FARM-LEVEL ENVIRONMENTAL RISK AND ECONOMIC RELATIONSHIPS, PESTICIDE PRODUCTIVITY, AND NITROGEN PERCOLATION RELATIONSHIPS

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PERCOLATION RELATIONSHIPS

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PREFACE

This dissertation consists of five separate essays. The reader is encouraged to refer to the individual abstracts for a complete, concise description of the work contained in each essay. Essays I, II, and III are entitled "Farm-Level Economic Analysis Incorporating Stochastic Environmental Risk Assessment," "Meeting Environmental Goals Efficiently on a Farm-Level Basis," and "Capturing the Multi-Dimensional Aspects and Economic Tradeoffs of Environmental Risk Using Indices," respectively. These three essays focus on farm-level economic/environmental relationships. Essay I develops a farm-level risk programming framework which incorporates the stochastic nature of environmental outcomes. This essay also uses a unique method for measuring environmental risk: environmental risk indices. Essay II makes use of the programming framework and indices developed in Essay I to compare the economic efficiency of regulatory actions with management-based solutions in meeting farm-level environmental goals. Essay III looks at various specifications of environmental risk indices in detail.

Essay IV, entitled "Pesticide Productivity: What are the Trends?" takes an aggregate look at pesticide productivity in United States agriculture. This essay moves beyond past research by determining the time-trend of pesticide productivity for various states using a random coefficient model. Past research on pesticide productivity gives only an "average" or "snap-shot" estimate obtained from production functions based on time-series data or cross-section data at a given point in time.

Essay V is entitled "Estimating Nitrogen Percolation Relationships: An Application of Tobit Analysis." This essay employs tobit analysis to complement the crop growth/chemical fate simulation model EPIC-PST by synthesizing results and providing information about the effect of selected variables (e.g. irrigation level and nitrogen applied) on the expected value and the probability of nitrogen percolation events. All vectors and matrices represented in the mathematical notation in all essays appear in bold type. Any reference to a product name does not imply endorsement by the author or Oklahoma State University.

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I am deeply convinced that Melissa Teague, my dear wife, is the most wonderful woman to ever grace the universe. Although I have no formal statistical tests to support my hypothesis, she gives me every reason to accept it as truth. This assertion is my opinion, and subject to bias, but very firmly held. Thank you, Melissa, for all of your love, support, encouragement, and free manuscript editing along the way. You're a magnificent person, and I am delighted that you chose me as your partner through life. It is wonderful to share the depth of love known only in matrimony, and a sincere faith in God, with a person like you. I consider the accomplishments written on the pages of this thesis, along with most of life's activities, to be insignificant when compared to the relationship that we hold and cherish.

I must also take a moment to praise my two children, Andrew and Megan. The joy and pleasure that you bring me is indescribable. I feel privileged to be your father. You make parenting fun. Thanks for understanding when I had to be away "at school", and for making life special during our times together. Just thinking about you fills my heart with joy.

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FARM-LEVEL ECONOMIC ANALYSIS INCORPORATING STOCHASTIC ENVIRONMENTAL RISK ASSESSMENT

Abstract

The objective of this analysis is to evaluate the tradeoffs that exist between income and environmental risks in the Central High Plains. A farm-level risk programming framework is presented which incorporates the stochastic and multi-attribute characteristics of environmental outcomes associated with agricultural production practices. Environmental risk is measured using environmental indices, estimated based upon 20-year distributions of environmental outcomes. These environmental indices account for differences in percolation and runoff of nitrates and pesticides, and differences in toxicity and persistence of the alternative pesticides, for each production strategy included in the model.

The model is applied to a representative farm in the Oklahoma Panhandle of the Central High Plains region. Tradeoffs between net returns and environmental risk were evaluated by imposing restrictions on the nitrate environmental index, pesticide environmental index, and both indices simultaneously. A complex array of responses were used to meet nitrate risk restrictions: crop substitution, moving nutrient-intensive production systems to heavier soils, reducing per-acre nitrogen applications, and increasing the use of fallow rotations. Results indicated that expected net returns were

sensitive to both the target level of the nitrate environmental index and the tolerance of exceeding the target. Opportunities for reducing environmental risk from pesticide sources were greater than for nitrates. Significant reductions in both the target of the pesticide environmental index (PEI) and the tolerance level were obtained without large effects on net returns. This was partially due to the large number of pesticide alternatives available. In addition, restrictions in the PEI were met by responses other than pesticide substitution (e.g., crop substitution, moving the use of more baneful pesticides to heavier soils).

Key words: farm-level environmental risk programming, environmental risk indices

FARM-LEVEL ECONOMIC ANALYSIS INCORPORATING STOCHASTIC ENVIRONMENTAL RISK ASSESSMENT

Introduction

Public concern over water quality has grown significantly in recent years and has focused increasingly on agriculture as a potential source of surface water and groundwater quality problems (Office of Technology Assessment, 1984 and 1990). Policy makers have several water quality protection strategies at their disposal, including management-oriented, incentive-based, and regulatory alternatives. The economic and environmental consequences of these alternatives are a topic of considerable debate.

The objective of this analysis is to evaluate the tradeoffs that exist between income and environmental risks in the Central High Plains. A farm-level risk programming framework is presented which incorporates the stochastic and multi-attribute characteristics of environmental outcomes associated with agricultural production practices. Environmental risk is measured using environmental indices, estimated based upon 20-year distributions of environmental outcomes. These environmental indices account for differences in percolation and runoff of nitrates and pesticides, and differences in toxicity and persistence of the alternative pesticides, for each production strategy included in the model. The model accounts for differences in soils, cropping systems, irrigation and nitrogen use levels, and pesticide alternatives in developing farm-level management strategies for achieving environmental goals.

Previous Research

Nonpoint source pollution problems have been studied at the watershed and/or regional levels (Park and Shabman; Gardner and Young; Jacobs and Casler). Some economic studies assume that the adverse effects of pollution are linked to fixed pollution delivery ratios (Miller and Gill; Osteen and Seitz; Boggess et al.; Guntermann, Lee, and Swanson). A few studies go beyond the fixed ratio approach and use environmental simulation models that capture the effects of management patterns on delivery ratios (Park and Shabman; Carvey and Croley; Lee, Lovejoy, and Beasley).

Attempts have been made to aggregate environmental outcomes of agricultural production practices by constructing environmental risk indices (Warner; Alt; Cabe, Kuch, and Shogren). A few studies incorporate environmental indices into economic analyses to evaluate income and environmental tradeoffs (Hoag and Hornsby; Hoag, Doherty, and Roka; Hoag and Manale); some include stochastic impacts when evaluating water quality policies (Braden, Larson, and Herricks; Carriker). In this article, the effects of various forms of pollution on several environments are combined into an index value, and application of the index is illustrated in assessing income and environmental tradeoffs. There are no studies which integrate environmental index concepts with stochastic loading estimates to assess farm-level economic and environmental tradeoffs.

Model Development

Target MOTAD

Target MOTAD is a computationally efficient mathematical programming formulation designed for decision makers who wish to maximize expected returns, but are concerned about returns falling below a critical level or target (Tauer). In this article, the Target MOTAD formulation is modified to incorporate the effect of environmental risk on decision making. The model is used to identify farm plans which maximize net returns, but maintain environmental risk below a critical level or target.

The Target MOTAD model proposed by Tauer is a two-attribute risk and return model. Income returns are measured as the sum of the expected returns of activities multiplied by their individual activity level. Income risk is measured as the expected value of the negative deviations of the solution below some target income level. A risk-return frontier is traced out by varying a risk aversion parameter. Mathematically, the model may be stated as

(1) $$Max\ E(z) = \sum_{j=1}^{n} c_j\, x_j$$

subject to

(2) $$\sum_{j=1}^{n} a_{kj}\, x_j \leq b_k \qquad k = 1, \ldots, m$$

(3) $$T - \sum_{j=1}^{n} c_{rj}\, x_j - y_r \leq 0 \qquad r = 1, \ldots, s$$

$$(4) \qquad \sum_{r=1}^{s} p_r y_r = \lambda \qquad \lambda = M \rightarrow 0$$

for all x_j and $y_r \geq 0$, where E(z) is expected return of the farm plan; c_j is expected return of activity j; x_j is level of activity j; a_{kj} is the technical requirement of activity j for resource k; b_k is level of resource k available; T is the target level of return; c_{rj} is the return of activity j for state of nature r; y_r is the net return deviation below T for state of nature r; p_r is the probability that state of nature r will occur; λ is the risk aversion parameter which is varied from M to 0; m is the number of resource equations or constraints; s is the number of states of nature; and M is a large number (Tauer).

In the present application, equations (1) and (2) are specified as above; that is, expected net returns are maximized subject to a set of resource constraints. However, the risk rows, equations (3) and (4), are now divided into two sets of equations (3a and 3b, 4a and 4b).

$$(3a) \qquad T_p - \sum_{j=1}^{n} ip_{rj} x_j - yp_r \geq 0, \qquad r = 1, \ldots, s$$

$$(3b) \qquad T_n - \sum_{j=1}^{n} in_{rj} x_j - yn_r \geq 0, \qquad r = 1, \ldots, s$$

$$(4a) \qquad \sum_{r=1}^{s} p_r yp_r = \lambda_p \qquad \lambda_p = M \rightarrow 0$$

$$(4b) \qquad \sum_{r=1}^{s} p_r yn_r = \lambda_n \qquad \lambda_n = M \rightarrow 0$$

where T_p is the target identified for the environmental index for pesticides; ip_{rj} is the pesticide index value for activity j for state of nature r; yp_r is the deviation above T_p for state of nature r; T_n is the target identified for the environmental index for nitrates; in_{rj}

is the nitrate index value for activity j for state of nature r; yn_r is the deviation above T_n for state of nature r; and λ_p and λ_n are the permissible levels of compliance to T_p and T_n, respectively.

Equations 3a and 3b estimate the amount that the farm-level pesticide and nitrate values exceed the specified target for each state of nature. Equations 4a and 4b estimate the expected value of deviations above the targets for the pesticide and nitrate indices by weighting each deviation by its probability of occurrence.

The solution to the Environmental Target MOTAD model produces farm plans which maximize income subject to achieving a satisfactory level of compliance with the target levels of pesticide and nitrate environmental risk. As in the traditional Target MOTAD formulation, both T and λ have an empirical interpretation. T is the maximum permissible level of the environmental index at the farm-level, while λ is the acceptable level of compliance with the target, measured as the average deviation above the target level. T and λ are in the same units as the environmental risk indices, except they are farm-level totals rather than per-acre figures. An intuitive explanation of λ is that any farm plan with λ equal to x will produce, on the average, x amount of pollution above the specified target, with x having the same units as the index. By specifying alternative targets for each index and varying λ parametrically, a series of environmental risk-net return frontiers is traced out.

Representation of environmental risk in this manner allows for designing farm plans which comply with environmental objectives. Environmental standards often permit some small amount of pollution, based on acceptable levels of exposure to humans, aquatic species, etc. (e.g. maximum contaminant levels, MCLs, established by the EPA). Environmental index target levels might be based upon similar criteria, and λ can be used to specify the acceptable tolerance of exceeding the environmental standards. For example, a λ value of zero imposes a zero tolerance of exceeding the standard.

Stochastic measures of environmental risk, when assessing income versus environmental risk tradeoffs, can produce very different prescriptions relative to deterministic measures. In many geographical areas, including the study region, probability distributions of annual percolation or runoff loadings for particular production systems are often highly skewed. This is because significant losses of nitrates and agrichemicals occur only in limited circumstances. Although the expected value of loadings may not indicate an environmental problem, the probability of a large loading event may still be significant. In such cases, policies should be directed toward reducing the probability of loadings above the threshold level. By specifying the appropriate targets and λ values, farm plans can be derived which account for the stochastic feature of environmental outcomes.

Environmental Risk Indices

In this study, two environmental indices are developed: one to indicate the level of environmental risk from pesticides, and the other to indicate environmental risk from nitrates. The environmental index for pesticides is estimated as:

$$EIP_{ij} = (PPERC_{ij} * HA_i * .5) + (PRUNOFF_{ij} * LC_i * .5) \quad (5)$$

where EIP_{ij} is the environmental index of pesticide i for crop activity j, $PPERC_{ij}$ is the quantity of pesticide i lost in percolation for crop activity j (grams/acre), and $PRUNOFF_{ij}$ is the quantity of pesticide i lost in runoff for crop activity j (grams/acre). HA_i is: 1 if $HAL_i > 200$; 3 if $10 < HAL_i \leq 200$; 5 if $HAL_i \leq 10$, or the EPA Carcinogenic Risk Category is A, B, B1, B2, or C. HAL_i is the lifetime Health Advisory Level (ppb) set by EPA for pesticide i. LC_i is: 1 if $LC_{50} > 10$, 3 if $1 \leq LC_{50} \leq 10$, 5 if $LC_{50} < 1$. LC_{50} is the acute toxicity to fish for 96 hours of exposure (ppm).

Surface water and groundwater are the environments of concern. HA_i serves as the toxicity weight for percolation, which affects groundwater; LC_i is the weight for runoff, which affects surface water. This indexing scheme uses a pesticide's lifetime HAL as a proxy for threats to human health through groundwater, and a pesticide's LC_{50} as a proxy for threats to aquatic life in surface water. Each environment is assigned an equal weight, but the weights could be modified.

The values for the aquatic LC_{50} of 1, 3, or 5 come from Kovach et al. Similar toxicity groups do not exist for the lifetime HAL, but they do exist for the oral and dermal LD_{50} of each pesticide. This discrete grouping, based on an oral or dermal LD_{50}, is used to determine the warning signals required on pesticide labels (Criswell and Campbell). The weighting system above is developed by ordering the pesticides from low to high based on the HAL, assigning a weight of 1, 3, or 5 to each pesticide based on the oral and dermal LD_{50} (Criswell and Campbell), and looking for a natural break in the ordering. If a pesticide has an EPA Carcinogenic Risk rating of A, B, B1, B2, or C, it's weight is 5, regardless of the value of the lifetime HAL (U.S. Environmental

Protection Agency). This procedure is applied to the herbicide and insecticide groups separately.

Once the environmental indices are calculated for each pesticide applied in a crop activity, a pesticide environmental index is calculated for each activity as:

(6) $$PEI_j = \sum_{i=1}^{n} EIP_{ij}$$

where PEI_j is the pesticide environmental index for crop activity j, EIP_{ij} is defined as above in equation (5), and n is the number of pesticides applied in crop activity j. The assumption of additivity means that risk from a particular pesticide does not change when it is combined with other pesticides.

The nitrate environmental index is calculated for each crop activity included in the model as follows:

(7) $$NEI_j = (NPERC_j * .5) + (NRUNOFF_j * .5)$$

where NEI_j is the nitrate environmental index for crop activity j, $NPERC_j$ is the quantity of nitrate lost in percolation for crop activity j (grams/acre), and $NRUNOFF_j$ is the quantity of nitrate lost in runoff for crop activity j (grams/acre). As in the case of PEI, both surface water and groundwater are assigned equal weights in the estimation of NEI.

Estimation of Chemical Loadings

The pesticide and nitrate environmental indices are calculated from chemical loading estimates gained from the crop yield and chemical movement model EPIC-PST. EPIC-PST combines the EPIC crop-growth model (Williams et al.) with the pesticide subroutines in the GLEAMS model (Leonard et al.). This model has been tested, validated and applied at several sites (Sabbagh et al.; Mapp et al.). EPIC-PST measures runoff and percolate at the edge of the field and just below the root zone, respectively, for pesticides and nitrates.

A 20-year EPIC-PST simulation was conducted for each crop activity included in the model. Sets of crop activities are developed for each representative farm resource situation, defined as combinations of soil type and irrigation system. Production activities for each resource situation represent different combinations of crops, irrigation levels, nutrient applications, insecticides, and pesticides. Daily weather data for 20 years and soil and crop parameters for the study area are used to simulate crop yields, pesticide losses in runoff and percolation, and nitrate losses in runoff and percolation for each crop activity. The annual pesticide and nitrate loss estimates are used in equations 5 through 7 to calculate distributions of the environmental indices. These 20-year distributions are used in the Environmental Target MOTAD model (ic_{rj} and in_{rj} in equations 3a and 3b) to represent the level of environmental risk associated with each production activity.

Farm Situation and Data Requirements

The model was used to derive a set of environmental risk-return frontiers for a representative farm in the Central High Plains. This region overlies the Ogallala Formation, an aquifer which supplies groundwater for human and animal consumption, and irrigation. Substantial potential for nitrate and pesticide leaching exists in parts of the Central High Plains region (Nielsen and Lee; Kellogg, Maizel, and Goss).

The representative farm, consisting of irrigated and dryland acreage, is located in the Panhandle region of western Oklahoma. Of the 1,440 total acres, 285 are irrigated and 1,155 are in dryland production. Rainfall averages 16 inches per year. Irrigated crops are corn, grain sorghum, and wheat; dryland crops are wheat and grain sorghum, produced continuously and with a wheat-fallow and wheat-grain sorghum-fallow rotation. Richfield clay loam soils represent about 75 percent of the total acreage, while the remaining 25 percent is comprised of Dalhart fine sandy loam soils. Irrigated acreage includes a 155-acre furrow irrigated field on the clay loam soil, and a 130-acre center pivot system on the fine sandy loam.

The farm plan assumes full participation in government commodity programs with planted acres (base acres less acreage-reduction-program acres) as follows: corn = 90 acres, wheat = 1107 acres, and grain sorghum = 219 acres. This leaves 24 acres of ARP, or fallow. Prices and costs are representative of 1993 production conditions. Total output eligible for deficiency payments is sold at the target price, and the remaining product is sold at the cash price.

To provide model flexibility, approximately 5,000 production activities were included for each crop, differing in terms of irrigation levels, nutrient use, and pesticide strategy. Irrigation schedules were based on a soil moisture criterion and range from a full-yield application to an extreme deficit irrigation schedule. Nitrogen applications range from those which assure avoidance of nutrient deficits to zero nitrogen use.

Selection of insecticides and herbicides for each crop was based on a survey of area extension specialists. A minimum of six herbicides and eight insecticides was included for each crop, varying in terms of toxicity, soil half-life, mobility, and effectiveness. To determine the yield impacts of various pesticide strategies, a survey of state and area agronomists and entomologists was conducted. These yield reduction percentages were then applied to the EPIC-PST yields to derive a unique yield for each pesticide strategy.

Results

Three sets of solutions are reported to assess the tradeoffs between net returns and environmental risk on the representative farm. In the first set, target levels (T_n) and levels of compliance (λ_n) on the nitrate environmental index (NEI) are varied to assess tradeoffs between income and environmental risk. The second set of solutions places restrictions on the pesticide environmental index (PEI). Both indices are constrained in the third set of solutions, reducing nitrate and pesticide loadings simultaneously.

To establish target levels for the environmental indices, the model was first run without constraints on the environmental risk indices. The maximum levels of the nitrate and pesticide environmental risk indices over the 20 states of nature were identified. These levels were then reduced by 25, 50 and 75 percent to derive three target levels. A net return-environmental risk tradeoff curve (or frontier) was derived for each target by parametrically varying λ, the average deviation above the target.

Nitrate Environmental Risk Restrictions

Tradeoff curves are presented for targets corresponding to 25, 50 and 75 percent reductions below the maximum NEI from the profit maximizing farm plan in figure 1. Table 1 presents optimal farm plans corresponding to points A through D on the tradeoff curve generated using the 50 percent target level. For λ_n greater than 1,200, the Target MOTAD solution is equivalent to the profit maximizing solution (plan A). Expected return above operating costs for the profit maximizing plan is $117,220. Nutrient, pesticide, and irrigation applications for the optimal activities correspond closely to practices currently in use.

As λ_n decreases, tightening the environmental target requirement, several changes to the optimal production plan occur. First, wheat is continually substituted for sorghum on the irrigated acreage. Nitrate loadings from wheat production are the lowest of the three irrigated crops, reflecting its lower nitrogen requirement and irrigation levels. Irrigated corn is moved from the lighter sandy-loam soil to the clay-loam soil to reduce total nitrate loadings. Reductions in the average deviation above the target are also achieved by decreasing per-acre nitrogen applications, particularly on dryland wheat. Sorghum is moved to dryland production through the increased use of a wheat-sorghum-fallow rotation. This also results in a continual increase in the number of fallow acres. Fallow acreages increase from 24 acres in the profit maximizing plan to 144 acres in plan D.

When λ_n equals zero (plan D), exceeding the NEI target is not permitted. For this restriction, the planted acreage of all three crops falls below their base acreage;

however, all 285 irrigated acres remain in production. In responding to farm-level nitrate restrictions, producers attempt to focus their adjustments on the less productive dryland acreage.

The tradeoff curves, figure 1, indicate expected net returns are relatively sensitive to both the level of the NEI target (T_n) and to the tolerance level of exceeding the target (λ_n). The sensitivity of expected net returns to the target can be illustrated by comparing returns across the three frontiers at a fixed tolerance limit. For example, if λ_n is 800, the profit maximizing plan remains feasible under the 25 percent target level, and expected returns are $117,200. Net returns are reduced to $111,180 for the 50 percent target, and to $86,000 for the 75 percent target. The sensitivity of expected net return to changes in the tolerance of exceeding the target NEI (λ_n) is reflected in the slope of the frontier. In the case of the 25 percent target, reductions in λ_n are attainable with only small effects on income. However, the income reductions from reducing expected deviations above the target NEI are much more apparent when the target is reduced to the 50 percent level. When λ_n is reduced from 1,200 to zero, expected net returns decrease $21,122. This sensitivity to changes in the tolerance level reflects the frequency and magnitude of annual nitrate loadings occurring in the study region. When λ_n is zero, the NEI cannot exceed the target level in any year. Essentially, the farm must be managed to avoid excessive nitrate loadings under the worst-case scenario.

Several studies have used deterministic measures of environmental risk. To compare solutions from the Target MOTAD model with those derived using deterministic environmental risk measures, the model was reformulated using the 20-year average of the indices to represent environmental risk. Rows 3b and 4b of the Environmental

Target MOTAD model were replaced with the constraint that the expected value of the NEI not exceed a specified limit. In this case, the NEI limit was set to the 75 percent reduction scenario ($NEI^* = 11{,}627$). Based on the optimal farm plan and annual NEI estimates, a 20-year distribution of farm-level NEI outcomes was estimated for the deterministic solution. The 20-year distributions of NEI values for the deterministic and Target MOTAD ($\lambda = 400$) solutions were approximated as gamma distributions, figure 2.

Although the deterministic solution constrains the expected value of NEI to below the target level, there is a large probability (approximately 40 percent) that a NEI outcome exceeding NEI^* will occur. In contrast, less than 10 percent of the area under the distribution derived using the Target MOTAD model lies to the right of the critical NEI level. If water quality protection policies are based on expected values of environmental damage, without considering the stochastic dimension of environmental outcomes, then water quality objectives may not be realized. Although the expected value of environmental outcomes does not indicate a problem, there still exists a significant probability that environmental damage may occur under the plan prescribed by the deterministic measure. In this case, the probability of environmental damage (i.e., a NEI value exceeding NEI^*) is four times greater under the plan derived using the stochastic risk measure.

Pesticide Environmental Risk Restrictions

Environmental risk - expected net return frontiers for targets of 25, 50 and 75 percent below the maximum PEI from the profit maximizing plan are shown in figure 3. Optimal farm plans corresponding to points A through D on the 75 percent frontier are reported in table 2. When λ_p exceeds 5,800, the optimal solution is the profit maximizing plan described earlier. In addition to the types of pesticide substitutions expected, several other adjustments to the farm plans must occur in order to meet reductions in λ_p. Many of these changes are similar to those employed in meeting the nitrate restrictions. These include: (1) substitution of wheat for sorghum on irrigated acreage, (2) movement of irrigated corn and sorghum to clay-loam soils, and (3) increased use of the wheat-sorghum-fallow rotation. The PEI is estimated as a function of both pesticide properties (e.g., health advisory limits, HAL, and acute toxicity, LC_{50}) and runoff and percolation loadings. These production responses contribute to reductions in the PEI by decreasing runoff and percolation losses.

Substitution of herbicides and insecticides represents the second type of adjustment used to meet reductions in the level of tolerance of exceeding the PEI target (λ_p). Pesticides included in the profit maximizing solution generally have the lowest yield reductions. Several of these pesticides have low HAL or LC_{50} values, implying their runoff and percolation loadings are heavily weighted in the calculation of the pesticide environmental index, equation 7. For example, several of the principal pesticides employed in the profit maximizing plan (e.g., Cygon, Atrazine, Dual, and Furadan) are assigned the maximum HA_i weight, 5, and have LC_i weights of 3 or more. As λ_p

decreases, pesticides with less baneful environmental effects are substituted into the optimal farm plan . Banvel, Prowl and 2-4,D all give reductions in HA_i and/or LC_i relative to the pesticide being replaced. Cygon remains in the optimal farm plans. Percolation and runoff loadings are very small for this pesticide; thus, its high HA_i and LC_i weights do not significantly increase the farm-level PEI.

A comparison of figure 3 with figure 1 indicates that greater opportunities exist for reducing environmental risk from pesticides than from nitrates. Under the 25 and 50 percent targets, net returns are reduced by less than $3,500 when going from the profit maximizing solution to a zero tolerance of exceeding the PEI target. Even when the target is reduced to 75 percent, the tolerance limit may be significantly reduced without having large effects on income. Expected net returns decrease by less than 7 percent in attaining a 75 percent PEI reduction with zero tolerance.

Nitrate and Pesticide Environmental Risk Restrictions

The frontiers in figure 4 were derived by simultaneously varying λ_n and λ_p from the NEI and PEI targets discussed earlier. The frontiers resemble those derived when environmental risk is measured by the NEI (figure 1). However, they lie below the nitrate environmental risk - net return frontiers, illustrating the increased cost of meeting the restrictions on PEI in conjunction with the nitrate restrictions. The added cost of meeting the pesticide restriction ranges from $0 to $3,100. The frontiers in figure 4, derived when environmental risk from both pesticide and nitrate sources is considered, also have more curvature than those in figures 1 and 3. Again, this property reflects the added cost of reducing both environmental risk measures as λ_n and λ_p are simultaneously decreased.

Summary and Conclusions

The objective of the analysis was to evaluate the tradeoffs between environmental risk and net returns in the Central High Plains. A farm-level risk programming model was presented which incorporated the stochastic and multi-attribute characteristics of environmental outcomes resulting from agricultural production practices. Environmental indices were developed which aggregated water quality effects across environments (surface water and groundwater) for a given form of contaminant (pesticides and nitrates). Restrictions on environmental outcomes were specified based on a target (or maximum) level of the environmental indices, and/or the acceptable level of compliance with that target.

The model was applied to a representative irrigated and dryland farm located in the Panhandle region of western Oklahoma. Tradeoffs between net returns and environmental risk were evaluated by imposing restrictions on the nitrate environmental index, pesticide environmental index, and both indices simultaneously. A complex array of responses were used to meet nitrate risk restrictions: crop substitution, moving nutrient-intensive production systems to heavier soils, reducing per-acre nitrogen applications, and increasing the use of fallow rotations. Results indicated that expected net returns were sensitive to both the target level of the nitrate environmental index and the tolerance of exceeding the target. Opportunities for reducing environmental risk from pesticide sources were greater than for nitrates. Significant reductions in both the target of the pesticide environmental index (PEI) and the tolerance level were obtained without large effects on net returns. This was partially due to the large number of pesticide alternatives available. In addition, restrictions in the PEI were met by responses other than pesticide substitution (e.g., crop substitution, moving the use of more baneful pesticides to heavier soils).

Previous studies have used deterministic measures of environmental risk to identify farm plans that meet specified environmental objectives. Deterministic environmental risk measures may not indicate a problem, even though there is a significant probability that the environmental standard may be exceeded. By using the Environmental Target MOTAD formulation, farm plans can be derived which limit the expected value of the environmental indices, and restrict the probability that the target will be exceeded. The importance of allowing for the stochastic nature of environmental outcomes was illustrated by the sensitivity of income to tolerance limits on the environmental indices.

Using environmental indices to aggregate environmental outcomes is a useful way to address the multidimensional aspects of water quality policy, but there are limitations. Indices involve value judgements and simplifications of reality. The weights can be changed to reflect different values, and more in-depth modeling efforts hold promise of portraying reality more accurately. Even with modeling improvements, the underlying processes of chemical fate and transport remain complicated, and the specific weights to place on various forms of pollution is debatable.

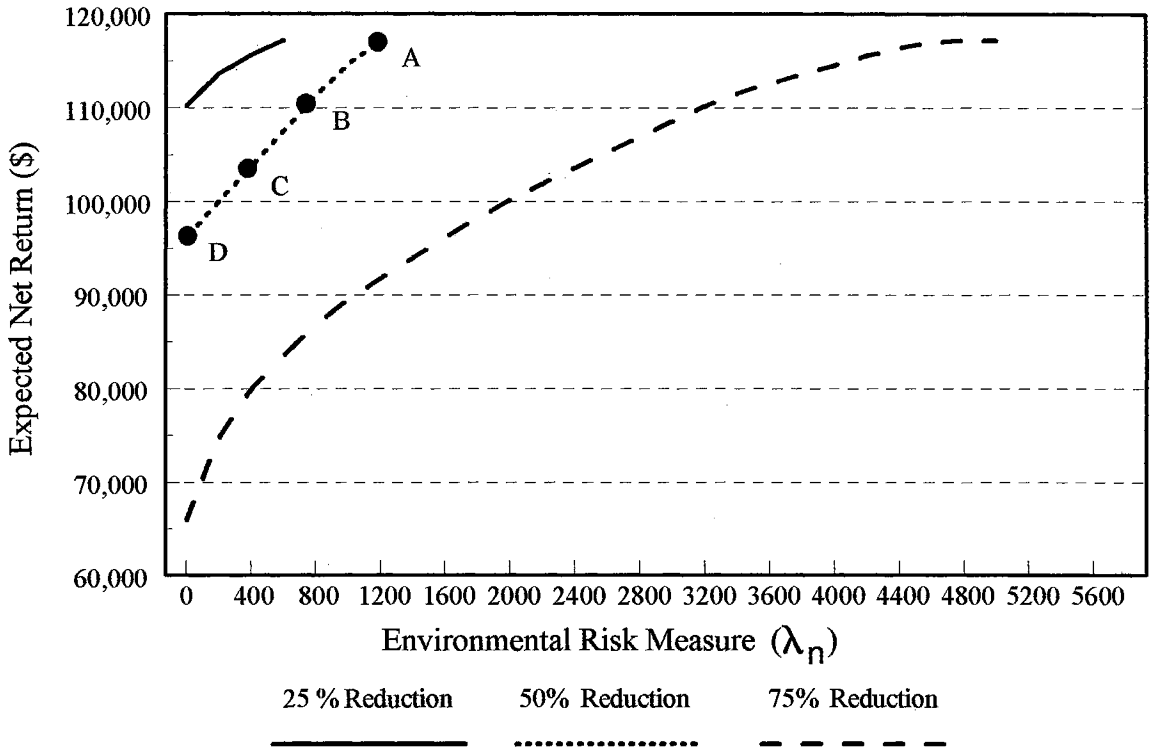

Figure 1. Tradeoff Between Environmental Risk and Expected Net Returns for Targets Corresponding to 25, 50, and 75 Percent Reductions Below the Maximum Nitrate Environmental Index.

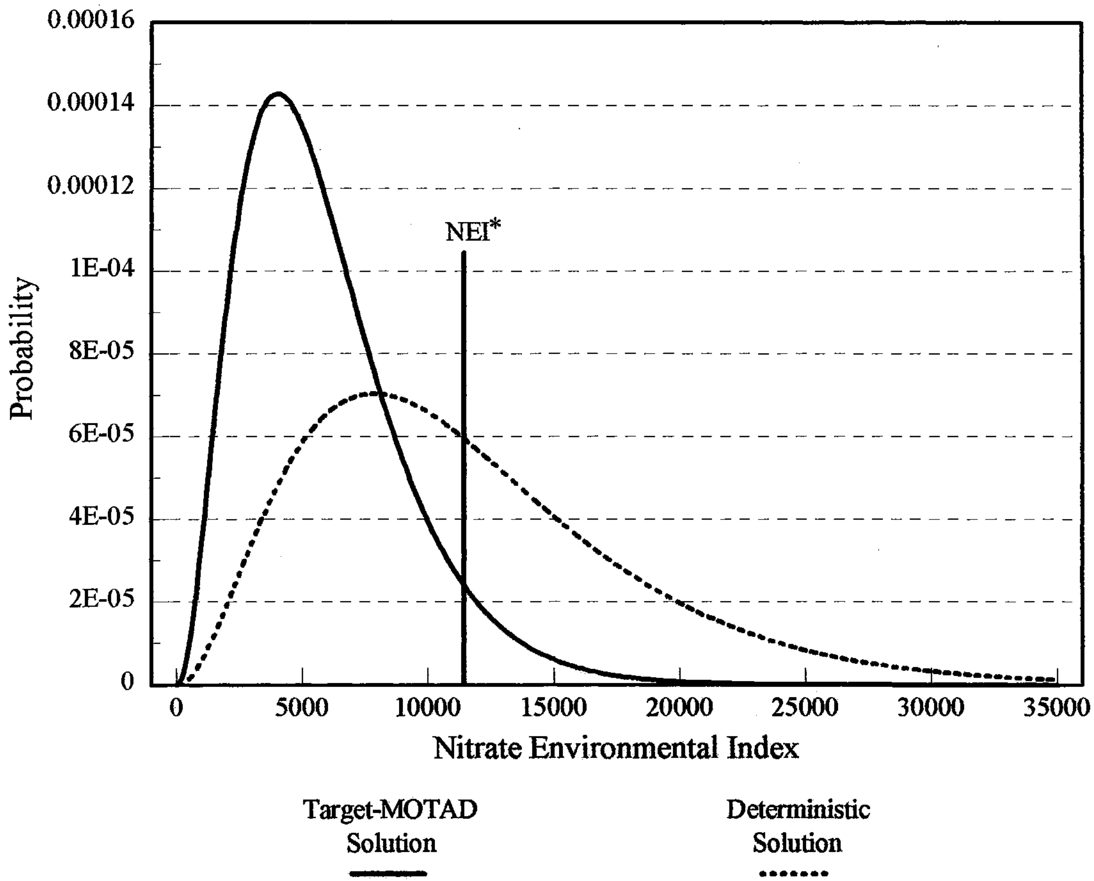

Figure 2. Probability Distribution of NEI Outcomes Under Deterministic and Target-MOTAD Solutions, Target NEI = Level Corresponding to 75 Percent Reduction Scenario.

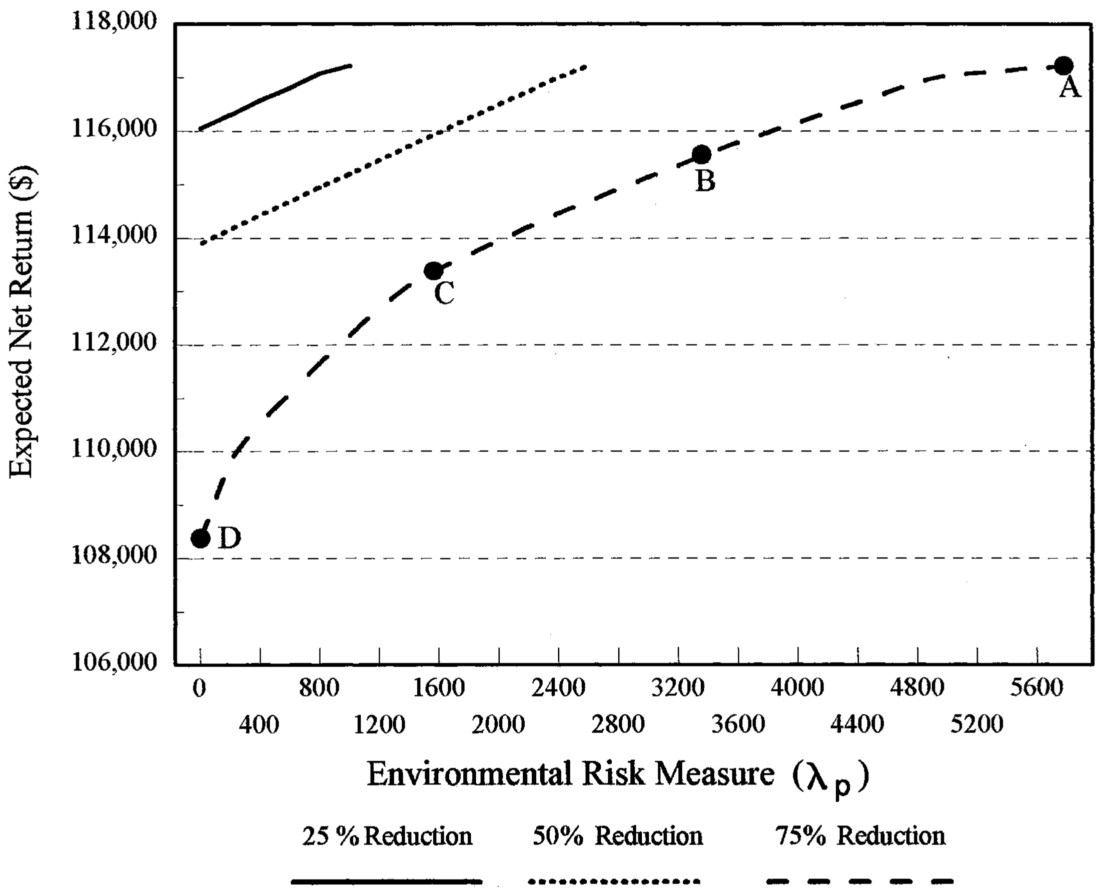

Figure 3. Tradeoff Between Environmental Risk and Expected Net Returns for Targets Corresponding to 25, 50, and 75 Percent Reductions Below the Maximum Chemical Environmental Index.

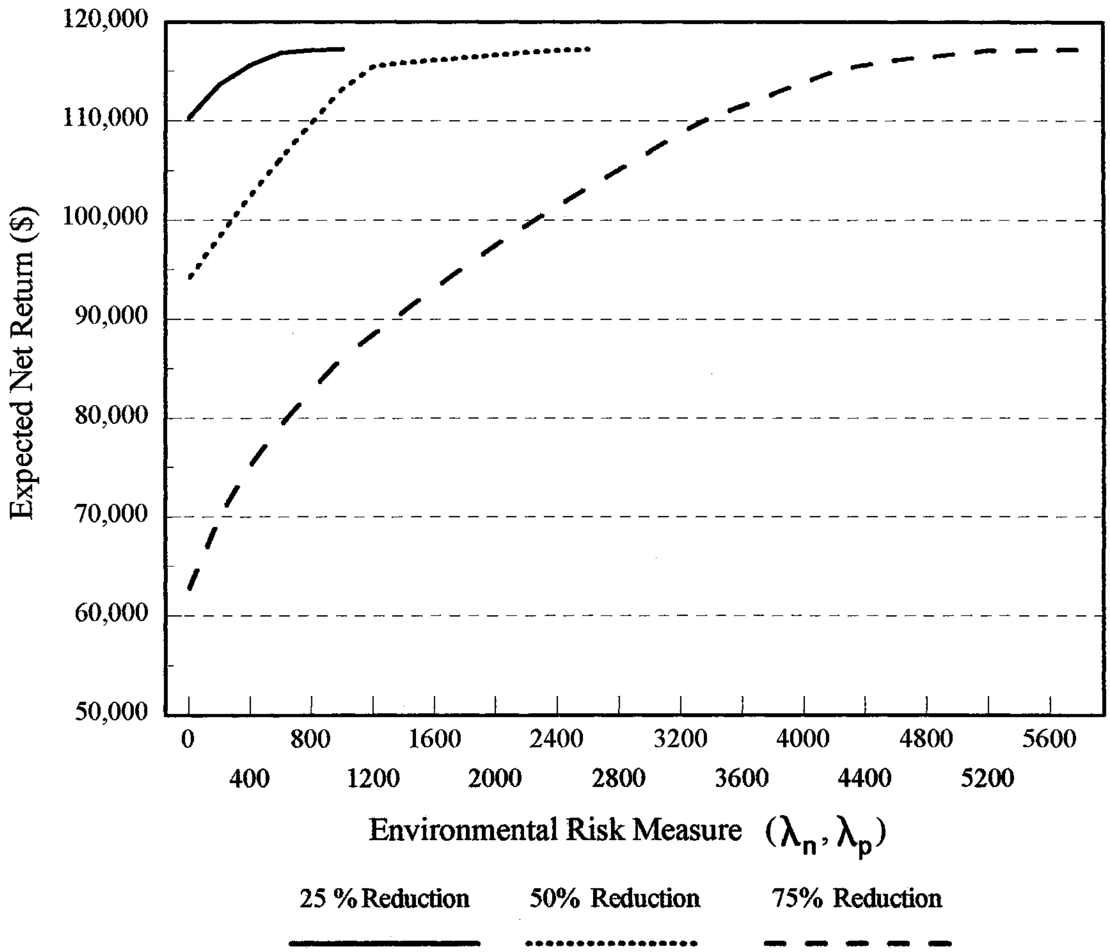

Figure 4. Tradeoff Between Environmental Risk and Expected Net Returns for Targets Corresponding to 25, 50, and 75 Percent Reductions Below the Maximum Nitrate Environmental Index and Chemical Environmental Index.

Table 1. Optimal Environmental Target-MOTAD Farm Plans, Target = 50 Percent of the Nitrate Environmental Index Maximum for the Profit Maximizing Plan, Four Levels of Permissible Compliance (λ_n).

Crop	Soil [a]	Irrigation [b] (System, Appl. (in))	Nitrogen Appl. (lb/ac)	Acres
Plan A (Profit Maximizing Plan, Net Returns = $117,220):				
Sorghum	light	Pivot, 20	152	40
	heavy	Furrow, 24	169	155
Corn	light	Pivot, 24	202	90
Wheat	light	Dryland	63	230
	heavy	Dryland	63	853
Wheat-Sorg.-Fallow	heavy	Dryland	30	72
Plan B (λ_n = 800, Net Returns = $111,181):				
Sorghum	heavy	Furrow, 24	169	155
Corn	light	Pivot, 24	202	90
Wheat	light	Pivot, 12	129	40
	heavy	Dryland	31	696
	light	Dryland	31	230
	heavy	Dryland	0	38
Wheat-Sorg.-Fallow	heavy	Dryland	30	191
Plan C (λ_n = 400, Net Returns = $103,732):				
Sorghum	heavy	Furrow, 24	169	111
Corn	light	Pivot, 24	202	46
	heavy	Furrow, 20	206	44
Wheat	light	Pivot, 12	129	84
	heavy	Dryland	31	344
	light	Dryland	31	230
	heavy	Dryland	0	258
Wheat-Sorg.-Fallow	heavy	Dryland	30	323
Plan D (λ_n = 0, Net Returns = $96,098):				
Sorghum	heavy	Furrow, 24	169	69
Corn	heavy	Furrow, 20	206	86
Wheat	light	Pivot, 12	129	130
	light	Dryland	31	230
	heavy	Dryland	0	491
Wheat-Sorg.-Fallow	heavy	Dryland	30	434

[a] light = Dalhart fine sandy loam, heavy = Richfield clay loam

[b] Pivot = Center pivot sprinkler system, Furrow = furrow (gated-pipe) irrigation system

Table 2. Optimal Environmental Target-MOTAD Farm Plans, Target = 75 percent of the Chemical Environmental Index Maximum for the Profit Maximizing Plan, Four Levels of Permissible Compliance (λ_c).

Crop	Soil [a]	Irrigation [b] (System, Appl. (in))	Insecticide	Herbicide	Acres
Plan A (Profit Maximizing Plan: Net Returns = \$117, 220):					
Sorghum	light	Pivot, 20	Cygon	Atrazine, Dual	40
	heavy	Furrow, 24	Cygon	Atrazine, Dual	155
Corn	light	Pivot, 24	Furadan	Atrazine, Dual	90
Wheat	light	Dryland	Cygon	Ally	230
	heavy	Dryland	Cygon	Ally	853
Wheat-Sorg.-Fal	heavy	Dryland	Cygon	Ally, Atraz., Dual	72
Plan B (λ_c = 3,500, Net Returns = \$115,650):					
Sorghum	light	Pivot, 20	Cygon	Atrazine, Dual	130
	heavy	Furrow, 24	Cygon	2, 4-D, Treflan	65
Corn	heavy	Furrow, 25	Furadan	Atrazine, Dual	90
Wheat	light	Dryland	Cygon	Ally	230
	heavy	Dryland	Cygon	Ally	853
Wheat-Sorg.-Fal	heavy	Dryland	Cygon	Ally, Atraz., Dual	72
Plan C (λ_c = 2000, Net Returns = \$113,935):					
Sorghum	light	Pivot, 20	Cygon	Atrazine, Dual	30
	heavy	Furrow, 24	Cygon	2, 4-D, Treflan	106
Corn	light	Pivot, 28	Furadan	Atrazine, Dual	41
	heavy	Furrow, 25	Furadan	Atrazine, Dual	49
Wheat	light	Pivot, 12	Ethyl Parathion	Ally	59
	light	Dryland	Cygon	Ally	230
	heavy	Dryland	Cygon	Ally	677
Wheat-Sorg.-Fal	heavy	Dryland	Cygon	Banvel	248
Plan D (λ_c = 0, Net Returns = \$108,032):					
Sorghum	heavy	Furrow, 24	Cygon	2, 4-D, Treflan	120
Corn	light	Pivot, 28	Furadan	Atrazine, Dual	55
	heavy	Furrow, 25	Furadan	2, 4-D, Prowl	35
Wheat	light	Pivot, 12	Ethyl Parathion	Ally	75
	light	Dryland	Cygon	Ally	230
	heavy	Dryland	Cygon	Ally	740
Wheat-Sorg.-Fal	heavy	Dryland	Cygon	Banvel	185

[a] light = Dalhart fine sandy loam, heavy = Richfield clay loam

[b] Pivot = Center pivot sprinkler system, Furrow = furrow (gated-pipe) irrigation system

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Essay II

MEETING ENVIRONMENTAL GOALS EFFICIENTLY ON A FARM-LEVEL BASIS

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Abstract

Policy makers have several groundwater protection strategies at their disposal, including moral suasion, design standards, performance standards, economic incentives, and research and development. The objective of this research is to determine if management-based means of protecting environmental quality on a representative farm in the Southern High Plains region are more efficient than regulation, and if an efficiency gain exists, to quantify it in dollar terms. Management-based means include policy options with freedom of producer choice as a key concept, such as performance standards, economic incentives, and research and development. Regulation refers to traditional regulatory policies, or design standards. A per-acre nitrogen application restriction and a pesticide ban are used in this study as the design standards to compare to management-based water quality protection strategies.

A farm-level risk programming framework is developed to incorporate the effect of environmental risk on decision making. This framework is used to identify farm plans which maximize net returns, but maintain environmental risk below a critical level, or target. Environmental risk is measured using environmental risk indices, which aggregate several sources and types of chemical loadings into a single value. 20-year distributions for the environmental indices are calculated based upon chemical loading estimates from the crop growth/chemical fate model EPIC-PST. This approach places considerable weight on the accuracy of the environmental indices, both in terms of the loading estimates and the structure of the environmental index equations. Any index used must capture the environmental problem of concern, and loading estimates must be accurate.

Results of this study indicate that management-based means, which allow producers maximum discretion in reaching farm-level environmental goals, can be much more efficient than a regulatory approach. A cost-benefit analysis indicates that up to $23,929 for nitrate environmental risk reduction, and $7,083 for pesticide environmental risk reduction, on a per-farm basis, can be spent by society to develop and encourage the adoption of management-based plans, and still maintain an efficiency gain over regulatory policies. This analysis is done for a representative farm, however, and the results should not be taken as a comprehensive evaluation of policy options across a region.

Key words: environmental risk reduction, regulation, management-based alternatives, economic efficiency

MEETING ENVIRONMENTAL GOALS EFFICIENTLY ON A FARM-LEVEL BASIS

Introduction

Public concern over water quality has grown significantly in recent years and has focused increasingly on agriculture as a potential source of surface water and groundwater quality problems. Increasing evidence of groundwater contamination from agrichemicals has heightened the call for government involvement in developing groundwater protection policies. Policy makers have several groundwater protection strategies at their disposal, including moral suasion, design standards, performance standards, economic incentives, and research and development (Abler and Shortle). The economic and environmental consequences of these alternatives are a topic of considerable debate. Recent federal policies dealing with nonpoint-source pollution and groundwater quality protection emphasize voluntary rather than mandatory controls (Crutchfield). Design and implementation of control measures have been left to state and local officials under both the 1987 Water Quality Act's nonpoint-source provisions and EPA's pesticides-in-groundwater strategy. This approach offers considerable flexibility to develop policies which better account for soil type and other site-specific characteristics that affect the vulnerability of groundwater to agricultural pollutants.

The objective of this research is to determine if management-based means of protecting environmental quality on a representative farm in the Southern High Plains region are more efficient than regulation, and if an efficiency gain exists, to quantify it in dollar terms. Management-based means include policy options with freedom of producer choice as a key concept, such as performance standards, economic incentives, and research and development. Although performance standards are a form of regulation, the emphasis is upon allowing producers to freely choose among production alternatives. Research and development is aimed at enhancing the choice set. Regulation refers to traditional regulatory policies, or design standards, such as chemical bans or nitrogen application restrictions (Abler and Shortle; Bohm and Russell).

Efficiency of water quality policies is determined by answering the question, "Can the distribution of environmental outcomes achieved under a regulatory policy be achieved at lower cost using management-based alternatives, or conversely, can a preferred distribution of environmental outcomes be achieved with management-based policies at the same cost incurred under a regulatory policy?" Regulatory and management-based approaches will be compared in a cost-benefit framework in terms of income lost versus amounts of pollution reduction achieved. Two regulatory policies, a per-acre nitrogen application restriction and a chemical ban, serve as a basis for comparison to a management-based water quality protection strategy.

The analysis incorporates the stochastic and multi-attribute characteristics of environmental outcomes associated with agricultural production practices. Environmental indices based upon 20-year distributions of environmental outcomes provide the multi-attribute stochastic measurement of environmental risk. These environmental indices account for differences in percolation and runoff of nitrates and pesticides, and differences in toxicity and persistence of the alternative pesticides for each production strategy included in the model. The model also accounts for differences in cropping systems, nitrogen use levels, and pesticide alternatives.

Model Development

Numerous mathematical programming techniques have been developed in recent years for analysis of decision making under risk. One formulation that is computationally efficient is Target MOTAD (Tauer). Target MOTAD is considered appropriate for decision makers who wish to maximize expected returns, but are concerned about returns falling below a critical level or target. In this analysis, the Target MOTAD formulation is transformed to incorporate the effect of environmental risk, rather than income risk, on decision making. The model is used to identify farm plans which maximize net returns, but maintain environmental risk below a critical level or target. Environmental risk is measured using environmental risk indices, which aggregate several sources and types of chemical loadings into a single value. An explanation of these indices is followed by a description of the Environmental Target MOTAD model.

Environmental Risk Indices

Several attempts have been made to aggregate environmental outcomes of agricultural production practices by constructing environmental risk indices. For example, the Potential Environmental Hazard index assigned each pesticide a ranking based on four factors: mobility, longevity, toxicity, and biomagnification (Warner). The Environmental Exposure Index (EEI) was an attempt to improve upon this approach by using a unique measure of persistence for each pesticide. This index considered the half-life, application rate, and toxicity of each pesticide (Alt). Warner criticized these indices because they failed to consider soil properties and the potential of a pesticide to contaminate ground or surface water. Warner proposed an index based upon a chemical's persistence, mobility and toxicity classifications. Cabe, Kuch, and Shogren reported a more comprehensive approach to evaluating the environmental and human health impacts of pesticides that focused on estimated rates of exposure to pesticides rather than pesticide loadings.

In this analysis, two environmental indices are developed, one to indicate the level of environmental risk from pesticides and the other to indicate the level of environmental risk from nitrates. The environmental index for chemicals is estimated as:

$$EIC_{ij} = (CPERC_{ij} * HA_i * .5) + (CRUNOFF_{ij} * LC_i * .5) \tag{1}$$

where EIC_{ij} is the environmental index of chemical i for crop activity j, $CPERC_{ij}$ is quantity of pesticide i lost in percolation for crop activity j (grams/acre), and $CRUNOFF_{ij}$ is quantity of pesticide i lost in runoff for crop activity j (grams/acre).

The toxicity weight HA_i is defined in equation 2 such that:

$$HA_i = \begin{cases} 5 \text{ if } HAL_i \leq 10 \text{ or the EPA Carcinogenic} \\ \qquad \text{Risk Category is A, B, B1, B2, or C} \\ 3 \text{ if } 10 < HAL_i \leq 200 \\ 1 \text{ if } HAL_i > 200 \end{cases} \tag{2}$$

where HAL_i is the lifetime Health Advisory Level set by EPA for chemical i. Likewise, the toxicity weight LC_i is defined in equation 3 such that:

$$LC_i = \begin{cases} 5 \text{ if } LC_{50} < 1 \\ 3 \text{ if } 1 \leq LC_{50} \leq 10 \\ 1 \text{ if } LC_{50} > 10 \end{cases} \tag{3}$$

where LC_{50} is acute toxicity to fish for 96 hours of exposure.

Surface water and groundwater are the environments of concern. HA_i serves as the toxicity weight for percolation, which affects groundwater, and LC_i is the weight for runoff, which affects surface water. This indexing scheme uses a chemical's lifetime HAL as a proxy for threats to human health through groundwater and a chemical's LC_{50} as a proxy for threats to aquatic life in surface water. For this application, each environment is assigned an equal weighting; however, the weights could be modified if one desired to assign a higher priority to surface water or groundwater in the estimation of the environmental index.

The 1, 3, or 5 breakdown for the aquatic LC_{50} is taken from Kovach et al. Similar toxicity groups do not exist for the lifetime HAL, but they do exist for the oral and dermal LD_{50} of each chemical. This discrete grouping concept based on an oral or dermal LD_{50} is used to determine the warning signals required on pesticide labels (Criswell and Campbell). The weighting system above is developed by ordering the chemicals from low to high based on the HAL, assigning a 1, 3, or 5 weighting to each chemical based on the oral and dermal LD_{50}, and looking for a natural break in the ordering. These natural breaks were found at a HAL level of 10 and 200. If a chemical has an EPA Carcinogenic Risk rating of A, B, B1, B2, or C, it is weighted with a 5, regardless of the value of the lifetime HAL (U.S. Environmental Protection Agency). This procedure is applied to the herbicide and insecticide groups separately.

Once the environmental indices are calculated for each chemical applied in a crop activity, a chemical environmental index is calculated for each activity as:

(4) $$CEI_j = \sum_{i=1}^{n} EIC_{ij}$$

where CEI_j is the Chemical Environmental Index for crop activity j, and n is the number of chemicals applied in crop activity j.

The second environmental index applies to nitrates. The nitrate environmental index is calculated for each crop activity included in the model as follows:

(5) $$NEI_j = (NPERC_j * .5) + (NRUNOFF_j * .5)$$

where NEI_j is the Nitrate Environmental Index for crop activity j, $NPERC_j$ is the quantity of nitrate lost in percolation for crop activity j (grams/acre), and $NRUNOFF_j$ is the quantity of nitrate lost in runoff for crop activity j (grams/acre). As in the estimation of CEI, both surface water and groundwater are assigned equal weights in the estimation of NEI.

Environmental Target MOTAD Model

The Target MOTAD model proposed by Tauer is a two-attribute risk and return model. Income returns are measured as the sum of the expected returns of activities multiplied by their individual activity level. Income risk is measured as the expected value of the negative deviations of the solution below some target income level. A risk-return frontier is traced out by varying a risk aversion parameter. Mathematically, the model may be stated as

(6) $$Max\ E(z) = \sum_{j=1}^{n} c_j\, x_j$$

subject to

(7) $$\sum_{j=1}^{n} a_{kj} x_j \leq b_k \qquad k = 1, \ldots, m$$

(8) $$T - \sum_{j=1}^{n} c_{rj} x_j - y_r \leq 0 \qquad r = 1, \ldots, s$$

(9) $$\sum_{r=1}^{s} p_r y_r = \lambda \qquad \lambda = M \longrightarrow 0$$

for all x_j and $y_r \geq 0$, where E(z) is expected return of the farm plan; c_j is expected return of activity j; x_j is level of activity j; a_{kj} is the technical requirement of activity j for resource k; b_k is the level of resource k available; T is the target level of return; c_{rj} is the return of activity j for state of nature r; y_r is the net return deviation below T for state of nature r; p_r is the probability that state of nature r will occur; λ is the risk aversion parameter which is varied from M to 0; m is the number of resource equations or constraints; s is the number of states of nature; and M is a large number (Tauer).

In this analysis, equations (6) and (7) are specified as above; that is, expected net returns are maximized subject to a set of resource constraints. However, the risk rows are modified in several important ways. Equations (8) and (9) are now divided into two sets of equations (8a and 8b, 9a and 9b) as follows:

(8a) $$T_c - \sum_{j=1}^{n} ic_{rj} x_j - yc_r \geq 0, \qquad r = 1, \ldots, s$$

(8b) $$T_n - \sum_{j=1}^{n} in_{rj} x_j - yn_r \geq 0, \qquad r = 1, \ldots, s$$

(9a) $$\sum_{r=1}^{s} p_r yc_r = \lambda_c \qquad \lambda_c = M \longrightarrow 0$$

(9b) $$\sum_{r=1}^{s} p_r \, yn_r = \lambda_n \qquad \lambda_n = M \longrightarrow 0$$

where T_c is the target identified for the environmental index for chemicals; ic_{rj} is the chemical index value for activity j for state of nature r; yc_r is the deviation above T_c for state of nature r; T_n is the target identified for the environmental index for nitrates; in_{rj} is the nitrate index value for activity j for state of nature r; yn_r is the deviation above T_n for state of nature r; and λ_c and λ_n are the permissible levels of compliance to T_c and T_n, respectively.

Equations 8a and 8b estimate the amount that the farm-level chemical and nitrate values exceed the specified target for each state of nature. Equations 9a and 9b estimate the expected value of deviations above the targets for the chemical and nitrate indices by weighting each deviation by its probability of occurrence.

Solving the Environmental Target MOTAD model produces farm plans which maximize income subject to achieving a satisfactory level of compliance with the target levels of chemical and nitrate environmental risk specified in the analysis. As in the traditional Target MOTAD formulation, both T and λ have an empirical interpretation with respect to risk preference. In this case, risk is measured in terms of annual average deviations in the environmental indices above the specified targets. T reflects some maximum permissible level of the environmental index at the farm-level, while λ determines the acceptable level of compliance with the target as measured by the expected deviation above the target level. An intuitive explanation of λ is that any farm plan with λ equal to x will produce, on the average, x amount of pollution above the specified target, with x having the same units as the index. By specifying a target for an index and varying λ parametrically, an environmental risk-net return frontier can be traced out.

The chemical environmental index (CEI) and nitrate environmental index (NEI) values are calculated based upon chemical loadings estimated using the crop yield and chemical movement model EPIC-PST. EPIC-PST combines the EPIC crop-growth model (Williams et al.) with the pesticide subroutines from the GLEAMS model (Leonard, Knisel, and Still), and has been tested, calibrated, and applied at several sites (Ramanarayanan et al.; Sabbagh et al.; Bernardo et al.).

A 20-year EPIC-PST simulation was conducted for each crop activity included in the model. Sets of crop activities are developed for each resource situation on the representative farm, defined as combinations of soil type and irrigation system. Production activities on each resource situation represent different combinations of crops, irrigation levels, nutrient applications, insecticides, and herbicides. Daily weather data for 20 years and soil and crop parameters appropriate for the study area are used to simulate crop yields, pesticide losses in runoff and percolation, and nitrate losses in runoff and percolation for each crop activity. The annual chemical and nitrate loss estimates are used in equations 1, 4, and 5 to calculate distributions of the environmental indices. These 20-year distributions are used in the Target MOTAD model (ic_{rj} and in_{rj} values in equations 8a and 8b) to represent the level of environmental risk associated with each production activity.

Method and Procedure

The procedure employed is to set up a representative farm and solve for the profit maximizing farm plan. Next, a selected regulatory policy is imposed and the model resolved for the profit maximizing solution. Two regulatory policies are imposed: a nitrogen restriction policy and a selected chemical ban policy. A distribution of environmental outcomes is associated with each solution.

To implement the nitrogen restriction policy, a 150 lbs./acre limit on nitrogen application was imposed. The limit was determined by listing out the nitrogen applied, nitrate in percolation, and nitrate in runoff for each production alternative and identifying a nitrogen application that represented a significant reduction in the per acre losses of nitrate in percolation and runoff. This limit was applied to every crop. Atrazine, ethyl parathion, and methyl parathion were selected for the chemical ban policy because of their extensive use in the area, EPA recommendations concerning ethyl and methyl parathion, and a pending EPA review of atrazine (Holloway, Criswell).

The third procedural step is to find the Target MOTAD solution with net returns equal to those under the regulatory policy and compare the distribution of environmental outcomes between these two solutions. This step is accomplished by setting λ to zero and searching for a target level, T, such that net returns are equal to those under the regulatory policy. If all feasible and relevant production activities are included and accurately represented in the model, no other Environmental Target MOTAD farm plan will have a better environmental distribution for this representative farm at this income level. This truth is evident from the structure of the model. Setting λ to zero allows no deviations of the environmental index above the target level, T. The only way to achieve a better environmental distribution is to decrease T, and this cannot occur without decreasing income, since T is a binding constraint upon the objective function.

The converse of step three, step four in the procedure, is to find a Target MOTAD solution that has a distribution of environmental outcomes matching that of the regulatory policy, and compare net returns. This is done by leaving T at the value found in step three and increasing λ until a distribution identical to the one found under the regulatory policy is obtained. Increasing λ will increase income and shift the environmental distribution to the right, and at each λ the distribution under the Target MOTAD plan is compared with the distribution obtained under the regulatory policy. This implies a tedious search process to be continued until the two distributions are similar. Actually, the model can be reformulated such that the mean of the environmental index in the Target MOTAD solution is constrained to be equal to the mean under the regulatory policy, and λ solved for directly. The distributions under the two plans can be graphed to ensure that they are identical. This last step should provide the set of possible farm plans that are preferred to a regulatory approach, since increasing λ with T held constant at the previous environmental target level partitions off a section of the environmental risk-net return frontier.

A gamma probability density function is used to represent the distribution of the environmental indices (CEI and NEI of equations 4 and 5) derived under each farm plan. An estimated gamma pdf carries the same information as the empirical distribution, and the property of continuity makes visual comparison easier. This specific function is chosen because of the properties of the indices: they are truncated at zero and can take any shape, ranging from an exponential shape to an approximate normal shape, over the positive range of index values. The gamma pdf allows this flexibility and is particularly adept at modeling a truncated, skewed distribution. Also, the parameters for the gamma pdf, α and β, can be estimated from the sample mean and variance of the 20-year distribution of index values.

Farm Situation and Data Requirements

The analysis is conducted using a representative farm in the Southern High Plains region of the Texas Panhandle. This region overlies the Ogallala Formation, an aquifer which supplies large quantities of groundwater for both human and animal consumption. In addition, the aquifer is the primary source of water for irrigated crop production, which is prominent in the region. In 1992, approximately 3 million acres in the region were under cultivation, and about 1.6 million acres were utilized for irrigated production of grain sorghum, corn, wheat, and cotton (Bernardo et al.). Crop production systems employed throughout the region have often included intensive use of nitrogen fertilizer, and herbicides and insecticides, particularly on irrigated crops. Nielsen and Lee reported a substantial potential for groundwater contamination by agricultural producers in the region, particularly from nitrate-nitrogen sources. More recently, Kellogg, Maizel, and Goss reported potential for pesticide leaching in parts of the High Plains region.

The representative farm has 1280 total acres, 570 acres in irrigated production and 710 acres in dryland production. The soil type is Pullman clay loam, and average rainfall in the area is about 16 inches per year. A single soil type is chosen for the farm because of the relative homogeneity of soil types in the region and the dominance of the clay loam soils. The farm possesses two conventional center pivot sprinkler systems of 125 acres each and two conventional furrow (gated pipe) systems of 160 acres each.

Dryland continuous crops include wheat, grain sorghum, and cotton. Dryland rotations include wheat-fallow and wheat-grain sorghum-fallow. Irrigated crops produced in a continuous rotation are corn, wheat, cotton, and grain sorghum. Cotton may be grown conventionally or in a wheat-kill rotation. This involves planting wheat after the cotton is harvested for a cover crop and killing it with chemicals in the spring, glyphosate to kill the wheat and 2,4-D to control early weeds (Bernardo et al.).

The farm plan assumes participation in the government commodity programs. Planted acres (base acres less acreage-reduction-program (ARP) acres) for the farm are as follows: 282 acres of corn, 448 acres of wheat, 182 acres of grain sorghum, 288 acres of cotton, and 80 acres of ARP, or fallow. Since flex acres are rarely planted to other crops in the study area, the assumptions are made that normal flex acres are planted to the base crop and optional flex is not used (Coombs, Dicks, and Just). Omitting flex acre options could possibly result in inflated estimates of income reduction under regulatory policies, particularly the nitrogen restriction policy. Prices and costs are representative of 1993 production conditions. Portions of total output eligible for deficiency payments are sold at the target price, and the remaining product is sold at the cash price.

Crop Production Activities

A large set of crop activities were developed for each crop, differing in terms of irrigation levels, nutrient use, and pesticide strategy. To provide the model flexibility, approximately 1,000 production activities were included for each crop. Irrigation schedules were applied based upon a soil moisture criterion and range from a full-yield application to an extreme deficit irrigation schedule. Alternative nitrogen applications range from those which assure the avoidance of nutrient deficits to zero nitrogen use. Selection of insecticides and herbicides included for each crop was based upon a survey of area extension specialists and published chemical use data (National Agricultural Statistics Service; Holloway). A minimum of six herbicides and six insecticides was included for each crop, varying in terms of toxicity, soil half-life, mobility, and effectiveness.

To determine the yield impacts associated with various pesticide strategies, a survey of state and area agronomists and entomologists was conducted. An elicitation of expert opinion was needed because EPIC-PST does not simulate crop damage from pests in the detail necessary in this analysis (i.e. for specific pesticides, herbicides and insecticides separately). A total of seven crop specialists familiar with the study region were provided specific scenarios and asked to estimate the yield reduction percentage for each strategy. Respondents were asked to assume that pesticides were applied under favorable weather conditions, the recommended rates and times of application were followed, and that common tillage practices under each pesticide strategy were employed. Separate responses were elicited for dryland and irrigated conditions, as well as for each of the rotations mentioned above. The major insect and weed pests in the area were identified for each crop, and two infestation levels, heavy and light, were specified. Respondents were also asked to ignore pesticide strategies they considered infeasible or uncommon for a particular crop, and to add strategies as needed. The mathematical average across respondents was used as the yield reduction in the analysis. The analysis was conducted assuming the presence of a light infestation of insects and a heavy infestation of weeds. These yield reduction percentages were applied to the EPIC-PST yields to derive a unique yield for each pesticide strategy.

Results

Per-acre Nitrogen Restriction Policy

Table 1 gives the results for the profit maximizing farm plan, the per-acre nitrogen restriction farm plan, the Target MOTAD plan with a Nitrate Environmental Index (NEI) distribution identical to that of the per-acre restriction, and the Target MOTAD solution with income equal to that under the per-acre restriction.

The nitrogen restriction plan differs from the profit maximizing plan only in the level of water and nitrogen used for irrigated corn. Corn is the only crop affected by the restriction since it is the most intensive user of water and nitrogen inputs. The restriction results in a positive impact on the environment, shown by the probability density functions (pdf's) of the NEI in Figure 1. The pdf for the nitrogen restriction plan clearly is superior to that of the profit maximizing plan. This improvement in the environment is not without cost, however, with annual income for the nitrogen restriction plan $26,796 less than the profit maximizing plan.

The third farm plan in Table 1 shows the Target MOTAD solution with an NEI pdf identical to that of the nitrogen restriction plan. The Target MOTAD production plan differs significantly from the plan derived under the nitrogen restriction, and the income of $210,246 is only $2,867 less than the profit maximizing income level. The Target MOTAD plan reduces input usage on furrow irrigated corn, but nitrogen applications on sprinkler irrigated corn remain at the profit maximizing level. This solution results in the same improvement in environmental quality and $23,929 more farm income than the regulatory approach.

The fourth plan in Table 1 is the Target MOTAD solution with net returns equal to those of the nitrogen restriction policy. This plan differs significantly from the nitrogen restriction plan. Furrow irrigated corn is completely replaced with wheat, which uses much less water and nitrogen. Conventional furrow cotton, with a lower nitrogen application rate, replaces a significant amount of furrow cotton-wheat kill. Dryland wheat and grain sorghum change from wheat-sorghum-fallow to continuous wheat and sorghum, and a significant amount of wheat is grown at a lower rate of nitrogen applied. Figure 1 shows the Target MOTAD solution to have a much better NEI distribution than the nitrogen restriction policy, even though the income reductions are the same for the two plans. This result clearly demonstrates the ability of the Environmental Target MOTAD model to identify farm plans that are economically/environmentally more efficient than a regulatory policy.

Figure 2 shows the range of potential improvement over a regulatory policy. This frontier was traced out by setting T_n at the level found for the Target MOTAD solution with income equal to that of the nitrogen restriction policy (the fourth plan in Table 1), setting λ_n to zero, and increasing λ_n to a large number. Point A in Figure 2 corresponds to the profit maximizing farm plan. Point B corresponds to the Target MOTAD solution with an NEI distribution the same as that found under the nitrogen restriction policy. Point C represents the Target MOTAD plan with an income level equal to that of the nitrogen restriction plan.

In essence, the nitrogen restriction policy produces a farm plan with an income level of point C and an NEI distribution of point B. Points between B and C, therefore, represent a series of farm plans that are preferred to a regulation limiting the quantity of nitrogen applied. All points below and/or to the right of the frontier in Figure 2 are inefficient. For all such points, a higher income can be achieved with the same level of environmental risk given the desired target, or a lower level of environmental risk given the desired target can be achieved with the same annual income. A nitrogen restriction policy represents an inefficient point.

Selected Chemical Ban

Table 2 follows the same format as Table 1, giving the profit maximizing plan first, then the regulatory policy of a chemical ban, followed by the Target MOTAD solution with a Chemical Environmental Index (CEI) distribution identical to that of the chemical ban, and then the Target MOTAD solution with income the same as the chemical ban. An outcome similar to the nitrogen restriction scenario is shown. Notice that insecticide and herbicide strategies often differ in alternative solutions. The same environmental outcome as with a chemical ban can be achieved with $7,083 more income by using a Target MOTAD solution. Examining this solution, the third farm plan in Table 2, shows that the banned chemicals can be allowed in production while achieving an identical reduction in environmental damage by changing chemical strategies on other crops. Bidrin is substituted for Temik, and Treflan is not applied on some of the cotton acres.

Figure 3 demonstrates the superiority of the Target MOTAD approach over regulatory action in dealing with farm pesticide use. The chemical ban results in a better CEI pdf than the profit maximizing plan, but it is clearly inferior to the Target MOTAD plan with the same income reduction. Figure 4 shows the potential range of improvement over a chemical ban, with point A being the profit maximizing farm plan, point B being the Target MOTAD solution with a CEI distribution identical to that of the chemical ban, and point C representing the Target MOTAD solution with an income equal to that of the chemical ban. Any farm plan on the risk frontier between point C and point B is preferred to a chemical ban, with B being the most preferred. As in the nitrogen restriction case, a chemical ban farm plan represents an inefficient point since it is below and/or to the right of the frontier.

Cost-Benefit Comparison

Table 3 provides a cost-benefit comparison for the representative farm in terms of income reductions (cost) versus index reductions (benefit). This table demonstrates that society would be better served by pursuing management-based solutions to reach environmental goals, rather than regulatory solutions. A management-based solution is superior as long as any costs incurred to ensure the adoption of management-based plan #1 (e.g. higher enforcement costs relative to regulation, public subsidization of research and extension), placed on a per-farm basis, do not exceed the difference in net return reductions for the regulatory restriction plan and management-based plan #1. This difference is $23,929 if nitrates are the problem of concern, and $7,083 if environmental risk from chemicals is targeted. Management-based plan #2 reflects the same farm income loss as the regulatory restriction plan, but achieves a greater reduction in environmental risk. The nitrate index is further reduced by an average of 3216 units, and the chemical index by 37,384 units. This plan is preferred only if the value society places on the further reduction in the average indices exceeds the costs required to secure its adoption.

The types of substitution shown in Tables 1 and 2, such as having two rates of nitrogen application for dryland wheat in the fourth plan of Table 1, withholding Treflan on some of the cotton acres in the third farm plan of Table 2, and withholding Dual on quite a few of the corn acres in the fourth plan of Table 2, are similar to the practices of prescription farming. In this type of farming, inputs are intensively managed to avoid overuse. For example, pesticides and nitrogen are applied only to parts of a field, and in the amounts needed. This increases the efficiency of inputs and helps protect the environment, while requiring more management effort (Cooke, Wallace). Prescription farming represents one opportunity for achieving the management plans mentioned above, and research and extension can play a role in this process. Table 3 approximates the amount of money on a per-farm basis that society can devote to this cause and still maintain an efficiency gain over regulatory policies.

Summary and Conclusions

Several policy options are available to address nitrate and pesticide non-point source pollution problems in agriculture, including regulatory and management-based options. Regulation refers to design standards such as pesticide bans and per-acre nitrogen application restrictions. Management-based policies refer to those designed with freedom of producer choice in mind, such as performance standards and economic incentives. Regulatory policies are attractive because harmful practices can be eliminated from consideration. However, the proposed Environmental Target MOTAD model provides a method of identifying farm plans that are more efficient than plans derived under regulatory policies such as nitrogen restrictions or pesticide bans. Efficiency, as it is used here, means obtaining the same environmental outcome as a regulatory policy at less cost, or achieving a better environmental outcome for the same cost. This paper develops the Environmental Target MOTAD model and demonstrates its usefulness on a representative farm in the Southern High Plains of the Texas Panhandle. This model allows for the stochastic assessment of environmental outcomes. Multi-attribute environmental indices are also developed and incorporated into the model.

Results of this study indicate that management-based means, which allow producers maximum discretion in reaching farm-level environmental goals, can be much more efficient than a regulatory approach. A cost-benefit comparison approximates the money that can be spent in order to gain the adoption of these management-based plans. Up to $23,929 for nitrate environmental risk reduction, and $7,083 for pesticide environmental risk reduction, on a per-farm basis, can be spent by society on programs such as prescription farming, and still maintain an efficiency gain over regulatory policies. This analysis is done for a representative farm, however, and the results should not be taken as a comprehensive evaluation of policy options across a region.

Caution is in order concerning the approach used here. Considerable weight is placed on the accuracy of the environmental index, both in terms of the loading estimates and the structure of the environmental index equations. The index used must capture the environmental problem of concern, and any estimate of loadings must be accurate. Continued research is needed in this area, including careful attention to the problem at hand through model calibration, and the evaluation of index equations (Konikow and Bredehoeft; Oreskes, Shrader-Frechette, and Belitz).

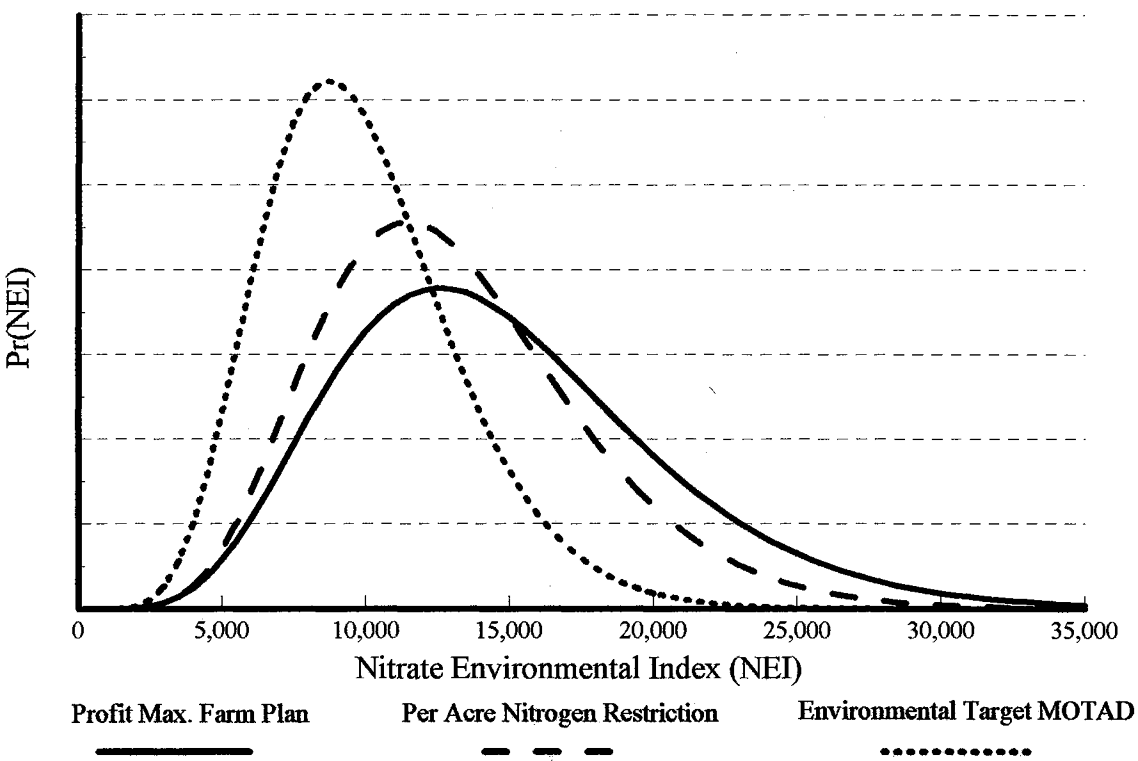

Figure 1. Probability Density Functions of the Nitrate Environmental Index for the Profit Max. Farm Plan, 150 lb/acre Nitrogen Applied Restriction, and the Environmental Target MOTAD Solution with Net Returns Equal to Net Returns for the Per Acre Nitrogen Restriction Farm Plan (NR = $186,317).

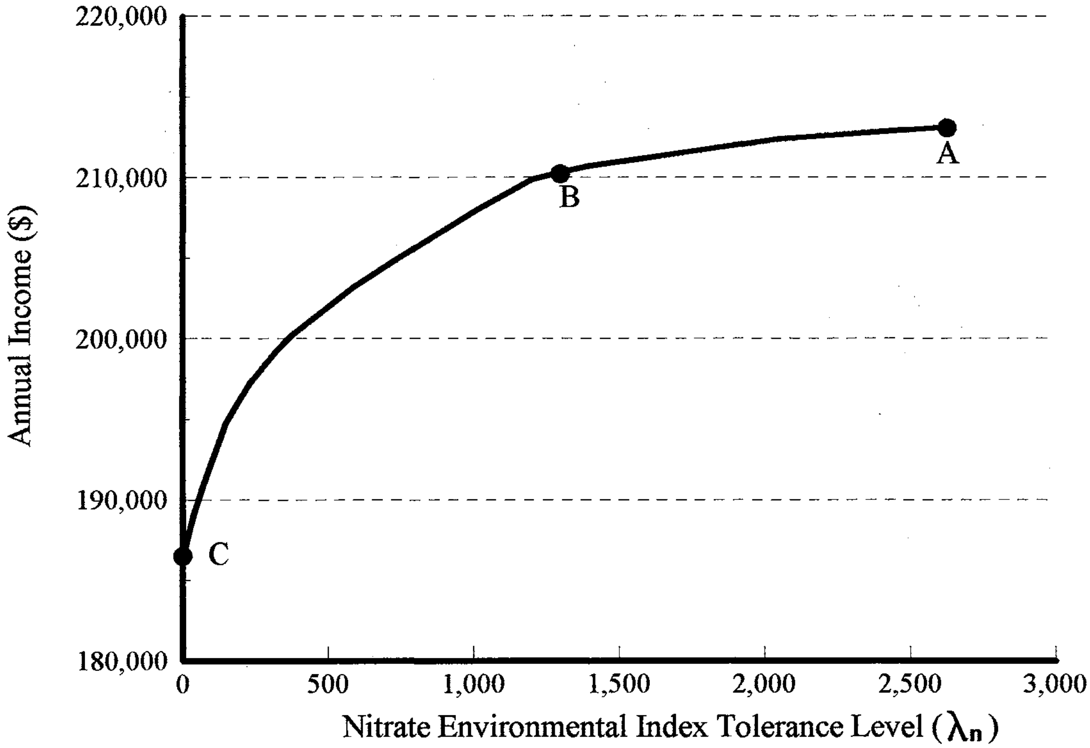

Figure 2. Risk Frontier for the Environmental Target MOTAD Solution with Net Returns Equal to Net Returns for the Per Acre Nitrogen Restriction Farm Plan (NR = $186,317)

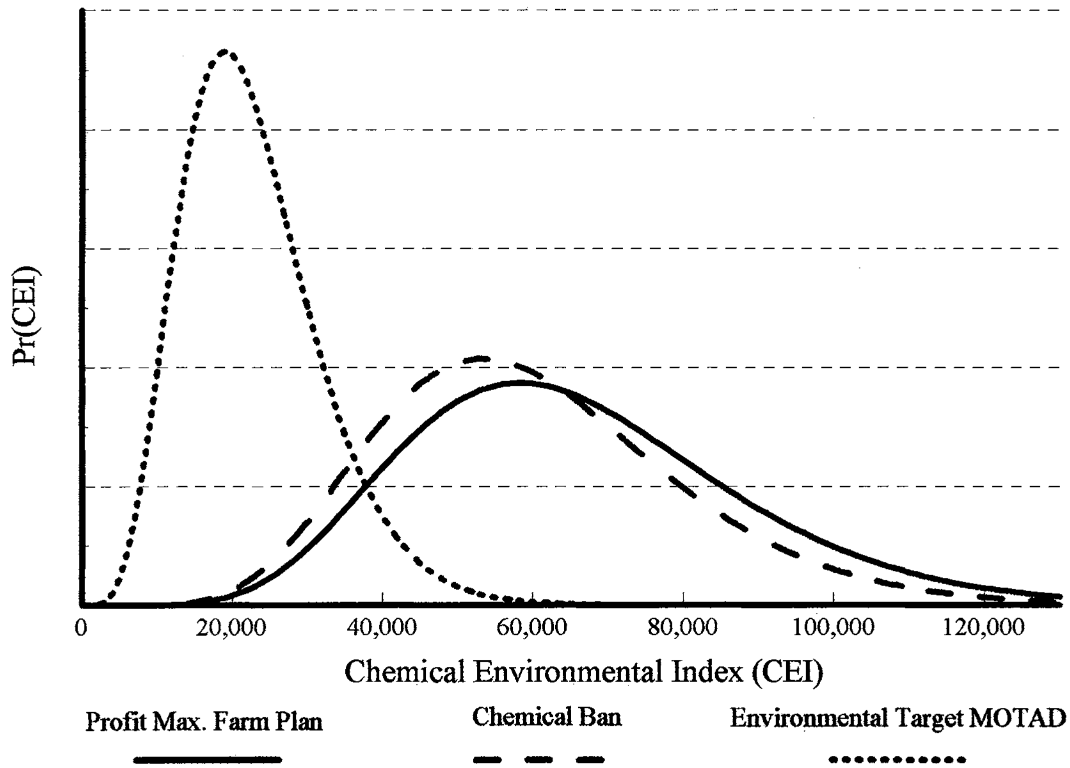

Figure 3. Probability Density Functions of the Chemical Environmental Index for the Profit Max. Farm Plan, Chemical Ban (Atrazine, Ethyl and Methyl Parathion), and the Environmental Target MOTAD Solution with Net Returns Equal to Net Returns for the Chemical Ban Farm Plan (NR = $205,281).

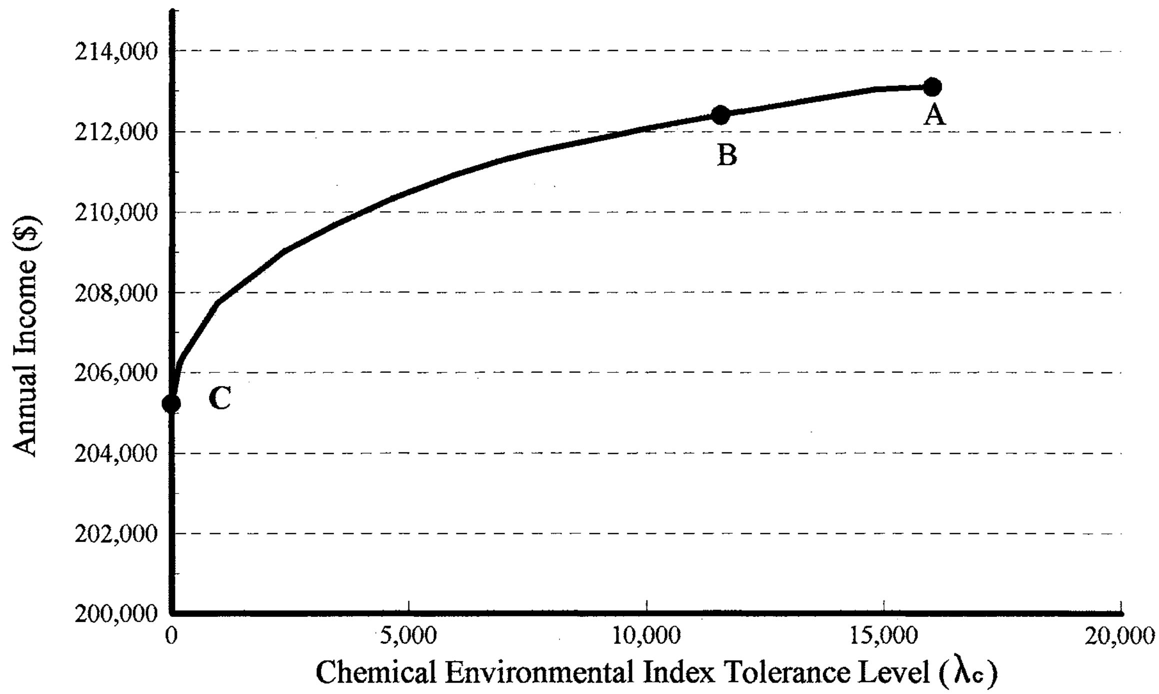

Figure 4. Risk Frontier for the Environmental Target MOTAD Solution with Net Returns Equal to Net Returns for the Chemical Ban Farm Plan (Atrazine, Ethyl and Methyl Parathion; NR = $205,281).

Table 1. Comparison of Profit Max. Farm Plan, Per-acre Nitrogen Restriction, and Target MOTAD Alternatives for a Texas Panhandle Rep. Farm, Soil Type = Pullman Clay Loam.

Crop	Irrig. System [a]	Water Appl. (in.)	Nitrogen Appl. (lbs/ac)	Acres
Profit Maximizing Plan, Net Returns = $213,113:				
Corn	Pivot	27	210	250
Corn	Furrow	30	225	32
Cotton-Wheat Kill	Furrow	17	98	288
Wheat	Dryland	-	28	368
Grain Sorghum	Dryland	-	31	102
Wheat-Sorghum-Fallow	Dryland	-	28	240
150 Lbs./Acre Nitrogen Application Restriction, Net Returns = $186,317:				
Corn	Pivot	12	129	250
Corn	Furrow	14	147	32
Cotton-Wheat Kill	Furrow	17	98	288
Wheat	Dryland	-	28	368
Grain Sorghum	Dryland	-	31	102
Wheat-Sorghum-Fallow	Dryland	-	28	240
Environmental Target MOTAD Solution w/ NEI Prob. Dist. = NEI Prob. Dist. of the Per-acre Restriction; Net Returns = $210,246; Index Target ($T_n$) = 14,325; Index Tolerance (λ_n) = 1,356:				
Corn	Pivot	27	210	250
Corn	Furrow	28	205	32
Cotton-Wheat Kill	Furrow	17	98	288
Wheat	Dryland	-	28	448
Grain Sorghum	Dryland	-	31	182
Environmental Target MOTAD Solution w/ Net Returns = Net Returns of the Per-acre Restriction; Net Returns = $186,317; Index Target ($T_n$) = 14,325; Index Tolerance (λ_n) = 0:				
Wheat	Furrow	12	85	32
Corn	Pivot	27	210	250
Cotton	Furrow	21	70	131
Cotton-Wheat Kill	Furrow	17	98	157
Wheat	Dryland	-	28	71
Wheat	Dryland	-	14	345
Grain Sorghum	Dryland	-	31	182

[a] furrow = conventional furrow gated-pipe system, pivot = center pivot sprinkler system.

Table 2. Comparison of Profit Max. Farm Plan, Chemical Ban (Atrazine, Ethyl and Methyl Parathion), and Target MOTAD Alternatives for a Texas Panhandle Rep. Farm, Soil Type = Pullman Clay Loam.

Crop	Irrig. Sys.,[a] Appl.(in.)	Insecticide	Herbicide	Acres
Profit Maximizing Plan, Net Returns = $213,113:				
Corn	Pivot,27	Asana,Cygon	Atrazine,Dual	250
Corn	Furrow,30	Asana,Cygon	Atrazine,Dual	32
Cotton-Wheat Kill	Furrow,17	Temik,Karate	Treflan,Caparol	288
Wheat	Dryland	Ethyl Parathion	Ally	368
Grain Sorghum	Dryland	-	Atrazine	102
Wheat-Sorg-Fallow	Dryland	-	MCPA,Atrazine	240
Chemical Ban (Atrazine, Ethyl and Methyl Parathion), Net Returns = $205,281:				
Corn	Pivot,27	Asana,Cygon	2,4-D,Prowl	250
Corn	Furrow,30	Asana,Cygon	2,4-D,Prowl	32
Cotton-Wheat Kill	Furrow,17	Temik,Karate	Treflan,Caparol	288
Wheat	Dryland	-	Ally	317
Wheat-Sorg-Fallow	Dryland	-	2,4-D	393
Environmental Target MOTAD Solution w/ CEI Prob. Dist. = CEI Prob. Dist. of the Chemical Ban; Net Returns = $212,364; Index Target ($T_c$) = 51,375; Index Tolerance (λ_c) = 11,374:				
Corn	Pivot,27	Asana,Cygon	Atrazine,Dual	250
Corn	Furrow,30	Asana,Cygon	Atrazine,Dual	32
Cotton-Wheat Kill	Furrow,17	Bidrin,Karate	Caparol	30
Cotton-Wheat Kill	Furrow,17	Bidrin,Karate	Treflan,Caparol	258
Wheat	Dryland	Ethyl Parathion	Ally	368
Grain Sorghum	Dryland	-	Atrazine	102
Wheat-Sorg-Fallow	Dryland	-	MCPA,Atrazine	240
Environmental Target MOTAD Solution w/ Net Returns = Net Returns of the Chemical Ban; Net Returns = $205,281; Index Target ($T_c$) = 51,375; Index Tolerance (λ_c) = 0:				
Corn	Pivot,27	Asana,Cygon	Atrazine	89
Corn	Pivot,27	Asana,Cygon	Atrazine,Dual	161
Corn	Furrow,28	Asana,Cygon	Atrazine	32
Cotton-Wheat Kill	Furrow,17	Bidrin,Karate	Caparol	288
Wheat	Dryland	Ethyl Parathion	Ally	368
Grain Sorghum	Dryland	-	Atrazine	102
Wheat-Sorg-Fallow	Dryland	-	MCPA,Atrazine	240

[a] furrow = conventional furrow gated-pipe system, pivot = center pivot sprinkler system.

Table 3. Cost-Benefit Comparison for a Texas Panhandle Representative Farm in Terms of Income Reductions Versus Nitrate and Chemical Environmental Risk Reductions for Regulatory and Management-Based Farm Plans.

	Net Returns		Average Index Value	
	Nitrates	Chemicals	Nitrates	Chemicals
Profit Maximum Farm Plan	$213,113	$213,113	14,735	65,976
Reduction from Profit Maximum Farm Plan Level:				
Regulatory Restriction Plan [a]	$26,796	$7,832	1,641	5,832
Management-Based Plan #1 [b]	$2,867	$749	1,641	5,832
Management-Based Plan #2 [c]	$26,796	$7,832	4,857	43,216

[a] The regulatory restriction for nitrates is a 150 lbs/ac maximum on nitrogen applied. The regulatory restriction for chemicals is a ban on atrazine, ethyl parathion, and methyl parathion.

[b] This is the Environmental Target MOTAD solution with an index pdf equal to that of the regulatory restriction.

[c] This is the Environmental Target MOTAD solution with net returns equal to that of the regulatory restriction.

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Essay III

CAPTURING THE MULTI-DIMENSIONAL ASPECTS AND ECONOMIC TRADEOFFS OF ENVIRONMENTAL RISK USING INDICES

CAPTURING THE MULTI-DIMENSIONAL ASPECTS AND ECONOMIC TRADEOFFS OF ENVIRONMENTAL RISK USING INDICES

Abstract

Agricultural non-point source pollution is a multi-dimensional problem encompassing several forms of contaminants and several environments (e.g. surface water and ground water). Environmental risk indices can account for differences in chemical attributes and aggregate environmental outcomes across several forms of contaminants and environments. The objective of this analysis is to develop three environmental risk indices and use the indices to compare the environmental risk and economic returns associated with alternative production systems in the Oklahoma Panhandle region of the Central High Plains. Three environmental risk indices are developed which incorporate different information concerning the environmental effects of pesticide use. The first index (EIQ) incorporates only chemical properties into the risk assessment, while the other two indices (CINDEX and CONC) also factor in estimates of expected annual runoff and percolation loadings and concentrations, respectively, in the calculation of environmental risk. Both statistical and graphical comparisons indicate that the three indices provide similar rankings of alternative production systems based upon their potential environmental consequences. The CONC index is characterized by greater volatility than the other indices, and its rankings of the production activities are least

correlated with those derived from the other two indices. Results suggest some potential for reduction in environmental risk without large reductions in net returns. Application of the EIQ index, which does not explicitly incorporate chemical loading or concentration estimates, provides the highest estimate of income reductions. Environmental risk can be reduced by the greatest amount without significant income losses when CONC is used as the risk measurement. Therefore, although the three indices generate similar rankings of alternative production activities, their application can provide very different estimates of the economic consequences of attaining environmental objectives.

Key words: environmental risk indices, economic/environmental relationships

CAPTURING THE MULTI-DIMENSIONAL ASPECTS AND ECONOMIC TRADEOFFS OF ENVIRONMENTAL RISK USING INDICES

Introduction

Public concern over water quality has grown significantly in recent years and has focused increasingly on agriculture as a potential source of surface and ground water quality problems. Use of inorganic fertilizer has increased fourfold, and agricultural pesticides threefold, in the last decade (Nielsen and Lee, 1987). The Office of Technology Assessment reports that in 1986 pesticides were used on approximately 57 percent, and commercial fertilizers on 75 percent, of U.S. farms (Office of Technology Assessment, 1990). In 1988, the Environmental Protection Agency (EPA) documented the presence of 46 pesticides in groundwater in 26 states, ostensibly from field applications (Office of Technology Assessment, 1990). Nitrate is the most commonly detected agricultural chemical in groundwater; however, several herbicides have also been detected in groundwater sources with notable frequency (Office of Technology Assessment, 1984).

The economic and environmental consequences of alternative means of protecting water quality are currently being debated. Recent federal policies dealing with nonpoint-source pollution and water quality protection emphasize voluntary rather than mandatory controls (Crutchfield, 1989). Design and implementation of control measures have been left to state and local officials under both the 1987 Water Quality Act's nonpoint-source provisions and EPA's pesticides-in-groundwater strategy. This approach offers considerable flexibility to develop policies which better account for soil type and other site-specific characteristics. Through judicious use of policy alternatives, it may be possible to design policies that meet groundwater protection objectives but mitigate the economic consequence to agricultural producers.

Development of effective water quality policies, including an assessment of their likely impacts on producers' economic returns and the environment, is complicated by several factors. First, agricultural nonpoint-source pollution is a multidimensional problem encompassing several forms of contaminants (e.g., nitrates, pesticides, and sediment) and several environments (e.g., surface water and ground water). Adoption of practices aimed at controlling one possible source of pollution, such as surface runoff, often increases the likelihood of other sources or forms of pollution, such as deep percolation (Hoag et al., 1991). Second, herbicides and insecticides which contribute to environmental damage are characterized by a wide array of attributes. The more effective the pesticide in eliminating pests, the more likely that it will be widely used by producers. However, some of the more widely used pesticides rank high in terms of toxicity, mobility, and/or persistence. Also, even if input levels are relatively homogeneous within an agricultural region, production usually occurs on a diverse set of physical resources that influence productivity and the potential for alternative sources of pollution. Estimates of environmental outcomes associated with alternative production practices must accurately account for the unique physical characteristics of the production setting.

Measures of environmental risk can be developed which account for differences in chemical attributes and aggregate environmental outcomes across several forms of contaminants and environments. Application of these environmental risk indices allows agricultural practices to be rank-ordered based upon their composite environmental consequences (Manale and Gassman, 1990). However, different measures of environmental risk emphasize different chemical and environmental attributes, and may imply different strategies for protecting water quality. Additional research is needed to refine these environmental risk indices and compare their values across production systems and in different physical environments.

The objective of this analysis is to evaluate the environmental risk and economic returns associated with alternative production systems in western Oklahoma. Environmental risk is measured using three alternative environmental risk indices which account for differences in the attributes of the pesticides, as well as quantities and concentrations of the pesticides in percolation and runoff. The production systems evaluated account for differences in crops, soils, irrigation systems, input levels, and pesticide alternatives.

Previous Research

Several attempts have been made to aggregate environmental outcomes of agricultural production practices by constructing environmental risk indices. For example, the developers of the Potential Environmental Hazard index assigned each pesticide a ranking based on four factors: mobility, longevity, toxicity, and biomagnification (Warner, 1985). Alt (1976) described an Environmental Harm Coefficient which incorporated both toxicity and the rate of decomposition of individual pesticides. Alt (1976) attempted to improve upon these indices by using a unique measure of persistence for each pesticide. This Environmental Exposure Index (EEI) considered the half-life, application rate, and toxicity of each pesticide. Warner (1985) criticized the above indices because they failed to consider soil properties and the potential of a pesticide to contaminate ground or surface water. Warner (1985) proposed an index based upon a chemical's persistence, mobility and toxicity classifications; however, this method assumed that if a chemical was classified as mobile in the soil, its destination was ground water, and if it was immobile in the soil, then its destination was surface water. Warner (1985) also showed that including toxicity and contamination potential when evaluating chemicals, as opposed to just comparing the loading rates of a chemical, could change the rankings of chemicals based upon environmental attributes.

Cabe et al. (1991) reported a more comprehensive approach to evaluating the environmental and human health impacts of pesticides. This study focused on rates of exposure to pesticides rather than pesticide loadings. Of interest were the quantities of the pesticides, measured in parts per million or parts per billion, to which humans, aquatic species, and terrestrial species were exposed. The exposure estimate was then divided by a benchmark measurement of concern, such as a health advisory level or a measure of toxicity, to calculate a risk index for each chemical. The importance of each individual environmental media was weighted, and all of the impacts of a particular chemical were combined to estimate a single index value for each chemical.

A few studies have incorporated environmental indices into economic analyses to evaluate income and environmental tradeoffs. Hoag and Hornsby (1991) developed a cost/environmental hazard frontier to illustrate the tradeoffs between cost and health hazards for alternative weed control strategies for soybeans in North Carolina. A simulation model estimated crop yields under alternative weed control strategies given high and low weed pressure. A groundwater hazard index related the amount of active ingredient of a herbicide leached per unit area relative to the health advisory level (HAL). This analysis only considered percolation of herbicides and ignored insecticides, nitrates, and surface water. Also, ground water was the only environment of concern.

Hoag et al. (1991) evaluated several measures of environmental quality, including soil erosion, excess nitrogen, pesticide leaching, and pesticide runoff, for 36 crop rotation systems in North Carolina. An index ranging from 0 to 100 was developed for each measure of environmental quality. A linear programming model was used to maximize net returns subject to constraints on environmental damage due to soil erosion, excess nitrogen, pesticide leaching, and pesticide runoff. They concluded that pollution could not be reduced in a consistent manner without involving tradeoffs among the various environmental measures.

Hoag and Manale (1991) used indices to compare the impacts of seven insecticides used to control corn rootworm on three environments: ground water, surface water, and air. A relative risk ranking was reported that showed the percentage of total risk that a particular chemical contributed within a single environment. The relative risk value was multiplied by a subjective weight for each environment, and summed over all three environments, to obtain a value-weighted ranking of the chemicals.

The studies mentioned above establish the concept of combining the effects of one form of pollution upon several environments into an index value. This study refines and expands upon this earlier work. Three alternative environmental indices are developed which incorporate different levels of information concerning chemical properties and alternative measures of the environmental effects of pesticide use. The indices are compared in terms of how they order a series of production alternatives based upon environmental risk. The relationship between the indices and net returns is also explored. A daily crop growth/chemical transport model is used to estimate chemical loadings in runoff and percolate, input use, and crop yield for each production alternative. This approach should provide more realistic estimates of environmental outcomes associated with crop production activities than the damage functions used in some previous applications of environmental indices. Also, none of the previous studies compare the attributes of different indices and their implications for environmental risk modeling and decision making.

Methods and Data Requirements

This section develops three environmental risk indices differing in terms of the type of information used to measure the environmental consequences of pesticide use. Next, the method used to obtain crop yield and chemical loading estimates is described, followed by a discussion of the sets of crop production systems used in the analysis. Finally, the methods of analysis used to compare indices and evaluate environmental risk - income tradeoffs are addressed.

Environmental Impact Quotient (EIQ)

The initial environmental risk index is a variation of the environmental impact quotient (EIQ) for pesticides developed by Kovach et al. (1992). This index is based upon the characteristics of the specific chemicals used in a production system. The environmental impact quotient used in this study is calculated for each chemical as:

$$\text{EIQ} = \frac{(\text{Farm Worker} + \text{Consumer} + \text{Ecology})}{3} \tag{1}$$

where, Farm Worker = C * DT * 5

Consumer = (C * P * SY) + L

$$\text{Ecology} = (F * R) + [D * (\frac{S + P}{2}) * 3] + (Z * P * 3) + (B * P * 5)$$

and, C = chronic toxicity

DT = dermal toxicity

P = plant surface half-life

SY = systemicity

L = leaching potential

F = fish toxicity

R = surface loss potential

D = bird toxicity

S = soil half life

Z = bee toxicity

B = beneficial arthropod toxicity

Values between 1 and 5 are assigned to each chemical for each chemical characteristic listed above (Kovach et al.). A ranking of 1 indicates the least toxicity or harm, and a ranking of 5 indicates the greatest toxicity or harm. These rankings are based on data available from the Extension Toxicology Network (Hotchkiss et al., 1989) and pesticide fact sheets published by the U.S. Environmental Protection Agency, Office of Drinking Water (1992). The equation above gives the EIQ for each chemical and can be used directly to draw comparisons among chemicals of a given weight of active ingredient (pounds, grams, etc.) in a given classification (herbicide, insecticide, or fungicide). Before making field comparisons, a modification is needed to account for the application rate and number of applications. The adjustment is as follows:

(2) EIQ Field Use Rating = EIQ * Rate (lbs. of Active Ingredient) * Number of Applications

After the field use rating is calculated, single chemicals can be compared based upon their field use, or entire pest management strategies can be compared. A pesticide strategy involving the application of multiple pesticides can be evaluated by calculating the field use rating for all chemicals used in the strategy and summing them. That is,

(3) $$EIQ_j = \sum_{i=1}^{n} EIQ_{ij}$$

where EIQ_j is the EIQ of pesticide strategy j, EIQ_{ij} is the EIQ field use rating for chemical i of pesticide strategy j, and n is number of chemicals applied in pesticide strategy j.

Chemical Environmental Index (CINDEX)

The second environmental index, which is based on the characteristics of the pesticides as well as the quantities of pesticides lost in runoff and percolation, is calculated as:

$$CINDEX_{ij} = (PERC_{ij} * HA_i * .5) + (RUNOFF_{ij} * LC_i * .5) \tag{4}$$

where $CINDEX_{ij}$ is the chemical environmental index for chemical i of pesticide strategy j, $PERC_{ij}$ is the quantity of chemical i of pesticide strategy j lost in percolation (grams/acre), and $RUNOFF_{ij}$ is the quantity of chemical i of pesticide strategy j lost in runoff (grams/acre).

The toxicity weights HA_i and LC_i are defined as follows:

$$HA_i = \begin{cases} 5 \text{ if } HAL_i \leq 10 \text{ or the EPA Carcinogenic} \\ \quad \text{Risk Category is A, B, B1, B2, or C} \\ 3 \text{ if } 10 < HAL_i \leq 200 \\ 1 \text{ if } HAL_i > 200 \end{cases}$$

$$LC_i = \begin{cases} 5 \text{ if } LC_{50} < 1 \\ 3 \text{ if } 1 \leq LC_{50} \leq 10 \\ 1 \text{ if } LC_{50} > 10 \end{cases}$$

where HAL_i is the lifetime Health Advisory Level set by EPA for chemical i, and LC_{50} is the acute toxicity to fish for 96 hours of exposure.

Surface water and ground water are the environments of concern. HA_i serves as the toxicity weight for percolation, which affects ground water, and LC_i serves as the toxicity weight for runoff, which affects surface water. This indexing scheme uses a chemical's lifetime Health Advisory Level (HAL) as a proxy for threats to human health through ground water and a chemical's lethal concentration (LC_{50}) as a proxy for threats to aquatic life in surface water. Each environment is assigned an equal weighting; however, the .5 weights can be changed if one desires to assign a higher weighting to surface water or groundwater in the estimation of the index.

The 1, 3, 5 breakdown for the aquatic LC_{50} is taken from Kovach et al. (1992). Toxicity groups do not exist for the lifetime HAL, but they do exist for the oral and dermal LD_{50} of each chemical (Criswell and Campbell, 1992). The weighting system above comes from ordering the chemicals from low to high based on the HAL, listing a 1, 3, 5 weighting beside each chemical based on the oral and dermal LD_{50}, and looking for a natural break in the ordering. If a chemical has an EPA carcinogenic risk rating of A, B, B1, B2, or C, it is weighted with a 5 regardless of the value of the lifetime HAL (U.S. Environmental Protection Agency, 1986). This weighting is performed for the herbicide and insecticide groups separately.

Once the environmental indices based on quantities of chemical lost in runoff and percolation are calculated for each chemical applied in a pesticide strategy, a chemical environmental index is calculated for each strategy as:

$$\text{(5)} \qquad \mathrm{CINDEX}_j = \sum_{i=1}^{n} \mathrm{CINDEX}_{ij}$$

where CINDEX_j is the Chemical Environmental Index for crop activity j, CINDEX_{ij} is the Chemical Environmental Index for chemical i of pesticide strategy j, and n equals the number of chemicals applied in pesticide strategy j.

Chemical Concentration Index (CONC)

The third environmental index is based on the characteristics of the pesticides, as well as concentrations of pesticides lost in runoff and percolation, for the production alternatives. This environmental index is calculated as:

$$\text{(6)} \qquad CONC_{ij} = (RCONC_{ij} * .5) + (PCONC_{ij} * .5)$$

where $CONC_{ij}$ is the chemical concentration index for chemical i of pesticide strategy j, and

$$RCONC_{ij} = \frac{\text{Concentration of chemical i (ppm) of pesticide strategy j in runoff}}{LC_{50}\text{(ppm) of chemical i}}$$

$$PCONC_{ij} = \frac{\text{Concentration of chemical i (ppb) of pesticide strategy j in percolate}}{\text{Lifetime HAL (ppb) of chemical i}}$$

As in the calculation of the previous indices, the chemical concentration index for pesticide strategy j ($CONC_j$) is derived by summing the indices over all chemicals used in strategy j.

Crop Growth and Chemical Transport Simulation

The chemical environmental indices are calculated based upon the characteristics of the pesticides and pesticide loadings estimated by the crop yield and chemical movement model EPIC-PST. EPIC-PST combines the EPIC crop-growth model (Williams et al., 1988) with the pesticide subroutines from the GLEAMS model (Leonard et al., 1987). EPIC operates on a daily time step, and its components can be divided into nine major submodels: hydrology, weather, erosion, nutrients, plant growth, soil temperature, tillage, economics, and plant environment. The pesticide component (GLEAMS) simulates the pesticide activities by six processes: degradation, extraction into runoff, leaching, transport with sediment, evaporation, and plant uptake (Sabbagh et al., 1991). EPIC-PST has been tested, validated and applied at several sites (Ramanarayanan et al., 1994; Sabbagh et al., 1991; Bernardo et al., 1994).

A 20-year EPIC-PST simulation was conducted for each crop production activity included in the analysis. Production activities represent different combinations of crops, soil types, irrigation systems, irrigation levels, and pesticide strategies. Daily weather data for 20 years, soil and crop parameters appropriate for the study area, and specified chemical characteristics are used to simulate crop yields and pesticide losses in runoff and percolation for each crop activity. Estimates of percolation loadings reflect the quantity of each chemical exiting the soil profile at the bottom of the root zone, and runoff estimates represent the quantity leaving the field. Percolation and runoff concentrations used in calculating CONC are based upon the average annual estimates of percolation and runoff water from the EPIC-PST simulations. Estimates of average annual pesticide runoff and percolation from the 20-year simulations are used to estimate the alternative measures of environmental risk. In addition, the average yield and input use from each 20-year simulation is used to estimate net returns from each crop activity.

Although EPIC-PST has been validated at several sites, actual chemical percolation and runoff measurements are not available for the study area. However, crop yield and input levels are available, and these are used to validate the productivity of EPIC-PST for the study region (Bernardo et al., 1994). The chemical loading estimates, and consequently the environmental index calculations, depend upon the structural accuracy of the EPIC-PST model.

Production Activity Sets

Two sets of production activities are developed and evaluated based upon environmental and net return outcomes for the panhandle region of western Oklahoma. The first set contains a broad array of production activities differing in terms of crop, soil type, irrigation system, irrigation level, and pesticide strategy. This set provides comparison of the environmental indices' performance across a broad range of production systems used in the study region.

A production system in the first set of activities consists of either corn or wheat produced using a particular combination of soil type, irrigation system, irrigation level, and pesticide strategy. The two soils included in the analysis are Richfield clay loam and Dalhart fine sandy loam. Richfield clay loam is the predominant cultivated soil in the region and is representative of many of the slowly permeable soils which dominate the region. Dalhart fine sandy loam is a moderately permeable soil that accounts for about 20 percent of the cultivated land in the region. Irrigation systems included in the analysis are furrow (gated-pipe) and low-pressure center-pivot sprinkler irrigation. These two systems account for over 85 percent of the irrigated acreage in the region (Mapp et al.).

Alternative combinations of the two crops (wheat and corn), two soils (Richfield clay loam and Dalhart fine sandy loam), two irrigation systems (furrow irrigation and center pivot), two irrigation levels, and four pesticide strategies yield 64 production activities for the first set. The four pesticide strategies used for each crop reflect combinations of the two herbicide strategies and two insecticide strategies listed in Table 1 under Production System Comparison. A complete listing of the 64 production activities and their environmental index values and ranks is provided in Appendix Table 1.

The second set of production activities focus exclusively on environmental index comparisons among pesticide selections. Alternative pesticide strategies are compared for the production of sprinkler irrigated corn on Dalhart fine sandy loam soil. Sixty-four pesticide strategies are developed as combinations of eight alternative insecticide strategies and eight herbicide strategies listed in Table 1 under Pesticide Strategy Comparison. A complete listing of the 64 pesticide strategies and their index values and ranks is provided in Appendix Table 2.

Selection of insecticides and herbicides included in both activity sets is based upon a survey of area extension specialists and published chemical use data (National Agricultural Statistics Service, 1992; Cooperative Extension Service, 1993). Chemicals are also selected to provide a range of characteristics in terms of toxicity, soil half-life, mobility, and effectiveness. An extensive survey of state and area extension weed specialists and entomologists provides the yield impacts associated with various pesticide strategies. Crop specialists estimated the percentage reduction in yield for each strategy given a specific scenario for each crop (weather condition, target pest, level of infestation, etc.). The yield reductions for the herbicide strategies assume a heavy infestation of weeds for both crops, while the insecticide strategies assume a light infestation of the target pests. These yield reductions are applied to the crop yields obtained from EPIC-PST, giving a unique yield for each crop activity.

Production practices used in the analysis are based upon tillage, nutrient, and irrigation practices currently used in the region. Net returns from each production activity are estimated as total revenue less annual operating costs. Production costs, with the exception of irrigation costs, are estimated using the procedures of the Oklahoma State University Enterprise Budget Generator (Kletke, 1979). Costs of production reflect 1993 input prices and production practices and input requirements employed in the EPIC-PST simulations. Irrigation costs are estimated using the OSU Irrigation Cost Generator (Kletke et al., 1978). Crop market prices used in estimating net returns are \$2.28/bu for corn and \$2.92/bu for wheat. Full participation in government commodity programs is assumed, with target prices equal to \$2.75/bu for corn and \$4.00/bu for wheat. Since flex acres are rarely planted to other crops in the study area, the assumptions are made that the portion of a base acre devoted to normal flex is planted to the base crop, and optional flex is not used (Coombs et al.). Portions of total output eligible for deficiency payments are sold at the target price, and the remaining product is sold at the cash price.

Methods of Analysis

A Spearman's Rank Correlation Test is used to test for correlation among the three sets of rankings of the 64 activities. The Spearman rank correlation coefficient (r_s) is a non-parametric statistic that may be used to test for correlation between two rank pairs (Mendenhall et al., 1990). The null hypothesis is no association between the rank pairs. A one-tailed test can be used for the alternative hypothesis that correlation between rank pairs is positive.

A visual representation of the correlation of the three environmental indices can also be obtained. This is done by normalizing each index through division by the maximum value of the index among the 64 activities. This gives the production activity with the highest index value a normalized value of 1.0. The production activities are then ranked based upon values for one of the indices, referred to as the base index, and plotted in descending order. The base index will be non-increasing from left to right across production activities. Positive correlation among ranks with the base index is shown by an index sloping downward and to the right. Index volatility indicates disagreement among ranks.

Tradeoffs between environmental risk measured by environmental risk indices and net returns can be illustrated by constructing an environmental risk - cost frontier. Normalized values for an index are plotted for each activity against the cost of adopting the cropping activity. The cost of adoption for an activity is estimated as the difference between net returns associated with the profit maximizing activity in a specific set, and the net returns from that activity. Connection of the minimum points of the scatter plots completes construction of the environmental risk - cost frontier for a particular index. This frontier indicates the cost of achieving incremental reductions in the EIQ index and is useful in assessing the tradeoffs between income and environmental risk measured by EIQ. Points along the frontier are efficient in that they represent the minimum cost of achieving each reduction in environmental risk. Points above the frontier are considered inefficient since the same level of environmental risk can be achieved at a lower cost.

Results and Discussion

First, results are discussed for the comparison of indices across production systems. Next, results of the comparison of indices across pesticide strategies are analyzed. Finally, tradeoffs between environmental risk measured by the indices and net returns are illustrated for both sets of activities.

Comparison of Indices Across Production Systems

Environmental indices are reported for two sets of eight production activities in Table 2. Within each set of activities, the pesticide strategy is held constant, and soil type, irrigation system, and irrigation level are varied. Comparison of the environmental indices across the eight activities allows isolation of the effect of each of these characteristics on the respective index. The insecticide strategy used in the corn activities involves application of Furadan and Cygon, while the herbicide strategy employs Atrazine and Dual. For wheat, the insecticide ethyl parathion and the herbicide Ally are applied.

As shown in Table 2, the EIQ values remain constant across all eight production activities for each crop. Since EIQ is only dependent upon the characteristics of the pesticides used in the chemical strategy, variations in soil type, irrigation system and irrigation level do not affect its value. Therefore, EIQ possesses no discriminatory power in ranking production activities using the same pesticide strategy, but differing in other production characteristics.

CINDEX and CONC values are sensitive to changes in soil type, irrigation system, and irrigation level. As expected, index values tend to decrease in moving from furrow to sprinkler irrigation. Similarly, both CINDEX and CONC decrease when moving from high to low irrigation levels, regardless of soil type and irrigation system. Comparisons of indices across soil types is less conclusive. In the case of wheat production, both CONC and CINDEX increase when moving from the heavier clay loam soil to the lighter fine sandy loam. In contrast, index values from corn production tend to be higher on the heavier clay loam soils. When corn is produced on the heavier soils, the majority of chemical loadings occur in runoff. When corn production shifts to coarse soils, reductions in these runoff loadings exceed increases in percolation loadings.

The Spearman r_s was estimated for each combination of the three rankings, and reported in Table 3. In all cases, the null hypothesis is rejected, indicating a positive association between each pair of rankings. This positive association suggests that similar environmental policies might result from reliance on the three different indices. Visual representation of rank correlation among indices is contained in Figure 1. CINDEX is the base index, and the other indices are plotted against it. Figure 1 shows a general downward trend among the three indices, with CONC showing the most volatility, or disagreement in ranking. This visual aid confirms the statistical tests in Table 3.

The rank disagreement for CONC is caused primarily by the manner in which toxicity is incorporated into the CONC index. As shown in equation 6, the concentration of chemical in percolate is divided by the HAL, and runoff concentration is divided by the LC_{50}. Therefore, concentrations of chemicals with very low HALs or LC_{50}s are heavily weighted in CONC estimates. For example, the highest spikes in the CONC normalized index reflect situations where concentrations of chemicals with low LC_{50}s (e.g., Asana) occur in runoff and/or concentrations of chemicals with low HALs (e.g., Furadan) occur in percolate.

Comparison of Indices Across Pesticide Strategies

The Spearman r_s estimated for each combination of the rank pairs is reported in Table 3. In this case, the null hypothesis of no association between the rankings provided by EIQ and CONC is not rejected. The Spearman r_s also indicates very weak positive association between the CONC and CINDEX rankings. As in the first analysis, the results of Table 3 can be seen graphically in Figure 2. CINDEX is again the base index, with the other two indices plotted against it. Figure 2 shows fairly strong correlation between EIQ and CINDEX, and very poor correlation between CONC and either of the other two indices. This agrees with the statistical tests in table 3.

Normalized CONC values exhibit significant rank disagreement, or volatility, across the production activities in this analysis, also. Again, this volatility reflects the computational procedures used in estimating CONC. Peaks in the CONC plot primarily reflect activities employing insecticide strategies 1 and 2, each of which apply Asana. Runoff loadings of this chemical are heavily weighted in the estimation of CONC because of its low LC_{50}. Both the graphical and statistical comparisons of the indices reveal that CONC does provide significantly different environmental rankings than the other indices. However, EIQ rankings are highly correlated with CINDEX rankings, even though chemical loadings are not explicitly incorporated into estimation of the EIQ index.

Environmental Risk - Income Tradeoffs

Figure 3 shows the environmental risk - cost frontiers for the indices calculated from the comparison of alternative pesticide strategies. The EIQ-cost frontier indicates that significant reductions in environmental risk, measured by EIQ, can be achieved with negligible cost to the producer. The pesticide strategy with the highest EIQ (normalized EIQ = 1) is also the profit maximizing strategy, and is represented by the point on the lower right corner of the graph. The environmental index can be reduced to .55 with negligible impacts on net returns. Significant reductions in income are necessary to achieve additional reductions in EIQ. The increasing absolute value of the slope of the frontier indicates the increasing marginal cost of achieving incremental improvements in the environmental risk index. To achieve an EIQ value of zero, a strategy which utilizes neither insecticides nor herbicides must be employed. Expected net returns associated with this strategy are negative; therefore, a very large cost is incurred in moving from the profit maximizing strategy to this activity.

The CINDEX frontier indicates larger economic consequences associated with initial reductions in environmental risk (from 1.0 to .40) than the EIQ-cost frontier. However, for reductions below .40, application of CINDEX indicates greater environmental risk - income tradeoff opportunities. For example, the cost of achieving a 90 percent reduction in risk (normalized index = .10) is over \$100/acre lower than when EIQ is used to measure environmental risk. Environmental risk can be reduced by the greatest amount without significant losses in income when CONC is used as the risk measurement. Over a 90 percent reduction in CONC can be achieved with less than a

$15/acre loss in net returns. Reductions in CONC below the .10 level are achieved at a much higher marginal cost.

Differences in the shapes of the environmental risk - cost frontiers have important implications for development of water quality protection policies. Application of a risk measurement such as EIQ, which does not explicitly incorporate chemical loading or concentration estimates, overestimates the environmental effects of some pesticide strategies. As a result, to achieve a specified reduction in environmental risk, several pesticide strategies are eliminated from the producer's choice set that would meet the environmental objective if another risk measure was used. For example, if the objective was to decrease risk by 80 percent (as measured by EIQ), 55 strategies having index values greater than .20 would be eliminated from consideration, and a cost of approximately $100/ac would be incurred by the producer. In contrast, only 31 strategies would be eliminated if CINDEX were used, and a reduction in net returns of less than $50/acre would be incurred. Only 16 strategies are eliminated if CONC is used to estimate environmental risk. These results illustrate the need for additional research aimed at detailed physical modeling and measurement of pesticide movements. Greater accuracy in estimating chemical movements results in larger reductions in environmental damage and a lower cost to the producer.

Environmental risk - cost frontiers derived from the comparison of alternative production systems are presented in Figure 4. As in Figure 3, some reduction in the EIQ index can be achieved with only negligible impacts on net returns; however, the marginal cost of achieving EIQ reductions below .65 are significant. The majority of both frontiers derived using the CINDEX and CONC indices lie below the EIQ cost frontier, indicating greater environmental risk - income tradeoff opportunities. For example, net return reductions associated with a 90 percent reduction in CINDEX (a normalized index of .10) are approximately half of the loss in income estimated from the EIQ cost frontier. When measured using the CONC index, equivalent reductions in environmental risk can be achieved with less than 25 percent of the reduction in net returns projected by EIQ. The CINDEX and CONC frontiers also indicate opportunities for reducing environmental risk below .10, as opposed to the EIQ cost frontier.

Summary and Conclusions

Agricultural non-point source pollution is a multi-dimensional problem encompassing several forms of contaminants and several environments. Development of policies aimed at controlling non-point source pollution is often frustrated by the fact that adoption of practices aimed at controlling one pollution source may increase another form of pollution. Improved policies may result from application of environmental risk indices which aggregate various environmental outcomes from agricultural practices. These indices could be extremely useful in comparing environmental effects of alternative production practices and assessing tradeoffs between environmental improvement and economic returns. However, the application of different indices may imply different strategies for protecting water quality. This research explores various environmental index specifications and net returns of agricultural practices.

Three measures of environmental risk were developed which incorporate different information concerning the environmental effects of pesticide use. The first index (EIQ) incorporates only chemical properties into the risk assessment. In addition to chemical properties, the other two indices (CINDEX and CONC) include estimates of expected annual runoff and percolation loadings and concentrations, respectively, in the calculation of environmental risk. The indices were applied to rank the environmental risk associated with alternative wheat and corn production systems used by producers in the Oklahoma Panhandle region of the Central High Plains.

An important shortcoming of EIQ, and similar indices which do not incorporate chemical loading estimates in the risk assessment, is that their value is strictly a function of the chemicals used in the production system. The index value is not influenced by other factors involving management decisions and natural conditions, such as soil type, irrigation system, and irrigation level. Therefore, identical values of the index result if the same pesticide strategy is applied to a furrow irrigated crop on coarse-textured soils or to a sprinkler irrigated field with clay loam soils, even though the probability of chemical losses is much higher in the former system. Failure to include these features of production systems when quantifying environmental risk can lead to erroneous conclusions when ranking production systems that differ in terms of characteristics such as soil type, irrigation system, etc. By incorporating percolation and runoff loadings and concentrations into their estimation, CINDEX and CONC do include the effects of non-pesticide elements in the risk assessment. Soil type, irrigation system, and irrigation level are all shown to significantly affect these measures of environmental risk.

Both statistical and graphical comparison of the three environmental risk indices indicate a positive relationship between the three indices. Even though EIQ does not explicitly incorporate chemical loading estimates, its rankings of alternative pesticide strategies are similar to CINDEX when crop, soil, and irrigation system are held constant. The CONC rankings of the production activities are not highly correlated with rankings derived from the other indices. This result primarily reflects the larger weights assigned to chemicals with a high toxicity, relative to the other two indices.

Construction of environmental risk - cost frontiers indicate a positive relationship between environmental risk measured by the indices and net returns. In general, the most effective pesticides are used in the most profitable production systems, and these pesticides also produce the highest index values. Environmental risk - cost frontiers do suggest some potential for reducing environmental risk without greatly reducing net returns. However, these opportunities differ significantly depending upon which indices are applied. Indices such as EIQ, which do not explicitly incorporate chemical loading or concentration estimates, provide the highest estimate of income reductions. Environmental risk can be reduced by the greatest amount without significant income losses when CONC is used as the risk measurement. Therefore, although the three indices generate similar rankings of alternative pesticide strategies, their application can provide very different estimates of the economic consequences of attaining environmental objectives. Each index specification implies a somewhat different measurement of environmental risk. This difference in risk measurement is small enough so that similar rankings are generated, but large enough to significantly influence income - environmental risk tradeoffs. Careful consideration of these income - environmental risk tradeoffs should be made before policies aimed at altering pesticide use are implemented.

Environmental indices which aggregate environmental effects of agricultural practices are useful in addressing the multi-dimensional problem. However, before these indices can be used to formulate policy or make farm-level prescriptions, additional refinement is necessary. Additional research is needed investigating alternative computational procedures for estimating environmental risk indices. On-going research to improve the accuracy of toxicity and mobility parameters used in the indices will also improve their reliability.

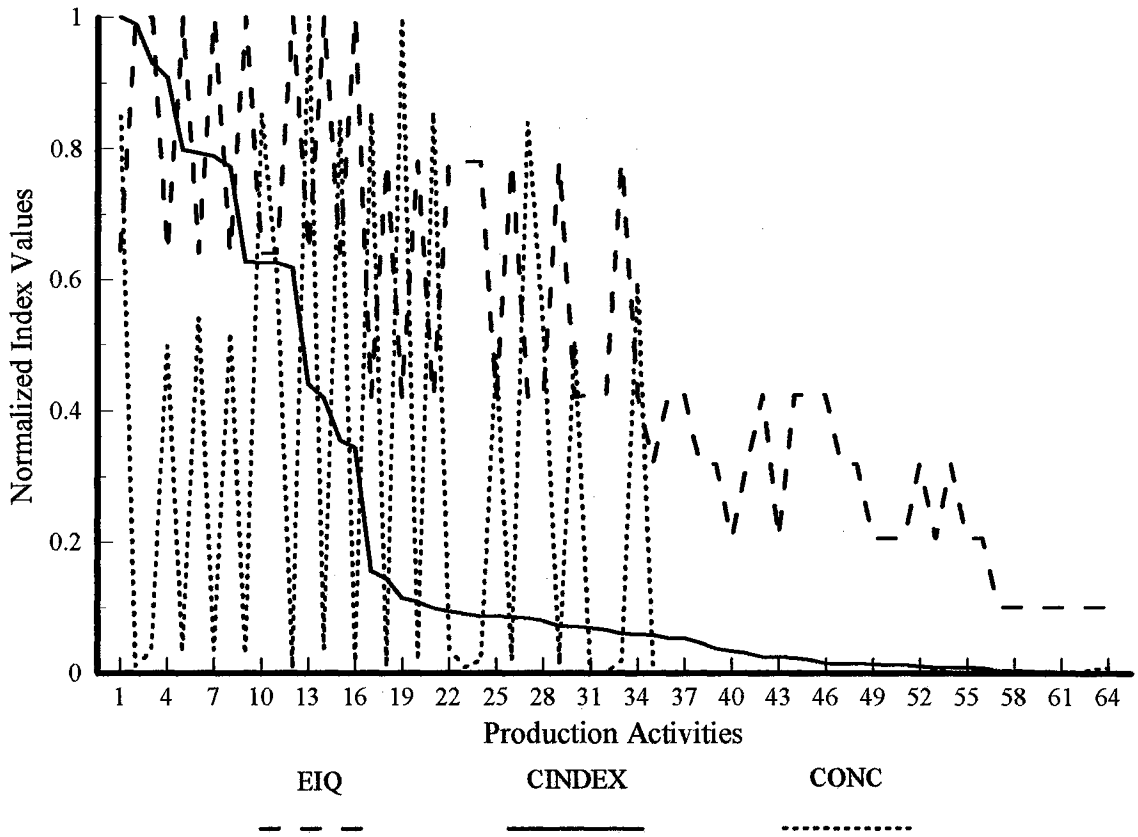

Figure 1. Comparison of Three Alternative Environmental Risk Indices Across 64 Alternative Corn and Wheat Production Systems in the Central High Plains.

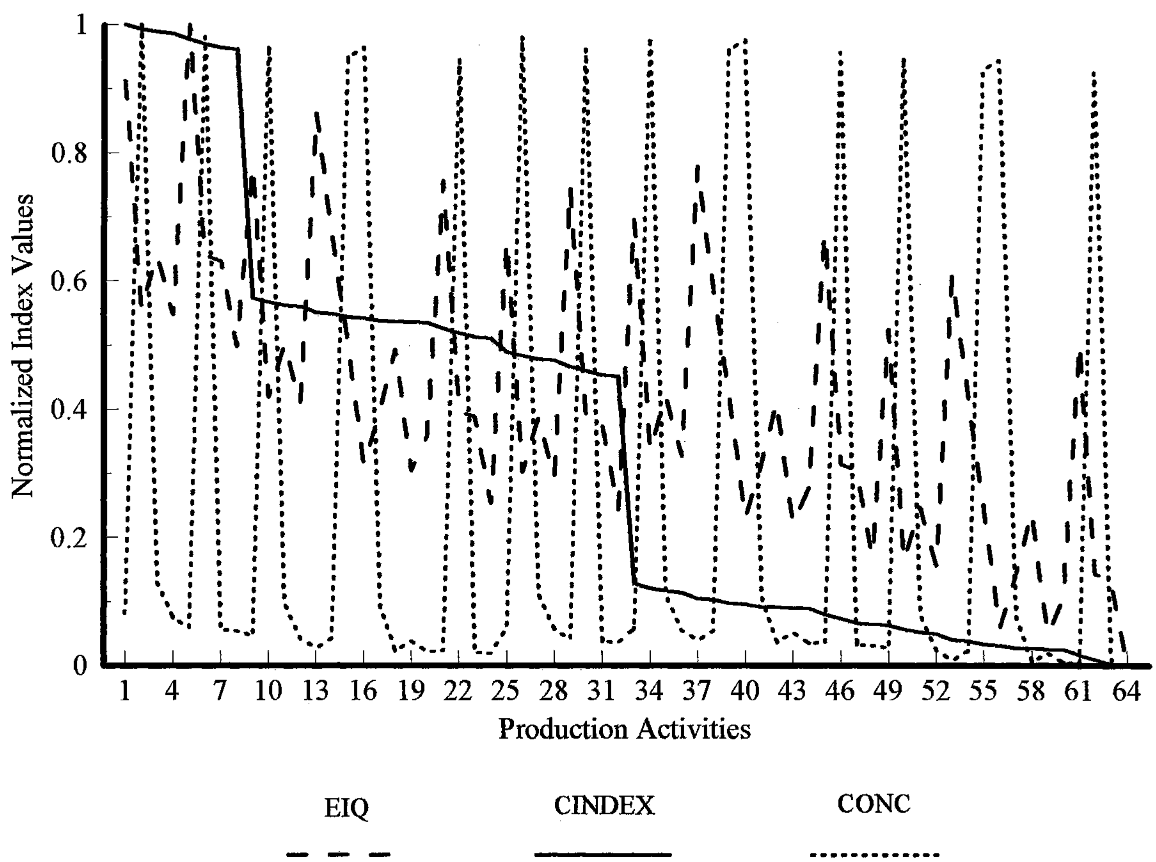

Figure 2. Comparison of Three Alternative Environmental Risk Indices Across 64 Alternative Corn Pesticide Strategies in the Central High Plains.

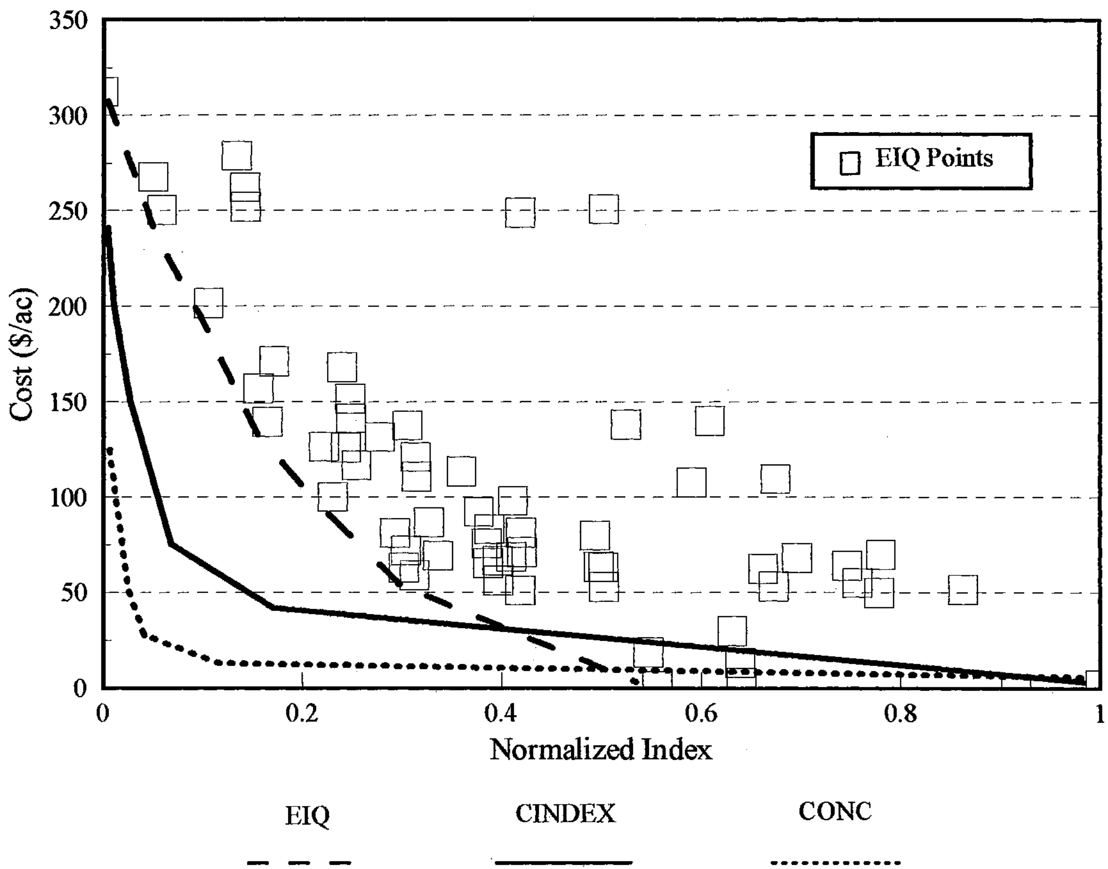

Figure 3. Environmental Risk - Cost Frontiers Associated with Alternative Pesticide Strategies in the Production of Irrigated Corn.

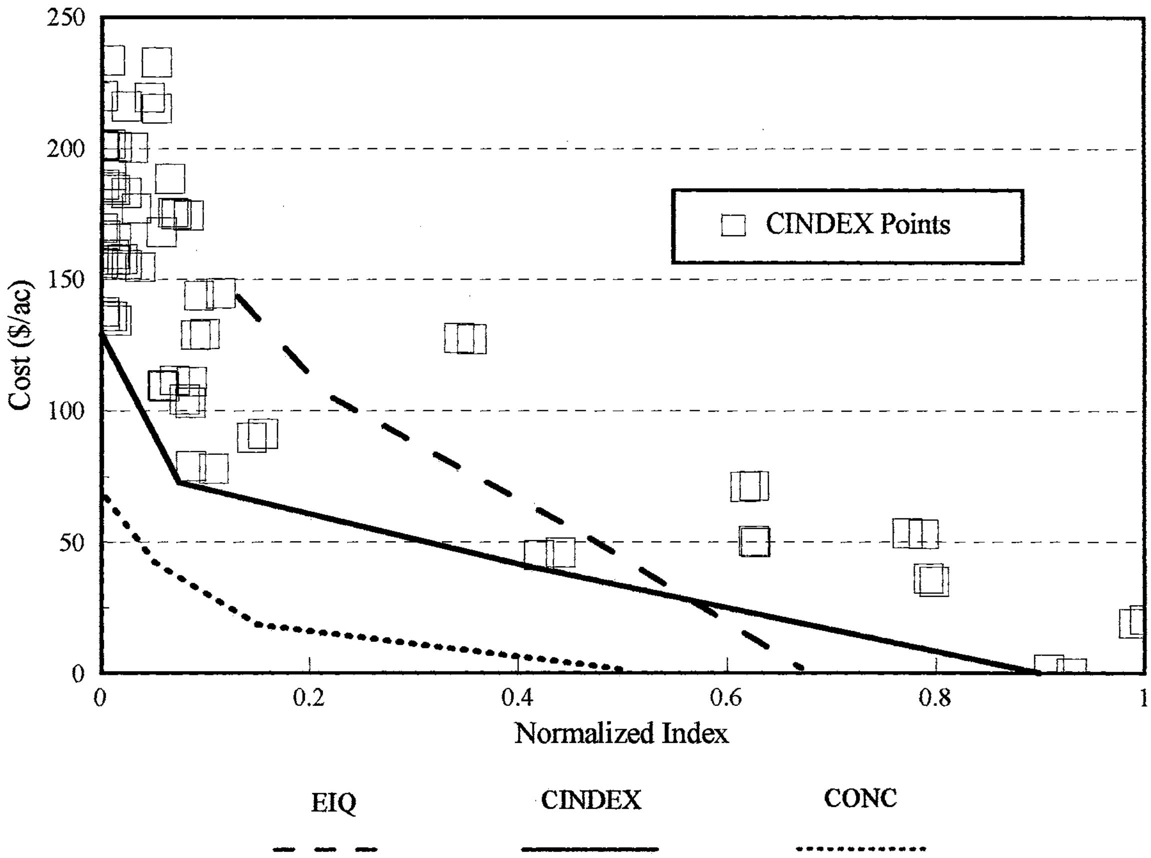

Figure 4. Environmental Risk - Cost Frontiers Associated with the Alternative Corn and Wheat Production Systems.

Table 1. Pesticide Strategies Employed in Alternative Production Activities.

	Insecticide Strategy	Herbicide Strategy
Production System Comparison		
Corn	(1) Asana, Cygon	(1) 2-4D, Prowl
	(2) Furadan, Cygon	(2) Atrazine, Dual
Wheat	(1) Cygon	(1) Ally
	(2) Ethyl Parathion	(2) 2-4D ester
Pesticide Strategy Comparison		
Corn	(1) Asana, Comite	(1) Dual
	(2) Asana, Cygon	(2) Atrazine
	(3) Ambush, Comite	(3) 2-4D ester
	(4) Comite	(4) Prowl
	(5) Cygon	(5) Atrazine, 2-4D
	(6) Furadan, Cygon	(6) 2-4D, Prowl
	(7) Furadan, Comite	(7) Atrazine, Dual
	(8) None	(8) None

Table 2. Comparison of Three Alternative Environmental Risk Indices for Two Sets of Eight Production Activities.

Crop	Irrigation System, Level	Soil [a]	Insecticide/ Herbicide Strategy [b]	EIQ	CINDEX	CONC	Net Returns ($/ac)
Corn	Furrow, High	Loam	2/2	132.3	63.1	0.0090	278
Corn	Sprinkler, High	Loam	2/2	132.3	59.3	0.0291	297
Corn	Sprinkler, High	Sand	2/2	132.3	50.9	0.0274	262
Corn	Sprinkler, Low	Loam	2/2	132.3	50.3	0.0298	244
Corn	Sprinkler, Low	Sand	2/2	132.3	40.0	0.0251	247
Corn	Furrow, Low	Loam	2/2	132.3	39.4	0.0082	226
Corn	Furrow, High	Sand	2/2	132.3	26.8	0.0317	216
Corn	Furrow, Low	Sand	2/2	132.3	21.9	0.0146	169
Wheat	Furrow, High	Sand	2/1	42.2	3.68	0.0014	129
Wheat	Furrow, Low	Sand	2/1	42.2	2.94	0.0017	78
Wheat	Furrow, High	Loam	2/1	42.2	2.40	0.0010	142
Wheat	Furrow, Low	Loam	2/1	42.2	1.95	0.0012	97
Wheat	Sprinkler, High	Sand	2/1	42.2	0.96	0.0012	163
Wheat	Sprinkler, Low	Sand	2/1	42.2	0.92	0.0012	131
Wheat	Sprinkler, High	Loam	2/1	42.2	0.69	0.0008	161
Wheat	Sprinkler, Low	Loam	2/1	42.2	0.58	0.0008	112

[a] Loam = Richfield clay loam, Sand = Dalhart fine sandy loam.

[b] Numbers refer to the insecticide/herbicide strategy described in the Production System Comparison section of Table 1.

Table 3. Spearman's Rank Correlation Coefficients Between Alternative Pairs of Environmental Rankings.

Comparison of Indices Across Production Systems:	r_s[a]
EIQ, CINDEX	.861
EIQ, CONC	.634
CINDEX, CONC	.808
Comparison of Indices Across Pesticide Strategies:	
EIQ, CINDEX	.640
EIQ, CONC	.076
CINDEX, CONC	.350

[a] Critical value ($\alpha = .05$, one tailed test) = .305. If $r_s > .305$, reject H_o: no association between pairs.

Appendix Table 1. Values of Environmental Risk Indices for 64 Alternative Production Systems.

Crop	Soil[a]	Irrigation Sys.[b]	Irrigation Level	Pesticide Strategy	EIQ Value	EIQ Rank	CINDEX Value	CINDEX Rank	CONC Value	CONC Rank
Corn	H	Fur	High	2/2	132.30	1	63.07	2	0.0090	29
Corn	H	Spr	High	2/2	132.30	1	59.27	3	0.0291	20
Corn	L	Spr	High	2/2	132.30	1	50.89	5	0.0274	21
Corn	H	Spr	Low	2/2	132.30	1	50.26	7	0.0298	19
Corn	L	Spr	Low	2/2	132.30	1	39.98	9	0.0251	22
Corn	H	Fur	Low	2/2	132.30	1	39.36	12	0.0082	30
Corn	L	Fur	High	2/2	132.30	1	26.76	14	0.0317	17
Corn	L	Fur	Low	2/2	132.30	1	21.92	16	0.0146	27
Corn	H	Fur	High	2/1	103.20	9	9.21	18	0.0081	31
Corn	H	Spr	High	2/1	103.20	9	6.89	20	0.0170	24
Corn	L	Fur	High	2/1	103.20	9	5.99	22	0.0308	18
Corn	H	Fur	Low	2/1	103.20	9	5.79	23	0.0072	32
Corn	H	Spr	Low	2/1	103.20	9	5.53	24	0.0169	25
Corn	L	Spr	High	2/1	103.20	9	5.45	26	0.0181	23
Corn	L	Fur	Low	2/1	103.20	9	4.60	29	0.0131	28
Corn	L	Spr	Low	2/1	103.20	9	3.85	33	0.0160	26
Corn	H	Fur	High	1/2	84.71	17	63.74	1	0.7128	4
Corn	H	Spr	High	1/2	84.71	17	57.90	4	0.4165	15
Corn	L	Spr	High	1/2	84.71	17	50.54	6	0.4525	11
Corn	H	Spr	Low	1/2	84.71	17	49.26	8	0.4330	13
Corn	H	Fur	Low	1/2	84.71	17	39.91	10	0.7137	3
Corn	L	Spr	Low	1/2	84.71	17	39.88	11	0.5045	9
Corn	L	Fur	High	1/2	84.71	17	28.08	13	0.8361	1
Corn	L	Fur	Low	1/2	84.71	17	22.67	15	0.7034	7
Wheat	H	Fur	High	2/2	56.15	25	4.41	31	0.0021	40
Wheat	L	Fur	High	2/2	56.15	25	4.19	32	0.0017	43
Wheat	L	Fur	Low	2/2	56.15	25	3.38	36	0.0021	40
Wheat	H	Fur	Low	2/2	56.15	25	3.37	37	0.0024	37
Wheat	L	Spr	High	2/2	56.15	25	1.58	42	0.0022	38
Wheat	L	Spr	Low	2/2	56.15	25	1.52	44	0.0022	38
Wheat	H	Spr	High	2/2	56.15	25	1.31	45	0.0018	42
Wheat	H	Spr	Low	2/2	56.15	25	0.96	46	0.0015	45
Corn	H	Fur	High	1/1	55.61	33	9.89	17	0.7119	6
Corn	L	Fur	High	1/1	55.61	33	7.32	19	0.8352	2

[a] H = heavy soil, Richfield clay loam; L = light soil, Dalhart fine sandy loam.

[b] Fur = Conventional furrow system, Spr = Center-pivot sprinkler system.

Appendix Table 1. Continued.

Crop	Soil[a]	Irrigation Sys.[b]	Irrigation Level	Pesticide Strategy	EIQ Value	EIQ Rank	CINDEX Value	CINDEX Rank	CONC Value	CONC Rank
Corn	H	Fur	Low	1/1	55.61	33	6.34	21	0.7127	5
Corn	H	Spr	High	1/1	55.61	33	5.51	25	0.4043	16
Corn	L	Fur	Low	1/1	55.61	33	5.35	27	0.7018	8
Corn	L	Spr	High	1/1	55.61	33	5.10	28	0.4433	12
Corn	H	Spr	Low	1/1	55.61	33	4.53	30	0.4200	14
Corn	L	Spr	Low	1/1	55.61	33	3.75	34	0.4954	10
Wheat	L	Fur	High	2/1	42.20	41	3.68	35	0.0014	46
Wheat	L	Fur	Low	2/1	42.20	41	2.94	38	0.0017	43
Wheat	H	Fur	High	2/1	42.20	41	2.40	39	0.0010	54
Wheat	H	Fur	Low	2/1	42.20	41	1.95	41	0.0012	47
Wheat	L	Spr	High	2/1	42.20	41	0.96	46	0.0012	47
Wheat	L	Spr	Low	2/1	42.20	41	0.92	48	0.0012	47
Wheat	H	Spr	High	2/1	42.20	41	0.69	52	0.0008	56
Wheat	H	Spr	Low	2/1	42.20	41	0.58	54	0.0008	56
Wheat	H	Fur	High	1/2	27.28	49	2.14	40	0.0011	51
Wheat	H	Fur	Low	1/2	27.28	49	1.54	43	0.0012	47
Wheat	L	Spr	High	1/2	27.28	49	0.86	49	0.0011	51
Wheat	L	Spr	Low	1/2	27.28	49	0.83	50	0.0011	51
Wheat	H	Spr	High	1/2	27.28	49	0.81	51	0.0010	54
Wheat	L	Fur	High	1/2	27.28	49	0.60	53	0.0062	35
Wheat	H	Spr	Low	1/2	27.28	49	0.56	55	0.0007	58
Wheat	L	Fur	Low	1/2	27.28	49	0.50	56	0.0071	33
Wheat	L	Spr	High	1/1	13.33	57	0.24	57	0.0001	59
Wheat	L	Spr	Low	1/1	13.33	57	0.23	58	0.0001	59
Wheat	H	Spr	High	1/1	13.33	57	0.19	59	0.0001	59
Wheat	H	Spr	Low	1/1	13.33	57	0.18	60	0.0001	59
Wheat	H	Fur	High	1/1	13.33	57	0.14	61	0.0000	63
Wheat	H	Fur	Low	1/1	13.33	57	0.12	62	0.0000	63
Wheat	L	Fur	High	1/1	13.33	57	0.09	63	0.0060	36
Wheat	L	Fur	Low	1/1	13.33	57	0.07	64	0.0067	34

[a] H = heavy soil, Richfield clay loam; L = light soil, Dalhart fine sandy loam.

[b] Fur = Conventional furrow system, Spr = Center-pivot sprinkler system.

Appendix Table 2. Values of Environmental Risk Indices for 64 Alternative Pesticide Strategies for Production of Sprinkler Irrigated Corn on Dalhart Fine Sandy Loam Soil, High Irrigation Level.

Insecticide	Herbicide	EIQ Value	EIQ Rank	CINDEX Value	CINDEX Rank	CONC Value	CONC Rank
Furadan/Cygon	Atrazine/Dual	132.30	1	50.89	5	0.0274	28
Furadan/Comite	Atrazine/Dual	121.18	2	52.09	1	0.0361	24
Furadan/Cygon	Atrazine/2-4D	114.10	3	28.68	13	0.0123	50
Furadan/Cygon	2-4D/Prowl	103.20	4	5.45	37	0.0181	40
Furadan/Comite	Atrazine/2-4D	102.98	5	29.87	9	0.0211	36
Furadan/Cygon	Atrazine	100.10	6	27.39	21	0.0106	54
Furadan/Cygon	Dual	98.70	7	24.31	29	0.0188	39
Furadan/Comite	2-4D/Prowl	92.08	8	6.64	33	0.0269	29
Furadan/Cygon	Prowl	89.20	9	4.16	45	0.0165	45
Furadan/Comite	Atrazine	88.98	10	28.58	14	0.0194	38
Furadan/Comite	Dual	87.58	11	25.51	25	0.0275	27
Asana/Cygon	Atrazine/Dual	84.71	12	50.54	6	0.4525	3
Ambush/Comite	Atrazine/Dual	84.58	13	51.51	3	0.0605	17
Cygon	Atrazine/dual	83.50	14	50.19	7	0.0258	31
Furadan/Cygon	2-4D	80.50	15	2.10	53	0.0038	59
Furadan/Comite	Prowl	78.08	16	5.35	38	0.0252	34
Asana/Comite	Atrazine/Dual	73.58	17	51.74	2	0.4613	1
Comite	Atrazine/Dual	72.38	18	51.39	4	0.0345	26
Furadan/Comite	2-4D	69.38	19	3.29	49	0.0125	49
Asana/Cygon	Atrazine/2-4D	66.50	20	28.33	15	0.4375	12
Furadan/Cygon	None	66.50	20	0.81	61	0.0021	61
Ambush/Comite	Atrazine/2-4D	66.38	22	29.30	11	0.0455	21
None	Atrazine/Dual	65.80	23	50.09	8	0.0253	32
Cygon	Atrazine/2-4D	65.30	24	27.98	18	0.0108	52
Asana/Cygon	2-4D/Prowl	55.61	25	5.10	39	0.4433	9
Ambush/Comite	2-4D/Prowl	55.48	26	6.07	35	0.0513	19
Asana/Comite	Atrazine/2-4D	55.38	27	29.52	10	0.4462	6
Furadan/Comite	None	55.38	27	2.00	54	0.0108	52
Cygon	2-4D/Prowl	54.40	29	4.75	42	0.0166	44
Comite	Atrazine/2-4D	54.18	30	29.17	12	0.0195	37
Asana/Cygon	Atrazine	52.50	31	27.04	22	0.4358	14
Ambush/Comite	Atrazine	52.38	32	28.01	17	0.0438	22
Cygon	Atrazine	51.30	33	26.69	23	0.0091	57
Asana/Cygon	Dual	51.11	34	23.96	30	0.4440	8

Appendix Table 2. Continued.

Insecticide	Herbicide	EIQ Value	EIQ Rank	CINDEX Value	CINDEX Rank	CONC Value	CONC Rank
Ambush/Comite	Dual	50.98	35	24.93	27	0.0520	18
Cygon	Dual	49.90	36	23.61	31	0.0172	42
None	Atrazine/2-4D	47.60	37	27.87	20	0.0102	55
Asana/Comite	2-4D/Prowl	44.48	38	6.29	34	0.4520	4
Comite	2-4D/Prowl	43.28	39	5.94	36	0.0253	32
Asana/Cygon	Prowl	41.61	40	3.81	46	0.4416	10
Ambush/Comite	Prowl	41.48	41	4.78	41	0.0496	20
Asana/Comite	Atrazine	41.38	42	28.23	16	0.4445	7
Cygon	Prowl	40.40	43	3.46	47	0.0149	47
Comite	Atrazine	40.18	44	27.88	19	0.0178	41
Asana/Comite	Dual	39.98	45	25.16	26	0.4527	2
Comite	Dual	38.78	46	24.81	28	0.0260	30
None	2-4D/Prowl	36.70	47	4.64	44	0.0160	46
None	Atrazine	33.60	48	26.58	24	0.0086	58
Asana/Cygon	2-4D	32.90	49	1.75	55	0.4289	15
Ambush/Comite	2-4D	32.78	50	2.72	51	0.0369	23
None	Dual	32.20	51	23.51	32	0.0167	43
Cygon	2-4D	31.70	52	1.40	58	0.0022	60
Asana/Comite	Prowl	30.48	53	5.00	40	0.4503	5
Comite	Prowl	29.28	54	4.65	43	0.0236	35
None	Prowl	22.70	55	3.35	48	0.0144	48
Asana/Comite	2-4D	21.78	56	2.94	50	0.4377	11
Comite	2-4D	20.58	57	2.59	52	0.0109	51
Asana/Cygon	None	18.91	58	0.46	62	0.4272	16
Ambush/Comite	None	18.78	59	1.42	57	0.0353	25
Cygon	None	17.70	60	0.11	63	0.0005	63
None	2-4D	14.00	61	1.29	60	0.0017	62
Asana/Comite	None	7.78	62	1.65	56	0.4360	13
Comite	None	6.58	63	1.30	59	0.0092	56
None	None	0.00	64	0.00	64	0.0000	64

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Essay IV

PESTICIDE PRODUCTIVITY: WHAT ARE THE TRENDS?

PESTICIDE PRODUCTIVITY: WHAT ARE THE TRENDS?

Abstract:

Pesticide use has been increasing steadily in the United States. Public concern over pesticide use has also increased due to the possible external effects of pesticides, including negative public health effects through groundwater and surface water contamination, negative environmental impacts, reduced farm worker safety, and an increase in pest resistance. An economic response to this situation is to obtain estimates of pesticide productivity. This type of research indicates the cost of limiting pesticide use in terms of foregone output.

Previous studies indicate a general range of $3 to $6 for pesticide MVP, suggesting that pesticides are under used. These empirical studies provide an estimate of pesticide MVP, but they do not show what is happening to this MVP over time. Studies using cross-sectional data for a single year, or a few select years, give a "snap-shot" look at the MVP of pesticides. Studies that use a substantial time-series only serve to give an "average" estimate of the pesticide MVP over the time-series. This research effort employs a random coefficient model to determine the trend of the marginal value product of pesticides in agriculture in the United States.

Results show a definite downward trend in pesticide MVP for the states of Iowa and Texas. The pesticide MVP in Iowa drops from $32.79 in 1949 to $3.19 in 1991,

with a low of \$1.85 in 1979. The pesticide MVP for Texas declines from \$15.87 in 1949 to \$3.32 in 1991, with a low of \$2.86 in 1971. The pesticide MVP for California, however, shows no discernable trend. Except for the years 1949 and 1951, the MVP holds steady between the approximate range of \$3 to \$9 over the entire period.

Key words: pesticide productivity, marginal value product, random coefficients

PESTICIDE PRODUCTIVITY: WHAT ARE THE TRENDS?

Introduction

Pesticide use has been increasing steadily in the United States. In 1935, just prior to the discovery of DDT, about 50 million pounds of pesticides were applied (Prokopy). Approximately 55 thousand pesticide products were formulated from about 600 active ingredients in 1986 (U.S. General Accounting Office). In 1991, corn and soybeans alone received 210.4 million pounds and 63.5 million pounds of pesticides, respectively (United States Department of Agriculture 1992).

Public concern over pesticide use has increased due to the possible external effects of pesticides, including negative public health effects through groundwater and surface water contamination, negative environmental impacts, reduced farm worker safety, and increased pest resistance. A natural response of economists is to conduct research on the productivity of pesticides. This type of research provides useful information, such as indicating the cost of limiting pesticide use in terms of foregone output (Campbell).

Headley produced the first study of pesticide productivity using cross-sectional (state) data from a single year, 1963. He concluded that the marginal value product (*MVP*) of pesticides exceeded its marginal factor cost (*MFC*) \$4.00 to \$1.00. Other studies give similar results, indicating a general range of \$3 to \$6 for pesticide *MVP*. This suggests that pesticides are under used (Campbell, Carlson, Pimentel et al., Lichtenberg and Zilberman, Carrasco-Tauber and Moffit).

These empirical studies determine the pesticide *MVP*, but they do not show changes in *MVP* over time. Studies using cross-sectional data for a single year, or a few select years, give a "snap-shot" look at the *MVP* of pesticides. Studies that use a substantial time-series only serve to give an "average" estimate of the pesticide *MVP* over the time-series. Roth, Martin, and Brandt show that estimates of pesticide *MVP* from cross-sectional studies using state data for a single year are sensitive to the year chosen, suggesting the possibility of a time-trend in pesticide productivity. Increasing pest resistance would cause the *MVP* of pesticides to decrease over time (Osteen and Suguiyama; Carlson). Other factors, such as technological breakthroughs that increase efficacy, may cause the productivity of pesticides to increase over time. The purpose of the research reported in this paper is to determine the trend of the marginal value product of pesticides in agriculture in the United States.

Theory

Random coefficient models allow each observation of an independent variable to have a unique slope coefficient. This can be useful for evaluating the time trend in a coefficient such as the marginal value product of pesticides. One type of random coefficient model takes the form:

$$(1) \qquad y_t = \beta_{t1} + \sum_{k=2}^{K} \beta_{tk} x_{tk} \qquad t = 1, \ldots, T$$

where t is the individual observation; cross-section, time-series, or a combination of both, and T is the total number of observations (Hildreth and Houck, Judge et al. 1988). Each β_{tk} is a random coefficient, so that

(2) $$\beta_{tk} = \bar{\beta}_k + \mu_{tk} \qquad k = 1, \ldots, K$$

where K is the number of independent variables, $\bar{\beta}_k$ is a nonstochastic mean response coefficient, and μ_{tk} is a random disturbance with

(3) $$\begin{aligned} E[\mu_{tk}] &= 0 \\ var(\mu_{tk}) &= \alpha_k^2 \\ cov(\mu_{tk}, \mu_{sl}) &= \begin{cases} 0, & t \neq s \\ \alpha_{kl}, & t = s \end{cases} \end{aligned}$$

Let $\boldsymbol{\beta}_t$ be the (K x 1) vector of random coefficients from equation (2), so that T of these vectors exist. Rather than estimating $\boldsymbol{\beta}_t$, it is more accurate to say that $\boldsymbol{\beta}_t$ is predicted. "Predicted" is preferred to "estimated" because the β_{tk}'s are random variables drawn from a probability distribution. In order to predict $\boldsymbol{\beta}_t$, two things must be estimated: the mean response vector $\bar{\boldsymbol{\beta}} = (\bar{\beta}_1, \ldots, \bar{\beta}_K)'$, and the covariance matrix of the disturbance vector $\boldsymbol{\nu}_t$, $E(\boldsymbol{\nu}_t \boldsymbol{\nu}_t') = \Sigma$. $\boldsymbol{\nu}_t$ contains the elements $(\mu_{t1}, \ldots, \mu_{tK})'$ from equation (2), and is a (K x 1) vector where T of these vectors exist. The covariance matrix Σ is a K x K matrix with individual elements from equation (3) of α_{kl}, $k,l = 1, \ldots, K$ (Judge et al. 1988).

The estimated generalized least squares (EGLS) estimator of $\bar{\boldsymbol{\beta}}$ is given by

(4) $$\hat{\bar{\boldsymbol{\beta}}} = (\mathbf{X}'\hat{\boldsymbol{\Phi}}^{-1}\mathbf{X})^{-1}\mathbf{X}'\hat{\boldsymbol{\Phi}}^{-1}\mathbf{y}$$

with covariance matrix of

(5) $$cov\left(\hat{\bar{\boldsymbol{\beta}}}\right) = (\mathbf{X}'\hat{\boldsymbol{\Phi}}^{-1}\mathbf{X})^{-1}$$

where $\hat{\Phi}$ is a diagonal matrix with estimated elements $\hat{\sigma}_1^2, \hat{\sigma}_2^2, \ldots, \hat{\sigma}_T^2$. After obtaining the estimated covariance matrix $\hat{\Sigma}$, with the method shown below, the elements of $\hat{\Phi}$ are given by $\hat{\sigma}_t^2 = \mathbf{x}_t' \hat{\Sigma} \mathbf{x}_t$, where $\mathbf{x}_t' = (1, x_{t2}, x_{t3}, \ldots, x_{tK})$ is the tth row vector of $\mathbf{X}$. $\hat{\Phi}$ is analogous to the variance-covariance matrix for the EGLS model when σ_t^2 is assumed to be a function of a set of explanatory variables (Judge et al. 1988).

In order to obtain the estimate $\hat{\Sigma}$, let $N = K(K + 1)/2$, and $\boldsymbol{\alpha}$ be an $(N \times 1)$ vector containing the distinct elements of Σ. For example, if $K = 3$, then $\boldsymbol{\alpha}' = (\alpha_1^2, \alpha_{12}, \alpha_{13}, \alpha_2^2, \alpha_{23}, \alpha_3^2)$. Let $\mathbf{X}$ be defined as above, the matrix of independent variables, and let $\mathbf{Z}$ be defined as a $(T \times N)$ matrix with tth row vector of $\mathbf{z}_t' = (1, z_{t2}, z_{t3}, \ldots, z_{tN})$. $\mathbf{z}_t'$ is found by calculating $\mathbf{x}_t' \otimes \mathbf{x}_t'$ and combining identical elements. Using the example of $K = 3$, $\mathbf{z}_t' = (1, 2x_{t2}, 2x_{t3}, x_{t2}^2, 2x_{t2}x_{t3}, x_{t3}^2)$. Based upon this,

$$\text{(6)} \qquad E(\hat{\mathbf{e}}^2) = \mathbf{F}\boldsymbol{\alpha}$$

where $\hat{\mathbf{e}}^2$ is a vector containing the squares of the least squares residuals from the model $\mathbf{y} = \mathbf{X}\beta + \mathbf{e}$. $\mathbf{F} = \dot{\mathbf{M}}\mathbf{Z}$, where $\dot{M}$ contains the squares of the elements of $\mathbf{M} = \mathbf{I}_K - \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'$ (Hildreth and Houck, Judge et al. 1985).

It is evident from equation (6) that the least squares estimate of $\boldsymbol{\alpha}$, and therefore of Σ, is $\hat{\alpha} = (\mathbf{F}'\mathbf{F})^{-1}\mathbf{F}'\hat{\mathbf{e}}^2$. This estimate is unbiased, but unfortunately, it is not guaranteed to produce a $\hat{\Sigma}$ that is positive semidefinite. This is an essential property for any variance-covariance matrix. Froehlich and Dent and Hildreth show through Monte Carlo studies that it is better to impose these properties when estimating Σ. This can be done through nonlinear programming with nonlinear inequality constraints (Judge et al. 1985). The estimated $\hat{\alpha}$ is the solution to the problem

$$\underset{\alpha}{\mathit{Minimize}} \quad (\hat{e}^2 - \mathbf{F}\alpha)'(\hat{e}^2 - \mathbf{F}\alpha) \tag{7}$$
$$\mathit{subject\ to} \quad |\mathbf{A}_i| \geq 0, \qquad i = 1, \ldots, K$$

where $|\mathbf{A}_i|$ is the determinant of the ith principal minor of $\hat{\Sigma}$. Using this method, $\hat{\alpha}$ is essentially the restricted least squares estimate of α.

Finally, an appropriate predictor of the disturbance vector $\boldsymbol{\nu}_t = (\mu_{t1}, \ldots, \mu_{tK})'$ must be found. Equation (8) gives such a predictor (Griffiths).

$$\hat{\boldsymbol{\nu}}_t = \hat{\Sigma}\mathbf{x}_t\left(\mathbf{x}_t{}'\hat{\Sigma}\mathbf{x}_t\right)^{-1}\left(y_t - \mathbf{x}_t{}'\hat{\bar{\beta}}\right) \tag{8}$$

Combining equations (2), (4), and (8), the prediction of $\boldsymbol{\beta}_t$ becomes

$$\hat{\boldsymbol{\beta}}_t = \hat{\bar{\beta}} + \hat{\boldsymbol{\nu}}_t \tag{9}$$

Before predicting $\boldsymbol{\beta}_t$ in a random coefficient modelling framework, a good question to ask is whether or not the coefficients are random. Since this type of model is based upon heteroskedastic error terms, a Breusch-Pagan type test is appropriate to use in testing for randomness in the coefficients (Judge et al. 1988, Judge et al. 1985). The implementation of this test is described below.

Data Description and Procedure

All data on agricultural output and inputs are from the United States Department of Agriculture, Economic Research Service for the years 1949-1991. Specifically, the data correspond to Table 4--Farm Income Indicators in recent versions of Economic Indicators of the Farm Sector, State Financial Summary, USDA-ERS. All variables are reported by state. In order to keep the size of the data set manageable for matrix manipulations, the top ten ranking states in cash receipts were used to estimate the model. These states are California, Florida, Illinois, Indiana, Iowa, Kansas, Minnesota, Nebraska, Texas, and Washington. Forty-three time periods and ten states yield 430 observations. After model estimation, the trend of pesticide *MVP* can be compared across states for the time period 1949-1991.

Aggregate output, the dependent variable, is the market value of all crops sold plus government payments and the value of home consumption, divided by the Index of Prices Received by Farmers, base year equal to 1991 (Agricultural Prices, USDA-NASS). This leaves aggregate output as a value in constant 1991 dollars. The inputs are seed, fertilizer and lime, pesticides, fuel and oil, electricity, repair and maintenance, miscellaneous (includes machine hire and custom work, marketing, storage, transportation, and other miscellaneous expenses), non-real estate interest, and hired labor (includes contract labor, wages, Social Security payments, and labor perquisites). The inputs are not adjusted for the amount spent on livestock enterprises, which may result in a bias in the parameters. All of the independent variables are deflated to the base year of 1991 by the Index of Prices Paid by Farmers (Agricultural Prices, USDA-NASS), leaving inputs as a value measured in constant 1991 dollars.

The nonlinear constraints of equation (7) make it necessary to have a small number of coefficients in the model. This requires a small K, the number of independent variables, and a relatively simple functional form to represent production technology. In order to reduce K to a reasonable number, the independent variables are grouped into three categories: pesticides, other material inputs (seed, fertilizer and lime, and hired labor), and machinery costs (miscellaneous, electricity, fuel and oil, repair and maintenance, and non-real estate interest). These three independent variables, along with a constant term, make $K = 4$.

Assuming that aggregate technology in agriculture takes a Cobb-Douglas form, and transforming all variables to natural logs, the production function becomes linear and compliant with the conditions mentioned in the paragraph above. A major limitation of the Cobb-Douglas function is constant elasticities of production for each observation, and therefore constant marginal value products for a given level of production and output price. This assumption is relaxed in the random coefficients framework by regarding the coefficients as a random drawing from a probability distribution with mean $\bar{\beta}$ and covariance matrix Σ (Griffiths et al.).

Although the input aggregation discussed above and the specification of Cobb-Douglas technology enable model estimation, these assumptions impose certain relationships on the data. For example, an input within an aggregate variable is assumed to be a perfect substitute for any other input within the same aggregate variable. Also, aggregate variables are assumed to be technically complementary in the Cobb-Douglas specification. This implies that inputs within an aggregate variable are technically complementary with inputs in another aggregate variable.

The elasticity of production for input i at observation t, ϵ_{pti}, is β_{ti}. This is the percentage change in the value of output associated with a one percent change in the amount spent on input i. Since outputs and inputs are measured in dollar units, the marginal value product of input i at observation t is $\partial y_t / \partial x_{ti} = \beta_{ti}(y_t / x_{ti})$. The *MVP* has units of dollars of output produced per dollar spent on input i, measured in constant 1991 dollars.

The null and alternative hypotheses for the Breusch-Pagan type test are H_0: $\sigma_t^2 = \sigma^2$ and H_1: $\sigma_t^2 = \mathbf{z}_t'\boldsymbol{\gamma}$, respectively. $\mathbf{z}_t'$ is defined as above and $\boldsymbol{\gamma}$ is an N x 1 vector of unknown coefficients. This test is implemented by regressing $\hat{\mathbf{e}}^2$, the vector containing the squares of the residuals from a least squares regression in equation (1), on $\mathbf{Z}$, the (T x N) matrix with $\mathbf{z}_t'$ as the tth row, and testing for the joint significance of all slope coefficients. This is done using a Wald χ^2 statistic, which has degrees of freedom equal to the number of restrictions. All matrix manipulations and hypothesis tests are done using the *SHAZAM* econometrics package (White), and the nonlinear optimization from equation (7) is accomplished using *GAMS* (Brooke et al.).

Results

Table 1 reports the EGLS estimates of $\bar{\beta}$, the mean response vector, from equation (4). All coefficients have the expected sign, and all are highly significant. The Wald χ^2 test for randomness in the coefficients has nine degrees of freedom and a test statistic value of 64.024. The critical value for a five percent confidence level is 16.919. Therefore, the null hypothesis of non-random coefficients is strongly rejected at the five percent level.

Table 2 reports the production elasticities and marginal value products of pesticides. The production elasticities are based on equation (9), and the marginal value products follow directly from the method outlined in the data description and procedure section. Pesticide *MVP* reflects dollars of output produced per dollar spent on pesticides, and in constant 1991 dollars.

The results are reported for three states: California, Iowa, and Texas. These states were selected because they have consistently been the top three ranking states in cash receipts from agricultural sales (U.S.D.A. Economic Indicators of the Farm Sector, State Financial Summary). Only the odd years are reported for the time period 1949-1991. This limits the results to a reasonable amount, and is sufficient to accomplish the original intent: determine the time trend of pesticide *MVP*.

The states of Iowa and Texas reflect a definite downward trend in pesticide *MVP*. The pesticide *MVP* in Iowa drops from $32.79 in 1949 to $3.19 in 1991, with a low of $1.85 in 1979. The pesticide *MVP* for Texas declines from $15.87 in 1949 to $3.32 in 1991, with a low of $2.86 in 1971. The pesticide *MVP* for California, however, shows no discernable trend. Except for the years 1949 and 1951, the *MVP* holds steady between the approximate range of $3 to $9 over the entire period.

Conclusions

Pesticide use has increased steadily in the United States, along with concerns about the negative impacts of pesticides. This situation calls for economic analysis of the value of pesticides in use. This paper provides such an analysis, and extends beyond other research by determining the trend of the marginal value product of pesticides over time. A random coefficient model is outlined and used with data from ten states and 43 years (1949-1991) to accomplish this.

A distinct downward trend in pesticide *MVP* is shown in two states, Iowa and Texas. California, however, shows no evidence of a downward trend. Pesticide *MVP* in this state fluctuates in a steady range of $3 to $9 over the entire time period. These results give economic justification for the observed growing aggregate demand for pesticides: the benefits exceed the costs. One limitation to this study, though, is that the cost of possible negative externalities is not considered (e.g. non-point source pollution, increased pest resistance, reduced farm worker safety). Although entrepreneurial farm managers have a strong economic incentive to increase pesticide use at the present, the trend in pesticide *MVP* indicates a change may be coming, at least in some production areas. As the dollar value of output per dollar spent on pesticides approaches one, the intensity of aggregate demand for pesticides should decrease.

Table 1. Estimates and *t* Ratios of Mean Response Coefficients from a Hildreth-Houck Random Coefficient Model for United States Agriculture 1949-1991.

Variable	Coefficient Estimate [a]	*t* Ratio
Constant	2.0970	17.851
Other Material Inputs	0.3305	18.363
Pesticides	0.2348	20.865
Machinery Costs	0.3376	16.209

[a] All coefficient estimates are highly significant at the five percent level.

Table 2. Estimated Random Production Elasticities (ϵ_p) and Marginal Value Products (*MVP*) of Pesticides for California, Iowa, and Texas, 1949-1991, Odd Years Only.

	California		Iowa		Texas	
Year	ϵ_p	*MVP* [a]	ϵ_p	*MVP* [a]	ϵ_p	*MVP* [a]
1949	0.0356	0.85	0.2340	32.79	0.1756	15.87
1951	0.0597	1.43	0.4039	26.00	0.2541	13.62
1953	0.2727	9.36	0.2413	30.62	0.2018	17.16
1955	0.3098	9.01	0.2631	22.19	0.1842	15.62
1957	0.2719	8.33	0.3095	19.80	0.1903	18.85
1959	0.2365	6.02	0.3523	13.98	0.1711	13.76
1961	0.2151	5.69	0.2757	11.72	0.2176	11.19
1963	0.2702	8.19	0.2491	10.71	0.2339	8.74
1965	0.2686	8.29	0.2407	7.01	0.2330	6.65
1967	0.2220	4.41	0.1825	2.87	0.2163	4.35
1969	0.2053	3.32	0.1974	3.10	0.2040	3.82
1971	0.2223	3.48	0.1922	2.86	0.1840	2.86
1973	0.2346	3.89	0.2582	4.82	0.2359	4.77
1975	0.2632	5.22	0.1462	2.22	0.2080	3.84
1977	0.3491	8.92	0.1785	2.75	0.2303	5.15
1979	0.2585	4.66	0.1665	1.85	0.2126	3.49
1981	0.2847	5.25	0.2126	2.82	0.2253	4.01
1983	0.2870	5.82	0.2450	3.93	0.2304	5.33
1985	0.3240	6.72	0.2744	4.69	0.2354	4.83
1987	0.3788	8.70	0.3232	6.29	0.2369	4.36
1989	0.3491	7.03	0.2386	2.96	0.2365	4.02
1991	0.3300	5.96	0.2570	3.19	0.2240	3.32

[a] Marginal value product of pesticides in dollars per dollar spent on pesticides, constant 1991 dollars.

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Essay V

ESTIMATION OF NITROGEN PERCOLATION RELATIONSHIPS

ESTIMATION OF NITROGEN PERCOLATION RELATIONSHIPS

Abstract

Application of simulation models in the water quality area allows researchers to realize many benefits, including replacing expensive field data collection with model estimates, assessing the impacts of operative actions on human health and the environment before these impacts actually occur, and screening alternative water quality policies before implementation. In this essay, regression analysis is used to complement a simulation model by synthesizing a large amount of data into clear and concise results.

The crop growth/chemical fate simulation model EPIC-PST is used to estimate annual nitrogen percolation loadings under irrigated wheat and corn production for various soil types, irrigation systems, and management practices in the Central High Plains. Annual nitrogen percolation values comprise a censored sample since non-zero values are only observed under certain climatic events and/or input levels. Therefore, tobit analysis is an appropriate regression technique. Tobit analysis synthesizes these results and provides information about the effect of selected variables (e.g. irrigation level and nitrogen applied) on the expected value and the probability of nitrogen percolation events.

The results of the tobit analysis indicate that the expected value of nitrogen percolation and probability of nitrogen leaching events are influenced by soil type,

irrigation system, and crop. Coarser soils produce more nitrogen percolation than heavier soils and center pivot sprinkler systems are less conducive to nitrogen percolation than furrow irrigation systems. Also, nitrogen percolation occurs less often and in smaller magnitudes in irrigated wheat production than in irrigated corn production. Although intuition and the original EPIC-PST results also lead to similar conclusions, tobit analysis provides some clear information in the form of partial derivatives and probabilities that is not directly available from EPIC-PST output. The tobit procedure also allows the freedom of working on an analytical expression rather than the full simulation model.

Key words: simulation models, tobit analysis, nitrogen percolation

ESTIMATION OF NITROGEN PERCOLATION RELATIONSHIPS

Introduction

Computer simulation modeling is a widely used tool in many fields of research because of the advantages it offers. In many cases, a simulation model is less expensive to build and operate than the real-world system that is being modeled. Also, computer modeling is quite often less expensive than field testing, although a certain amount of field testing is necessary in order to validate the model. System trials can be speeded up by orders of magnitude relative to the amount of time necessary to obtain real-world data.

Although computer modeling can be advantageous, the amount of output can be quite large (Martin 1968). Along with a large amount of output, "Bonini's paradox" can be encountered by the users of a simulation model. A quotation from Dutton and Starbuck best describes this phenomenon (Lehman 1977):

> "A model is built in order to achieve understanding of an observed causal process, and the model is stated as a simulation program in order that the assumptions and functional relations may be as complex and realistic as possible. The resulting program produces outputs resembling those observed in the real world, and inspires confidence that the real causal process has been accurately represented. However, because the assumptions incorporated in the model are complex and their mutual interdependencies are obscure, the simulation program is no easier to understand than the real process was."

Because of the dearth of experimental data on agrichemical fate and transport, computer simulation models have been used extensively in the area of water quality management. Examples of simulation models developed to study agrichemical fate and transport include GLEAMS (Leonard et al. 1987), CREAMS (Knisel 1980), PRZM (Carsel et al. 1984), and EPIC-PST (Sabbagh et al. 1991). Application of these models in the water quality area allows researchers to realize many benefits, including replacing expensive field data collection with model estimates, assessing the impacts of operative actions on human health and the environment before these impacts actually occur, and screening alternative water quality policies before implementation. However, problems of large amounts of output and uncertain internal relationships are also experienced when applying simulation models in the water quality area (Cabe et al. 1991).

Researchers need a means of synthesizing the copious data from simulation models into clear and concise results. Regression analysis may be used to summarize simulation results, and eliminate the need of re-running the model every time its predicted outcome is required (Cabe et al. 1991). A regression equation also yields useful information, such as a partial derivative (the change in a variable of interest due to a one unit change in another variable), that is not available directly from a simulation model.

The objective of this paper is to propose and illustrate the use of tobit analysis as a means of synthesizing computer simulation results. In this analysis, output data from the crop growth simulation/chemical fate model EPIC-PST (Sabbagh et al. 1991) are used to estimate a tobit censored regression model describing the relationship between nitrogen percolation and a chosen set of independent variables. The reason for "modeling the model" so to speak, is straightforward: the regression equation provides clear, useful information that is not readily apparent in the full simulation model. This information includes partial derivatives, the probability of nitrogen percolation being above zero, and the expected value of nitrogen percolation, given the soil type, irrigation system, and values for the continuous independent variables. This method is by no means intended to replace EPIC-PST as a predictor of nitrogen percolation, but rather it is an attempt to add to the interpretability of EPIC-PST simulation runs and, hopefully, add to its effectiveness as a water quality management tool.

Limited Dependent Variables and Tobit Estimation

An often made assumption in regression analysis is that the dependent variable is a continuous variable. The continuity assumption is violated in the case of a censored sample, where some observations on the dependent variable that correspond to known sets of independent variables are not observable (Maddala 1983). In other words, the independent, or **X**, variables are observed for the entire sample, but the dependent, or **Y**, variable is not. Censored samples are often encountered in agricultural production systems and can pose a challenge to researchers attempting to summarize simulation results. In this example, annual nitrogen percolation values comprise a censored sample since non-zero values are only observed under certain climatic events and/or input levels. Since there is a grouping of values for the dependent variable at zero and no value for **Y** can occur below zero, the sample is said to be censored at zero (Judge et al. 1980, Tobin 1958). Researchers are not only concerned about the magnitude of nitrogen percolation, but the probability of a positive percolation event as well.

Since **Y** only occurs over a limited range of the independent variables, some choices present themselves in the process of estimating the effects of the **X** variables on **Y**. One alternative is to ignore all observations for the **Y** and **X** variables for which **Y** is equal to zero, assume the dependent variable to be continuous, and use OLS (Ordinary Least Squares) estimation procedures. This amounts to having a truncated sample, and OLS parameter estimates are biased and inconsistent (Maddala 1983, Amemiya 1984). Another alternative is to create an index such that $I_i = 1$ if $Y_i > 0$, and $I_i = 0$ otherwise, where i denotes the individual observation in the vectors **Y** and **I**. This alternative amounts to having a dummy endogenous variable, in which case logit or probit models are appropriate. These models result in a prediction of the probability of the dependent variable **Y** being above the limit, usually zero (Maddala 1983, Judge et al. 1980).

Tobin noted that an important weakness of both the logit and probit approaches is that the value of the dependent variable is ignored when it is above the limit. Failure to use all available information in the estimation procedure is inefficient. Probit analysis cannot explain the effect of **X** variables on the value of a **Y** variable, and the assumptions of the standard OLS model are not realized (Tobin 1958). Tobin proposed using a hybrid of probit and multiple regression; this model has been dubbed Tobin's probit, or the tobit model (Goldberger 1964, Maddala 1983).

The standard tobit model takes the following form:

$$(1) \qquad \begin{aligned} Y &= X\beta + \mu & \text{if } X\beta + \mu > 0 \\ &= 0 & \text{if } X\beta + \mu \leq 0 \end{aligned}$$

where **Y** is a T x 1 dependent variable vector, **X** is a T x K independent variable matrix, β is a K x 1 vector of unknown parameters, and μ is a T x 1 vector of normal, independently distributed error terms with mean zero and constant variance σ^2. T is the total number of observations, including both limit and nonlimit observations (Maddala 1983, Judge et al. 1988, McDonald and Moffit 1980).

One way of viewing the tobit model is that it assumes there is an underlying stochastic process represented by ($\mathbf{X}\beta + \mu$) which is observed only when it is positive. **Y**, therefore, qualifies as an unobserved, or latent variable (McDonald and Moffit 1980, Maddala 1983). This latent variable may be defined as $\mathbf{Y}^*$, such that:

$$(2) \qquad Y^* = X\beta + \mu$$

$$(3) \qquad \text{and} \qquad \begin{aligned} Y &= Y^* & \text{if } Y^* > 0 \\ Y &= 0 & \text{otherwise} \end{aligned}$$

Statistical Tests and Measures of Goodness-of-Fit

The tobit model requires the estimation of β and σ. Amemiya (1984) and Tobin (1958) show that maximum likelihood estimation (MLE) produces consistent estimators for β and σ, here called **b** and s. This research uses a tobit MLE procedure in the econometrics computer program SHAZAM to estimate **b** and s (White 1990).

The tobit estimation follows the procedure in Tobin's article in that normalized coefficients are estimated rather than the β coefficients themselves. This amounts to obtaining estimates for β/σ. The regression coefficients are then calculated as the normalized coefficients times s, the standard error of the estimate. These regression coefficients do not hold the same meaning as the estimated coefficients from a standard ordinary least squares regression equation. The regression coefficients from a tobit model must be multiplied by $\Phi(\mathbf{X}\beta/\sigma)$, the cumulative distribution function of the standard normal evaluated at $\mathbf{X}\beta/\sigma$, to hold an equivalent interpretation (Maddala 1983, Judge et al. 1988, McDonald and Moffit 1980).

Asymptotic t-ratios are used to test the statistical significance of each coefficient versus zero. For the classification variables, this test determines whether or not the coefficient is significantly different from the constant term. This statistic is not very meaningful in this model; however, joint hypothesis tests can be conducted on the various groups of classification variables. A Wald's chi-square test, which is an asymptotic test (Judge et al. 1988), is used for these joint hypothesis tests.

Two goodness-of-fit measures are reported for the tobit models in this paper. These are root mean square error (RMS error) and the correlation between actual and predicted values of nitrogen percolation (ρ_{ap}). RMS error is a measure of the deviation of predicted nitrogen percolation (estimated by the tobit model) from the original nitrogen percolation values generated from the EPIC-PST simulation runs (Pindyck and Rubinfeld 1976). ρ_{ap} is a measure of the linear association between the actual and predicted values for nitrogen percolation which ranges from -1 to 1. The square of ρ_{ap} can be interpreted as the R-squared that is commonly reported in a standard linear regression model (Wallace and Silver 1988).

Data Description

The tobit model is used to synthesize the results of a series of simulation runs. These simulation runs estimate the impact of alternative agricultural management practices on water quality in the central High Plains. The crop growth/chemical fate and transport model EPIC-PST was used to simulate the effects of different agricultural management practices on crop yield and chemical losses (nutrient and pesticide) by surface runoff, sediment runoff, and leaching below the soil profile. EPIC-PST is a combination of EPIC (Erosion Productivity Impact Calculator) and the pesticide subroutines from the GLEAMS model (Groundwater Loading Effects of Agricultural Management Systems). EPIC operates on a daily time step, and its components can be divided nine major submodels: hydrology, weather, erosion, nutrients, plant growth, soil temperature, tillage, economics, and plant environment. The pesticide component (GLEAMS) simulates the pesticide activities by six processes: degradation, extraction into runoff, leaching, transport with sediment, evaporation, and plant uptake (Sabbagh et al. 1991).

EPIC-PST simulations were conducted for two crops, irrigated corn and irrigated wheat, produced in the Texas High Plains region. Twenty-year simulations were conducted for a variety of production activities, differing in terms of soil types (four), irrigation systems (four), nitrogen applications (split applications and correlated in amount with the irrigation levels), and irrigation levels (six). Twenty years of daily historical weather data for Amarillo, Texas were used to represent climatic variability. This process developed a data set of twenty annual observations on yield, input levels, and environmental variables (chemical loadings) for each production activity (combination of soil type, irrigation system, and irrigation level).

Table 1 provides a statistical description of the dependent variable (nitrogen percolation or NPERC) and the five continuous independent variables that are included in the nitrogen percolation tobit model for irrigated corn and irrigated wheat. The table includes the number of observations, along with the mean, standard deviation, minimum, and maximum for each variable. The dependent variable of the tobit model is the annual quantity (pounds/acre) of nitrogen percolating past the root zone in the soil profile. The five continuous independent variables in the model are yield (YIELD), rainfall (RAIN), nitrogen applied (NAPL), irrigation water applied (IRRIG), and evapotranspiration (ET_p). Table 2 provides the amount of nitrogen applied for both crops at each irrigation level by soil type and irrigation system.

Yield and evapotranspiration are expected to have a negative influence on nitrogen percolation, while rainfall, nitrogen applied, and irrigation are expected to have a positive influence on nitrogen percolation. Yield and evapotranspiration are inversely related to nitrogen percolation because they provide an outlet for nitrogen other than through percolation, e.g. plant use. Nitrogen applied, of course, will have a positive relationship with nitrogen percolation because as nitrogen applied increases, more nitrogen is available to percolate. Rainfall and irrigation both have a positive influence on the quantity of water percolating through the soil; therefore, they are expected to have a positive impact on nitrogen percolation as well.

The tobit model uses classification or dummy variables to represent the four soil types. The four soils with their abbreviated names and a short description are listed below.

Sherm silty clay loam (S_1) - This soil produces high grain yields with very low percolation volume and relatively high runoff volume.

Dallam fine sandy loam (S_2) - This soil is characterized by medium simulated crop yields, high water percolation, and low runoff.

Sunray clay loam (S_3) - This soil produces relatively low grain yields along with high percolation and runoff volumes.

Gruver clay loam (S_4) - This soil has high crop yields, low leaching, and medium runoff volumes.

The model also uses dummy variables to represent the four different irrigation systems. The four systems, along with their abbreviated names and descriptions (Earls and Bernardo 1992) are:

Conventional Furrow (SYS_1) - Conventional gated pipe gravity-flow irrigation system.

Improved Furrow (SYS_2) - Improved furrow, or surge-flow system. This system increases application efficiency by using a series of electronically controlled on-off watering periods to furrows.

Sprinkler (SYS_3) - Conventional low-pressure center pivot system.

LEPA (SYS_4) - Low energy precision application system. This system employs drop tubes which hang from the pivot lateral and transport water to nozzles 12 to 15 inches from the ground.

Sixteen combinations of soil type and irrigation system are possible; however, four combinations are not included in the original EPIC-PST data set. Combinations of SYS_1 and SYS_2 systems on soils S_2 or S_3 are not considered because they involve the use of furrow irrigation systems on highly permeable soils. The 1440 irrigated corn and irrigated wheat nitrogen percolation observations include 1133 limit, or zero, observations and 307 nonlimit, or above zero, observations for corn, and 1235 limit observations and 205 nonlimit observations for wheat. The observed frequency of nitrogen percolation > 0 is .2132 in irrigated corn and .1424 in irrigated wheat.

Application to Irrigated Corn

Equation 4 gives the specified tobit model for irrigated corn, including all variables and their associated unknown coefficients. S_4 and SYS_4 are the base dummy variables, and their influence is contained in the intercept term. The model also includes a set of two-way interaction terms between nitrogen applied and soil type, nitrogen applied and irrigation system, irrigation and soil type, and irrigation and irrigation system. Other interaction effects are ignored due to lack of statistical significance and a desire to simplify the model. Abbreviated names are listed for the interaction effects between 1) soil type and nitrogen applied: S_1NAPL, S_2NAPL, and S_3NAPL; 2) irrigation system and nitrogen applied: SYS_1NAPL, SYS_2NAPL, and SYS_3NAPL; 3) soil type and irrigation water applied: S_1IRRIG, S_2IRRIG, and S_3IRRIG; and 4) irrigation system and irrigation water applied: SYS_1IRRIG, SYS_2IRRIG, and SYS_3IRRIG.

$$NPERC = X\beta + \mu \qquad \text{if} \qquad X\beta + \mu > 0,$$

$$\text{where} \quad X\beta = \beta_0 + \beta_1 YIELD + \beta_2 RAIN + \beta_3 NAPL + \beta_4 IRRIG$$

$$(4) \qquad + \beta_5 ET_p + \sum_{i=1}^{3} \alpha_i S_i + \sum_{i=1}^{3} \delta_i SYS_i + \sum_{i=1}^{3} \gamma_i S_i NAPL$$

$$+ \sum_{i=1}^{3} \lambda_i SYS_i NAPL + \sum_{i=1}^{3} \tau_i S_i IRRIG + \sum_{i=1}^{3} \psi_i SYS_i IRRIG$$

Table 3 presents the regression coefficients and the asymptotic t-ratios for each variable in the model estimated for corn. The estimate of σ, the standard error of the estimate, is 7.818. RMS, ρ_{ap}, and $(\rho_{ap})^2$ for the tobit corn model equals 3.17, .74, and .55, respectively. The normalized coefficients are not reported, but they can be calculated by dividing the regression coefficients by σ. The signs of the estimated coefficients for the continuous independent variables are consistent with a priori expectations. The estimated coefficients indicate a negative effect of yield and evapotranspiration on nitrogen percolation, while showing a positive effect of rainfall, nitrogen applied, and irrigation on nitrogen percolation. The coefficients for yield, rainfall, irrigation, and evapotranspiration are all significantly different from zero at the 1% level. The coefficient for nitrogen applied is significant at the 10% level.

As stated earlier, the statistical significance of the classification variables should be based upon the joint significance of combinations of the coefficients. Line one of Table 4 gives the joint significance of all coefficients in the model, and indicates a high level of statistical significance for the combination of all coefficients. The soil type classification variables (line two) are significant at the six percent level, and the irrigation system classification variables (line three) are significant at the twelve percent level. Soil type and irrigation system dummy variables together (line four) are highly significant.

Lines seven and ten of Table 4 show the joint significance of the two-way interaction terms between the soil type and irrigation system classification variables, and nitrogen applied and irrigation. These results show a high significance level for the two groups of interaction terms. Lines five, six, eight, and nine provide some statistical grounds for dropping the interaction terms involving soil type from the model. However, these interaction terms were retained because of the test results in lines seven and ten.

Interpretation of the Partial Derivatives

The equations for the expected values of nitrogen percolation in the tobit model are nonlinear in all of the independent variables. The truncation of the dependent variable causes the cumulative density function and the probability density function to appear in the expectation formulas, producing the nonlinearity. As a result, the partial derivatives are also nonlinear and dependent upon the value of the **X** variables (Maddala 1983). A common practice is to evaluate the partial derivatives at the mean of the **X** variables. However, the mean of a dummy variable is not relevant to the problem at hand. In the context of this problem, a sensible method is to choose a value for the continuous **X** variables and calculate the results for each combination of classification variables. Twelve sets of partial derivatives for the five continuous explanatory variables are estimated in this manner. The choice for the value of the five continuous **X** variables is representative of the current agricultural production practices in the study region. This choice is based upon visits with extension personnel in the area. Use of the current level for input and environmental variables should give partial derivatives that are most relevant for policy evaluation (Mapp et al. 1991).

Table 5 contains the expected values of nitrogen percolation and the partial derivatives of nitrogen percolation with respect to the five continuous independent variables for irrigated corn. The expected values of nitrogen percolation at the chosen values for the independent variables are reported in the E(NPERC) column. Differences in expected nitrogen percolation across soil types are evident. Nitrogen percolation is highest on Soil 2 and Soil 3, with Soil 2 having the highest propensity to percolate. Soils 1 and 4 are the heaviest soils and yield the lowest levels of nitrogen percolation. These results are consistent with intuition given the description of each soil type.

The E(NPERC) column also portrays differences in nitrogen percolation across irrigation systems. The use of LEPA and sprinkler systems on Soil 1 and Soil 4 result in far less nitrogen percolation than conventional furrow and improved furrow systems on either soil type. This is consistent with intuition since sprinkler and LEPA irrigation systems are designed to reduce irrigation percolation losses, relative to furrow systems.

The partial derivatives in Table 5 show the change in pounds of nitrogen percolation associated with a one unit change in the independent variable. The variables nitrogen applied and irrigation should be focused upon since these are controlled or management variables. As an example of interpretation, on Soil 1, a one pound increase in nitrogen applied causes an increase in expected nitrogen percolation of .59 pounds with a conventional furrow system, but only a .07 pound increase in nitrogen percolation under a sprinkler system. A one inch increase in irrigation water on Soil 2 under a sprinkler system increases nitrogen percolation by 1.09 pounds, while the same increase in irrigation water for a sprinkler system on Soil 4 increases nitrogen percolation by only .02 pounds, and so forth. This type of comparison clearly shows the superiority of center pivot systems over furrow systems in managing nitrogen percolation.

Table 6 gives additional information from a tobit model that is not available from a standard linear regression model: the probability of nitrogen percolation being above zero and the change in this probability given a one unit change in each of the independent variables. The last column in Table 6, which is the probability of nitrogen percolation being above zero, is given by the standard normal cumulative density function (CDF) evaluated at $\mathbf{X}\beta/\sigma$. The first five columns in Table 6 show the change in the probability of nitrogen percolation being above zero given a one unit change in each of the independent variables. This information is given by the partial derivative of the CDF with respect to each independent variable (McDonald and Moffit).

As an example of interpretation, Soil 1 with a conventional furrow irrigation system has a seventy five percent chance of a leaching event occurring, and nitrogen applied and irrigation, the two management variables, both have a three percent effect upon this probability at the margin. That is, a one unit increase in either nitrogen or irrigation water will increase the probability of a leaching event by three percent. When improved furrow is used on Soil 1 there is an eighty seven percent probability of nitrogen percolating past the plant root zone. Irrigation has a four percent marginal effect on this probability and nitrogen applied has only a one percent marginal effect. Irrigation consistently has a larger marginal effect upon the probability of a leaching event taking place than nitrogen applied, with the exception of conventional furrow on Soil 1 and Soil

4. This information, combined with the results in Table 5, is very useful to policy makers attempting to design policies aimed at controlling nitrogen percolation in the study area. Based upon the partial derivatives and probabilities, soils and irrigation systems can be identified which contribute to nitrate contamination of the groundwater. More importantly, policies aimed at reducing irrigation water and/or nitrogen applications can be assessed based upon their capability of reducing both the expected value and probability of nitrogen percolation.

Application to Irrigated Wheat

The tobit procedure is applied to irrigated wheat in the same region to give a contrast to irrigated corn. Like the irrigated corn data, the irrigated wheat data are obtained from twenty year EPIC-PST simulation runs for alternative production systems. The same soil types and irrigation systems are employed, and classification variables divide the data set into the same twelve combinations of soil type and irrigation system. The same estimation procedures used for the corn model were also used for the wheat model.

Equation 5 gives the specified tobit model for irrigated wheat including all variables and their associated unknown coefficients. As in the corn model, S_4 and SYS_4 are the base dummy variables. Due to lack of significance, no interaction terms were included in the wheat model.

$$
(5) \quad
\begin{aligned}
NPERC &= X\beta + \mu \qquad \text{if} \qquad X\beta + \mu > 0, \\
\text{where} \quad X\beta &= \beta_0 + \beta_1 YIELD + \beta_2 RAIN + \beta_3 NAPL + \beta_4 IRRIG \\
&\quad + \beta_5 ET_p + \sum_{i=1}^{3} \alpha_i S_i + \sum_{i=1}^{3} \delta_i SYS_i
\end{aligned}
$$

Table 7 lists the regression coefficients and asymptotic t-ratios for the wheat model. The estimate of σ, the standard error of the estimate, is 3.449. RMS, ρ_{ap}, and $(\rho_{ap})^2$ for the tobit wheat model equals 1.19, .59, and .35, respectively. All of the coefficients for the continuous independent variables are significant at the one percent level except yield, and it is significant at the five percent level. All of the signs on the coefficients are consistent with prior expectations and identical to the corn model, with the exception of yield, which has a positive sign instead of a negative sign.

Table 8 gives results of the joint significance tests for the wheat model. All of the coefficients in the model are jointly significantly different from zero, as are the soil type classification variables, and the combination of soil type and irrigation system classification variables. The irrigation system classification variables by themselves are not significantly different from zero even at the twenty percent level, but due to the joint significance of soil type and irrigation system classification variables together, they were kept in the model.

Table 9 contains the expected value of nitrogen percolation and partial derivatives for the wheat model. Comparison of these results with those presented in Table 5 provides a crop comparison between the two tobit models. In general, the expected value for nitrogen percolation in wheat production is much lower than that for corn production. Nitrogen percolation is of little concern in irrigated wheat production except on soil types

2 and 3. The most important reason for this is that irrigated wheat production involves considerably lower levels of both nitrogen and water inputs relative to corn production, as Table 2 shows. The large nitrogen applications applied to corn in the spring can combine with large rainfall events to produce significant percolation levels. The partial derivatives for irrigation on Soil 2 show that the reduction in nitrogen percolation associated with a one unit reduction in irrigation water applied in wheat production is about one-third of what is expected under corn production. Changes in expected percolation levels in response to a unit change in nitrogen applications are similar for both crops. Tables 4 and 8 imply that irrigated corn production is a more significant contributor to nitrogen percolation in the study area than irrigated wheat.

Discussion

Regression analysis can be a useful tool for summarizing the large amount of data generated from a simulation model into concise and interpretable results. While conventional ordinary least squares procedures can often be used to summarize simulation results, problems occur when the dependent variable violates the continuity assumption. Censored samples, where many observations on the dependent variable are grouped at zero, often occur in agricultural production systems (e.g. nitrogen percolation). In these cases, tobit censored regression models may be used to synthesize simulation results and provide predictions of both the expected value and probability of the dependent variable being above some limit, usually zero. The tobit technique is illustrated through its application to a censored sample of annual nitrogen percolation values.

The summarized results from the tobit model can be used to better understand what is happening within a simulation model and to make field recommendations and policy prescriptions. The tobit models provide a useful tool for estimating the expected value of nitrogen percolation at various levels of the independent variables. In addition, the partial derivatives provide useful information concerning the sensitivity of nitrogen percolation to unit changes in an independent variable. Such information could be useful to policymakers attempting to evaluate the effectiveness of various policies aimed at controlling, in this case, nitrate percolation. For example, the effect of policies aimed at reducing irrigation water or nitrogen applied can be compared based upon their partial derivatives. Probabilities of positive nitrogen percolation events also provide a meaningful measure of environmental risk for assessing alternative production systems.

The results of the tobit analysis indicate that the expected value of nitrogen percolation and probability of nitrogen leaching events are influenced by soil type, irrigation system, and crop. Coarser soils produce more nitrogen percolation than heavier soils and center pivot sprinkler systems are less conducive to nitrogen percolation than furrow irrigation systems. Also, nitrogen percolation occurs less often and in smaller magnitudes in irrigated wheat production than in irrigated corn production. Although intuition and the original EPIC-PST results also lead to similar conclusions, tobit analysis provides some clear information in the form of partial derivatives and probabilities that is not directly available from EPIC-PST output. The tobit procedure also allows the freedom of working on an analytical expression rather than the full simulation model.

Table 1. Statistical Description of Variables, Irrigated Corn Production and Irrigated Wheat Production.

Variable Name	Obs. [a]	Mean	Std.Dev.	Minimum	Maximum
Irrigated Corn Production					
NPERC (lbs.) [b]	1440	1.56	4.73	0.00	50.90
YIELD (bu.) [c]	1440	187.38	28.56	108.23	248.19
RAIN (in.) [d]	1440	18.32	3.69	13.37	25.21
NAPL (lbs.) [e]	1440	166.96	20.98	121.43	202.68
IRRIG (in.) [f]	1440	18.60	6.31	4.49	40.00
ET_p (in.) [g]	1440	30.87	6.22	21.53	39.35
Irrigated Wheat Production					
NPERC (lbs.) [b]	1440	0.43	1.46	0.00	14.29
YIELD (bu.) [c]	1440	54.68	22.81	0.00	104.61
RAIN (in.) [d]	1440	18.32	3.69	13.37	25.21
NAPL (lbs.) [e]	1440	74.90	20.80	40.18	116.96
IRRIG (in.) [f]	1440	13.40	6.44	0.00	35.00
ET_p (in.) [g]	1440	27.14	4.74	1.07	39.31

[a] Total number of observations. Limit observations, those at zero, and nonlimit observations, those above zero, are included in NPERC.

[b] Pounds of nitrogen percolating past the plant root zone in the soil profile; the dependent variable in the tobit model.

[c] Grain production in bushels per acre.

[d] Actual rainfall in inches per year.

[e] Actual nitrogen applied per year in pounds per acre.

[f] Inches of irrigation water applied per year.

[g] Moisture loss due to evaporation and transpiration measured in inches per year.

Table 2. Nitrogen Applied (lbs. of Actual N) Per Acre by Irrigation Level for Each Soil Type and Irrigation System, Irrigated Corn Production and Irrigated Wheat Production.

	Irrigation Level					
Irrigated Corn	1	2	3	4	5	6
Soil 1						
Conv. Furrow	138	154	169	181	188	199
Impr. Furrow	138	154	171	187	195	203
Sprinkler	138	151	162	172	183	194
LEPA	138	154	165	175	184	193
Soil 2						
Sprinkler	154	166	176	184	192	198
LEPA	156	167	178	185	191	197
Soil 3						
Sprinkler	121	134	146	155	158	160
LEPA	124	138	146	155	160	163
Soil 4						
Conv. Furrow	138	154	169	180	191	197
Impr. Furrow	137	154	167	181	190	199
Sprinkler	134	149	161	171	180	188
LEPA	134	147	163	173	183	189
Irrigated Wheat						
Soil 1						
Conv. Furrow	45	48	61	78	89	98
Impr. Furrow	45	54	69	79	91	98
Sprinkler	40	46	62	74	85	91
LEPA	40	47	61	77	86	92
Soil 2						
Sprinkler	59	77	91	101	105	109
LEPA	65	82	97	109	115	117
Soil 3						
Sprinkler	49	61	77	84	88	94
LEPA	49	63	77	86	93	96
Soil 4						
Conv. Furrow	45	56	70	80	90	103
Impr. Furrow	45	55	59	81	96	100
Sprinkler	40	47	64	75	83	88
LEPA	40	53	65	79	87	92

Table 3. Coefficient Estimates and Asymptotic T-Ratios, Irrigated Corn Production.

Variable Name [a]	Regression Coeff. [b]	Asymptotic T-Ratios	Variable Name	Regression Coeff. [b]	Asymptotic T-Ratios
YIELD	-0.109***	-4.666	S_2NAPL	-0.541	-1.524
RAIN	1.118***	7.896	S_3NAPL	-0.324	-0.862
NAPL	0.586**	1.674	SYS_1NAPL	0.272	0.734
IRRIG	1.356***	3.187	SYS_2NAPL	-0.176	-0.512
ET_p	-0.151***	-2.815	SYS_3NAPL	0.032	0.489
S_1	14.519	0.596	S_1IRRIG	0.062	0.267
S_2	122.280*	1.879	S_2IRRIG	0.159	0.386
S_3	75.411	1.119	S_3IRRIG	0.289	0.644
SYS_1	-33.153	-0.487	SYS_1IRRIG	-0.661	-1.586
SYS_2	37.697	0.598	SYS_2IRRIG	0.242	0.588
SYS_3	-5.465	-0.547	SYS_3IRRIG	-0.309*	-1.646
S_1NAPL	-0.064	-0.473	CONSTANT	-147.550*	-2.288

[a] YIELD = crop yield (bu./acre), RAIN = rainfall (inches/year), NAPL = nitrogen applied (lbs./year), IRRIG = irrigation applied (inches/year), ET_p = evapotranspiration, S_i = Soil i, SYS_1 = conventional furrow, SYS_2 = improved furrow, SYS_3 = center pivot.

[b] ***, **, and * are .01, .05, and .10 significance levels, respectively. Two-tailed tests versus zero were conducted.

Table 4. Joint Hypothesis Tests, Irrigated Corn Production.

Combinations of Coefficients [a]	Wald χ^2 Statistic	Prob. Value [b]
1. All Coefficients	413.07	.0000
2. S_1, S_2, S_3	7.45	.0588
3. SYS_1, SYS_2, SYS_3	5.84	.1199
4. S_1, S_2, S_3, SYS_1, SYS_2, SYS_3	37.89	.0000
5. S_1NAPL, S_2NAPL, S_3NAPL	3.99	.2623
6. SYS_1NAPL, SYS_2NAPL, SYS_3NAPL	7.37	.0611
7. S_1NAPL, S_2NAPL, S_3NAPL, SYS_1NAPL, SYS_2NAPL, SYS_3NAPL	25.63	.0003
8. S_1IRRIG, S_2IRRIG, S_3IRRIG	.47	.9257
9. SYS_1IRRIG, SYS_2IRRIG, SYS_3IRRIG	14.69	.0021
10. S_1IRRIG, S_2IRRIG, S_3IRRIG, SYS_1IRRIG, SYS_2IRRIG, SYS_3IRRIG	15.81	.0148

[a] S_i = Soil i, SYS_1 = conventional furrow, SYS_2 = improved furrow, SYS_3 = center pivot, NAPL = nitrogen applied (lbs./year), IRRIG = irrigation applied (inches/year).

[b] If the probability value is less than the critical value of the reader's choice, the set of coefficients is significantly different from zero.

Table 5. The Partial Derivatives of Nitrogen Percolation With Respect to the Independent Variables, Irrigated Corn Production.

	Partial Derivatives [a]					
Soil Type/ Irr. System	YIELD bu.	RAIN in.	NAPL lbs.	IRRIG in.	ET_p in.	E(NPERC) [b] lbs.
Soil 1						
Conv. Furrow	-0.08	0.84	0.59	0.57	-0.11	6.41
Impr. Furrow	-0.10	0.97	0.30	1.44	-0.13	9.32
Sprinkler	-0.01	0.13	0.07	0.13	-0.02	0.46
LEPA	-0.02	0.16	0.08	0.21	-0.02	0.58
Soil 2						
Sprinkler	-0.10	1.01	0.07	1.09	-0.14	10.54
LEPA	-0.10	1.02	0.04	1.38	-0.14	10.85
Soil 3						
Sprinkler	-0.03	0.29	0.08	0.34	-0.04	1.22
LEPA	-0.05	0.50	0.12	0.74	-0.07	2.65
Soil 4						
Conv. Furrow	-0.06	0.66	0.51	0.41	-0.09	4.13
Impr. Furrow	-0.08	0.83	0.30	1.18	-0.11	6.26
Sprinkler	0.00	0.02	0.01	0.02	0.00	0.05
LEPA	-0.01	0.05	0.03	0.07	-0.01	0.16

[a] Values represent the change in pounds of expected nitrogen percolation, E(NPERC), that is associated with a one unit change from the point of evaluation in each of the respective X variables, ceteris paribus. YIELD = crop yield (bu./acre), RAIN = rainfall (inches/year), NAPL = nitrogen applied (lbs./year), IRRIG = irrigation applied (inches/year), ET_p = evapotranspiration.

[b] E(NPERC) is the predicted value of nitrogen percolation using the estimated coefficients from the tobit model and setting the X variables at levels representative of current production practices in the study area.

Table 6. The Partial Derivatives of the Cumulative Density Function With Respect to the Independent Variables, Irrigated Corn Production.

	Probability Partials [a]					
Soil Type/	YIELD	RAIN	NAPL	IRRIG	ET_p	P(NPERC>0) [b]
Irr. System	bu.	in.	lbs.	in.	in.	
Soil 1						
Conv. Furrow	0.00	0.05	0.03	0.03	-0.01	0.75
Impr. Furrow	0.00	0.03	0.01	0.04	0.00	0.87
Sprinkler	0.00	0.03	0.01	0.03	0.00	0.12
LEPA	0.00	0.03	0.02	0.04	0.00	0.14
Soil 2						
Sprinkler	0.00	0.02	0.00	0.03	0.00	0.90
LEPA	0.00	0.02	0.00	0.03	0.00	0.91
Soil 3						
Sprinkler	0.00	0.05	0.01	0.06	-0.01	0.26
LEPA	-0.01	0.06	0.01	0.08	-0.01	0.45
Soil 4						
Conv. Furrow	-0.01	0.06	0.04	0.03	-0.01	0.59
Impr. Furrow	0.00	0.05	0.02	0.07	-0.01	0.74
Sprinkler	0.00	0.01	0.00	0.01	0.00	0.02
LEPA	0.00	0.01	0.01	0.02	0.00	0.05

[a] Values represent a change in the probability of expected nitrogen percolation being above zero that is associated with a one unit change from the point of evaluation in each of the respective X variables, ceteris paribus. This is done for each of the soil types and irrigation systems. YIELD = crop yield (bu./acre), RAIN = rainfall (inches/year), NAPL = nitrogen applied (lbs./year), IRRIG = irrigation applied (inches/year), ET_p = evapotranspiration.

[b] The probability that nitrogen percolation is greater than zero at the point of evaluation for the X variables is given by Φ, the cdf of the standard normal evaluated at $X\beta/\sigma$.

Table 7. Coefficient Estimates and Asymptotic T-Ratios, Irrigated Wheat Production.

Variable Name [a]	Regression Coeff. [b]	Asymptotic T-Ratios
YIELD	0.026**	2.142
RAIN	0.781***	11.424
NAPL	0.095***	4.359
IRRIG	0.445***	6.895
ET_p	-0.765***	-5.387
S_1	0.870	0.546
S_2	5.992***	3.812
S_3	5.734***	3.726
SYS_1	-35.785	-1.186
SYS_2	-35.255	-1.148
SYS_3	-0.498	-1.176
CONSTANT	-16.821***	-5.942

[a] YIELD = crop yield (bu./acre), RAIN = rainfall (inches/year), NAPL = nitrogen applied (lbs./year), IRRIG = irrigation applied (inches/year), ET_p = evapotranspiration, S_i = Soil i, SYS_1 = conventional furrow, SYS_2 = improved furrow, SYS_3 = center pivot.

[b] *** = .01, ** = .05, and * = .10 significance levels. Two-tailed tests versus zero were conducted.

Table 8. Joint Hypothesis Tests, Irrigated Wheat Production.

Combinations of Coefficients	Wald χ^2 Statistic	Prob. Value [a]
All Coefficients	269.97	.0000
S_1, S_2, S_3	28.12	.0000
SYS_1, SYS_2, SYS_3[b]	3.91	.2708
S_1, S_2, S_3, SYS_1, SYS_2, SYS_3	34.58	.0000

[a] If the probability value is less than the critical value of the reader's choice, the set of coefficients is significantly different from zero.

[b] SYS_1 = conventional furrow, SYS_2 = improved furrow, SYS_3 = center pivot.

Table 9. The Partial Derivatives of Nitrogen Percolation With Respect to the Independent Variables, Irrigated Wheat Production.

	Partial Derivatives [a]					
Soil Type/ Irr. System	YIELD bu.	RAIN in.	NAPL lbs.	IRRIG in.	ET_p in.	E(NPERC) [b] lbs.
Soil 1						
Conv. Furrow	0.00	0.00	0.00	0.00	0.00	0.00
Impr. Furrow	0.00	0.00	0.00	0.00	0.00	0.00
Sprinkler	0.00	0.00	0.00	0.00	0.00	0.00
LEPA	0.00	0.00	0.00	0.00	0.00	0.00
Soil 2						
Sprinkler	0.02	0.55	0.07	0.31	-0.54	2.46
LEPA	0.02	0.51	0.06	0.29	-0.50	2.13
Soil 3						
Sprinkler	0.02	0.54	0.07	0.31	-0.53	2.44
LEPA	0.02	0.49	0.06	0.28	-0.48	2.01
Soil 4						
Conv. Furrow	0.00	0.00	0.00	0.00	0.00	0.00
Impr. Furrow	0.00	0.00	0.00	0.00	0.00	0.00
Sprinkler	0.00	0.00	0.00	0.00	0.00	0.00
LEPA	0.00	0.00	0.00	0.00	0.00	0.00

[a] Values represent the change in pounds of expected nitrogen percolation, E(NPERC), that is associated with a one unit change from the point of evaluation in each of the respective X variables, ceteris paribus. YIELD = crop yield (bu./acre), RAIN = rainfall (inches/year), NAPL = nitrogen applied (lbs./year), IRRIG = irrigation applied (inches/year), ET_p = evapotranspiration.

[b] E(NPERC) is the predicted value of nitrogen percolation using the estimated coefficients from the tobit model and setting the X variables at levels representative of current production practices in the study area.

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VITA 2

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