional form, yield variable and averaging time.

Tables 6-15 - 6-21 display our estimated functions for peanuts, corn hybrids, wheat varieties, corn varieties Pioneer 3780, and PAG 397, Hodgson soybeans, Essex and Williams soybeans, Acala SJ2 cotton and Davis soybeans. In all but one instance the nonlinear Box-Tidwell estimation approach performed quite well. In the case of function SE1 (Table 6-20) the estimation algorithm did not converge to a satisfactory level of confidence. At the present time we have not identified the source of the problem.

We draw attention to a series of experiments conducted on Davis soybeans by NCLAN researchers at North Carolina State University. In this set of experiments concentrations of sulfur dioxide were administered to open-top-chambers in addition to ozone concentrations. Three alternatives SO_2 regimes including no SO_2 were administered. In the absence of any SO_2 the relationship between yields of Davis soybeans and ozone concentrations is remarkably linear. As SO_2 concentrations are increased in steps to a maximum of .367 ppm the functions become more nonlinear. Finally, it is possible to pool all the data across SO_2 regimes and estimate a Box-Tidwell function of the following form.

$$Y = \alpha + \beta O_3^{\lambda_1} + \gamma SO_2^{\lambda_2}$$

The RFF estimate of this function is given below.

$$Y = 933.347 - 1109.74(O_3)^{.2089} - 297.483(SO_2)^{1.175} \qquad R^2 = .9310$$

TABLE 6-14. RESOURCES FOR THE FUTURE DOSE-RESPONSE FUNCTIONS

Crop: SOYBEAN (CORSOY)
NCLAN Region: Central States

Function ID	Measure of Output	Dose	#OBS	$\hat{a}$	$\hat{b}$	$\hat{\lambda}$	R^2
SC1	NS	OZ3MO	6	760.4634	-2145473.	3.8167	.9254
SC2	SW	OZ3MO	6	115.749	-44348.2	2.8017	.9728
SC3	SWP	OZ3MO	6	15.43259	-2025.42	2.3099	.9734
SC4	SWHP	OZ3MO	6	28.06625	-220.277	1.0364	.9853
SC5	WS	OZ3MO	6	.156729	-2.57102	1.7415	.9912
SC6	NS	OZ2MO	6	755.5221	-76216.6	2.6383	.9278
SC7	SW	OZ2MO	6	113.3243	-4261 12	1.99905	.9738
SC8	SWP	OZ2MO	6	14.8961	-318.683	1.6995	.9739
SC9	SWHP	OZ2MO	6	23.998	-113.573	.93716	.9841
SC10	WS	OZ2MO	6	.152759	-.66197	1.3227	.9914

TABLE 6-15. RESOURCES FOR THE FUTURE DOSE-RESPONSE FUNCTIONS

Crop: PEANUTS (NC-6)
NCLAN Region: Southeast U.S.

Function ID	Measure of Output	Dose	#OBS	$\hat{a}$	$\hat{b}$	$\hat{\lambda}$	R^2
PS1	SHTW	OZ5MO	6	1264.378	-7654.69	.94902	.9350
PS2	RTW	OZ5MO	6	24.1078	-265.083	1.25525	.9332
PS3	PODW	OZ5MO	6	211.2775	-4158.15	1.52339	.8611
PS4	MPODW	OZ5MO	6	156.9733	-4995.8	1.78762	.8747

TABLE 6-16. RESOURCES FOR THE FUTURE DOSE-RESPONSE FUNCTIONS

Crop: WHEAT (RED WINTER, BLUEBOY II, COKER 47-27, HOLLY, OASIS)
NCLAN Region: Southeast U.S.

Function ID	Measure of Output	Dose	#OBS	$\hat{a}$	$\hat{b}$	$\hat{\lambda}$	R^2
WB1	SDWBB	OZ2MO	5	5.8993	-48.888	1.6222	.7497
WC1	SDWCOK	OZ2MO	5	5.8657	-15.6303	.83509	.9117
WH1	SDWHOL	OZ2MO	5	4.6979	-149335.	5.6777	.7858
WO1	SDWOA	OZ2MO	5	4.4423	-172.732	2.4582	.9247

TABLE 6-17. RESOURCES FOR THE FUTURE DOSE-RESPONSE FUNCTIONS

Crop: CORN (PIONEER 3780, PAG 397)
NCLAN Region: Central States

Function ID	Measure of Output	Dose	#OBS	$\hat{a}$	$\hat{b}$	$\hat{\lambda}$	R^2
CPI1	KGHAPI	OZ4MO	7	11163.32	-515292.	2.3004	.9669
CPG1	KGHAPA	OZ4MO	7	12075.55	-6960261.	3.707221	.9664

TABLE 6-18. RESOURCES FOR THE FUTURE DOSE-RESPONSE FUNCTIONS

Crop: SOYBEAN (HODGSON)
NCLAN Region: Northeast U.S.

Function ID	Measure of Output	Dose	#OBS	$\hat{a}$	$\hat{b}$	$\hat{\lambda}$	R^2
SH1	NOS	OZ3MO	6	77.892	-221.175	1.1738	.9922
SH2	SDW	OZ3MO	6	13.252	-49.467	.9465	.9922
SH3	NOSSDW	OZ3MO	6	1061.823	-3938.49	.8335	.9952

TABLE 6-19. RESOURCES FOR THE FUTURE DOSE-RESPONSE FUNCTIONS

Crop: SOYBEAN (ESSEX and WILLIAMS)
NCLAN Region: Southeast U.S.

Function ID	Measure of Output	Dose	#OBS	$\hat{a}$	$\hat{b}$	$\hat{\lambda}$	R^2
SE1	YIELDE	OZFM	4	NONCONVERGENCE			
SW1	YIELDW	OZFM	4	397.132	-934.339	.8008	.9342
SE2	YIELDE	OZSEA	4	491.162	-547.452	.3063	.9998
SW2	YIELDW	OZSEA	4	383.508	-2748.27	1.1906	.9167

TABLE 6-20. RESOURCES FOR THE FUTURE DOSE-RESPONSE FUNCTION

Crop: Cotton (ACALA SJ2)
NCLAN Region: Southwest U.S.

Function ID	Measure of Output	Dose	#OBS	$\hat{a}$	$\hat{b}$	$\hat{\lambda}$	R^2
CA1	YLD	OZ	7	1561.073	-4540.42	.9193	.9543

TABLE 6-21. RESOURCES FOR THE FUTURE DOSE-RESPONSE FUNCTIONS

Crop: SOYBEANS (DAVIS)
NCLAN Region: Southeast U.S.

Function ID	Measure of Output	Dose	#OBS	SO_2	$\hat{a}$	$\hat{b}$	$\hat{\lambda}$	R^2
SD1	SDW	OZ	7	0.000	469.553	-2283.45	1.0453	.9510
SD2	SDW	OZ	6	0.026	1126.782	-1353.00	0.1817	.9588
SD3	SDW	OZ	6	0.085	807.73	-1199.88	0.3108	.98816
SD4	SDW	OZ	6	0.367	1467.863	-1509.07	0.0664	.9447

6.7. AVERTING BEHAVIOR AS EMBODIED IN VARIETY SWITCHING

The dose-response function evidence provided in the previous section demonstrates clearly that the sensitivity of a particular crop to concentrations of ozone varies with the variety of that particular crop. If the dose-response relationship across varieties is merely a neutral displacement of a common relation then for our benefit estimates the differing varieties are not a problem. However, if a nonneutral displacement is found then the benefit estimates will vary with variety.

Ideally, we would like to know exactly which varieties were planted in what quantities in which areas at each point in time. Our contacts of the Economic Research Service (ERS) of USDA are inclined to believe that this data at the level of resolution required by the RMF is not available. We shall continue to pursue our efforts with ERS but must have a fallback position which is acceptable from an economic standpoint and within the time and budget limitations of the project.

We propose the following based on the simple assumptions that farmers choose crop varieties in an effort to maximize yields in their respective regions presuming that all varieties receive identical applications of fertilizer and other inputs. Under these assumptions farmers choose varieties which maximize yields given their ambient ozone concentrations, climate, soil type, etc.. Consider the four varieties of wheat study by Heagle et al. (1979). If we were to form the uppermost envelope of this set of functions we would have defined what we shall term the "frontier dose-response function." Under our assumption of producer behavior the variety Blueboy will be chosen by all wheat farmers which experience ambient ozone concentrations from 0.0-.24 ppm. Since this variety provides the greatest yield where ozone concentrations are less than .24. If concentrations exceed this terminal value then the farmers are induced to switch to Coker.

In each instance where we have multiple, variety specific dose-response functions we form the frontier of these functions and use that frontier as the relevant dose-response curve reflecting the variety choice of the producers.

6.8. CONCLUDING REMARKS

It is fair to say that the NCLAN experiments conducted over the last two years have added to the evidence suggesting the existence of harmful ozone effects on plants, both in terms of leaf injury and yield. However, the design and results of these recent experiments, though extremely useful, do not provide all of the desired information for theoretically and empirically sound national benefit estimates.

When we speak of an agricultural yield response-ozone dose function in the narrowest sense, we presume that all other factors affecting yield of the particular crop under consideration -- climate, soil type, farming practices, concentrations of other pollutants and the like -- are held constant in the design of the experiments which generate the data. In these circumstances, an attempt to empirically relate crop yield and ozone dose, say in a regression context, could be made. But for either of two reasons, the influence of other candidate variables on yield cannot be accounted for because of data limitations. Specifically the experiments could either have been designed to hold these variables constant or, improperly, could have inadvertently allowed them to vary but failed to obtain their measurements.

If the crop yield response to ozone is in fact independent of the levels of all other potential explanatory variables, this method, labeled the "classical one-variable-at-a-time strategy" (Box *et al.*, 1978) is, at least mathematically, benign. However, even if independence holds, relating yield to each separate variable (such as ozone, rainfall, soil type) in a sequence of one-variable ordinary least squares (OLS) regressions can have serious and quite undesirable consequences if all theoretically important explanatory variables apart from the one of interest in the one-variable regressions were not actually held constant in the experiments. Allowing omitted variables to vary in the experiments but failing to measure their levels means that, to the extent that such omitted explanatory variables are correlated with the included explanatory variable, the parameter estimates of any single variable yield regression will be biased and inconsistent. Even in the absence of such correlation, the intercept parameter estimate will be biased, as will the estimated variance of the slope (Kmenta, 1971, Ch. 10).

We presume that, because the NCLAN dose-response experiments were carefully designed, all omitted variables in any particular experiment were in fact held constant, so that omitted variable bias is not a problem. The results presented in this report are conditioned on the assumption that crop yield can be legitimately estimated as a function of ozone dose alone to accurately represent what happened at a particular experiment station. To predict what could happen across the nation on the basis of this information is another question altogether.

CHAPTER 6 FOOTNOTES

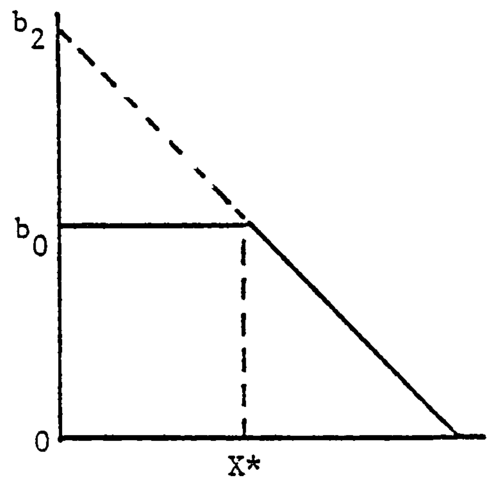
[1]Some experiments investigated the simultaneous effects of ozone and sulfur dioxide.

[2]Specification error tests are designed to discriminate between random (white noise) variation in the residuals and systematic variation which can be related to other variables. Misspecified models produce the latter, but sometimes the net effect of several simultaneous specification errors may lead to apparent white noise residuals, defeating the tests.

[3]For an example of the application of the Ramsey-type tests to linear epidemiological dose-response models relating human morbidity and pollution see Smith (1975). The RESET test is a cousin to the method of using the higher powers of the explanatory variables as a test for nonlinearity discussed in the next section (see Thursby and Schmidt, 1977, p. 637).

[4]The same GRC report also produced a wide range of opinion over the appropriate way to measure ozone dosage, particularly the common assumption of equivalent yield reductions from mathematically equivalent doses (e.g., 0.06 ppm for 100 hours versus 12 ppm for 50 hours).

[5]It is easy to visualize the plateau model and its representation in the regression context. Graphically, let b_2 be the Y axis intercept of the downward sloping segment of the function (with slope b_1) and b_0 be the plateau level for $X < X^*$.



Algebraically we can write the model without error as:

$$Y = (1 - D)b_0 + D(b_2 - b_1X) \qquad \text{where } D = 1 \text{ if } X > X^*$$

To force the horizontal line segment and the downward sloping line segments of the plateau model to join at X* the following restriction must be imposed:

$$b_2 - b_1X^* = b_0 \quad \text{or} \quad b_2 = b_1X^* + b_0$$

Substituting for b_2 given by the restriction we get:

$$Y = (1 - D)b_0 + D(b_1X^* + b_0 - b_1X)$$

which can be simplified to the equation in the text:

$$Y = b_0 + b_1(D(X^* - X)).$$

[6]A more sophisticated approximation method is the cubic spline function. Cubic splines are cubic polynomials in a single independent variable joined together smoothly at known points.

If the break points (changes in regression regimes) are unknown a priori, an attempt to locate them empirically can be made using a variety of methods which are frequently applied in time series analysis. (See Hackl, 1980, for an exhaustive survey, and Harvey, 1981, for a lucid discussion of the cumulative sum of recursive residuals (CUSUM) test for structural misspecification).

[7]A similar sort of model specification test was performed for alternative functional forms of the travel cost model in Smith (1975). Also, see Aneuryn-Evans and Deaton (1980) for a theoretical treatment and some Monte Carlo evidence on the performance of Cox-Pesaran test.

[8]Note that the observed values of yield for any given value of dose in this formulation theoretically can extend from minus infinity to plus infinity because we have assumed a normal distribution for the error term. Put otherwise, there always exists a finite probability that observed yield will be nonpositive. To get around this problem, we can either truncate the distribution of the error term or assert that the expected value of the dependent variable will always be, say, five standard errors above zero. Practically speaking, the latter means that the probability of observing a nonpositive Y is so close to zero that it can be ignored. Without using this

dodge or arbitrarily truncating the error term we must be willing to use the natural log of yield as the dependent variable in all the models considered (i.e., the linear model is rejected outright). Then, the logit model would be:

$$Y_i = e^{b_0/(1+b_1 e^{b_2 X_i})} e^{\varepsilon_i}$$

We do not entertain this possibility here.

[9] Box-Tidwell: First and Second Derivatives with Respect to X:

$$Y = f(X) = b_0 + b_1 X^{\lambda}$$

$$f'(X) = \lambda b_1 X^{\lambda-1}$$

$$f''(X) = (\lambda-1)\lambda b_1 X^{\lambda-2}$$

Logistic: First and Second Derivatives with Respect to X:

$$Y = g(X) = b_0 + (1/(1+b_1 e^{b_2 X}))$$

$$g'(X) = -b_2 b_1 e^{b_2 X}/(1+b_1 e^{b_2 X})^2 < 0 \qquad \text{iff } b_1, b_2 > 0 \text{ or } b_1, b_2 < 0$$

$$g''(X) = \frac{-(1+b_1 e^{b_2 X})^2 b_2^2 b_1 e^{b_2 X} + 2b_2 b_1 e^{b_2 X}(1+b_1 e^{b_2 X})(b_2 b_1 e^{b_2 X})}{(1+b_1 e^{b_2 X})^4}$$

To find the point of inflection given b_1, b_2 set:

$$2b_2b_1e^{b_2X}(1+b_1e^{b_2X})(b_2b_1e^{b_2X})$$

equal to:

$$(1+b_1e^{b_2X})^2b_2^2b_1e^{b_2X}$$

Cancelling terms and simplifying:

$$b_1e^{b_2X} = 1 \qquad \text{or} \qquad X = -\ln b_1/b_2$$

[10]For testing nested hypotheses, -2(LR) has, for large samples, a chi-square distribution with degrees of freedom equal to the number of parameters restricted to specific values under H_0. In the nonnested case, it is only a measure of plausibility with no such distributional properties.

[11]The discussion assumes both models have an identical number of parameters to be estimated.

[12]See Davidson and MacKinnon (1981) for a theoretical derivation of the asymptotic properties of their tests which they show are similar to the asymptotic properties of the Pesaran and Deaton (1978) tests.

CHAPTER 7

YIELD CHANGES USING EPA OZONE SCENARIOS

In this chapter we exploit the dose-response functions described in Chapter 6 in conjunction with the air quality and crop yield information contained in the RMF to examine the impact of alternative ozone exposure scenarios on the yields of selected crops. We note at the outset that these calculations assume no economic adjustments on the part of agricultural producers to changing crop yields. We simply employ the RFF re-estimated NCLAN dose-response functions to calculate the change in yield associated with a particular change in ozone concentrations and then multiply this change in yield by the 1978 yields contained in the FEDS.

The actual calculations are described below.

1. Actual 1978 ozone concentrations by FEDS areas contained in the RMF data base are associated with the quantity of soybeans, wheat, corn, cotton and peanuts produced by the respective areas in 1978.

2. The actual 1978 ozone concentrations for each FEDS area are located on the appropriate NCLAN dose-response function and the value of the yield proxy variable (the response variable) recorded.

3. Using EPA/OAQPS supplied ozone exposure scenarios (see Table 7-1) we bring all FEDS areas to the same ozone concentration as specified by the scenario.

4. The scenario concentrations are then located on the dose-response functions and the new level of the proxy yield variable recorded.

5. For each FEDS area for each crop the following formula (reproduced from Chapter 5) is calculated.

$$\Delta YIELD = \frac{Y^*}{Y} - 1$$

where Y is the yield at the 1978 ozone concentration

Y^* is the yield associated with each ozone scenario.

6. (ΔYIELD + 1) is multiplied by the 1978 quantities of each crop produced in each FEDS area and then summed by crop across areas.

The relevant dose-response functions used in this exercise along with their pictorial representations are displayed on Tables 7-2 - 7-8. The specific dose-response functions (highlighted by rectangles in the tables) were chosen to be regionally consistent with FEDS areas. In the cases of wheat and corn we employ the method of frontier Tidwell discussed in Chapter 6.

Tables 7-9 - 7-15 report the changes in biological yield for the five crops examined in this study across the seven ozone concentrations displayed in Table 7-1. Soybeans, wheat and corn are dimensioned in bushels, peanuts in pounds and cotton in bales.

TABLE 7-1

EPA/OAQPS OZONE CONCENTRATION SCENARIOS

Scenario No.	Concentration in PPM
1	.01
2	.02
3	.03
4	.04
5	.05
6	.06
7	.07
8	.08
9	.09
10	.10

Note: Ozone concentrations are measured as seasonal 7 hour daily means.

TABLE 7-2. RESOURCES FOR THE FUTURE DOSE-RESPONSE FUNCTIONS ESTIMATED FROM NCLAN EXPERIMENTAL DATA: SOYBEANS

Crop: SOYBEAN (CORSOY)
NCLAN Region: Central States

Function ID	Measure of Output	Dose	#OBS	$\hat{a}$	$\hat{b}$	$\hat{\lambda}$	R^2
SC1	NS	OZ3MO	6	760.4634	-2145473.	3.8167	.9254
SC2	SW	OZ3MO	6	115.749	-44348.2	2.8017	.9728
SC3	SWP	OZ3MO	6	15.43259	-2025.42	2.3099	.9734
SC4	SWHP	OZ3MO	6	28.06625	-220.277	1.0364	.9853
SC5	WS	OZ3MO	6	.156729	-2.57102	1.7415	.9912
SC6	NS	OZ2MO	6	755.5221	-76216.6	2.6383	.9278
SC7	SW	OZ2MO	6	113.3243	-4261.12	1.99905	.9738
SC8	SWP	OZ2MO	6	14.8961	-318.683	1.6995	.9739
SC9	SWHP	OZ2MO	6	23.998	-113.573	.93716	.9841
SC10	WS	OZ2MO	6	.152759	-.66197	1.3227	.9914

TABLE 7-3. RESOURCES FOR THE FUTURE DOSE-RESPONSE FUNCTIONS ESTIMATED FROM NCLAN EXPERIMENTAL DATA: SOYBEANS

Crop: SOYBEAN (HODGSON)
NCLAN Region: Northeast

Function ID	Measure of Output	Dose	#OBS	$\hat{a}$	$\hat{b}$	$\hat{\lambda}$	R^2
SH1	NOS	OZ3MO	6	77.892	-221.175	1.1738	.9922
SH2	SDW	OZ3MO	6	13.252	-49.467	.9465	.9922
SH3	NOSSDW	OZ3MO	6	1061.823	-3938.49	.8335	.9952

TABLE 7-4. RESOURCES FOR THE FUTURE DOSE-RESPONSE FUNCTIONS ESTIMATED FROM NCLAN EXPERIMENTAL DATA: SOYBEANS

Crop: SOYBEAN (ESSEX and WILLIAMS)
NCLAN Region: Southeast

Function ID	Measure of Output	Dose	#OBS	$\hat{a}$	$\hat{b}$	$\hat{\lambda}$	R^2
SE1	YIELDE	OZFM	4	NONCONVERGENCE			
SW1	YIELDW	OZFM	4	397.132	-934.339	.8008	.9342
SE2	YIELDE	OZSEA	4	491.162	-547.452	.3063	.9998
SW2	YIELDW	OZSEA	4	383.508	-2748.27	1.1906	.9167

TABLE 7-5. RESOURCES FOR THE FUTURE DOSE-RESPONSE FUNCTIONS ESTIMATED FROM NCLAN EXPERIMENTAL DATA: COTTON

Crop: Cotton (ACALA SJ2)
NCLAN Region: Southwest

Function ID	Measure of Output	Dose	#OBS	$\hat{a}$	$\hat{b}$	$\hat{\lambda}$	R^2
CA1	YLD	OZ	7	1561.073	-4540.42	.9193	.9543

TABLE 7-6. RESOURCES FOR THE FUTURE DOSE-RESPONSE FUNCTIONS ESTIMATED FROM NCLAN EXPERIMENTAL DATA: CORN

Crop: CORN (PIONEER 3780, PAG 397)
NCLAN Region: Central States

Function ID	Measure of Output	Dose	#OBS	$\hat{a}$	$\hat{b}$	$\hat{\lambda}$	R^2
CPI1	KGHAPI	OZ4MO	71	1163.32	-515292.	2.3004	.9669
CPG1	KGHAPA	OZ4MO	71	2075.55	-6960261.	3.707221	.9664

TABLE 7-7. RESOURCES FOR THE FUTURE DOSE-RESPONSE FUNCTIONS ESTIMATED FROM NON-NCLAN EXPERIMENTAL DATA: WHEAT

Crop: WHEAT (RED WINTER, BLUEBOY II, COKER 47-27, HOLLY, OASIS)
NCLAN Region: Southeast

Function ID	Measure of Output	Dose	#OBS	$\hat{a}$	$\hat{b}$	$\hat{\lambda}$	R^2
WB1	SDWBB	OZ2MO	5	5.8993	-48.888	1.6222	.7497
WC1	SDWCOK	OZ2MO	5	5.8657	-15.6303	.83509	.9117
WH1	SDWHOL	OZ2MO	5	4.6979	-149335.	5.6777	.7858
WO1	SDWOA	OZ2MO	5	4.4423	-172.732	2.4582	.9247

TABLE 7-8. RESOURCES FOR THE FUTURE DOSE-RESPONSE FUNCTIONS ESTIMATED FROM NCLAN EXPERIMENTAL DATA: PEANUTS

Crop: PEANUTS (NC-6)
NCLAN Region: Southeast

Function ID	Measure of Output	Dose	#OBS	$\hat{a}$	$\hat{b}$	$\hat{\lambda}$	R^2
PS1	SHTW	OZ5MO	6	1264.378	-7654.69	.94902	.9350
PS2	RTW	OZ5MO	6	24.1078	-265.083	1.25525	.9332
PS3	PODW	OZ5MO	6	211.2775	-4158.15	1.52339	.8611
PS4	MPODW	OZ5MO	6	156.9733	-4995.8	1.78762	.8747

TABLE 7-9. OUTPUT CHANGES

Crop: SOYBEANS
NCLAN Region: Central States

Ozone concentrations	Output	Output change from .04 ppm	Change by increment
.04 ppm	1,541,393,410		
.05 ppm	1,454,137,600	-87,255,810	-87,255,810
.06 ppm	1,340,680,450	-200,712,960	-113,457,150
.07 ppm	1,199,492,100	-341,901,310	-141,188,350
.08 ppm	1,029,211,650	-512,181,760	-170,280,450
.09 ppm	828,609,792	-712,783,618	-200,601,858
.10 ppm	596,553,984	-944,839,426	-232,055,808

TABLE 7-10. OUTPUT CHANGES

Crop: SOYBEANS
NCLAN Region: Northeast

Ozone concentrations	Output	Output change from .04 ppm	Change by increment
.04 ppm	29,081,344		
.05 ppm	27,061,936	-2,019,408	-2,019,408
.06 ppm	25,109,168	-3,972,176	-1,952,768
.07 ppm	23,210,080	-5,871,264	-1,899,088
.08 ppm	21,355,808	-7,725,536	-1,854,272
.09 ppm	19,539,840	-9,541,504	-1,815,968
.10 ppm	17,757,232	-11,324,112	-1,782,608

TABLE 7-11. OUTPUT CHANGES

Crop: SOYBEANS
NCLAN Region: Southeast

Ozone concentrations	Output	Output change from .04 ppm	Change by increment
.04 ppm	837,101,056		
.05 ppm	790,301,952	-46,799,104	-46,799,104
.06 ppm	741,672,704	-95,428,352	-48,629,248
.07 ppm	691,467,264	-145,633,792	-50,205,390
.08 ppm	639,872,512	-197,228,544	-51,594,752
.09 ppm	587,029,248	-250,071,808	-52,843,264
.10 ppm	533,053,440	-304,047,616	-53,975,808

TABLE 7-12. OUTPUT CHANGES

Crop: COTTON
Region: U.S.

Ozone concentrations	Output	Output change from .04 ppm	Change by increment
.04 ppm	7,837.458,430		
.05 ppm	7,520,448,510	-317,009,920	-317,009,920
.06 ppm	7,208,534,020	-628,924,410	-311,914,490
.07 ppm	6,900,822,020	-936,636,410	-307,712,000
.08 ppm	6,596,636,670	-1,240,821,760	-304,185,350
.09 ppm	6,295,523,330	-1,541,935,100	-301,113,340
.10 ppm	5,997,109,250	-1,840,349,180	-298,414,080

TABLE 7-13. OUTPUT CHANGES

Crop: CORN
Region: U.S.

Ozone concentrations	Output	Output change from .04 ppm	Change by increment
.04 ppm	7,029,059,580		
.05 ppm	6,994,669,570	-34,390,010	-34,390,010
.06 ppm	6,935,658,500	-93,401,080	-59,011,070
.07 ppm	6,843,064,320	-185,995,260	-92,594,180
.08 ppm	6,706,827,260	-322,232,320	-136,237,060
.09 ppm	6,515,740,670	-513,318,910	-191,086,590
.10 ppm	6,257,717,250	-771,342,330	-258,023,420

TABLE 7-14. OUTPUT CHANGES

Crop: WHEAT
Region: U.S.

Ozone concentrations	Output	Output change from .04 ppm	Change by increment
.04 ppm	2,135,484,420		
.05 ppm	2,127,833,340	-7,651,080	-7,651,080
.06 ppm	2,077,558,780	-57,925,640	-50,274,560
.07 ppm	2,021,774,590	-113,709,830	-55,784,190
.08 ppm	1,960,794,620	-174,689,800	-60,979,970
.09 ppm	1,894,871,550	-240,612,870	-65,923,070
.10 ppm	1,824,221,440	-311,262,980	-70,650,110

TABLE 7-15. OUTPUT CHANGES

Crop: PEANUTS
Region: U.S.

Ozone concentrations	Output	Output change from .04 ppm	Change by increment
.04 ppm	4,060,651,260		
.05 ppm	3,779,529,220	-281,122,040	-281,122,040
.06 ppm	3,467,225,860	-593,425,400	-312,303,360
.07 ppm	3,126,350,590	-934,300,670	-340,875,270
.08 ppm	2,758,942,210	-1,301,709,050	-367,408,380
.09 ppm	2,366,644,220	-1,694,007,040	-392,297,990
.10 ppm	1,950,814,980	-2,109,836,280	-415,829,240

CHAPTER 8

SOME WELFARE EXERCISES USING THE REGIONAL MODEL FARM

8.1. INTRODUCTION

The purpose of this chapter is to demonstrate the capabilities of the RMF as a tool for the analysis of societal welfare effects forthcoming from the agricultural production sector in response to changes in rural ozone concentrations. We note at the outset that the estimates of net producer and consumer surplus reported in this chapter are solely illustrative. These EPA supplied ozone scenarios treat the standard as a strict equality, not as a less than or equal to inequality constraint. If, for example, the standard is tightened to .10 ppm, which might translate to average rural concentrations of .05 ppm, all counties below .05 ppm are assumed to pollute up to .05 ppm. In a Regulatory Impact Analysis (RIA) proposed standards would be translated into expected ozone monitor readings at the actual monitor sites (primarily urban areas). These expected readings would then serve as data to an interpolation procedure which would predict expected ozone concentrations in rural areas. Finally, these interpolated ozone concentrations would serve as data for the RMF.

In the illustrations to follow simple ozone scenarios are employed to obtain the area specific ozone exposures. Specifically, we assume that the ozone concentrations in all rural counties (indeed all counties rural or urban) attain uniform levels as specified by the EPA ozone scenarios displayed in Table 8-1. Welfare estimates are then based upon the difference between the sum of producer and consumer surplus calculated at 1978 ambient county level ozone concentrations (these ambient concentrations vary county to county) and the sum of producer and consumer surplus calculated at each EPA scenario ozone concentration. Thus, if we are examining the .05 ppm scenario some county concentrations will rise to the .05 ppm level from 1978 ambient while others will fall. This information is then used to calculate the increment benefits between alternative ozone scenarios.

8.2. MAINTAINED ASSUMPTIONS USED IN THE ILLUSTRATIVE WELFARE EXERCISES

The process by which the RMF calculates net producer and consumer surplus (welfare) estimates is discussed in section 5.3 of this report and will not be repeated. The purpose of this section is to identify those assumptions which underlie the illustrative results reported below.

The first assumption concerns the differential effect which ozone has on the productivity of preharvest and harvest factors of production. The results reported in this chapter assume that the preharvest production function is neutrally displaced in input-output space in accordance with the NCLAN dose-response functions discussed and reported in Chapter 6. We further assume that harvest production function is unaffected by charges in ozone concentration and is therefore "ozone stationary". This set of assumptions is manifested in the parameter γ (Equation 37, Chapter 5), where $\gamma = 0$ for all our illustrations. The sensitivity of the RMF welfare estimates to this set of maintained assumptions is examined in the following chapter.

The second set of maintained assumptions concerns the dose-response functions used in the welfare calculations. In the case of soybeans we

TABLE 8-1. EPA/OAQPS OZONE CONCENTRATION SCENARIOS

Scenario No.	Concentration in ppm
1	.01
2	.02
3	.03
4	.04
5	.05
6	.06
7	.07
8	.08
9	.09
10	.10

employ region-specific dose-response functions. But for wheat, corn, cotton and peanuts we must use a single function for all regions. Further, each dose-response function employs a common nonlinear form referred to as a Box-Tidwell. The specific dose-response functions utilized are displayed in Chapter 7.

In the case of wheat and corn we have been able to estimate dose-response functions for alternative varieties of each crop. Since *a priori* we do not know which variety farmers are planting or would plant under differing ozone regimes we have adopted the behavioral rule that farmers plant that variety which produces the greatest yield. This rule allows us to envelope the uppermost portions of a set of varietal specific dose-response functions and employ that envelope as a function which in some sense incorporates varietal switching behavior. The sensitivity of our results to this particular assumption is examined in the following chapter.

The third assumption concerns the assumed elasticity of demand assigned to each crop. The elasticities employed in this study are drawn from the USDA model entitled "A Mathematical Programming Model for Agricultural Sector Policy Analysis" and are displayed in Table 8-2. The sensitivity of our results to the elasticity estimates is examined in the following chapter.

8.3. BENEFIT CALCULATIONS WITH ELASTIC DEMAND

In what follows we describe the methods employed to compute net producer and consumer surplus when the aggregate demand for agricultural crops possesses some elasticity. Table 8-2 below displays the point estimates of demand elasticities for the five crops covered in this study.

TABLE 8-2: PRICE ELASTICITIES OF DEMAND FOR SELECTED AGRICULTURAL CROPS

Crop	Demand Elasticity
Cotton	-.22
Corn	-.33
Soybeans	-.80
Wheat	-.35
Peanuts	-.80

*These estimates were drawn from "A Mathematical Programming Model for Agricultural Sector Policy Analysis," Robert House, Oct. 20, 1982 United States Dept. of Agriculture, Economic Research Service.

Figures 8-1 and 8-2 display the heuristics of the benefit calculation under alternative scenarios concerning the level of ambient ozone. In Figure 8-1 ozone concentrations are reduced below current ambient. This has the effect of shifting the agricultural supply function from S^0 to S^* and thus increasing output from Q^0 to Q^*. The shaded area represents the net gain in consumer and produce surplus. Area S^0ABS^* is obtained by suitable integration of the appropriate marginal cost curves. The area ABC is calculated with knowledge of the elasticity given in Table 8-2 and thus the slope of DD' and the change in output given by $Q^* - Q^0$.

Figure 8-2 displays a case in which ambient ozone concentrations rise reducing crop yields and forcing the supply function upward as indicated by the shift from S^0 to S^1. To evaluate the welfare loss we must determine the area S^0S^1ABCD. We first determine S^0S^1AB by suitable integration under the supply curves from 0 to Q^1 and then determine DABC with knowledge of $Q^0 - Q^1$ and the slope of DD'.

8.4. WELFARE ESTIMATES UNDER EPA/OAQPS SUPPLIED OZONE SCENARIOS

Tables 8-3 - 8-9 display the net producer and consumer surplus estimates generated by the RMF under the EPA/OAQPS specified ozone scenarios and the maintained assumptions discussed in section 8.2. We remind the reader that each welfare estimate represents the difference in the sum of producer and consumer surplus, based on the production of a specific crop between the base ozone regime and the scenario regime. The base regime represents an estimate of the actual 1978 ambient ozone concentrations prevailing in each FEDS area and the consumer and producer surplus calculated on the basis of 1978 factor prices and yields. The ten alternative scenario regimes assume that the

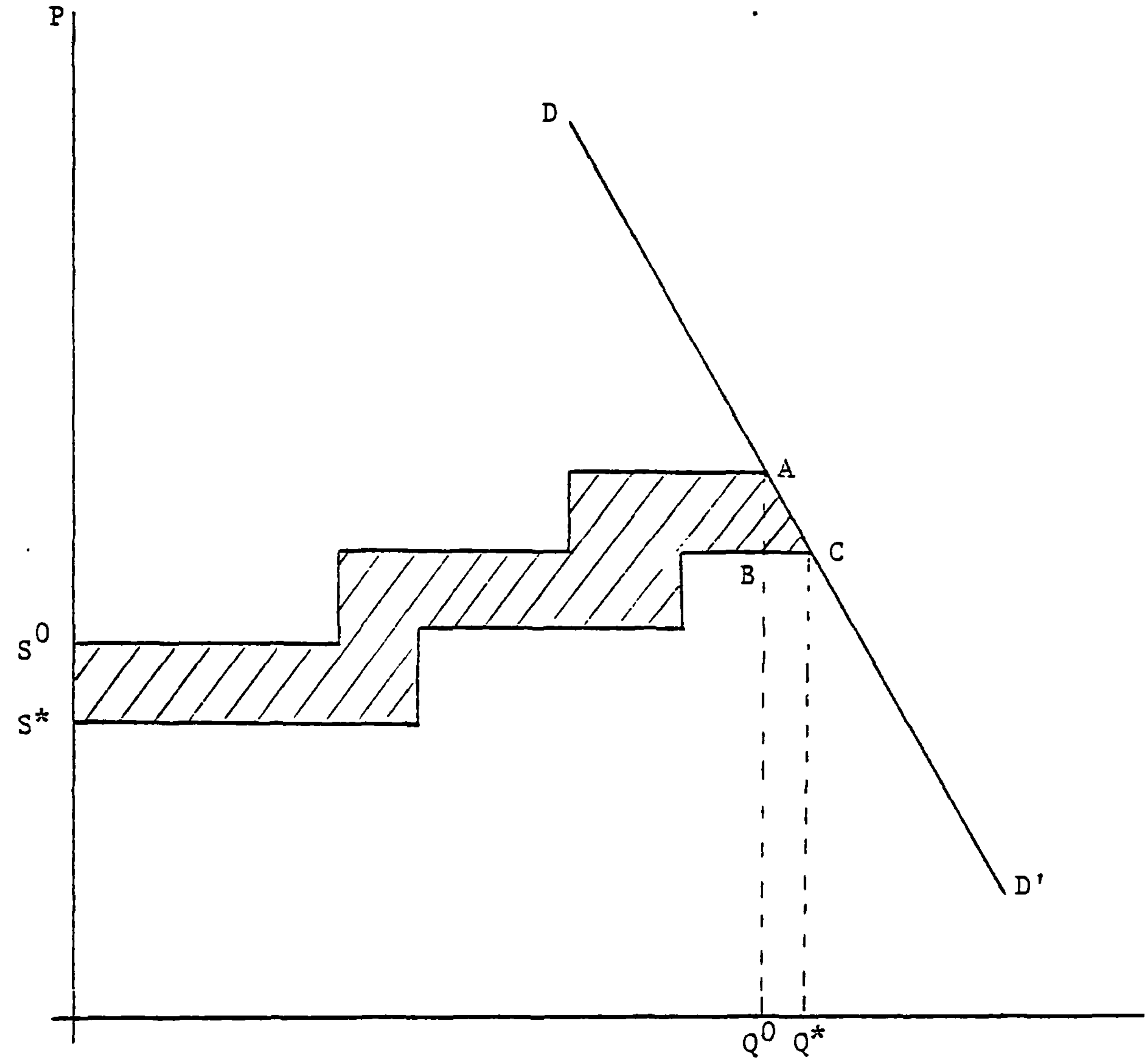


Figure 8-1.

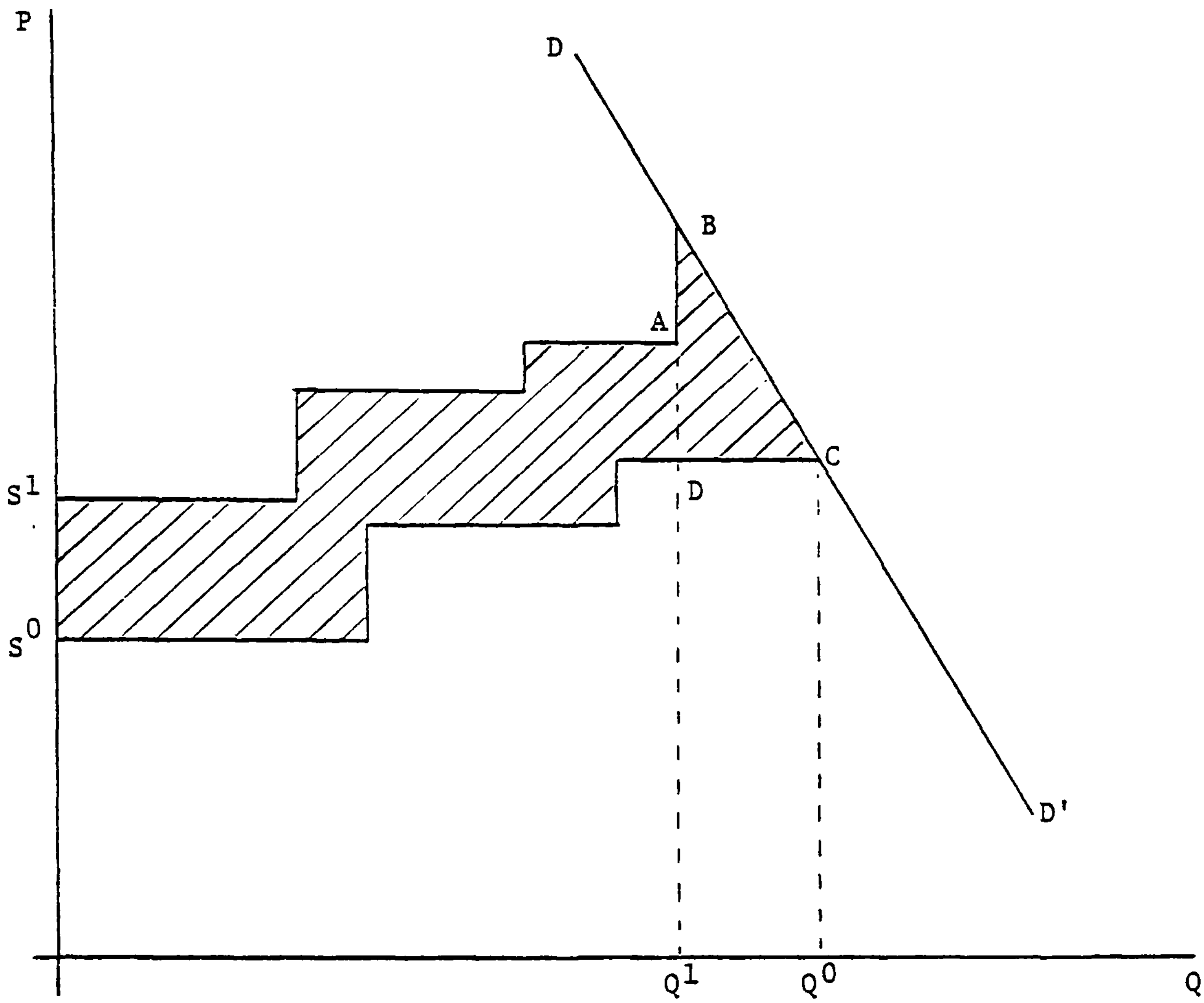


Figure 8-2.

ambient levels either rise or fall to the concentration given by the scenario. Thus, for any particular scenario, the actual percentage change in 1978 ambient ozone will vary across FEDS regions.

As an example let us consider the results reported in Table 8-3 where we examine the welfare gains and losses associated with the EPA scenarios for the production of soybeans in the northeast United States. In this area of the country the estimated mean growing season ambient ozone concentration is approximately .055 ppm. Thus, if ozone concentrations in all FEDS areas in this region rose to a uniform level of .06 ppm, one would expect economic loss which is reflected in Table 8-3 as net welfare loss of $3,525,134. Decreasing ozone concentrations from 1978 ambient to a uniform level of .05 ppm results in a net increase in welfare of $1,236,760. In the extreme scenarios reductions to .01 ppm would yield welfare gains of $18,366,336 and increases in ozone to a uniform .10 ppm would result in losses of $30,367,024.

Tables 8-5 and 8-6 round out these illustrative soybean examples by reporting results for soybean production in the Southeast and Midwest. Tables 8-6 - 8-9 represent national estimates for the crops corn, wheat, cotton and peanuts respectively.

8.5. CONCLUDING REMARKS

For the purposes of regulatory impact and other analyses welfare estimates based on alternative ozone standards would be constructed in a manner quite different from these estimates reported in the previous section. In Chapter 10 we address some of the issues and particularly the need for additional rural monitoring sites. One should also bear in mind that the welfare estimates will vary dramatically from one portion of the country to another, even from one portion of a state to another. Thus, while we have not done so in these illustrations, estimates made for actual policy simulations should be regionally disaggregated at least to the state level.

TABLE 8-3. WELFARE ESTIMATES UNDER EPA/OAQPS OZONE SCENARIOS FOR SOYBEAN PRODUCTION IN THE NORTHEAST REGION OF NCLAN: ESTIMATES IN 1978 DOLLARS

Concentration	Net welfare gain/loss	Incremental welfare gain/loss
.01	$ 18,366,336	
.02	13,932,556	4,433,780
.03	9,690,281	4,242,275
.04	5,052,414	4,637,867
.05	136,379	4,916,035
.06	-3,525,134	3,661,513
.07	-8,986,080	5,460,946
.08	-15,409,551	6,423,471
.09	-22,730,768	7,321,217
.10	-30,367,024	7,636,256

TABLE 8-4. WELFARE ESTIMATES UNDER EPA/OAQPS OZONE SCENARIOS FOR SOYBEAN PRODUCTION IN THE SOUTHEAST REGION OF NCLAN: ESTIMATES IN 1978 DOLLARS

Concentration	Net welfare gain/loss	Incremental welfare gain/loss
.01	$ 651,690,496	
.02	570,665,472	81,025,024
.03	481,455,360	89,210,112
.04	343,926,272	137,529,088
.05	189,834,000	154,092,272
.06	9,038,215	180,795,785
.07	-191,245,908	200,284,123
.08	-367,553,280	176,307,372
.09	-547,632,640	180,079,360
.10	-742,565,632	194,932,992

TABLE 8-5. WELFARE ESTIMATES UNDER EPA/OAQPS OZONE SCENARIOS FOR SOYBEAN PRODUCTION IN THE CENTRAL STATES REGION OF NCLAN: ESTIMATES IN 1978 DOLLARS

Concentration	Net welfare gain/loss	Incremental welfare gain/loss
.01	$ 428,407,712	
.02	399,954,944	28,452,768
.03	341,329,152	58,625,792
.04	245,927,920	95,401,232
.05	77,812,576	168,115,344
.06	-198,836,368	276,648,944
.07	-552,760,064	353,923,696
.08	-1,086,211,330	533,451,266
.09	-1,901,005,570	814,794,240
.10	-3,074,742,020	1,173,736,450

TABLE 8-6. WELFARE ESTIMATES UNDER EPA/OAQPS OZONE SCENARIOS FOR CORN PRODUCTION IN THE U.S.: ESTIMATES IN 1978 DOLLARS

Concentration	Net welfare gain/loss	Incremental welfare gain/loss
.01	$ 141,439,728	
.02	138,554,752	2,884,976
.03	125,264,480	13,290,272
.04	91,308,864	33,955,616
.05	34,874,448	56,434,416
.06	-68,029,264	102,903,712
.07	-221,512,768	153,483,504
.08	-447,547,392	226,034,624
.09	-792,965,376	345,417,984
.10	-1,315,634,690	522,669,314

TABLE 8-7. WELFARE ESTIMATES UNDER EPA/OAQPS OZONE SCENARIOS FOR WHEAT PRODUCTION IN THE U.S.: ESTIMATES IN 1978 DOLLARS

Concentration	Net welfare gain/loss	Incremental welfare gain/loss
.01	$ 262,120,464	
.02	224,526,304	37,594,160
.03	165,511,312	59,014,992
.04	79,262,624	86,248,688
.05	-17,772,240	97,034,864
.06	-132,422,384	114,650,144
.07	-257,741,504	125,319,120
.08	-401,955,840	144,214,336
.09	-563,645,184	161,689,344
.10	-751,795,712	188,150,528

TABLE 8-8. WELFARE ESTIMATES UNDER EPA/OAQPS OZONE SCENARIOS FOR COTTON PRODUCTION IN THE U.S.: ESTIMATES IN 1978 DOLLARS

Concentration	Net welfare gain/loss	Incremental welfare gain/loss
.01	$ 634,018,304	
.02	512,547,584	121,470,720
.03	389,435,392	123,112,192
.04	253,104,528	136,330,864
.05	94,547,872	158,556,656
.06	-76,303,344	170,851,216
.07	-290,614,272	214,310,928
.08	-540,368,384	249,754,112
.09	-831,184,128	290,815,744
.10	-1,172,176,380	340,992,252

TABLE 8-9. WELFARE ESTIMATES UNDER EPA/OAQPS OZONE SCENARIOS FOR PEANUT PRODUCTION IN THE U.S.: ESTIMATES IN 1978 DOLLARS

Concentration	Net welfare gain/loss	Incremental welfare gain/loss
.01	$ 111,490,240	
.02	94,479,968	17,010,272
.03	82,811,520	11,668,448
.04	60,723,424	22,088,096
.05	22,996,576	37,726,848
.06	-35,673,600	58,670,176
.07	-78,029,184	42,355,584
.08	-127,927,056	49,897,872
.09	-187,841,216	59,914,160
.10	-263,253,008	75,411,792

CHAPTER 9

SENSITIVITY STUDIES

9.1. INTRODUCTION

The purpose of this chapter is to discuss the results of three sensitivity studies designed to examine the impact which particular characteristics of our data and set of maintained assumptions has had on the producer and consumer surplus estimates discussed in the previous chapter. Specifically, we shall examine: 1) the nature of the harvest-nonharvest cost differential discussed in Chapter 4, 2) the choice of the frontier Tidwell approach to varietal switching, and 3) the USDA estimates of crop demand elasticity.

9.2 HARVEST-NONHARVEST COST DIFFERENTIAL

If we think of the agricultural production process for field crops as a sequence of production activities we may logically draw a boundary between those activities which are associated with harvesting the crop and those which are not. The nonharvest or preharvest activities involve all of the land preparation activities, the dispersement of herbicides, fertilizer, seed and pesticides and the general maintenance of the crop until harvest. The biological experiments forming the basis for the dose-response functions reported in Chapter 6 are concerned with this first stage of production since it is during this stage that ozone is expected to have an impact on crops.

If the ozone impact is such that it neutrally displaces the preharvest production function (as biological evidence suggests and as we have assumed in our analysis) then one can think of the ozone effect as displacing the productivity of each input by equal proportions.

Since we are unaware of any impact which ozone might have on the production activity of harvesting, we assume that the harvest production function is unaffected by ozone and remains stationary with respect to changes in ambient concentrations. Since the RMF explicitly recognizes the stages of production we are able to adjust the productivity of preharvest factors of production without changing the productivity of the harvest factors. Economic assessment models which do not explicitly recognize the sequence of production activities must assume that both the preharvest and harvest production functions are impacted (shifted) equally by changes in ozone concentrations and will therefore lend to over/under estimates of welfare gains associated with decreases/increases in ambient ozone.

To determine the possible magnitude of these errors in the measurement of welfare changes we report in the table to follow changes in net consumer and producer surplus for all crops in our study when ozone concentrations fall from estimated 1978 ambient levels to a uniform level of .04 ppm across all FEDS areas. We calculate the welfare changes under the assumption that the productivity of all inputs is enhanced equally and then under the assumption that only the preharvest factors are affected.

Recalling from our discussion in Chapter 4, we reproduce below the sequenced formula for the marginal cost of production.

$$MC = (1/1+\Delta YIELD)(MARNONHRV) + (1/1+Y\Delta YIELD)(MARHRV)$$

where γ = differential harvest effect parameter $0 \leq \gamma \leq 1$

MARNONHRV = marginal nonharvest cost

MARHRV = marginal harvest cost.

We note that if $\gamma = 1$ then the productivity of factors employed in harvesting is enhanced by the same proportion as the nonharvest factors. However, if $\gamma = 0$ the harvest factors are unaffected.

Table 9-1 displays the change in net producer and consumer surplus brought about by a reduction in ozone from 1978 ambient levels to .04 ppm. The first column of estimates assumes that the productivity of nonharvest factors is impacted positively by the reduction in ozone but that the productivity of nonharvest input remains unaffected ($\gamma = 0$). The last column assumes that all factors, harvest and nonharvest, have their productivities enhanced in equal proportions by ozone reductions ($\gamma = 1$). The middle column allows for some productivity enhancement of harvest factors due solely to economies of scale in harvesting bumper crops ($\gamma = 0.2$).

It is readily apparent from Table 9-1 that a failure to dichotomize the stages of production and to explicitly recognize differential productivity affects leads to wild overstatements of benefits.

9.3. THE PROBLEM OF VARIETAL SWITCHING

The agricultural producer of field crops may choose from several different varieties of particular crops. These varieties differ in their growing characteristics with regard to soil and moisture requirements and to air pollutants. If, for example, concentrations of ambient ozone increase, production managers will choose in subsequent planting seasons varieties of

TABLE 9-1. ESTIMATES OF NET CONSUMER AND PRODUCER SURPLUS FORTHCOMING FROM A DECLINE IN AMBIENT OZONE TO .04 PPM UNDER ALTERNATIVE ASSUMPTIONS REGARDING HARVEST PRODUCTIVITY EFFECTS

	Harvest productivity parameters		
Crop/region	$\gamma = 0.0$	$\gamma = 0.2$	$\gamma = 1.0$
Soybeans (NERCLAP)	5,052,414	7,283,587	16,245,349
Soybeans (SERCLAP)	343,834,000	404,077,312	590,561,024
Soybeans (CSRCLAP)	245,927,920	348,942,848	714,143,744
Corn	91,308,864	106,100,544	164,707,424
Wheat	79,262,124	96,374,688	163,819,824
Cotton	253,104,528	302,895,184	488,226,048
Peanuts	60,723,424	72,485,632	117,834,480

corn, wheat, soybeans, etc. with a higher tolerance to ozone concentrations. If the price and cost of alternative varieties is equal then the manager will choose that variety which produces the greatest yield.

The data which we have available for this study does not permit us to identify the particular variety planted in each FEDS area. Thus, we have assumed that the price and cost of each variety is uniform and therefore the variety producing the greatest yield under alternative ozone regimes is the variety chosen by agricultural producers.

The results reported in Chapter 8 are based upon the varietal choice principle stated above and therefore this principle determines the specific dose-response function to be used under alternative ozone regimes. Over the ozone range 0.00 ppm to .24 ppm the variety BLUEBOY produces the greatest yield and is the variety whose dose-response function we employ in Chapter 8.

To determine the sensitivity of our Chapter 8 results to our choice of dose-response function we report below a set of welfare estimates for wheat comparable to those presented in Chapter 8 but based on the extreme assumption that farm managers choose that variety which produces the poorest yield. We realize that such an assumption is unreasonable but we take this extreme position in order to place bounds on our estimates.

Table 9-2 displays the net producer and consumer surplus estimates for wheat production that can be expected to obtain if the ambient ozone concentration of all FEDS areas attained a uniform concentration as specified in the first column. The column of estimates labeled "Full Frontier" corresponds to the estimates presented in Chapter 8 and utilizes the notion of frontier dose-response functions discussed in Chapter 6. The last column entitled "Antifrontier" provides estimates on net producer and consumer sur-

TABLE 9-2. NET PRODUCER AND CONSUMER SURPLUS DERIVED FROM WHEAT PRODUCTION UNDER VARYING OZONE CONCENTRATION REGIMES DIFFERENTIATED BY ASSUMED VARIETAL SWITCHING BEHAVIOR

Concentration	Full frontier	Antifrontier
.01	262,120,464	105,558,640
.02	224,526,304	95,482,992
.03	165,511,312	75,290,832
.04	79,262,624	39,960,240
.05	-17,772,240	-9,544,298
.06	-132,422,384	-77,965,520
.07	-257,741,504	-36,460,208
.08	-401,955,840	-85,183,440
.09	-563,645,184	-173,051,008
.10	-751,795,712	-319,173,632

plus under the assumption that a lower envelop of the varietal dose-response functions is consistent with the choice behavior of agricultural producers.

Table 9-2 highlights the importance of the varietal problem and suggests that errors of as much as 50% can be made in the estimation of benefits if the wrong varietal dose-response function is employed. The reliable estimation of welfare benefits requires the knowledge of varietals currently being planted, varietals within a specific region's choice set and finally a battery of dose-response functions for these varietals. Unfortunately, such information does not exist and one must resort to fairly ad hoc rules such as the full frontier approach advocated in this study.

In the case of corn the frontier function is set by PAG 397 and is the function used for the estimates presented in Chapter 8. The antifrontier function is PIONEER 3780. Using our ad hoc rule that agricultural managers plant that crop variety which ceteris paribus maximizes yield, leads to the column of net producer and consumer surplus estimates given on Table 9-3 labeled "Full Frontier". If managers had chosen to plant PIONEER 3780 which produces a lower yield the welfare estimates would be those displayed under the heading antifrontier.

9.4. ALTERNATIVE ESTIMATES OF CROP DEMAND ELASTICITY

The elasticity of demand estimates embedded in the RMF are reasonably close to the estimates one will find in USDA's model entitled "A Mathematical Programming Model for Agriculture Sector Policy Analysis." While one may acknowledge that these estimates are generally reliable one may still be concerned with the sensitivity of producer and consumer surplus estimates to the magnitudes of these elasticities. In this section we shall specifically

TABLE 9-3. NET PRODUCER AND CONSUMER SURPLUS DERIVED FROM CORN PRODUCTION UNDER VARYING OZONE CONCENTRATION REGIMES DIFFERENTIATED BY ASSUMED VARIETAL SWITCHING BEHAVIOR

Concentration	Full frontier	Antifrontier
.01	141,439,728	614,787,584
.02	138,554,752	574,511,104
.03	125,264,480	462,406,400
.04	91,308,864	233,101,312
.05	37,874,448	103,655,280
.06	-68,029,264	-200,046,256
.07	-221,512,768	-578,447,616
.08	-447,547,392	-1,094,658,050
.09	-792,965,376	-1,812,615,680
.10	-1,315,634,690	-2,797,287,680

examine this issue by forming an interval around the USDA estimates. Our low elasticity estimate is 75% of the USDA figure and our high estimate is 125% of the figure. As an extreme case we employ a perfectly inelastic demand function and calculate welfare estimates under the assumption that any shortfalls in supply are made up by imports at a price equal to the marginal cost of the last domestically produced crop unit. Table 9-4 below presents the alternative elasticity estimates used in this sensitivity analysis.

For each crop under consideration we vary ozone concentrations from 1978 ambient to .04 ppm and then calculate the net producer and consumer surplus gain under the three elasticity estimates. Naturally, the more elastic the estimates the larger will be the gain. We then vary the concentration from ambient to .08 ppm and calculate the welfare loss. Tables 9-5 - 9-9 display the results of this analysis for soybeans, wheat, corn, cotton and peanuts respectively.

Examining Table 9-5 - 9-9 one quickly sees that the sensitivity of the estimates to alternative elasticity assumptions is considerably less than the sensitivity to varietal choice. If one were to attempt a refinement of the estimates reported in Chapter 8 it would seem that further work on elasticity refinement would be unwarranted.

9.5. ALTERNATIVE DOSE-RESPONSE EQUATIONS

Upon completion of the research described in this report two papers (Heck et al. (1984a, 1984b)) authored by members of NCLAN presented dose-response equations for a wide variety of agricultural crops based on a Wybul functional specification. The intersection of the crops covered by these new functions and the crops found in FEDS contains soybeans, corn, wheat, cotton, peanuts,

TABLE 9-4. DEMAND ELASTICITIES EMPLOYED IN THE SENSITIVITY ANALYSIS

	Alternative elasticity estimates		
Crop	USDA	High	Low
Soybeans	-.80	-1.0	-.60
Wheat	-.35	-.44	-.26
Corn	-.33	-.41	-.25
Cotton	-.22	-.28	-.17
Peanuts	-.80	-1.0	-.60

TABLE 9-5. NET PRODUCER AND CONSUMER SURPLUS ESTIMATES UNDER ALTERNATIVE ASSUMPTIONS REGARDING THE DEMAND ELASTICITY OF SOYBEANS

	Elasticity Ranges			
Concentration	High	USDA	Low	Inelastic
.04	612,691,572	594,906,606	589,417,321	413,250,880
.08	-1,380,893,693	-1,469,174,161	-1,622,899,744	1,662,523,472

TABLE 9-6. NET PRODUCER AND CONSUMER SURPLUS ESTIMATES UNDER ALTERNATIVE ASSUMPTIONS REGARDING THE DEMAND ELASTICITY OF CORN

	Elasticity Ranges			
Concentration	High	USDA	Low	Inelastic
.04	91,524,592	91,308,864	91,088,944	86,814,720
.08	-437,176,064	-447,547,392	-464,832,512	-501,420,032

TABLE 9-7. NET PRODUCER AND CONSUMER SURPLUS ESTIMATES UNDER ALTERNATIVE ASSUMPTIONS REGARDING THE DEMAND ELASTICITY OF WHEAT

	Elasticity Ranges			
Concentration	High	USDA	Low	Inelastic
.04	79,802,688	79,262,624	81,381,347	76,537,856
.08	-387,188,736	-401,955,840	-426,716,672	-434,364,,416

TABLE 9-8. NET PRODUCER AND CONSUMER SURPLUS ESTIMATES UNDER ALTERNATIVE ASSUMPTIONS REGARDING THE DEMAND ELASTICITY OF COTTON

	Elasticity Ranges			
Concentration	High	USDA	Low	Inelastic
.04	253,373,824	253,104,528	253,077,440	251,437,056
.08	-482,269,952	-540,368,389	-550,005,504	-601,348,957

TABLE 9-9. NET PRODUCER AND CONSUMER SURPLUS ESTIMATES UNDER ALTERNATIVE ASSUMPTIONS REGARDING THE DEMAND ELASTICITY OF PEANUTS

	Elasticity Ranges			
Concentration	High	USDA	Low	Inelastic
.04	62,531,984	60,723,424	58,921,760	31,847.424
.08	-122,173,936	-127,927,056	-137.475,728	-204,983,040

sorghum, and barley. For each of these seven crops we have modified the RMF by replacing the Box-Tidwell dose-response equation with the Wybul equations found in Heck et al. (1984a, 1984b) and adding production cost information for sorghum and barley.

The Wybul functional form may be written

$$Y = a \exp[-(x/b)^c]$$

where: Y = a measure of yield

x = ozone

a, b, c parameters to be estimated

The results presented in this section are based on nine Wybul dose-response equations given in Table 9-10.

The standard set of maintained assumptions (see Chapter 8, Section 8.2) are employed in the model runs described below. We have arbitrarily set the demand elasticities for sorghum and barley equal to -.5 due to the lack of alternative estimates. Given the sensitivity results of Section 9.4 we believe such assumed values will not greatly distort our welfare estimates. For each of the seven crops and the three distinct regions for soybean production we have calculated welfare estimates using the EPA supplied scenarios displayed in Table 9-11. These scenarios are identical to those used in Chapter 8.

The welfare calculations made from the RMF using the NCLAN Wybul dose-response equations are reported in Tables 9-12 through 9-20. To provide a comparison of the Wybul and Box-Tidwell results we have calculated the ratio of the welfare estimates made using the Box-Tidwell dose-response equations to

TABLE 9-10: NCLAN DOSE-RESPONSE EQUATIONS BASED ON THE WYBUL FUNCTIONAL SEPCIFICATION

Species Cultivar Date, Location	Estimated Parameters	
Barley		
'Poco'	a =	1.988
1982 - Shafter, Calif.	b =	0.205
	c =	4.278
Bean, Kidney		
'Calif. Light Red'	a =	2878.
(Full Plots - FP)	b =	0.120
1982 - Ithaca, NY	c =	1.171
Corn		
'PAG 397', 1981	a =	13963.
- Argonne, Ill.	b =	0.160
	c =	4.280
Cotton		
'Acala SJ-2'	a =	5546.
1981 - Shafter, Calif.	b =	0.199
(Irrigated - I)	c =	1.288
Peanut		
'NC-6'	a =	7485.
1980 - Raleigh, NC	b =	0.111
	c =	2.249
Sorghum		
'DeKalb - 28'	a =	8137.
1982 - Argonne, Ill.	b =	0.296
	c =	2.217

Table 9-10 continued

Species Cultivar Date, Location	Estimated Parameters
Soybean	
'Corsoy'	a = 2785.
1980 - Argonne, Ill.	b = 0.133
	c = 1.952
'Williams'	a = 4992.
1981 - Beltsville, Md.	b = 0.211
	c = 1.100
'Hodgson'	a = 2590.
1981 - Ithaca, NY	b = 0.138
(Full Plots - FP)	c = 1.000
Tomato	
'Murrieta'	a = 32.9
1981 - Tracy, Calif.	b = 0.142
	c = 3.807
Wheat, Winter	
'Abe', 1982	a = 5363.
- Argonne, Ill.	b = 0.143
	c = 2.423

TABLE 9-11. EPA/OAQPS OZONE CONCENTRATION SCENARIOS

Scenario No.	Concentration in ppm
1	.01
2	.02
3	.03
4	.04
5	.05
6	.06
7	.07
8	.08
9	.09
10	.10

TABLE 9-12. WELFARE ESTIMATES UNDER EPA/OAQPS OZONE SCENARIOS FOR SOYBEAN PRODUCTION IN THE NORTHEAST REGION OF NCLAN: ESTIMATES IN 1978 DOLLARS BASED ON NCLAN WYBUL DOSE-RESPONSE EQUATIONS

Concentration	Net welfare gain/loss
.01	15,657,280
.02	12,273,369
.03	8,735,396
.04	5,024,708
.05	1,121,977
.06	-3,399,020
.07	-8,390,933
.08	-13,900,266
.09	-19,774,416
.10	-25,757,584

TABLE 9-13. WELFARE ESTIMATES UNDER EPA/OAQPS OZONE SCENARIOS FOR SOYBEAN PRODUCTION IN THE SOUTHWEST REGION OF NCLAN: ESTIMATES IN 1978 DOLLARS BASED ON NCLAN WYBUL DOSE-RESPONSE EQUATIONS

Concentration	Net welfare gain/loss
.01	498,443,776
.02	423,408,640
.03	339,527,680
.04	244,486,720
.05	141,413,632
.06	43,799,744
.07	-135,775,952
.08	-249,254,592
.09	-356,041,728
.10	-458,332 928

TABLE 9-14. WELFARE ESTIMATES UNDER EPA/OAQPS OZONE SCENARIOS FOR SOYBEAN PRODUCTION IN THE CENTRAL STATES REGION OF NCLAN: ESTIMATES IN 1978 DOLLARS BASED ON NCLAN WYBUL DOSE-RESPONSE EQUATIONS

Concentration	Net welfare gain/loss
.01	432,759,040
.02	390,963,456
.03	307,099,648
.04	210,175,344
.05	-45,044,720
.06	-158,656,384
.07	-391,853,568
.08	-672,811,776
.09	-1,007,974,400
.10	-1,401,567,230

TABLE 9-15. WELFARE ESTIMATES UNDER EPA/OAQPS OZONE SCENARIOS FOR CORN PRODUCTION IN THE U.S.: ESTIMATES IN 1978 DOLLARS BASED ON NCLAN WYBUL DOSE-RESPONSE EQUATIONS

Concentration	Net welfare gain/loss
.01	170,826,736
.02	168,713,408
.03	158,458,672
.04	126,192,016
.05	53,624,192
.06	-98,725,904
.07	-314,127,872
.08	-593,981,184
.09	-1,021,463,810
.10	-1,693,116,160

TABLE 9-16. WELFARE ESTIMATES UNDER EPA/OAQPS OZONE SCENARIOS FOR WHEAT PRODUCTION IN THE U.S.: ESTIMATES IN 1978 DOLLARS BASED ON NCLAN WYBUL DOSE-RESPONSE EQUATIONS

Concentration	Net welfare gain/loss
.01	395,600,640
.02	368,051,456
.03	308,114,944
.04	201,541,696
.05	-78,489,184
.06	-317,720,832
.07	-586,202,368
.08	-927,098,368
.09	-1,380,957,700
.10	-1,954,862,080

TABLE 9-17. WELFARE ESTIMATES UNDER EPA/OAQPS OZONE SCENARIOS FOR COTTON PRODUCTION IN THE U.S.: ESTIMATES IN 1978 DOLLARS BASED ON NCLAN WYBUL DOSE-RESPONSE EQUATIONS

Concentration	Net welfare gain/loss
.01	634,127,104
.02	529,935,360
.03	410,888,704
.04	274 312 960
.05	72,711,248
.06	-83,150,640
.07	-321,918,464
.08	-599,386,624
.09	-926,649,344
.10	-1,304,902,660

TABLE 9-18. WELFARE ESTIMATES UNDER EPA/OAQPS OZONE SCENARIOS FOR PEANUT PRODUCTION IN THE U.S.: ESTIMATES IN 1978 DOLLARS BASED ON NCLAN WYBUL DOSE-RESPONSE EQUATIONS

Concentration	Net welfare gain/loss
.01	82,988,832
.02	77,972,496
.03	68,426,672
.04	52,822,080
.05	22,302,848
.06	-35,117,504
.07	-77,737,584
.08	-127,325,984
.09	-184,010,272
.10	-249,357,152

TABLE 9-19. WELFARE ESTIMATES UNDER EPA/OAQPS OZONE SCENARIOS FOR SORGHUM PRODUCTION IN THE U.S.: ESTIMATES IN 1978 DOLLARS BASED ON NCLAN WYBUL DOSE-RESPONSE EQUATIONS

Concentration	Net welfare gain/loss
.01	58,697,168
.02	53,528,944
.03	43,798,384
.04	28,930,272
.05	1,659,738
.06	-23,320,848
.07	-52,791,424
.08	-81,747,600
.09	-110,017,696
.10	-141,185,088

TABLE 9-20. WELFARE ESTIMATES UNDER EPA/OAQPS OZONE SCENARIOS FOR BARLEY PRODUCTION IN THE U.S.: ESTIMATES IN 1978 DOLLARS BASED ON NCLAN WYBUL DOSE-RESPONSE EQUATIONS

Concentration	Net welfare gain/loss
.01	1,968,748
.02	1,924,958
.03	1,707,037
.04	792,822
.05	-396,877
.06	-3,178,408
.07	-7,960,204
.08	-15,519,651
.09	-25,280,720
.10	-35,859,824

TABLE 9-21. RATIO OF WELFARE ESTIMATES CALCULATED USING BOX-TIDWELL DOSE-RESPONSE FUNCTION TO NCLAN WYBUL FUNCTIONS

Crop	Ozone concentration	
	.03 ppm	.08 ppm
Soybeans	1.27	1.57
Corn	0.79	0.75
Wheat	0.54	0.43
Cotton	0.95	0.90
Peanuts	1.21	1.00
All*	1.00	0.94

*This ratio is calculated by aggregating across the welfare estimates and then computing the ratios; it is not a simple average of the ratios in the table.

those estimates using the NCLAN Wybul equations for two ozone concentrations .03 ppm and .08 ppm. These ratios are displayed in Table 9-21.

An examination of these ratios, crop by crop, reveals a substantial difference in the welfare estimates. For example, in the case of soybeans the Box-Tidwell equation leads to welfare estimates of gains and losses in excess of 27% and 57% respectively over the Wybul equations. On the other hand, calculations made for the wheat crop show that the Tidwell form leads to gain and loss estimates much smaller than the Wybul form. However, if one aggregates across all crops, the resulting national welfare estimate is remarkably similar.

Unfortunately, the above analysis is not sufficient to discriminate between the Box-Tidwell and Wybul forms for the Regulatory Impact Analysis. While the differences in welfare estimates are disturbingly large, one cannot attribute the differences to functional form alone. Recall from Chapter 6 the Box-Tidwell equations were estimated from published, aggregated NCLAN experimental results, while the Wybul functions were estimated by NCLAN researchers from the unpublished, disaggrregate experimental results. Given this disparity in data sets, conclusions as to the correct functional form, or statements regarding the differences in welfare estimates due to alternative forms, cannot be made on the basis of the above results.

If one were to proceed directly to a Regulatory Impact Analysis without the ability to research the functional form issue further it would be our recommendation that the NCLAN Wybul dose-response functions be employed, solely upon the criterion that they were estimated from the original disaggregate data.

9.6. CONCLUDING REMARKS

This chapter has reported the results on four sensitivity studies dealing with differential productivity effects, the varietal choice problem, estimates of crop demand elasticity, and the choice of dose-response equation function specification studies. Of the four studies the choice of dose-response functional specification leads to the greatest sensitivity in welfare estimates. The problem of harvest/nonharvest differential productivity is substantive in the sense that a failure to recognize the distinction seriously distorts the perceived welfare impacts, but since we feel that a model of differentiable productivity is the only defendable approach we believe little concern should be directed toward this problem. The impact of alternative elasticity estimates on the welfare calculations is minor and probably not worth pursuing further.

While there are many other issues one could have pursued in an expanded sensitivity analysis, the four issues cited above seem the most important to examine with a limited budget. If we were to expand the effort we would concentrate on those aspects of the study concerned directly with the dose-response functions. Our experience has led us to believe that minor variations in these functions can have marked impacts on welfare estimates; and unfortunately, these functions are the weakest link in the sequence of analysis that has led to the welfare estimates of this chapter and of Chapter 8.

CHAPTER 10

CONCLUSIONS AND AGENDA FOR FUTURE RESEARCH

10.1. INTRODUCTION

We have organized this discussion of future research around two topics: 1) further analysis of ozone's impact using biologically determined dose-response functions and microtheoretic economic assessment models, and 2) further analysis of ozone using statistically determined dose-response relations and microtheoretic assessment models. We are led to believe that the second topic is important to consider in future air pollution studies since it addresses the problems we have encountered in using the biological evidence amassed by NCLAN, and the difficulty of using yield experiments to learn about production activities which may be nonneutrally impacted by pollutants other than ozone.

For the purposes of the eventual RIA for ozone the hypothesized neutrality of ozone on agricultural production activities justifies the use of biologically driven economic assessment models. The biologically driven Regional Model Farm assessment model discussed in this report provides for broad crop coverage and significant regional disaggregation in a sound microtheoretic structure and hence possesses the qualities necessary to provide benefit estimates to an RIA.

10.2. FURTHER ANALYSIS OF OZONE USING BIOLOGICAL DOSE-RESPONSE FUNCTIONS

This report has described an economic assessment model capable of estimating the welfare gains or losses emanating from the agricultural production sector in response to changes in rural ozone concentrations. The assessment model is comprised of four major components which may be improved to lead to more reliable welfare estimates. These components are: 1) the biological information contained in the dose-response functions, 2) the air quality data supplied by EPA for both baseline and alternative exposure scenarios, 3) the economic information on agricultural cost and production contained in the RMF, and 4) crop specific demand functions. In the paragraphs below we shall discuss some areas of future research which could lead to improved components of the assessment model without changing the basic structure of the assessment framework.

10.2.1. Improvements in Biological Dose-Response Functions

Improved biological dose-response functions will require a greater emphasis on the selection of crops, the selection of particular varieties and hybrids, and the specification of dose-response relationship functional form. Certainly, the development of full dose-response surfaces would also lead to greatly improved functions. However, such surfaces may take more time and be more costly to develop. Therefore, we confine our remarks to the three areas noted above.

To appropriately assess the economic impact of a change in ozone concentrations one must be able to model the reactions of agricultural producers to their awareness of decreased or increased yields. The ozone neutrality property referred to in Chapter 5 only holds for input demands and suggests that agricultural managers will not adjust the mix of their inputs in response to changes in ozone. However, ozone neutrality does not extend to output mix considerations of farm managers. In particular, if ozone differentially affects corn and wheat, then in areas of the country where both crops are feasible production choices farmers will adjust the mix of such crops in response to ozone. This output mix nonneutrality suggests that the appropriate methodology for choosing crops to study would be to choose crops which comprise feasible output choices in given areas. The failure to do so prevents the economic modeling of the output choice and therefore leads to an understatement of benefits and an overstatement of losses associated with changes in ozone concentrations.

In addition to the problem of crop coverage, the companion problem of variety choice within a single crop type must also be addressed. Again we recommend a choice methodology which will provide the basis for economic assessments. Research should not be focussed on varieties which are believed to be ozone sensitive. Rather it should examine those feasible varieties within the choice set of agricultural producers. The rationale for such a methodology again rests on the ability of farm managers to choose varieties in response to yield changes. If one excludes the possibility of varietal switching (averting behavior) one will, ceteris paribus, always understate benefits and overstate losses.

The correct functional specification of the dose-response relationship is vital to biologically driven assessments models since it in large measure determines the magnitude of supply function shifts. In this report RFF proposed a specific functional form (Box-Tidwell) only because it was impossible using the aggregate summary NCLAN data to undertake rigorous statistical tests of functional specification. Without strong a priori theoretical justification for a particular specification such statistical analysis seems the most prudent path to pursue when one is choosing alternative specification for the RIA benefits analysis.

10.2.2. Air Quality Data

Rural ozone concentrations are required by the assessment model for two different purposes. First, concentrations determine the relative position of current crop yields on the biological dose-response functions. Any deviation between the actual concentration and the concentration supplied to the model will falsely position the baseline yield. If the dose-response function were linear this false positioning would not affect the welfare estimates since the change in yield relative to the change in ozone is constant at all ozone concentrations. However, the dose-response functions are for the most part decidedly nonlinear, and thus false positioning can over or understate yield changes given a change in concentrations.

The relative difference in ozone concentrations across areas of the country is important in modeling the range of regulatory alternatives to the current standard. For example, if a concentration of .06 ppm mean 7 hour growing season concentration recorded in Iowa is consistent with the .12 ppm hourly, one expected exceedence per year standard, then regulatory scenarios which tighten the standard to say .10 ppm hourly, one expected exceedence per year, would lead to reductions in Iowa concentrations of .05 ppm, mean 7 hour growing season concentration which the model would reflect in increased yields and positive welfare benefits. However, if there exist errors in the ozone data such that a baseline rural ambient value of .07 ppm was passed to the model, then benefits larger than actual would be reported by the model.

Similarly, a false baseline ambient value of .04 ppm would lead to no benefits at all.

Unfortunately, few ozone monitors exist in rural areas and as a consequence county level ozone concentrations used in the assessment model described in this report are interpolated values based primarily on metropolitan monitors. It is believed that in the future these interpolated data will be supplanted with concentrations derived from a more detailed air model. However, the data will still represent extensions of urban air modeling.

Given the strong biological evidence supporting the hypothesis that ozone seriously reduces important crop (grains) yields it seems only natural to begin monitoring ozone concentrations in crop growing areas. Even a handful of monitoring sites in the Great Basin, would increase the reliability of interpolated or model generated air quality data.

10.2.3. The Economic Modeling Component

Under the ozone neutrality assumption implicit in the NCLAN experiments and maintained in the structure of the assessment model described in this report, there exists only one area in which refinement of the RMF would lead to more reliable benefit estimates. This area of research concerns the output choices of agricultural managers in response to changing relative crop yields brought about by changes in ambient ozone concentrations. See Kopp et al. (1984) for a discussion of such a model.

10.2.4. Crop Demand Functions

The final area for improved economic assessment modeling using biological dose-response functions concerns the estimates of consumer demand.

In the present study we have employed USDA crop specific demand elasticities in conjunction with the assumption of linear demand functions to determine probable equilibrium prices and quantities. In preparation for the RIA one would want to investigate the possibility of using region specific demand equations rather than the national estimates employed in this study. Moreover, to the extent possible demand equations which possess cross-price responses are again more desirable than those employed in the current study.

10.3. NON DOSE-RESPONSE FUNCTION APPROACHES TO THE AGRICULTURAL IMPACTS OF OZONE

In section 2 of this chapter we have discussed improvements which might be made to the assessment methodology described in this report. In this section we briefly discuss an alternative methodology for assessing the economic impact of air pollutants on agriculture and society which does not employ biologically based dose-response functions. Rather, the methodology we shall discuss employs a statistical dose-response function estimated jointly with the agricultural supply function within the context of a microtheoretic econometric economic assessment model (see Chapter 3 for details).

The statistically identified dose-response relationship has two important advantages over experimentally derived relationships. First, the statistical relations do not assume ozone neutrality but leave the assumption as a hypothesis which may be subjected to rigorous statistical test. Second, the statistical functions incorporate the reactions of farm managers to changing crop yields; reactions which may manifest themselves in varietal switches, crop mix changes and changes in input composition. If the geographic area over which the statistical relations are estimated is sufficiently small or explanatory variables such as soil characteristics, weather patterns and the like added to the model, the statistical functions become more characteristic of specific areas than experimental functions which must often be applied far from the original experimental site.

Techniques for implementing this methodology and the benefits to be gained are described fully in Chapter 3 along with the methodology's drawbacks. The two greatest stumbling blocks are informational requirements. The first requirement is a set of detailed U.S. production and cost information at a fine level of regional disaggregation. While many researchers such as Crocker _et al._ (1981) have been unsuccessful in developing such a national data set, researchers at RFF have assembled and are employing such a data set at this time in the analysis of acid rain impacts. Thus, the extraordinarily detailed economic information required by the nonbiological statistical approach is readily available for a significant set of crops.

The second piece of information is reliable estimates of rural ozone concentrations. As stated above, the current source of such information is an interpolated data set for 1978. In the past months this data set has been revised and improved and now a second data series for 1980 exists. Furthermore, advances continue to be made in the development of air models for ozone which will also be able to provide rural estimates of ozone concentrations. While neither of these two approaches can be as reliable as actual monitoring information we believe it is prudent to develop a statistical dose-response econometric model based on such data for comparison with the biological dose-response model described in this report. Such an approach will enable us to better bound the benefit estimates.

REFERENCES

1. Adams, R. M., T. D. Crocker and N. Thanavibulchai. An Economic Assessment of Air Pollution Damages to Selected Annual Crops in Southern California. Journal of Environmental Economics and Management 9(1): 1982.

2. Amemiya, T. and J. L. Powell. A Comparison of the Box-Cox Maximum Likelihood Estimator and the Non-linear Two-Stage Least Squares Estimator. Journal of Econometrics 17(3): 351-382, 1981.

3. Aneuryn-Evans, G. and A. Deaton. Testing Linear Versus Logarithmic Regression Models. Review of Economic Studies 47(146): 275-291, 1980.

4. Bhide, S., E. O. Heady and A. Chowdhury. Potential Impacts of Alternative Energy Situations on Land Use and Values. Energy in Agriculture 1: 41-53, 1981/1982.

5. _____, _____ and _____. Energy Supply and Agricultural Production: An Assessment of Regional and National Allocation Schemes. Energy Systems and Policy 5(3): 195-218, 1981.

6. Biles, W. E. and J. J. Swain. Optimization and Industrial Experimentation. John Wiley and Sons, New York, 1980.

7. Bogess, W. G. and E. O. Heady. A Separable Programming Analysis of U.S. Agricultural Export, Price and Income, and Soil Conservation Policies in 1985. CARD Report No. 89, Iowa State University, Ames, Iowa, 1980.

8. Box, G. E. P. and P. H. Tidwell. Transformation of the Independent Variables. Technometrics 4(4): 531-550, 1962.

9. _____, W. G. Hunter and J. S. Hunter. Statistics for Experimenters. John Wiley and Sons, New York, 1978.

10. Brown, R. S., D. W. Caves and L. R. Christensen. Modelling the Structure of Cost and Production for Multiproduct Firms. Southern Economic Journal 46: 256-273, 1979.

11. Carriere, W. M., A. D. Hinkley, W. Harshbarger, J. Kinsman and J. Wisniewski. The Effect of SO_2 and O_3 on Selected Agricultural Crops. General Research Corporation Report 1235-01-82-CR for Electric Power Research Institute (McLean, Va., GRC), 1982.

12. Castle, E. N. and I. Hoch. Farm Real Estate Price Components, 1920-78. American Journal of Agricultural Economics 64(1): 8-18, 1982.

13. Collins, G. S. and C. R. Taylor. Econometric-Simulation Models for Major Field Crops and Livestock. Final Report to the U. S. Environment Agency on Contract No. 68-01-5041, 1982.

14. Cox, D. R. The Analysis of Binary Data. Metheun, London, 1970.

15. Crocker, T. D., B. L. Dixon, R. E. Howitt and R. Oliveria. A Program for Assessing the Economic Benefits of Preventing Air Pollution Damages to U.S. Agriculture. Discussion paper prepared for the National Loss Assessment Network (NCLAN), September 1981.

16. Daniel, C. and F. S. Wood. Fitting Equations to Data. Second Edition. John Wiley and Sons, New York, 1980.

17. Davidson, R. and J. G. MacKinnon. Several Tests for Model Specification in the Presence of Alternative Hypotheses. Econometrica 49(3): 781-793, 1981.

18. _____ and _____. Some Non-Nested Hypothesis Tests and the Relations Among Them. Review of Economic Studies 49: 551-565, 1982.

19. Deaton, A. and J. Muellbauer. Economics and Consumer Behavior. Cambridge University Press, New York, 1980.

20. Debreu, G. The Coefficient of Resource Utilization. Econometrica 19: 1957.

21. Diewert, W. E. Applications of Duality Theory. In Frontiers of Quantitative Economics, Vol. II, edited by M. D. Intriligator and D. A. Kendrick. North-Holland, Amsterdam, 1974.

22. _____. Duality Approaches to Microeconomic Theory. Unpublished, 1978.

23. Draper, N. and H. Smith. Applied Regression Analysis. John Wiley and Sons, New York, 1966.

24. Farrell, M. J. The Measurement of Productive Efficiency. Journal of the Royal Statistical Association (Series A) 120(3): 253-290, 1957.

25. Forsund, F. R., C. A. K. Lovell and P. Schmidt. A Survey of Frontier Production Functions and of Their Relationships to Efficiency Measurement. Journal of Econometrics 13: 5-25, 1980.

26. Friedman, M. (ed.). Essays in Positive Economics. University of Chicago Press, Chicago, 1935.

27. Griliches, Z. Specification Bias in Estimates of Production Functions. Journal of Farm Economics 39(1): 8-20, 1957.

28. Hackl, P. Testing the Constancy of Regression Models Over Time. Gottingen, Vandenhoeck and Ruprecht, 1980.

29. Haitovsky, Y. Regression Estimation from Grouped Observations. Hafner Press, New York, 1971.

30. Hall, H. H., E. O. Heady and Y. Plessner. Quadratic Programming Solution of Competitive Equilibrium for U. S. Agriculture. American Journal of Agricultural Economics 50(3): 536-555, 1968.

31. Hallett, G. The Economics of Agricultural Policy. Second Edition. John Wiley and Sons, New York, 1981.

32. Harvey, A. C. The Econometric Analysis of Time Series. John Wiley and Sons, New York, 1981.

33. Heady, E. O. and H. R. Jensen. Farm Management Economics. Prentice-Hall, New York, 1954.

34. Heagle, A. S., S. Spencer and M. B. Letchworth. Yield Response of Winter Wheat to Chronic Doses of Ozone. Canadian Journal of Botany 57: 1999-2005, 1979.

35. Heck, Walter W., William W. Cure, John O. Rawlings, Lawrence J. Zaragoza, Allen S. Heagle, Howard E. Heggestad, Robert J. Kohut, Lance W. Kress, and Patrick J. Temple. "Assessing Impacts of Ozone on Agricultural Crops: Overview." Journal of the Air Pollution Control Association, forthcoming 1984.

36. Heck, Walter W., William W. Cure, John O. Rawlings, Lawrence J. Zaragoza, Allen S. Heagle, Howard E. Heggestad, Robert J. Kohut, Lance W. Kress, and Patrick J. Temple. "Assessing Impacts of Ozone on Agricultural Crops: Crop Yield Functions and Alternative Exposure Statistics." Journal of the Air Pollution Control Association, forthcoming 1984.

37. Heck, W. W., A. S. Heagle, W. C. Cureg, D. S. Shriner, and R. J. Olsen. Ozone Impacts on Productivity of Selected Crops. Appendix D of a draft report to the Office of Technology Assessment, U.S. Congress, n.d..

38. Heck, W. W., O. C. Taylor, R. Adams, G. Bingham, J. E. Miller and L. H. Weinstein. National Crop Loss Assessment Network 1980 Annual Report. Environmental Research Laboratory, Office of Research and Development, U.S. Environmental Protection Agency, Corvallis, Oregon, 1981.

39. Heck, W. W., O. C. Taylor, R. Adams, G. Bingham, J. Miller, E. Preston and L. Weinstein. Assessment of Crop Loss from Ozone. Journal of the Air Pollution Control Association 32(4): 353-361, 1982.

40. Hildebrand, J. R. Some Difficulties with Empirical Results from Whole-Farm Cobb-Douglas-Type Production Functions. Journal of Farm Economics 42(4): 897-904, 1960.

41. Hoch, I. Simultaneous Equation Bias in the Context of the Cobb-Douglas Production Function. Econometrica 26(4): 566-578, 1958.

42. Hoch, I. Production Functions and Supply Applications for California Dairy Farms. Giannini Foundation Monograph No. 36, University of California, Davis, California, 1976.

43. Johnson, P. R. Land Substitutes and Changes in Corn Yields. Journal of Farm Economics 42(2): 294-306, 1960.

44. Judge, G. G., R. H. Day, S. R. Johnson, G. C. Rausser and L. R. Martin (eds). A Survey of Agricultural Economics Literature, Vol. 2, Quantitive Methods in Agricultural Economics, 1940s to 1970s. University of Minnesota Press, Minneapolis, 1977.

45. Judge, G. G., W. Griffiths, R. C. Hill and T. C. Lee. The Theory and Practice of Econometrics. John Wiley and Sons, New York, 1980.

46. Just, R. E., D. L. Hueth and A. Schmitz. Applied Welfare Economics and Public Policy. Prentice-Hall, Englewood Cliffs, N.J., 1982.

47. Kmenta, J. Elements of Econometrics. Macmillan, New York, 1971.

48. Kopp, R. J. and W. E. Diewert. The Decomposition of Frontier Cost Function Deviations into Measures of Technical, Allocative and Overall Productive Efficiency. Journal of Econometrics: 1982.

49. Kopp, R. J. and W. J. Vaughan. "Consistent Incorporation of National Science Information in Econometric Models of Production: An Application to Agriculture." Resources for the Future, July 1983.

50. Krenz, R. D. Current Efforts at Estimation of Costs of Production in ERS. American Journal of Agricultural Economics 57(5): 929-939, 1975.

51. Lahiri, K. and D. Egy. Joint Estimation and Testing for Functional Form and Heteroskedasticity. Journal of Econometrics 15(2): 299-308, 1981.

52. Leung, S., W. Reed, S. Cauchois and R. Howitt. Methodologies for Valuation of Crop Yield Changes: A Review. EPA 600/5-78-018, U. S. Environmental Protection Agency, Office of Research and Development, Corvallis Environmental Research Laboratory, Washington, D.C., 1978.

53. Maddala, G. S. Econometrics. McGraw-Hill, New York, 1977.

54. Millelhammer, R. C., S. C. Matulich and D. Bushaw. On Implicit Forms of Multiproduct-Multifactor Production Functions. American Journal of Agricultural Economics: 164-168, 1981.

55. Mohring, H. "Alternative Welfare Gain and Loss Measures." Western Economic Journal, vol. 9: 349-368, (December) 1971.

56. National Research Council, Committee on Medical and Biologic Effects of Environmental Pollutants. Ozone and Other Photochemical Oxidants. National Academy of Sciences, Washington, D.C., 1977.

57. Naylor, T. H. and J. M. Vernon. Microeconomics and Decision Models of the Firm. Harcourt, Brace and World, New York, 1969.

58. Nerlove, M. and K. L. Bachman. The Analysis of Changes in Agricultural Supply: Problems and Approaches. Journal of Farm Economics 42(3): 531-551, 1960.

59. Nicol, K. J. and E. O. Heady. A Model for Regional Agricultural Analysis of Land and Water Use, Agricultural Structure, and the Environment. Iowa State University Center for Agricultural and Rural Development, Ames, Iowa, 1975.

60. Olson, K. D., E. O. Heady, C. C. Chen, and A. D. Meister. Estimated Impacts of Two Environmental Alternatives in Agriculture: A Quadratic Programming Analyses. CARD Report No. 72. Iowa State University, Ames, Iowa, 1977.

61. Osburn, D. D. and K. C. Schneeberger. Modern Agriculture Management. Reston Pub. Co., Reston, Virginia, 1978.

62. Oury, B. Allowing for Weather in Crop Production Model Building. Journal of Farm Economics 47(4): 270-283, 1965.

63. _____. Supply Estimation and Predictions by Regression and Related Methods. In Economic Models and Quantitative Methods for Decisions and Planning in Agriculture, edited by E. O. Heady. The Iowa State University Press, Ames, Iowa, 1971.

64. Page, W. P., G. Arbogast, R. G. Barian and J. Ciecka. Estimation of Economic Losses to the Agricultural Sector from Airborne Residuals in the Ohio River Basin Region. Journal of the Air Pollution Control Association 32(2): 151-154, 1982.

65. Pesaran, M. H. On the General Problem of Model Selection. Review of Economic Studies 41(126): 153-172, 1974.

66. _____. Comparison of Local Power of Alternative Tests of Non-Nested Regression Models. Econometrica 50(5): 1287-1305, 1982.

67. _____ and A. S. Deaton. Testing Non-Nested Nonlinear Regression Models. Econometrica 46(3): 677-694, 1978.

68. Ramsey, J. B. Tests for Specification Errors in Classical Linear Least-Squares Regression Analysis. Journal of the Royal Statistical Society (Series B) 31(2): 307-371, 1969.

69. Resources for the Future. Methodologies for Estimating the National Welfare on Agriculture of Alternative Ozone Standards: A Research Agenda. Submitted to EPA OAQPS, Durham, N.C., April 1982.

70. _____. Agricultural Benefit Analysis: Alternative Ozone and Photochemical Oxidant Standards. Technical Proposal. Submitted to EPA OAQPS, Durham, N.C., June 1982.

71. Rosse, J. N. Equivalent Structures of Production, Cost and Input Demand with Multiple Inputs and Outputs. Memorandum 101, Research Center in Economic Growth, Stanford University, Stanford, California, 1970.

72. Schertz, L. P. et al. Another Revolution in U.S. Farming? Agricultural Information Bull. No. 443. Economics, Statistics and Cooperatives Service, U.S. Department of Agriculture, Washington, D.C., 1979.

73. Shepherd, D. W. Cost and Production Functions. Princeton University Press, Princeton, 1953.

74. Silberberg, E. "Duality and the Many Consumer's Surpluses." American Economic Review, vol. 62: 942-952, (December) 1972.

75. _____. The Structure of Economics. McGraw-Hill, New York, 1978.

76. Smith, V. Kerry. Travel Cost Demand Models for Wilderness Recreation: A Problem of Non-Nested Hypotheses. Land Economics 51(2): 103-111, 1975.

77. Smith, V. Kerry. Mortality-Air Pollution Relationships: A Comment. Journal of the American Statistical Association 70(350): 341-343, 1975.

78. Spitzer, John J. A Primer on Box-Cox Estimation. Review of Economics and Statistics 64(2): 307-313, 1982.

79. Takayama, T. and G. G. Judge. Spatial Equilibrium and Quadratic Programming. Journal of Farm Economics 46: 67-93, 1964.

80. Taylor, C. R., G. S. Collins, G. A. Carlsen, F. T. Cook, Jr., K. H. Reichelderfer and I. Starbird. Aggregate Economic Evaluation of Alternative Boll Weevil Management Strategies. Unpublished xerox, 1982.

81. Theil, H. Econometrics. John Wiley and Sons, New York, 1971.

82. Thursby, J. G. Alternative Specification Error Tests: A Comparative Study. Journal of the American Statistical Association 74(365): 222-225, 1979.

83. _____ and P. Schmidt. Some Properties of Tests for Specification Error in a Linear Regression Model. Journal of the American Statistical Association 72(359): 635-641, 1977.

84. Varian, H. R. Microeconomic Analysis. W. W. Norton, New York, 1978.

85. Walters, A. A. Production and Cost Functions: An Econometric Survey. Econometrica 31(1-2): 1-66, 1963.

86. Weaver, R. D. Measurement and Forecasting Agricultural Productivity. Draft technical paper 15, National Agricultural Lands Study, xerox, 1980.

87. Yaron, D. Y., Plessner and E. O. Heady. Competitive Equilibrium-Application of Mathematical Programming. Canadian Journal of Agricultural Economics 13(2): 65-79, 1965.

88. Yotopoulos, D. A. and L. J. Lau. Resource Use in Agriculture: Applications of the Profit Function to Selected Countries. Food Research Institute Studies, vol. 42, no. 1, Stanford University, Stanford, California, 1979.

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16. ABSTRACT

This report describes the development of an applied model capable of using exogenously supplied agricultural sector dose response information, agricultural cost of production data, and air quality information to estimate changes in producer and consumer welfare due to changes in ozone exposures for agriculture.

17. KEY WORDS AND DOCUMENT ANALYSIS

a. DESCRIPTORS	b. IDENTIFIERS/OPEN ENDED TERMS	c. COSATI Field/Group
Benefit Analysis Air Pollution, O_3 Agricultural Economic Models		

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