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Tradeoffs in balancing multiple objectives of an integrated agricultural economic and environmental system

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Tradeoffs in balancing multiple objectives of an integrated agricultural economic and environmental system

by

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To
MY FATHER

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CHAPTER I. INTRODUCTION

Nonpoint source (NPS) pollution of ground and surface water resources is a national concern. Agriculture is the major source of nonpoint contamination of rivers and lakes (USEPA 1992). More than 60 percent of pollution of these water bodies is from sediment, nutrients, and pesticides. Because of the continuing NPS pollution, and despite more than a decade of policy, research, and intervention, the relation between agricultural production and environmental quality is still the subject of ongoing debate. Encouraged by the federal commodity programs, agricultural production is becoming chemically intensive and less sustainable. Furthermore production is being extended into marginal and environmentally susceptible lands at an increasing rate. These are but examples of the type of conflicts between agriculture and environment. To address these conflicts, farm policies have been reoriented to reduce the environmental impacts of agricultural production (Reichelderfer 1990, Johnson et al. 1990). The Food Security Act (FSA) of 1985 was a timely move in terms of farm legislation and USDA environmental policy.[1]

The conflicts among environmental objectives, such as soil erosion and agricultural chemical pollution control, makes the integrated economic and environmental management more difficult. Agricultural nonpoint source pollution control policies targeted to a specific pollutant may negatively impact other environmental systems. For instance, conservation tillage, aimed at controlling soil

[1] The two major policies proposed in the FSA of 1985, Conservation Compliance and the Conservation Reserve Programs, tie program eligibility with soil conservation and are examples of coordination.

erosion, may substitute chemical weed control for tillage. Increased chemical use and greater surface water retention with conservation tillage may lead to increased chemical loading. Groundwater, in particular, is more vulnerable because of the increased chances for leaching (Hinkle 1983), suggesting that certain soil conservation policy/measures may lead to increased groundwater pollution.

On the other hand, water quality policy, such as a regulatory standard on the allowable maximum contaminant level (MCL) of a target pollutant, may shift cultivation practices away from chemical-intensive conservation tillage. These shifts may lead to increased soil erosion, surface runoff, and sediment loading suggesting a conflict between water quality and soil conservation policy. Ground and surface water quality are multidimensional described by attributes, such as sediment, nutrient, and chemical content. Therefore, evaluations of water quality and NPS pollution policies must be carried out in a comprehensive framework capable of accommodating the unfavorable tradeoffs and unwanted conflicts of alternative interventions or measures. Lee and Lovejoy (1991; pp. 61) succinctly spell out the need for an integrated assessment of environmental effects from agricultural production:

> Society's new demands for a cleaner environment coupled with the traditional demands for productivity enhancement will require a multi-disciplinary research effort to address these complex issues and tradeoffs. Therefore, a challenge for future research is to consider the simultaneous impact of crop production practices on multiple factors from the vast array of environmental parameters. A contemporary example would be for our research to consider both soil conservation and water quality impacts of alternative production systems and alternative policies.

Theoretical results of evidence on agricultural and environmental policy conflicts is inconclusive, at best (Leathers and Quiggin 1991). Answers to policy issues involve empirical questions and are crucial for successful NPS pollution policy. Sharp and Bromley (1979) were among the first to conceptualize the problem of coordinating targeted nonpoint controls. Milon (1986) suggested an analytical framework to address the interdependent risks created by nonpoint externalities. But, this research effort has remained more at the conceptualization stage for the past decade. Lack of data and research methods and tools, were primary reasons for the limited empirical research and applications of the targeting results in policy contexts.

Mounting environmental concerns and problems of sustainable agricultural productivity increases linked to improvements in environmental quality underlie the urgent need for added research and methods for supporting improved integrated economic and environmental management. With the growing focus on ecosystems and policy tradeoffs the tools for analysis must have the capacity to address regional as well as local and farm level management. To date, the CEEPES (Comprehensive Economic and Environmental Policy Evaluation System) developed jointly by the Center for Agricultural and Rural Development, Iowa State University and the U.S.Environmental Protection Agency (USEPA) is the most comprehensive analytical system available for applied regional scale policy analysis (Johnson et al. 1990, Bouzaher and Shogren 1993).

Integrating economic and environmental systems capable of comprehensive public policy evaluation typically incorporate multiple objectives. Particularly for agricultural NPS pollution and water quality problems, policy issues involve multiple economic and water quality objectives. In an integrated system, sometimes in addition to them, there are also often several competing environmental objectives. Invariably, these objectives conflict with one another and the policy choices involve significant tradeoffs. Also these multiple objectives are not independent. Thus, there may be significant gains from simultaneous consideration of all these objectives in a multiple objective framework instead of a piecemeal evaluation. A piecemeal evaluation that redirects the crop production and management decisions in favor of achieving a single objective may worsen the desirable levels of other objectives.

Given the current state of heightened environmental concern, the single objective approach is limited because it must intrinsically accord less importance to economic or environmental objective. Also, because of certain characteristics from the underlying real processes, which are interdependent, and the inherent uncertainty in virtually all natural resource systems, the single objective approach has major drawbacks as to formulation for such problems. This research will develop a conceptual framework for integrated agricultural economic and environmental modeling using multicriteria decision making approach grounded in multiattribute utility and social welfare theory. The empirical analysis and policy exercise is on a regional scale defined for an environmentally meaningful geographical unit (watershed). However, for more meaningful measurement of production and resource quality parameters at the regional scale, models should adequately capture the spatial heterogeneity of these parameters as well (Braden et al. 1989).

Therefore, a major challenge of the policy exercise is in obtaining the excessive site-specific data for quantifying the selected environmental attributes. Also, a simple and scientifically valid statistical tool for extrapolation and aggregation of these site-specific attributes to regional levels is required. The tool applied is called the

Metamodel, a statistically validated response function fitted to the biogeophysical outputs from calibrated mathematical simulation models (Bouzaher et al. 1993). Using mathematical simulation models to simulate the complex processes is gaining popularity among research community for NPS evaluations (Ellis et al. 1991). Studies by Anderson et al. (1985), Milon (1987), Taylor (1991), Setia and Piper (1992), and Crutchfield (1992) have all used simulation models for analysis of agricultural NPS pollution. These studies, however, have tied the simulation models directly to the economic specification resulting in limited scope and expensive computations if alternative policy scenarios are to be evaluated.

Conducting site-specific field experiments at various locations within a region to obtain detailed data is an immense task. Hence, calibrated crop-growth and resource-impact simulation models have come to be applied to augment this extensive task. Mathematical process models which can be used to estimate nonpoint impacts of alternative production and management practices, *ex ante*, are available. These models facilitate site-specific evaluations based on computer simulations of real-life processes. Combining the simulation systems with statistical design and the metamodeling technique, spatial and technical heterogeneity can be captured with reasonable confidence and at reduced cost. Furthermore, these spatial results can be statistically aggregated to regional levels—the appropriate scale for most resource policy analysis.

The metamodeling approach is robust, enabling "efficient" integration of process models in economic analysis. Efficient in the sense that the evaluation of alternative policies can be accomplished by extrapolating the estimated metamodels for the new sets of underlying parameters without having to resimulate the system. Additionally, the multivariate statistical procedures applied permit joint estimation of multimedia (groundwater and surface water) attributes, which is not possible with the currently available simulation models (Clendening et al. 1990). Therefore, the metamodeling approach is a major research innovation in the economic analysis of environmental policy. Estimating simple response functions to explain the output from complex process models is a powerful tool that simplifies the burden of computation implied by this integrated policy evaluation system.

The comprehensive multiobjective decision making model is empirically verified for a specific watershed in the Corn Belt. Specifically, the hydrologic area representing the water resources aggregate sub area 703 (WRC 1970) is the area of study. This aggregate sub area is commonly referred to as producing area 41 (PA 41) and it comprises most of central and eastern Iowa. This is an agriculturally important area and a major watershed drained by the two major river systems, Mississippi and Des Moines river systems. It is important both for crop production and nonpoint pollution potential. This watershed comprises nearly 25 million acres of cropland (6% of the national cropped area). In 1990 it produced $4.3 billion worth of crops, representing about 5% of total U.S. crop receipts. Corn grain and soybeans are the two major crops in the area accounting for nearly $4.1 billion and 21 million acres.

In 1990, nearly 3,048 million pounds of commercial fertilizers and 51 million pounds of pesticide active ingredients (a.i.) were used on major crops grown in Iowa (USDA 1991). On an average, 127 pounds of nitrogen and 58 pounds of phosphorus were applied per acre per crop year. Nearly 96 percent of corn acres is treated with atrazine, a major corn and sorghum herbicide, at an average rate of 1.27 pounds a.i.

per acre per crop year. With such intensive chemical use the potential for agricultural NPS pollution is significant. The intensive production and chemical use coupled with the existence of diverse ecosystems makes this an ideal watershed for this study examining the potential tradeoffs of economic-environmental policies.

The Mississippi river which flows through the watershed serves as a major carrier of surface water pollutants (sediment, nutrients, and chemicals) posing a potential threat to downstream. The U.S. Geological Survey (1991) reported that 27% of the samples tested from the river showed concentrations of atrazine exceeding the maximum contaminant level for drinking water. A similar study for groundwater, reported that in Iowa 24% of the municipal wells had detectable concentrations of atrazine. Madison and Brunett (1984) also reported that 5-10% of the wells sampled in Iowa showed Nitrate-Nitrogen (NO_3-N) concentrations exceeding the MCL (10 mg/L). The rate of eutrophication of surface water bodies is suspected to have been accelerated by the NPS loading of phosphorous. The annual rate of sediment loading and the associated costs of desilting is also of concern. Craig and Anderson (1992) reported that suspended sediments in the Mississippi river, as it leaves Iowa, increased to 240 mg/L from 18 mg/L at a point East of Minneapolis. In the same stretch of the river, nitrogen and phosphorous loads increased to 1.0 and 0.28 mg/L, respectively, from 0.9 and 0.13 mg/L.

The empirical application in this thesis will test the following general hypothesis: "Given that environmental externalities are products of complex physical processes and interactions, influenced by management and production decisions, evaluations of resource and environmental protection policies should be accomplished in a comprehensive framework to minimize conflicts and maximize social welfare gains." The intent is to develop and implement a framework for policy analysis that provides better information for understanding why some environmental problems persist despite evolving policies, technologies, and market incentives. This research evolves from the CEEPES framework, which is an operational system addressing policy questions concerning atrazine, and extends it to address the nutrient and soil erosion elements of the water quality vector. The specific objectives of the study are:

1. to more fully motivate the importance of incorporating environmental externalities in agricultural production decisions;
2. to demonstrate that piecemeal and media specific NPS pollution policies are suboptimal since they ignore the complex physical process interactions;
3. to develop a framework integrating economic and environmental policies, using a multiobjective decision system, directly motivated by multiattribute utility and social welfare theories;
4. to show that metamodeling is a robust tool for estimating reduced form equations for multimedia environmental impacts from soil erosion and chemical fate and transport, capturing both spatial and technical heterogeneity thus allowing regionalization and aggregation; and
5. to develop an integrated multicriteria decision model for a specific Corn Belt watershed, apply the integrated economic and environmental policy model for understanding the tradeoffs and optimum choices.

The thesis is organized as follows.

Chapter I gives a general background and sets out the objectives and scope of the study. Chapter II reviews issues concerning agricultural NPS pollution assessment and multicriteria optimization principles and techniques. In Chapter III, using a social utility function the consequences of piecemeal approach to water quality problem are derived and the tradeoff between soil and water quality is illustrated with this model. A theoretical multiobjective decision model is developed based on social welfare and multiattribute utility theories. Based on the principles of multidisciplinary integration, a conceptual framework is suggested to integrate the economic-environmental models.

In Chapter IV description of the empirical tools, sampling procedures and simulation experiment design, data and technology sets, and spatial aggregation procedures are provided, including a description of the interface between the physical process model and the economic behavioral model provided by metamodels. The major crops grown in this watershed, such as corn, soybeans, oats, winter wheat, hay, and sorghum, are included in this analysis. The environmental indicators modeled are soil erosion, nitrate-N in runoff and percolate, and atrazine in runoff and percolate. Besides conventional tillage, soil conserving tillage systems, such as reduced till and no-till were modeled to study the impacts of tillage on environmental loading. Chapter V summarizes the results. The first section summarizes the physical model results of long term average values of environmental indicators, briefly describes metamodel development process and the estimated metamodels for each of the environmental indicators. The second section elaborates the alternative policy scenarios and the economic and environmental impacts and tradeoffs as indicated by the multiple objective scenario analysis.

The spatial distribution of various environmental indicators are valuable information for targeting the policies to problem areas within this watershed. Since the data on soil, hydrology, weather, and production practices are specific to this watershed, the results are not directly applicable to other areas. But, the results could be generalized to areas with similar spatial attributes. Long term average nitrate-N concentration in surface water is estimated at 5.3 ppm, which is close to the actual measurements in the region, 5.6 ppm. Likewise, the predicted long term average leaching losses of nitrate-N is within the range of actual measurements from sample wells and near surface aquifers.

The results from simulating four different policy scenarios, representing soil quality (S1), surface water quality (S2), groundwater quality (S3), and a comprehensive scenario addressing soil and water quality jointly (S4) are discussed. Major findings and conclusions of the policy simulation exercise are: (i) there is significant tradeoff between the economic and environmental goals and, even between the environmental goals, therefore a comprehensive analysis with reasonable compromise will give an ideal solution; (ii) a soil loss reduction goal of not exceeding the 2T level will reduce the net returns by 21%, which translates into $1.88 per ton of soil. Also, this policy resulted in increased impairments to groundwater quality; and (iii) a multiobjective scenario minimizing soil loss to 2T levels and not allowing nitrate-N and atrazine leaching to exceed the baseline resulted in 43% decrease in returns, but both surface and groundwater quality improved relative to baseline.

CHAPTER II. LITERATURE REVIEW

Agricultural Pollution Externality and Social Optimum

Agriculture is the single largest contributor of sediment and chemical pollutants to the major water bodies, including groundwater. Agricultural production decisions and the physical environment in which the effects of these decisions are realized influence soil erosion, surface runoff, and subsurface leaching, and are reflected as soil and water quality problems. Phipps (1991) and Lee and Lovejoy (1991) identify potential environmental problems related to agriculture. The pollution from agricultural runoff and leaching is in general a nonpoint externality. An externality may arise when there exists a good for which market / price guided allocation fails. As a result of such market failures and price distortions private decisions do not produce a socially desirable allocation of resources (Baumol and Oates 1975).

Nonpoint externality is different from point externality, in that it is not economical to continuously monitor emissions on a wide spread scale. Furthermore the technical problems are abound in measuring nonpoint emissions. The uncertainty introduced by weather and hydrologic conditions coupled with spatial heterogeneity makes monitoring on a regional scale impractical. Griffin and Bromley (1982) give the following definition, "A nonpoint externality exists whenever the externality contributions of individual economic agents can not be practically measured by direct monitoring." Ever since Griffin and Bromley suggested a theoretical framework for addressing nonpoint externality and policy instruments to control it, several theoretical and empirical works were published (Shortle and Dunn 1986, Milon 1987, Braden et al.

1989, Zeitounni 1990, Weinberg 1991, Setia and Piper 1992, Zhu et al. 1993). Two major conclusion of these studies are: (1) agricultural nonpoint source pollution is heterogenous requiring evaluation at a site-specific level, preferably the soil level; and (2) the pollutants are related to one another and as a result a simultaneous evaluation is required if the ultimate goal is to reduce all pollutants in the resource media.

The first major conclusion from these diverse studies is that the relative performance of alternative soil-conserving and water quality-preserving production systems is site-specific. Therefore, any evaluation of these systems at a regional or watershed level should consider the spatial heterogeneity. That is, to determine the sustainability of alternative tillage and management systems, spatial factors such as climate, hydrology, soil type, and the production and management factors and their interactions need to be fully captured. However, conducting site-specific field experiments at various sites within a region or monitoring each field is an immense task, hence calibrated crop-growth and resource-impact simulation models can play a important role. Mathematical models which estimate nonpoint emissions from alternative production and management practices, *ex ante*, are available to facilitate site-specific evaluation using computer simulation of real-life processes (Wagenet and Hutson 1991, Ellis et al. 1991, and Dillaha and Gale 1992). These models, however, have to be calibrated to the site-specific parameters before they can be used for prediction. Another limitation of using these models is that they are accurate only to within a factor of 2 or 3, and their predictions should be used with full consideration of these factors (Jones et al. 1991). Lastly, uncertainty exists in our comprehension of physical processes and in our ability to characterize those processes quantitatively. Therefore, uncertainty exists in the output of any such mathematical models.

Even though the theory recognizes the need for simultaneity in addressing nonpoint source pollution, as production decisions result in more than one pollutant simultaneously impacting the quality of more than one media, the empirical attempts were thus far piecemeal or sequential. As a result, the problem of NPS pollution persists despite a decade of policy and research effort. Milon 1987, Crutchfield et al. (1992), Yakowitz et al. (1992), Setia and Piper (1992), Wossink et al. (1992), and Zhu et al. (1993) are the pioneering works addressing the agricultural NPS pollution problem by simultaneously prescribing controls on all potential pollutants. These studies indicate that an evaluation of multiple soil and water quality objectives can be an important planning tool for designing nonpoint source controls for innovative programs to promote cost-effective nonpoint source regulations. Thus, the need for a comprehensive analysis of NPS pollution is currently gaining precedence. In preparation for the 1995 farm bill and the upcoming Clean water Act reauthorization the USDA has moved comprehensive resource policy evaluation on top of its agenda.

Economic and Environmental Tradeoffs

Two types of tradeoffs are recognized: (1) the tradeoffs between farm income support programs and environmental quality protection measures and (2) the tradeoffs between piecemeal environmental protection programs. To facilitate the development of appropriate sustainable agricultural policies, the nature of these tradeoffs need to be fully understood. The tradeoff between economic goal and environmental quality is a widely recognized and researched topic (Taylor and Frohberg 1977, Heimlich and Ogg 1982, Milon 1987, Crutchfield et al. 1992, Setia and Piper 1992, Bouzaher and Shogren 1993). These studies conclude that the soil and water quality regulations imply shifts in cropping patterns and resource use. They also find commodity prices to go up as a result of such environmental regulations.

Significant research has been done to analyze the tradeoff between economic efficiency and soil conservation (Fox et al. 1991). The published evidence, however, on the relative profitability of alternative soil-conserving systems is mixed. Studies by Klemme (1983), Berglund and Michalson (1981), Mikesell et al. (1988), and Setia and Piper (1992) all find conventional tillage systems to be profitable, relative to chisel and no-till systems, but more erosive. They also conclude that a farmer's choice of tillage systems is influenced by his or her risk taking capacity as most of the conservation tillage systems are risky relative to conventional tillage. Klemme evaluated net returns to land and management from conventional and no-till planting systems in corn. Conventional tillage system gave a net return of $179 per acre compared to $162 per acre from no-till system. Even though in a few cases soil-conserving systems tend to be profitable, additional gains of soil conservation can be obtained only at the expense of farm income. That is, the marginal cost curve is a positive and increasing function of soil conserved at least after a certain point. Besides income loss, there is also evidence that conservation systems tend to increase the potential for chemical residue in ground and surface waters because of increased chemical dependence of these systems (Milon 1987). Therefore, soil-conservation in isolation, is not the answer to reducing erosion without compromising on income and water quality.

Several studies have addressed the problem of Nitrogen (N) and Phosphorus (P) contamination of water resources. Swanson (1982) reviews studies addressing pollution caused by excessive N fertilizer and the economic impacts of alternative controls on N fertilizer and nitrate-N emissions. Nitrate-N is the major nonpoint pollution problem resulting from inorganic N-fertilizer application. Research over the past 10 years has shown that agriculture is the most extensive source of nitrate-N delivered to groundwater and surface waters (Hallberg 1987). During major rainfall events levels of nitrate-N exceeding the drinking water standard of 10 ppm have been detected in the ground and surface waters of Iowa (Keeney and DeLuca 1993). Most of the work done in this area used mathematical programming models, which allows adjustments in cropping pattern in response to regulations on N use or emissions.

Crop substitution, mostly substituting soybean for corn, split and stress based application of N, reducing N rates according to seasonal soil test prescribed "agronomic" rates of application, and lastly taking credits for N fixed by legumes are some of the alternative decisions available to minimize economic impacts of N controls (Swanson 1982, Taylor and Frohberg 1977). Phosphorus is mostly a surface water problem showing up as labile (soluble) P concentration in lakes and reservoirs. Milon (1987) addressed the problem of controlling multiple effluents including phosphorous loading in ground and surface water bodies. His results suggest that the multiple effluent constraints significantly increase the cost of nonpoint controls but the effect vary by control alternative.

A potential tradeoff resulting from fertilizer use restrictions is the shift in chemicals used to control pests. These shifts could either be positive or negative depending on the production and management decisions and risk bearing capacity of the farmers. For instance, risk-averse farmers tend to substitute pesticides if policy regulations limit their use of fertilizers, primarily to minimize the yield risk (de Janvry 1972, Pope and Kramer 1979). If as mentioned before, a crop substitution takes place substituting soybeans for corn then overall chemical use may decline. It is widely recognized that a corn-soybean rotation requires no insecticides and possibly less herbicides, because crop rotations tend to break the pest cycle.

Modeling Economic-Environmental Decisions

Lately, the strategy of combining simulation models with mathematical programming models in order to evaluate alternative resource policy scenarios has become the state-of-the-art technique for integrated assessment. Studies by Anderson et al. (1985), Milon (1987), Taylor (1991), Wossink et al. (1992), Setia and Piper (1992), Zhu et al. (1993) are examples of using this strategy for integrated assessment. A bibliographic survey of these and other related studies can be found in Ellis et al. (1991). Lee and Lovejoy (1991) identify problem areas where integrated assessment of environmental effects from agricultural production is a rule rather than exception. NPS pollution policy making to protect soil and water quality is one such area needing integrated assessment.

Single objective linear and nonlinear programming, recursive dynamic programming, goal programming, and multiple criteria optimization using weighted goal programming and compromise programming techniques are the popular decision tools. Programming methods are well suited for economic and environmental research because: (1) they allow relative flexibility in depicting a large array of economic and ecological conditions, so that many activities and restrictions can be modelled at the same time, (2) an explicit and efficient optimizing procedure is provided, and (3) new production techniques and BMPs can be easily incorporated.

Anderson et al. (1985) propose an analytical model for water quality evaluation. The model specifies that the farmers select vector of inputs, which simultaneously maximizes net revenues and satisfies the water quality constraint that the total loading be less than the permissible loading (MCL). Millon (1987), using an integrated watershed model specified in a chance-constrained framework, generates probability distributions for agricultural effluent in ground and surface water resulting from agricultural practices. In this framework, surface runoff and infiltration models were combined to estimate expected values and distributions of effluent for alternative BMPs. He concludes that evaluating multiple water quality objectives is an essential planning tool.

Wossink et al. (1992) extends the linear programming optimization models employed in farm economics with an environmental component to analyze and evaluate the effects of alternative environmental policy instruments for agriculture. Yakowitz et al. (1992) develop a prototype decision support system, with embedded computer simulation models to rank feasible management practices using multiobjective theory. Zhu et al. (1993) developed a multiobjective dynamic programming model with the embedded physical simulation model to empirically evaluate the economic and environmental impacts of 14 agricultural management systems. Bouzaher, Lakshminarayan, and Johnson (1993) use a goal programming framework to analyze simultaneous restrictions on soil erosion, fertilizer use, and herbicide use with the economic goal of achieving not less than the baseline level of profits. These studies suggest that multicriteria decision making model is an important planning tool for evaluating agricultural economic and environmental policies.

Multicriteria Decision Methods

Several decision methods are available to solve the vector maximization problem. In general, multicriteria decision methods are categorized into:

1. Preference-Based Direct Methods: methods that use fully prespecified preferences and multiple objective decompositions in a multiattribute utility / value theory context.
2. Mathematical Programming Based Tools: methods that do not require complete prespecification of the DM's preferences. They use the mathematical distance measures to approximate DM's preferences (Zeleny 1974).
3. Interactive Approach: methods that use progressively revealed preferences from the DM (Zionts and Wallenius 1976).
4. Outranking Relations Approach: methods that use partial ranking of the feasible decisions in order to help the DM (Roy 1973, Vincke 1986).

The outranking and interactive methods require costly and frequent man-machine interaction requiring the DM to provide precise estimates of local tradeoffs, which is infeasible and expensive for public policy applications involving several objectives. Wallenius (1975) and Szidarovsky et al. (1986, pp 103-172) provide an overview of the these two approaches.

By standard convention, multiattribute value theory (MAVT) addresses deterministic problems and multiattribute utility theory (MAUT) deals with the case where uncertainties are present (French 1983). The axiomatic development of MAUT (Fishburn 1970, Keeney and Raiffa 1976) is mostly based on the von Neumann and Morgenstern (1947) expected utility theories. Farquhar (1977) provides an excellent review of these methods. In public policy problems: (1) it is hard to find a scale for measuring the value of each attribute, and (2) the impact of stochastic elements in these decision processes is very common. Therefore, specifying deterministic value functions is not possible, whereas MAUT is more appropriate for such problems.

As a first step, MAUT requires that DM's preferences for each attribute (criterion) i, can be represented by a real-valued function u_i such that the choice vector $\underline{x}'$ is better than $\underline{x}^{*}$ iff $u_i(\underline{x}') > u_i(\underline{x}^{*})$. The existence of the utility function u_i and its uniqueness up to a positive affine transformation, that is utility function u_i preserved for linear transformations, are proved in the axiomatic development of utility theory. As a next step, these multiattribute utility functions are aggregated into an unique global preference function, such that the initial multicriteria problem is translated into an optimization problem.

Two fundamental assumptions (additive independence and utility independence) are invoked to explain the aggregation of multiattribute utility functions. To explain these assumptions, the following notations will be used. Let the consequences of alternative decisions be represented by a vector of attribute levels: $\underline{x} = (x_1, x_2, \ldots, x_n) \in X$. This simply states that the consequences in X are n-tuples. That is, X is a subset of the Cartesian product of other sets $X = X_1 \otimes X_2 \otimes, \ldots, \otimes X_N$, where X_i is the set of possible levels for the i^{th} attribute. Given that $I \subset \{1,2,\ldots,N\}$, $I \neq \phi$, define

$X^A = \otimes X_i, \forall i \in I$ and $X^B = \otimes X_i, \forall i \notin I$,

such that,

$X = X^A \otimes X^B$ and $\underline{x} = (\underline{x}^a, \underline{x}^b)$.

French (1983) labels this type of restructuring of X as "decomposition".

Additive Independence: Given a decomposition (X^A X^B) of X, then X^A and X^B are additively independent of each other if preferences between probability measures (gambles) on both X^A and X^B, depend only on the marginal[2] gambles of X^A and X^B.

Utility Independence: Given a decomposition (X^A X^B) of X, then X^A and X^B are utility independent if preferences for gambles over (X, $\underline{x}^b$), conditioned on a fixed level of $\underline{x}^b \in X^B$ depend only on the marginal gambles over X and are independent of those fixed level of $\underline{x}^b$.

Keeney and Raiffa (1976) show that if the decompositions (X_i^A, X_i^B) are mutually utility independent for all decompositions of the n-tuples of X and the utility function on X is bounded, then the DM's preferences will be represented by either the multiplicative form, or, if additionally the additive independence condition holds for all decompositions, then the multiattribute utility function takes a simple additive form.

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[2] If P is a probability measure defined on the set of all subsets of X, then the marginal probability measure of P on X_i is defined as: $P_i(Z_i) = P\{(\underline{a}|\underline{a} \in X, a_i \in X_i)\}$, $\forall Z_i \subseteq X_i$.

There are several mathematical programming methods available for generating nondominated solutions for multicriteria decision problem. Hwang and Masud (1979), Romero (1986), and Lieberman (1991) are excellent survey articles of multiobjective mathematical programming methods. Some of the widely used programming methods are the method of sequential optimization, the ϵ-constraint method, the weighting method, and the distance based methods.

The method of sequential optimization, or, the lexicographic method, as it is usually called, involves preemptive ranking of the objectives according to some priority list and solves the multiple objective problem sequentially in the order of priority (Waltz 1967). Here, one solves the following problem at the n^{th} step:

maximize $f_n(\underline{x})$, s.t. $\underline{x} \in X$ and $f_i(\underline{x}) \geq \mu_i$, $i = 1,2,\ldots,n-1$,

where μ_i is the optimal value of n^{th} objective. The motivation for this approach is that individuals tend to make decisions in this manner. The disadvantage of this method is that it cannot identify all nondominated solutions. Also, note that the solution will be sensitive to the preemptive ranking, and therefore caution is warranted in applying this method when two or more objectives are equally important.

The ϵ-constraint method is identical to the constraint method proposed by Cohon and Marks (1973). Here the DM arbitrarily chooses an objective f_k for maximization subject to the regular feasibility conditions and for the remaining objectives f_j, $j \neq k$ and $j,k = 1,2, \ldots,q$, there exists some thresholds ϵ_j. Thus the method involves solving for f_k subject to the additional constraints representing these ϵ_j . The disadvantage of this method is in choosing f_k and the bounds ϵ_j. In terms of

MAUT, this approach implies that the benefits to society from objective f_k is a constant as long as the bounds ϵ_j are satisfied, and infinitely harmful otherwise.

The weighting method, proposed by Zadeh (1963), requires the use of nonnegative weights (with at least one being positive), which determine the relative importance of the objectives. From utility theoretic perspective this implies additively linear utilities. The implication of additively linear utilities is that the marginal utility of the kth objective is constant and is equal to the kth weight, and the negative of the ratio of weights is independent of the level of objectives (constant MRS between the objectives). That is the willingness to tradeoff between the objectives is independent of the level of objectives. The formulation is as follows:

$$\text{maximize} \sum_{i=1}^{q} c_i f_i(\underline{x}), \quad \text{s.t. } \underline{x} \in X.$$

These methods impose unrealistic behavioral assumptions and there is need for preference articulation. In a complex integrated system with several objectives, all of which are equally important, articulation of preference information either in the form of preemptive ranking or parametric weights is quite difficult. So it is absolutely necessary to do sensitivity analysis by parametrically varying these weights. This will produce a large number of nondominated solutions and to choose the best-compromise solution from this set of nondominated solutions is not a trivial matter.

The distance based methods, which do not require explicit articulation of subjective preferences in identifying the nondominated solution set, seem to be appropriate for public policy problems. They use the mathematical notions of distance from the "ideal" point, which is infeasible (Zeleny 1974 1982). Suppose $\underline{f}^*$ is the ideal pay-off vector (set of "ideal" simultaneous pay-off values), then the problem is,

maximize $L\ (f_i(\underline{x}),\ f_i^*;\ i=1,2,\ldots,q)$ s.t. $\underline{x} \in X$,

where L is the distance measure. The L_p-norm with $p \in (1,\infty)$ and the L_g-norm (geometric distance) are the two standard distance measures used. It can be proved that all these methods yield nondominated solutions (Szidarovsky et al. 1986).

The L_p-norm, where the best-compromise solution is chosen based on a geometric notion of best, is stated as

$$L_p = \Big[\sum_{i=1}^{q} |f_i^* - f_i(\underline{x})|^p\Big]^{1/p}, \quad 1 \leq p \leq \infty.$$

If all objectives are defined as maximization objectives and $f_i^* > f(\underline{x})$ then we can drop the absolute sign. Depending on how the distance metrics and the ideal point f_i^* are defined we have two different but related distance-based techniques, namely, goal programming and compromise programming. In the goal programming problems the ideal point is defined by a set of goals (target values) for the objectives, and in the compromise programming problem the point whose coordinates are the optimal values of the individual objectives is the ideal point.

Goal programming was first presented by Charnes and Cooper (1961). It is used in solving wide range of problems, including agricultural resource management problems. Romero (1986) provides a state of the art survey of both theoretical and empirical applications of goal programming. Goal programming employs a minimum-distance notion of best, and the L_p-norm with p = 1 is usually used. The goal programming problem minimizes deviation from the goals,

$$\text{minimize } L_1 = \sum_{i=1}^{q} \left| f_i^G - f_i(\underline{x}) \right| \text{ s.t. } \underline{x} \in X.$$

A piecewise linear version of the above equation, where the positive and negative deviations of the i^{th} objective from its goal is minimized,

$$\text{minimize } \sum_{i=1}^{q} (d_i^+ + d_i^-),$$

$$\text{s.t.} \quad f_i(\underline{x}) - d_i^+ + d_i^- = f_i^G,\ i=1,2,\ldots,q,$$

$$\underline{x} \in X \text{ and } \underline{x},\ d_i^+,\ d_i^- \geq 0.$$

The above problem can be solved by preemptive ranking of the objectives, which is a lexicographic method, or by a nonpreemptive weighting method. Sherali and Soyster (1983) show that, in the linear case, these two methods are equivalent.[3] Besides the usual limitations of the lexicographic and the weighting methods, in goal programming it is possible that a set of goals may indeed lead to an inefficient solution.

Compromise programming proposed by Zeleny (1974) minimizes the deviations from an ideal point, which is the solution to the problem of maximizing or minimizing the objectives individually. The alternative noninferior solutions are traced by varying the distance metric p between 1 and infinity. The parameter p plays the role of scaling factor between the L_1, weighted sum of objectives, and L_∞, the largest individual

[3] It could be demonstrated that, if a preemptive problem has an optimal solution then there exists a set of weights for the nonpreemptive problem, such that its optimal solution is identical to the preemptive optimum.

regret. The L_2-metric corresponds to minimizing quadratic deviations. Usually the compromise solutions corresponding to the L_1, L_2, and L_∞ metrics are determined. But a major weakness of this approach is that it is possible that the solutions corresponding to alternative choice of p may all be the same.

Multiattribute utility theory provides the motivation for multiple objective problems. This analytical tool has a strong axiomatic foundation for identifying and improving upon one's preferences based on the premise of rational choice in decision making. But using MAUT as a solution method for public policy problems is hard to implement. Since the programming methods are compatible with a wide range of problems, a natural option is to choose one of these methods. It is not a good practice, however, to arbitrarily choose a method (Hobbs et al. 1992) because (1) it inappropriately match methods with problem and (2) some of these methods impose unrealistic assumptions.

CHAPTER III. MULTICRITERIA EVALUATION OF NPS POLLUTION

The need for integrating the economic and environmental models to jointly evaluate agricultural chemical and soil erosion policies vis-a-vis economic efficiency was briefly outlined in the introduction. This chapter develops an analytical framework for integrated analysis of economic-environmental tradeoffs resulting from agricultural NPS pollution policies. The framework is developed as a multicriteria decision making (MCDM) problem so that economic goals and environmental policies can be jointly evaluated. The multicriteria evaluation is the most appropriate method for agricultural NPS pollution policies because of interactions among the various environmental processes and the influence of production decisions on these interactions.

Before outlining the conceptual framework, a theory of agricultural pollution externality will be developed and the factors motivating the farmers to endogenize environmental goals within the firms production decisions will be discussed. Also, optimality of the comprehensive and simultaneous treatment of the NPS pollution problem, where different resource media and different pollutants are addressed jointly, will be demonstrated.

Environmental Externalities and Social Optimum

Soil and water quality problems are typical environmental externalities resulting from agricultural production. These externalities, which are characterized by a lack of market and price signals, generally result in Pareto-suboptimal allocation of resources from society's point of view (Baumol and Oates 1975). Usually, Pigouvian taxes (that is, taxes set equal to the marginal social cost of damage of the effluent, evaluated at the optimum effluent level) achieve socially optimal solutions to environmental externality problems in the absence of other market distortions and transaction costs. *Transaction costs* are the costs associated with information gathering and policy design, implementation, and monitoring. The social costs of NPS damage is generally unknown, therefore, quantity based regulations are usually prescribed for NPS control. The parallel between the price and quantity guided instruments is clearly seen from the following proposition, demonstrated by Baumol and Oates (1975) for point externalities and Griffin and Bromley (1982) for nonpoint externalities.

Proposition 1. *The social cost of damage is generally unknown, in which case effluent taxes assure that any predetermined effluent standard will be achieved at least cost. If the standard is set equal to the socially optimal level, then the solution to the standards problem is also the optimum solution.*

Because of the difficulties in estimating social costs of damage, the later approach of achieving an effluent standard at least cost is used to show that the private profit maximizing solution is different from the social optimum when there are externalities. Assume that the effluent is produced by a subset of inputs. That is, the input vector comprises two subsets, of which one is environmentally safe input x and the other is polluting input z, such as tillage and chemical inputs. Consider a profit maximizing producer who chooses the inputs (x,z) to produce output Q. Associated with the input z is the effluent production D. The output and the effluent production functions are,

$$Q = f(x,z) \tag{1}$$

$$D = d(z) \tag{2}$$

Assume $f_x > 0$ and $f_z > 0$, that the set of feasible solutions (input choices) is a closed convex set, and that $f(.)$ is a twice-differentiable concave function over the feasible set. The effluent function d is assumed to be a continuous convex function with $d_z > 0$, which implies that z is a polluting input. The second-order conditions are assumed to hold. The usual assumptions on the effluent production function, namely that all effluents are discharged without any provision for storage or recycling and that equation (2) can adequately measure the emissions, are supposed.

The social objective is to maximize welfare, measured as net returns to the producer, subject to the constraint that the emissions do not exceed D^T the prescribed effluent standards[4]:

$$\text{Max}_{z,x,\mu} NR = pf(x,z) - p_z z - p_x x + \mu[D^T - d(z)], \text{ s.t. } z,x,\mu \geq 0, \tag{3}$$

where p is the price of output, p_z and p_x are the input prices, and μ is the shadow value (the opportunity cost) of the emissions constraint. The nonnegativity of the choice variables x and z is also imposed. The first-order conditions for an interior solution are:

$$pf_z = p_z + \mu d_z \tag{3.1}$$

$$pf_x = p_x \,. \tag{3.2}$$

Optimality requires that the value of the marginal product for each input be set equal to the price of input and the social marginal costs of the input, if any. The social marginal

[4] The effluent standard can be related to water quality or soil erosion. Water quality standards could be specified as the maximum contaminant levels (MCLs) of agricultural chemicals in the drinking water and the soil quality standards are the usual "T" restrictions (soil loss tolerance levels).

cost of the polluting input z is marginal emissions, multiplied by the shadow value of emissions. Therefore, the marginal unit cost of the input, z, is increased by the marginal cost of emissions. If the constraint is binding, it forces a reduction in the use of z and/or a simultaneous increase in the use of x.

The private optimization problem and the first-order conditions for an interior solution are given by:

$$\operatorname*{Max}_{z,x} \Pi = pf(x,z) - p_z z - p_x x, \tag{4}$$

$$pf_z = p_z \tag{4.1}$$

$$pf_x = p_x, \tag{4.2}$$

which is the standard competitive equilibrium solution of setting the marginal value product for each input equal to the price of input. If the emissions constraint is nonbinding, then $\mu = 0$, in which case the social and private solutions are the same. The environmental damages are strict externalities; therefore, in the absence of incentives or any alternative mechanism the social costs of damage will not be internalized from an individual producer's perspective.[5] An implication of this is that the producer will equate the ratio of marginal physical products to the price ratio of the inputs (ratio of private costs alone), as opposed to equating it to the ratio of private and social marginal costs. Given the assumptions on emission causing input z ($d_z > 0$), it can be seen that the ratio of marginal physical products at the social optimum will be greater than required to achieve the private profit maximizing solution.

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[5] Internalization is an approach commonly used to determine social optimality in the presence of externalities by considering jointly all of the involved agents.

There are several options by which the social optimum can be obtained in the presence of environmental externalities. These policy options generally include Pigouvian taxes or subsidies, direct regulations by way of design standards (limiting polluting input use) or performance standards (effluent standards / permits), assignment of property rights, moral suasion and education, and research and development. References abound in the NPS pollution literature to show that one or more of these options are in place to motivate the decision maker to internalize the externalities caused by agricultural production (Miranda 1992, Offutt 1991).

There are several factors which motivate agricultural producers to internalize the on- and off-farm damages resulting from soil erosion. A recent study by Miranda (1992) finds that the farmers in the two major farm producing regions, Corn Belt and Lake States, incorporate the intertemporal consequences of land management decisions, particularly the on-farm productivity losses from top soil erosion. The off-farm damages, measured as the cost of desilting drainage systems, rivers, and other water bodies, which is likely to increase the property tax, is a market force motivating internalization of soil erosion (Ribaudo 1986). In addition to the economic motivation, public-policy induced motivation can also be cited. The conservation reserve and conservation compliance programs, which tie program benefits to good stewardship, would be an adequate incentive to minimize soil erosion (Johnson et al 1991). Another example is the institution of Conservation District, which empowers producers and allow them to tap the technical/extension/education resources of the government, thus constituting to internalizing agricultural externalities.

Unlike soil erosion, the motivation to internalize externalities from chemical emissions is not obvious. However, the current NPS pollution policy debate motivated by the societal concern over groundwater and surface water pollution is likely to mandate specific institutional water quality regulations. For instance, the Clean Water Act of 1987 and the Rural Clean Water Program (RCWP) are some of the policies that motivate producers to internalize the externalities. Such potential (foreseeable) policies encourage producer to embrace NPS pollution control strategies (Offutt 1991). Furthermore, the ethical and equity concerns influence producers to internalize the externalities. Lastly, by assuming a single decision maker at the watershed level, preferably a watershed manager, adequate motivation through the assignment of property rights over an area potentially large enough to internalize the externalities is provided. The President's Water Quality initiative instituted in 1989 providing farmers with the knowledge and technical means to respond voluntarily to groundwater quality concerns related to agricultural activities is another example.

Piecemeal Versus Comprehensive Approach

A primary goal of the 1989 President's Water Quality Initiative[6] is to encourage adoption of best management practices (BMPs) that are both economically and environmentally sound and prescribe public policies that are consistent with this goal. Despite concerted efforts to mitigate NPS pollution, the problem is still significant. One reason for not being able to alleviate the NPS pollution is the piecemeal approach

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[6] The President's water quality initiative, launched in 1989 that will extend through 1995, is a vigorous national effort to protect water resources from contamination by fertilizers and pesticides without jeopardizing the economic vitality of U.S. agriculture.

embodied in resource and environmental protection policies. That is, the agency-specific public policies focus on a single criteria, while we know that ecosystems are highly interrelated systems where the niches and attributes are related to each other. The following proposition precisely characterizes the need for multiple objective treatment for agricultural NPS problem.

Proposition 2. *A fundamental assumption in piecemeal NPS regulation is that the externalities addressed by them are independent, which is unrealistic given the highly interdependent biogeophysical processes determining soil and water quality. As these are interrelated processes, the regulations must focus on the vector of attributes to minimize unfavorable tradeoffs and maximize welfare gains.*

Such interactions are very well understood in the case of water quality, which is a multidimensional concept described by a vector of attributes. The NPS pollution processes determining the elements of this vector and their magnitudes are highly interrelated. Because of these interactions, unfavorable tradeoffs occur if the focus is on a single attribute at a time. For instance, water quality policies that generally emphasize regulating a single attribute for a targeted resource, independent of other attributes that are elements of the resource quality vector, may lead to elevated levels of unregulated attributes. Additionally such piecemeal environmental policies will impair the quality of the resources that are not subject of the current policy.

Several illustrations of a sequential approach can be drawn from current NPS pollution policy niche. For instance, detection of herbicides in ground and surface waters has led to increased pressure on the USEPA to prescribe quantity based agricultural chemical policies such as achieving design / performance standards for water quality based on chemical constituents, unilaterally. If, however, this induces farmers to shift away from chemical intensive weed control systems to mechanical tillage it can cause increased erosion and runoff. Contrarily, if the traditional soil conservation policies are promoted vigorously, then conservation tillage (reduced and no-tillage) systems that are more intensive in chemical use may be adopted widely eventually leading to increased detection of chemicals in water. In some instances, a management practice designed to protect one resource may inadvertently impair another. For example, the sustainable agricultural policy of including a legume crop such as alfalfa into a rotational sequence with corn to control soil erosion can significantly reduce erosion but only at the expense of elevated levels of nitrate-nitrogen in the saturated zone (Foltz et al. 1990).

In what follows, a simple mathematical treatment of the contradictions among NPS policies prescribed by different agencies is presented. Assume that the Soil Conservation Service (SCS) and the Environmental Protection Agency (EPA) are the two federal agencies, each with its own independent mission. Namely, the SCS's mission is to control soil erosion and preserve soil (land) quality and the EPA is responsible for protecting water resources from chemical contamination. In addition, the producer has the goal of maximizing net returns. In pursuit of economic efficiency the individual producer may not achieve environmental objectives. Mishan (1976) and Lave (1984) have discussed how an agency should behave in order to optimize social welfare in pursuing a particular objective.

Assume the existence of a well-defined social utility function that measures the net societal welfare. Let the social utility U be a function of land quality (L), water quality (W), and economic returns (R),

$$U = u(L, W, R). \tag{5}$$

Assume all attributes are desirable. That is, U is an increasing function of L, W, and R. Assume that each of the attributes is determined by one or more of the following factors: tillage (t), chemicals (c), and output (Q). That is,

$$L = l(t,c,Q),\ l_t, l_Q < 0 \text{ and } l_c > 0, \tag{6}$$

$$W = w(t,c),\ w_t > 0 \text{ and } w_c < 0, \tag{7}$$

$$R = r(Q),\ r_Q > 0, \tag{8}$$

where the output Q is as determined by the function $f(\underline{x}, \underline{z})$. The vector x is the nonpolluting inputs and the vector z is the polluting inputs including t and c. To simplify the discussion, water quality is assumed to be directly related to the level of inputs. Soil erosion, which is captured by the intensity of tillage, could be measured by the amount of residue cover plowed into the field by the intensity of the tillage operation. Subscripts denote partial derivatives and all the functions are assumed twice differentiable. More tillage (meaning less residue cover) impairs land quality by eroding the topsoil at increased rate, while more tillage implies less chemical dependence, and therefore, less chemical residue in water. Increased use of chemicals offsets tillage, thereby protecting the soil from erosion but potentially increases the chemical residue. In general, a conservation tillage system, such as no-till, is a chemical-intensive system relative to conventional tillage (USDA 1993).

Substituting the expressions (6) through (8) into (5), we rewrite the social utility function as,

$$U = u[l(t,c,Q);\ w(t,c);\ r(Q)]. \tag{9}$$

The underlying preferences are assumed to satisfy the axiomatic conditions and the function u is assumed smooth and quasi-concave. The following proposition, proved in (Varian 1984 p.113), will assert the existence of u:

Proposition 3. *Suppose preferences are complete, reflexive, transitive, continuous, and nonsatiating, then there exists a continuous utility function $u{:}\mathbb{R}^3 \rightarrow \mathbb{R}$ which represent those preferences.*

The agencies, who are concerned with their own mission, will act in a myopic fashion. According to this simplified model, the SCS will encourage adoption of BMPs that limit soil erosion, independent of the impact on other attributes. That is, they will choose the optimal level of tillage that maximizes land quality.

Proposition 4. *The optimal level of tillage is the point where the incremental land quality from the last unit of tillage is zero. In other words, the optimal level of tillage is the point where marginal land quality is zero.*

The SCS problem can be expressed as choose tillage to maximize land quality [$\mathrm{Max}_t L$], which gives the following first-order condition proving proposition (4):

$$\mathrm{Max}_t L{:}\ (\partial l/\partial t) = 0. \tag{10}$$

Likewise, the EPA will choose an optimal level of chemical to maximize water quality.

Proposition 5. *The optimal chemical use is the point where marginal water quality is zero.*

The EPAs problem can be stated as $\mathrm{Max}_c W$ with the following first-order condition, which proves proposition (5),

$$\mathrm{Max}_c W{:}\ (\partial w/\partial c) = 0. \tag{11}$$

Clearly, these solutions are myopic in nature; they ignore the inter-relationship between the underlying physical processes and also the simultaneity. From a social perspective of minimizing contradictions and maximizing social welfare, each agent would take the first derivative of equation (9) with respect to all relevant and interdependent variables and set the resulting expression to zero.

Proposition 6. *The SCS, who is an agent of society, should choose tillage such that the sum of the marginal utility from increased land and water quality is zero.*

The SCS problem is restated as $\mathrm{Max}_t U$, and the first-order condition of this problem proves proposition (6),

$$\mathrm{Max}_t U: [\,(\partial u/\partial l)\,(\partial l/\partial t) + (\partial u/\partial w)\,(\partial w/\partial t)\,] = 0. \tag{12}$$

The condition in (12) considers the impact of tillage on all environmental attributes and not just its impact on land quality as in the myopic condition (10). The net social welfare gains in (12) are adjusted for the tradeoffs from such interactions.

Proposition 7. *The EPA should choose chemical use such that the sum of the marginal utility from increased water and land quality is zero.*

That is, the EPA will solve the following first-order condition to determine optimum c:

$$\mathrm{Max}_c U: [\,(\partial u/\partial w)\,(\partial w/\partial c) + (\partial u/\partial l)\,(\partial l/\partial c)\,] = 0. \tag{13}$$

The conditions in (11) and (13) represent a comparison between examining the impact of chemical use only on water quality and examining the impact of chemical use on both water and land quality.

Proposition 8. *The private producer will choose an optimal output level so that the sum of the marginal utility from increased revenue and increased land quality is zero.*

That is, the producer will choose optimum output according to:

$$\mathrm{Max}_Q U: [\,(\partial u/\partial r)\,(\partial r/\partial Q) + (\partial u/\partial l)\,(\partial l/\partial Q)\,] = 0. \qquad (14)$$

This proposition can be motivated by the on-farm productivity gains to preserving topsoil (Langdale and Shrader 1982) and also by the cross-compliance provisions of the commodity program. The provision requires conservation plans on highly erodible lands as a prerequisite for access to program benefits.

The solutions to (12), (13), and (14) are nonmyopic but lack simultaneity. To minimize the conflicts and achieve the full benefits of a comprehensive approach, however, the conditions in (12), (13), and (14) should be solved as a system, which is tantamount to optimizing equation (9) with respect to t, c, and Q, simultaneously, as shown here:

$$\mathrm{Max}_{t,c,Q} U = u[l(t,c,Q);\ w(t,c);\ r(Q)]. \qquad (15)$$

Assuming an interior solution, the first-order conditions for maximization are,

$$\partial u/\partial t = [\,(\partial u/\partial l)\,(\partial l/\partial t) + (\partial u/\partial w)\,(\partial w/\partial t)\,] = 0, \qquad (15.1)$$

$$\partial u/\partial c = [\,(\partial u/\partial w)\,(\partial w/\partial c) + (\partial u/\partial l)\,(\partial l/\partial c)\,] = 0, \qquad (15.2)$$

$$\partial u/\partial Q = [\,(\partial u/\partial r)\,(\partial r/\partial Q) + (\partial u/\partial l)\,(\partial l/\partial Q)\,] = 0, \qquad (15.3)$$

The system of equations (15.1) through (15.3) in them solves simultaneously for the optimal levels of decision variables, t^*, c^*, and Q^*. Second-order conditions are assumed to hold.

Evaluating the objective function at the optimum levels of decision variables, and substituting them in (15) get U^*. Contrasting this solution with the myopic and piecemeal solution, U^p the following holds:

$$U^* \geq U^p, \tag{15.4}$$

which proves proposition (2) stated at the outset.

Proposition 9. *If the underlying physical processes are independent then U^* and U^p are equal.*

If the social utility function is additively separable, then the second cross-partial term in equations (15.1) through (15.3) are zero. Therefore, the solution to problem (15), represented by U^*, is the same as the myopic and piecemeal solution U^p, which proves proposition (9).

Using the multiattribute utility function (5) we can graphically show the condition for optimality and the tradeoff between soil and water quality, holding net returns at a predetermined level $\bar{R}$. Figure 1 illustrates the model for analyzing the tradeoff between soil and water quality. Soil and water quality are plotted, respectively, on the vertical and horizontal axis. Point B is the initial distribution of soil and water quality. Curve XY is the tradeoff frontier or the transformation function which is an envelop of all feasible BMPs for a given level of net returns. Along this frontier, marginal rate of transformation (MRT) measures the sacrifice of soil quality for a unit increase in water quality, that is,

$$MRT_{L,W} = -(dL/dW) = (\partial h/\partial W) / (\partial h/\partial L) \tag{16.1}$$

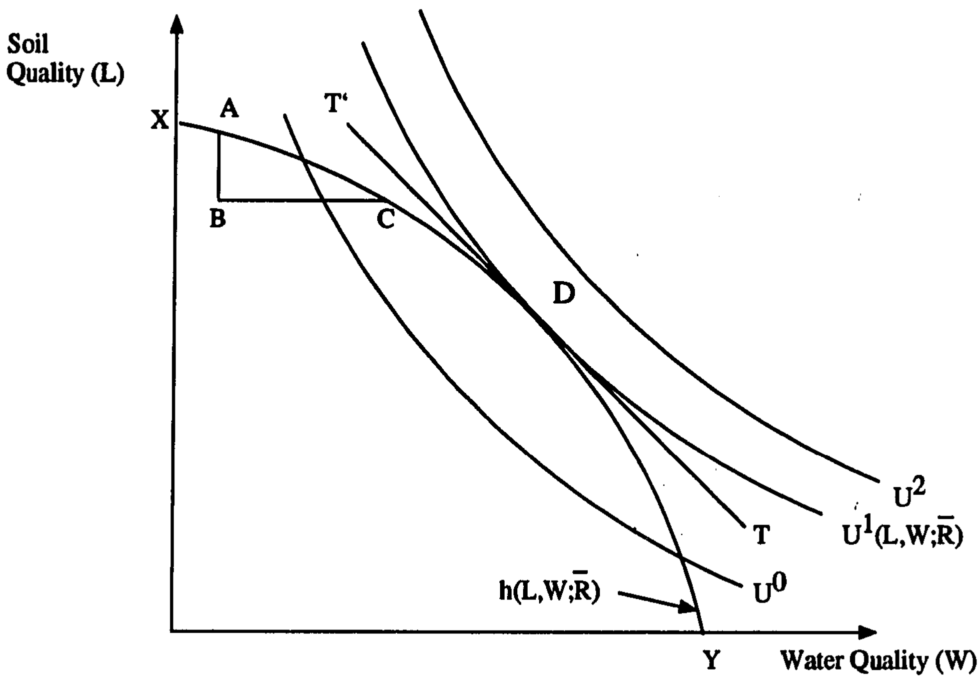

Figure 1. An illustration of soil and water quality tradeoff

where $h(W,L;\bar{R})$ is a convex function, the transformation locus. The utility function of the agent, expressed as iso-value utility (indifference) curves, is overlaid on the transformation curve. The indifference curve measures the marginal rate of substitution (MRS) between soil and water quality and is defined as

$$MRS_{L,W} = -(dL/dW) = (\partial U/\partial W) / (\partial U/\partial L). \qquad (16.2)$$

The initial allocation B is feasible but the agent can move towards the boundary of the feasible set, which is the transformation locus, and achieve higher utility. The agent maximizes his utility at point D, where MRT = MRS, that is the point of tangency between transformation frontier (XY) and the iso-value utility curve (U^1). This follows from the separating hyperplane theorem. The negative slope of the hyperplane (TT′) that separates the two sets, which is tangent to transformation locus and indifference curve, indicates the relative marginal values of soil and water quality for a given return $\bar{R}$. Denoting the marginal tradeoff of soil quality for the water quality as a weight λ, then the slope of the indifference curve U^1 at point D is the negative of the ratio of the weights attached to soil and water quality in the utility function. Therefore, by changing the weights the transformation frontier can be traced.

The Conceptual Framework

There is growing awareness of the far-reaching environmental impacts of economic activities. Environmental policy analysis concerns conflicting goals and competing social interests and power structures; therefore, a multiattribute treatment is necessary (Nijkamp 1980, Brouwer 1987). NPS pollution problems are typically multidimensional because the pertaining phenomena emerge from different disciplines, such as economics, ecology, physical and natural sciences, and sociopolitical sciences. Therefore, an integrated modeling framework that embraces all the disciplines and is represented as a multicriteria decision problem is appropriate. Furthermore, such a holistic approach is a key to understanding the interactions between the agricultural and environmental factors in determining the nature and intensity of pollution and the policy implications.

The integrated system conceptualized for the NPS pollution problem consists of an economic module, an ecological module, and a policy module. The conceptual framework is represented in Figure 2. This framework demonstrates the economic relevance of the agricultural production decisions, as well as the ecological consequences of those decisions that involve intensive use of chemicals and tillage. It also depicts simultaneous interactions with the policy module and the implications of alternative policy regulations on the economic and ecological systems.

The economic module simulates the agricultural economic decision making process and the behavior of producers, and evaluates the economic and ecological impacts of management and policy alternatives. To simulate the resource adjustment decisions, the economic module must have a detailed analytical decision system defined at the watershed level.

The environmental module is structured mainly to describe the impact of runoff and emissions into various media. It is integrated with the economic system through the coefficient matrix of emissions loading and standards. It is linked to the policy module, which is fed with information on environmental (multimedia) quality and

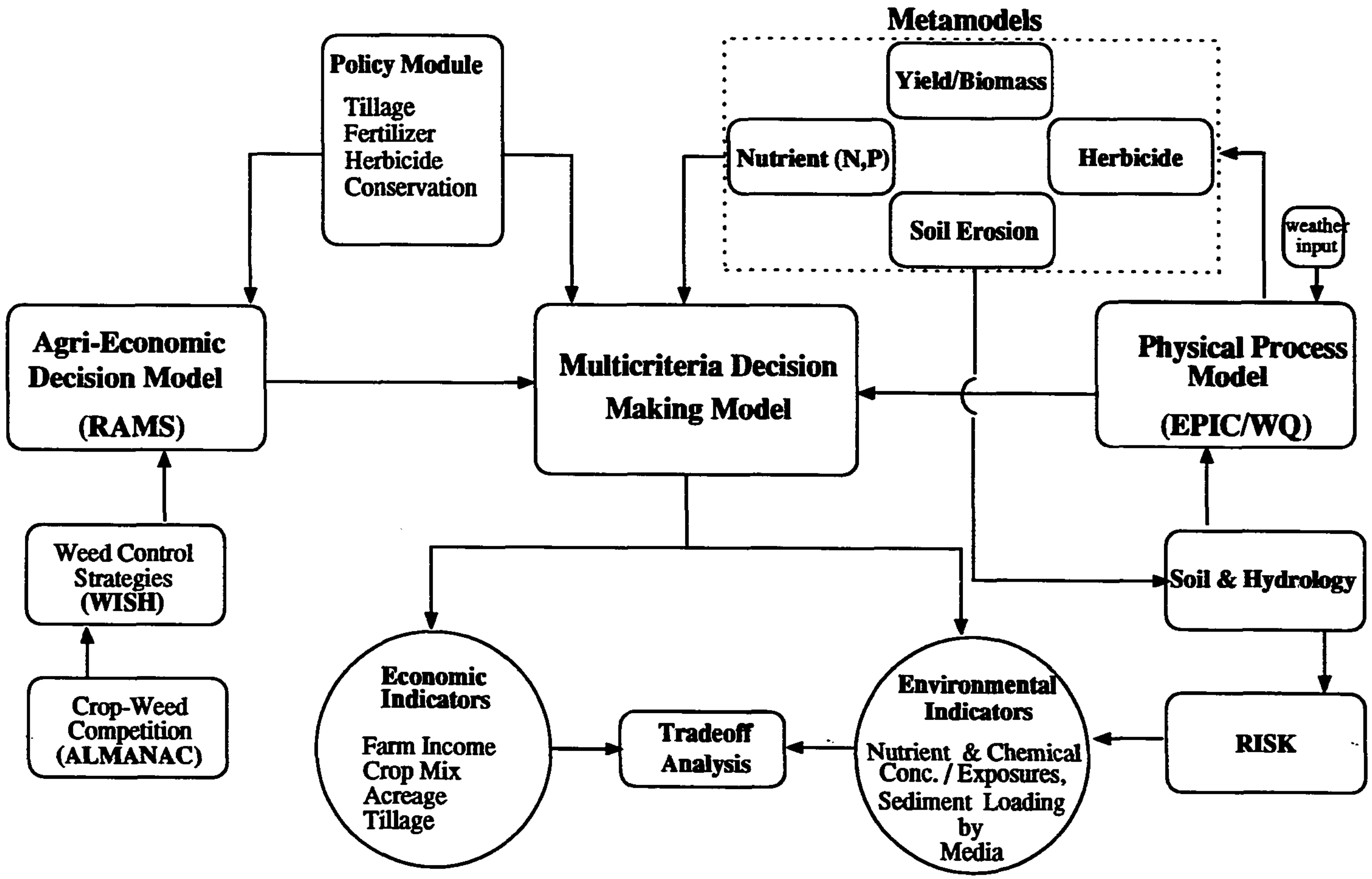

Figure 2. A multicriteria decision framework for integrating agricultural and environmental policies

potential producer and public concerns. The environmental system will be made operational by a set of reduced form equations (response functions) predicting the environmental fate and transport of soil, chemicals, and nutrients. The process that identifies and estimates these response functions is called *metamodeling*. The use of metamodeling to provide an interface between the ecological and economic systems is a novel concept (Bouzaher et al. 1993). Metamodels are statistically validated response functions fitted to a vector of environmental attributes, which are outputs from a comprehensive mathematical simulation model that simulates the underlying physical processes. The policy module reflects the public and producer concerns in the form of regulations that balance the interests of conflicting groups.

Empirical implementation of this integrated modeling system in a multiobjective context is challenging because it requires an enormous amount of data, a wide range of models and research tools, and coordination of agencies and disciplines. Coordination is defined primarily as a team approach with cost-sharing across agencies so that their decisions are in harmony with the goals of the society. The idea is that the coordination effort must transcend the boundaries of all participants so that the complimentarities, if any, are utilized and the contradictions are minimized. The choice of tools and methods in each discipline must be consistent with the goal of integrating various modules.

In the following sections, the integrated framework is formalized as a multicriteria decision making problem. Multiattribute utility theory (MAUT) and social welfare theory are invoked to motivate the MCDM problem. Finally, a solution method is presented and related to the multiattribute utility and social welfare concepts.

The MCDM Problem

Let $\underline{\epsilon}$ be the vector of spatial and environmental characteristics of the basic unit of production in the given watershed that impacts the production of both output and nonpoint pollution. The nonpoint pollution generating functions for each resource media by pollutant type is represented by the following set of metamodels:

$$\underline{D} = d(\underline{z}, \underline{\theta}_z, \underline{\epsilon}), \tag{17}$$

where $\underline{D}$ is the vector of media-specific emission, $\underline{z}$ is the vector of environmentally benign input levels, and $\underline{\theta}_z$ is the vector of characteristics (properties) of z including the management conditions that influence emission. This is a detailed specification for the emission function, d(z), in equation (2). All it says is that the environmental emissions are functions of input quantities and their characteristics, and also the spatial and environmental attributes such as meteorological conditions, local hydrological features, and soil properties. Because of spatial and production heterogeneity, this level of detail in measuring NPS emissions is essential for informed decisions on NPS policies. The coefficients of the emission function will be empirically estimated by combining the physically calibrated simulations with statistically validated metamodeling procedures.

The economic model, which is the basic agricultural decision making model for optimal allocation of resources in crop production, is a function of policy parameters $\underline{\Gamma}$, prices $\underline{p}$, and the environmental characteristics $\underline{\epsilon}$, besides $\underline{x}$ and $\underline{z}$. Assuming an exogenously given price and policy vector the watershed manager's problem is

$$\text{Max}_{x,z}\ \Pi = f(\underline{x}, \underline{z}, \underline{p}, \underline{\Gamma}, \underline{\epsilon}) \text{ and} \tag{18}$$

$$\text{Min}_{\underline{z}} \underline{D} = d(\underline{z}, \underline{\theta}_z, \underline{\epsilon}), \tag{19}$$

subject to resource, technological, physical, and institutional constraints. $\underline{D}$ is a vector of conflicting and non-commensurable attributes. An objective is in conflict with other objectives if an increased achievement of that objective reduces the levels of achievement of one or more of the other objectives. They are non-commensurable in the sense that the economic efficiency is measured in monetary units while the environmental quality is measured in units of pollutant concentrations / loading (for example, tons of soil eroded, chemical concentrations in μg/L [ppb], nutrient concentrations in mg/L [ppm]).

Note, Π and $\underline{D}$ are functions of input use and environmental characteristics. Therefore, the production decisions generate a joint distribution of output, input use, and pollution implying that targeting a single factor will affect the joint distribution that may exhibit undesirable tradeoffs. Hence, solving this problem in a multiple objective framework will be "efficient" in an overall welfare sense. In this framework, objective importance can be varied by assigning different weights, either arbitrarily or from *a priori* information, and the efficient frontier can be traced by parameterizing the weights.

To simultaneously evaluate these conflicting objectives vector maximizing tools are required. Vector maximization (multiobjective programming) has been one of the widely researched topics in management science, operations research, and economics (Cohon 1978, Rietveld 1980, Zeleny 1982). MCDM represents a very useful generalization of more traditional single-objective approaches to planning problems.

Informed decision making requires a knowledge of the wide range of alternatives, which can be provided by multiobjective analysis. In the public policy area MCDM is the rule rather than the exception, due primarily to the multiplicity of interests that are embodied by social welfare.

Mathematically the MCDM problem is stated as,

$$\text{maximize } \underline{f}(\underline{x}) = [f_1(\underline{x}), f_2(\underline{x}), \ldots, f_q(\underline{x})] \tag{20}$$

$$\text{s.t. } \underline{x} \in X = \{ \underline{x} \mid g_j(\underline{x}) \leq 0, \; j=1,2,\ldots,m; \; \underline{x} \geq 0 \}, \tag{20.1}$$

where $\underline{x}$ is an n-dimensional vector of decision variables. The functions $f_1, f_2, \ldots, f_q$ are the q-real valued attribute functions defining the attribute of relevance and X is a nonempty, closed, and compact set defined by a set of m constraints dictated by the physical processes and resource endowments. The feasible set X is convex and f_i is smooth and concave supposed. The solution method essentially involves aggregation of these attributes f_i by some rule. The most formal and theoretically sound method is the multiattribute utility method, where the solution is found by directly aggregating the underlying preferences. However, its applicability to public policy problems in agriculture is fraught with empirical difficulties. An alternative is the subjective weighting method. Weights on objectives are the simplest form of stating the preferences. However, the DM's value judgement introduced through the articulation of these subjective preferences is a drawback. But given the limitations of other methods, the weighting method is more intuitive for this problem.

Unlike in the scalar optimization problems, there is no single "optimum" solution to vector maximization problems because a solution which maximizes one objective will not, in general, maximize any of the other objectives.[7] The vector maximization problem identifies a set of efficient solutions $\underline{x}^*$ in the decision space, or equivalently, noninferior (nondominated) solution $f(\underline{x}^*)$ in the criterion space.

Definition. A point $x^* \in X$ is said to be an efficient solution if and only if there does not exist $\underline{\bar{x}} \in X$ such that $f(\underline{\bar{x}}) \geq f(\underline{x}^*)$ and for at least one value of i, $f_i(\underline{\bar{x}}) > f_i(\underline{x}^*)$.

That is, any solution for which none of the criterion functions can be improved without causing a degradation in any other is a noninferior solution.

The noninferior solution, $f(\underline{x}^*)$, is an image of $\underline{x}^*$ in the decision space. In the welfare economics literature it is referred to as the Pareto efficient solution.[8] The Pareto ranking, which states that allocation A is socially preferred to allocation B if at least one person's utility is higher in A and no other person's utility is lower, is not complete. The noninferior solutions, which lie on the northeast boundary[9] of the feasible region in objective space, also are characterized by *partial* ordering. Therefore, the objectives must be traded off against each other if we prefer one solution over the other. *Tradeoff* between two objectives is defined as how much one objective must be sacrificed to gain an increase in the other. The preferred solution in the noninferior set is the "best-compromise" solution.

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[7] This follows directly from whether all feasible solutions can be *completely* ranked, or, only a *partial* ranking is possible (as is the case in the multiple objective problems).

[8] Pareto efficiency is defined as: "there is no feasible allocation where everyone is at least as well off and at least one agent is strictly better off."

[9] It can be graphically demonstrated, in the two objective case, that all interior solutions must be inferior for one can find a feasible solution that improves both the objectives and any feasible solution on the boundary that is not on the northeast side of the feasible set is inferior (Cohon 1978).

Kuhn-Tucker (1951) conditions for noninferiority are (see Zadeh 1963 for proof):

Theorem. Given that the feasible set X is nonempty and convex and the attribute functions, f_i, are each smooth and quasi-concave, then $\underline{x}^*$ solves (20) if and only if there exists Lagrangean multipliers $\mu_j \geq 0$ for $j = 1,2,\ldots,\bar{m}$, and $\lambda_i \geq 0$ $\forall i$ such that

$$\underline{x}^* \in X, \tag{21.1}$$

$$\mu_j g_j(\underline{x}^*) = 0, \; j = 1,2,\ldots,m, \text{ and} \tag{21.2}$$

$$\sum_{i=1}^{q} \lambda_i \, \nabla f_i(\underline{x}^*) - \sum_{j=1}^{m} \mu_j \, \nabla g_j(\underline{x}^*) = 0. \tag{21.3}$$

The noninferior condition, stated in (21.1), requires feasibility and the condition (21.2) is a statement of complementary slackness.[10] Condition (21.3) relates the gradient of the objective function at $\underline{x}^*$ to the negative of the gradient of the binding constraints, evaluated at $\underline{x}^*$, where the gradient is the n-dimensional vector of partial derivatives. Note, (21.3) can be interpreted geometrically as follows: The nonnegative linear combination of the objective function gradients has to lie within the cone of the constraint gradients, evaluated at $\underline{x}^*$. This follows from the separating hyperplane theorem (Varian 1984).

Theorem. If A and B are two convex sets that are disjoint, there exists a linear functional $p \neq 0$ such that $\underline{p}\,\underline{x} \geq \underline{p}\,\underline{y}$ $\forall$ $\underline{x}$ in A and $\underline{y}$ in B.

Proposition 10. *Given feasible set X is convex, noninferior solutions are those points $\underline{x}^*$ on the boundary of X through which hyperplanes that separate X and the set of all vectors in $\mathbb{R}^r$ that are superior to $\underline{x}$ can be passed* (Zadeh 1963).

[10] The complementary slackness is interpreted as, if $\mu_j = 0$ the expansion of currently unused resource will not increase the objective function value; or, if $\mu_j > 0$ then all of the presently available resource must be used.

This condition implies that movement from $\underline{x}^*$ along any direction that increases the value of the objective function must be infeasible and, further, that any move in a feasible direction cannot result in an increase in the objective function value. In other words, the direction of improvement and the direction of feasibility are exactly opposite. The conditions in (21.1) through (21.3) are necessary for noninferiority. They are also sufficient since $f_i(\underline{x})$ are concave $\forall$ i = 1,2, ..., q, and X is convex set.

Social welfare, multiattribute utility, and MCDM

The alternative solutions in the noninferior set are not comparable just on the basis of the objective function values alone. Complete, unambiguous ranking of alternative solutions based on objective function values alone is possible only when one alternative dominates the other. As the name indicates, the alternative solutions in the noninferior set are nondominated; therefore, a function (transformation) that will allow complete ordering of the alternative solutions and define a ("nonsubjective") "scalar indicator" of overall welfare is required. By complete ordering it is meant that the preferences must be completely ordered by the binary relation "is at least as good as [$\succeq$]" and must satisfy the conditions of completeness, reflexivity, and transitivity. Thus, if there are many states of x, given by a,b,c,..., between every pair of states, say a and b, just one of the three cases hold for completeness:

$$a \succeq b \text{ and } b \succeq a, \tag{22.1}$$

$$a \succeq b \text{ and not } b \succeq a, \text{ and} \tag{22.2}$$

$$b \succ a \text{ and not } a \succeq b. \tag{22.2}$$

It means that the individual is able to compare each arbitrary pair of elements of x. Thus, a ~ a implying reflexivity and, for any 3 states, a ≥ b and b ≥ c implies a ≥ c (transitivity).

Given these and other topological properties, there will always exist an infinity of such functions, each such function being a monotone stretching of any other (Samuelson 1965). Utilizing one of an infinity of possible welfare indices, we may write this aggregate function as

$$W = W[u_1(\underline{x}), u_2(\underline{x}), \ldots, u_n(\underline{x})]. \tag{23}$$

This is the Bergson-Samuelson social welfare function (SWF), which is the focus of the modern welfare theory (Bergson 1938, Samuelson 1965, 1977). Social welfare function (W) is a mapping of utilities of individuals of a society into the real line, so that it will be able to select the most desirable distribution from the set of all feasible distributions of private utilities.

Assuming W is increasing in each of its arguments, the problem of choosing the most desirable utility distribution can be formalized as:

$$\text{maximize } W = W[u_1(\underline{x}), u_2(\underline{x}), \ldots, u_n(\underline{x})], \text{ s.t. } \underline{x} \in X \tag{24}$$

As in consumer theory, an ordinal welfare function W is sufficient to derive the optimum. Suppose $\underline{x}^*$ is an optimum allocation, then the following propositions (proved in Varian 1984) hold.

Proposition 11. *If $\underline{x}^*$ maximizes a social welfare function then $\underline{x}^*$ is Pareto efficient.*

Proposition 12. *Given x^* is Pareto efficient with $x_i \gg 0 \; \forall \; i$ and u_i's are concave, continuous, and monotonic, then there is some choice of weights c_i^* such that $\underline{x}^*$ maximizes $\sum c_i^* \; u_i(\underline{x})$ subject to the resource constraints.*

The existence of a well-defined social welfare function has been questioned. According to Arrow (1951), any social preference structure must satisfy the following five axioms: (1) complete order, (2) responsiveness to individual preferences, (3) nonimposition, (4) nondictatorship, and (5) independence of irrelevant alternatives. Arrow's impossibility theorem states that, in general, it is not possible to construct a social preference structure that satisfies all the five axioms, simultaneously. There is an ongoing debate in welfare literature on this issue. However, for this study the existence of SWF is supposed.[11]

Now, assume that there is a centralized planner (watershed manager) who is the sole decision maker. The DM is confronted with multiple objectives, namely, the maximization of revenue and the minimization of environmental damages, or equivalently, maximization of environmental quality. Assume that the DM's preferences for the i^{th} objective are known and satisfy all the regular axioms (Fishburn 1970, Keeney and Raiffa 1976). Assume the existence of global preferences so the DM can aggregate the utility derived from various attributes. This presumes that the DM derives utility by simultaneously maximizing the revenue and environmental quality. Then, the DM's problem is a multiattribute utility maximization problem. Given that U(.) represents aggregate preferences, the multiattribute utility maximization problem is stated as,

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[11] Samuelson in his writings about Bergson welfare economics shows constructively that a well-behaved Bergson-Samuelson SWF does exist.

$$\text{maximize } U = U[f_1(\underline{x}), f_2(\underline{x}), \ldots, f_q(\underline{x})], \text{ s.t } \underline{x} \in X \tag{25}$$

where U[ ] is q-dimensional vector of attributes, which implies that economic and environmental objectives are to be maximized simultaneously. We will assume f_i is smooth and concave and U is smooth, concave, and monotonic. Between the f's there will be a number of "technological" relations limiting our freedom to vary them independently. The content of these technological relations will be determined by the level of abstraction desired by the planner. Assuming regularity conditions, it would be possible to derive formal conditions for the maximum.

Consider the multiattribute utility maximizing problem represented by additively separable preferences:

$$\text{maximize } U = \sum c_i\, f_i(\underline{x}), \text{ s.t } \underline{x} \in X. \tag{26}$$

Solution vector $\underline{x}^*$ solves the problem if there exist a vector of nonnegative numbers $\underline{m}$, such that:

$$c_i\, \nabla f_i(\underline{x}\ ) = \underline{m}\ . \tag{27}$$

Note the similarity of the expression in (26) and the Benthomite type SWF, which is a weighted sum of utilities with $c_i = c_j$, except that here different relative weights are possible. The use of positive weights is equivalent to the construction of a linear indifference curve with the slope equal to the negative of the ratio of weights. That is, a constant marginal rate of substitution (MRS) between, say, f_j and f_1 equal to the ratio of weights $[c_k/c_1]$, where f_1 is an arbitrarily chosen *numeraire*, is implied. It is standard to choose economic efficiency as the reference objective; therefore, the tradeoffs are measured in terms of dollars per unit of environmental quality. The implication of constant MRS is that the willingness to trade one objective for another is independent of the level of objectives.

Returning to the generalized utility function postulation (25) of the multicriteria decision making problem, assume complete ordering of all combinations of objectives; therefore, the indifference curves span the entire objective space. The set of all feasible allocations that are indifferent to each other is called an indifference curve. The collection of indifference curves is called an "indifference map." These indifference curves are similar to the iso-welfare curves (the locus of the same welfare for a different set of allocations). Just as one moves towards an allocation such that the iso-welfare curve is tangent to the grand utility possibility frontier to find the unique Pareto-efficient welfare maximizing allocation, here the best-compromise solution is that noninferior point at which an indifference curve is tangent to the nondominated set. This is essentially the first-order condition of the maximization problem in (25).

Consider Figure 3, in which is illustrated an indifference map, feasible set X, and nondominated set N^d for a two dimensional case in the criterion space. The indifference curve U^0 goes through many feasible solutions, but none of them qualify to be a best-compromise solution because we can move to higher indifference curves and still be able to find feasible solution. How farther can we go is determined by the point of tangency of the indifference curve with the nondominated set. The tangency condition can be restated as, the equality of desirable tradeoff (the negative slope of the indifference curve) and the feasible tradeoff (the slope of N^d).

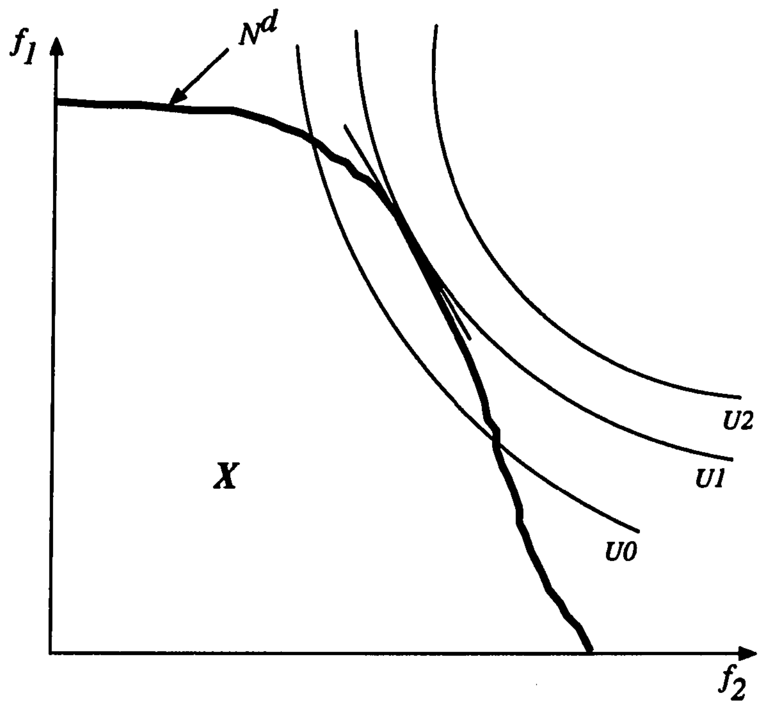

Figure 3. An illustration of the necessary condition for efficiency in a bi-criterion case

The difficulty in identifying a functional form for U for real world public policy problems calls for additional structure and more restrictive assumptions on utility "decompositions" to get simplified representations. If an extreme decomposition, namely the additive preferential independence,[12] is supposed then a simple additively separable utility representation as in (26) is obtained. Alternatively, if a less restrictive decomposition, namely utility independence,[13] is supposed, then it reduces to a more complicated multiplicative form. If the assumptions on f_i, u, and x hold, then the preferences summarized by the additive (multiplicative) function are strictly concave (strictly quasi-concave), implying any local optima is a global optima (Harrison and Rosenthal 1988).

Multiattribute utility function representation is useful for conceptual reasons because it enables us to define optimality in a multiple objective framework. In spite of the conceptual elegance, its use as a practical tool for public policy problems is limited. Major limitations are: (1) the representation of global preference relation and identification of the correct functional form to capture this relation, and (2) the ability to test the underlying assumptions and properties. Even if we can identify the utility function, most of the time it is nonlinear and thus hard to solve empirically. Therefore,

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[12] Given (X^A X^B) decomposition of X, then X^A and X^B are additively independent of each other if preferences between probability measures (gambles) on both X^A and X^B, depend only on the marginal gambles of X^A and X^B.

[13] Given (X^A X^B) decomposition of X, then X^A and X^B are utility independent if preferences for gambles over (X, x^b), conditioned on fixed level of $x^b \in X^B$ depend only on the marginal gambles over X and is independent of those fixed level of x^b.

for solving this problem researchers generally prefer programming methods, which are of course implicitly related to some simple preference structure.

Solution method

The need for a careful choice of a solution method cannot be overlooked. The method chosen should be valid and simple to implement and it should be adequately related to the theoretically appealing multiattribute utility. Keeping these points in perspective, a solution method that combines the best elements of the direct method (preference based method) and the distance based programming method is suggested. More specifically, the distance method minimizes some measure of weighted distance from a reference point. By carefully selecting weights, distance metric, and reference point we can adequately relate the resulting method to the preference based method.

Depending on the choice of distance metric and the definition of reference point, the methods differ. The L_p-metric (Minkovsky metric) is the most common measure employed. It is represented in its general form as,

$$L_p = \left[\sum_{i=1}^{q} |a_i - b_i|^p \right]^{1/p}, \quad 1 \leq p \leq \infty \tag{28}$$

where $(a_1, a_2, ..., a_q)$ and $(b_1, b_2, ..., b_q)$ are the coordinates of the two points, the distance between them is being minimized. In a multiobjective problem context, the distance between the objective and its reference point is minimized. If the reference points are goal levels for each of the attribute then it is solved as a *goal programming* problem (Charnes and Cooper 1961). Alternatively, if some notion of "ideal" as suggested by Zeleny (1973, 1974) and Yu (1985) is used as the reference point, then the method is called *compromise programming* (CP). Both *goal* and *compromise* programming has applications in agricultural planning (Romero and Rehman 1989, Romero 1991), agricultural and industrial nonpoint pollution (Lakshminarayan et al. 1991, Briassoulis 1987). Because of the simplicity of these two methods and the availability of solution algorithms, these are favored by many researchers.

The general specification for the programming problem of minimizing the weighted distance is:

$$\text{minimize } L(\lambda,\text{p;q}) = \sum_{i=1}^{q} \lambda_i^{p} \,|f_i^{*} - f_i(\underline{x})|^{p}, \quad 1 \leq p \leq \infty. \tag{29}$$

Note that the solutions to this optimization problem are not changed by dropping the exponent (1/p). Furthermore, the deviations are weighted by the scaling parameter λ to account for the relative importance of the objective deviations. Only the *relative* weights on the objectives matters. As long as the weights are nonnegative, the solution to the weighted objective problem is in the noninferior set. Therefore, by parametrically varying λ we can trace out the noninferior set. The parameterization of weights to find the noninferior set eliminates the subjective judgment involved in the general weighting method. Finding the solution $\underline{x}^*$ that is optimal with respect to a set of weights reflecting a compromise in some way is an interesting approach to identifying the noninferior set.

The idea of using weights to identify the efficient points stems from the second fundamental welfare theorem. That is, the method follows directly from the Kuhn-Tucker conditions for noninferiority stated in (21). The Khun-Tucker conditions for noninferiority stated in (21.1) through (21.3) require that a solution $\underline{x}^*$ is noninferior if there exist $\lambda_i \geq 0$ and $\mu_j \geq 0$. If $\underline{x}^*$ satisfies these conditions, then it is also an optimal solution to weighted objective problem since,

$$\nabla f(\underline{x}, \underline{\lambda}) = \sum \lambda_i \nabla f_i(\underline{x}). \tag{30}$$

Only other qualification that is needed is that the weights be strictly positive for the sufficiency condition to hold.

The parameter p also plays the role of additional scaling factor. Its property, proved in Yu (1985), is summarized in this proposition.

Proposition 13. *If the feasible set is compact and convex then the solution to (29), for $1 < p < \infty$, is continuous in p. If additionally, L_1 and L_∞ solutions are unique, which is true if X is strictly convex, then the solution is continuous in p for $1 \leq p \leq \infty$ and the solution is bounded from the top when $p = 1$, and from the bottom when $p = \infty$.*

Thus the parameter p plays the role of the balancing factor between the L_1, weighted sum of the objectives, and L_∞, the largest individual regret. But a major weakness of the L_p-metric is that it is possible that the solutions for $1 \leq p \leq \infty$ may all be the same, thereby limiting the number of alternative solutions available for the DM to make a choice. Because of this weakness, only solution corresponding to the L_1-metric will be generated for different choice of weights λ. The case $p = 1$, where the sum of deviations are minimized, is the preferred metric in most of the empirical analysis since it reduces to a standard weighted goal programming technique. See Appendix 1 for a mathematical representation of the solution algorithm, which is a piecewise linear approximation of the goal programming formulation. The implications of this metric for the underlying preferences and their aggregation are explained later in this section. Rietveld (1980) evaluated 14 alternative noninferior solutions and concludes that the solution to L_1-metric satisfied the following "necessary" conditions: impartiality, efficiency (noninferiority), and nonextremity.

Another limitation of the compromise programming method is attributed to the specification of the reference point. The reference point f_i^* in the compromise programming method, called the ideal point, is the optimal solution corresponding to when the i^{th} objective is maximized individually, ignoring the other objectives; that is,

$$\underline{f}^* = \max \{f_i(\underline{x}) | \underline{x} \in X, i=1,2,\ldots,q\}. \tag{31}$$

A drawback of using the ideal vector, as defined in (31), for NPS pollution problems is that it is too restrictive. First, the environment has a certain capacity to assimilate emissions. Second, the NPS emissions have aquatic and human health impacts only if they exceed a certain benchmark (MCLs). Therefore, referencing the ideal vector as the *goal* vector, where the goals are represented by the environmental benchmark values, is less restrictive. For nutrients and chemicals, the MCLs for human health and aquatic exposure can serve as a typical vector of goals, and for the soil erosion, the soil loss tolerance limits (T-values) can serve as a natural goal. Choosing the elements of the ideal vector by *a priori* information is parallel to prescribing realistic goals.

Since the objectives are noncommensurable, it is standard to normalize them either as percentage deviations from the goal, or to use the absolute difference between the best and the worst solution for each objective as the normalizing factor (Duckstein and Opricovic 1980). For notational simplicity, the normalization of objectives is supposed. Assuming that all are maximization objectives, then for $p=1$

$$\min L(\lambda,1;q) = \sum_{i=1}^{q} \lambda_i \, [f_i^{*} - f_i(\underline{x})], \tag{32}$$

$$= \min -\sum_{i=1}^{q} \lambda_i \, f_i(\underline{x}) = \max \sum_{i=1}^{q} \lambda_i \, f_i(\underline{x}) \tag{33}$$

since f_i^{*} are constants. Here a weighted linear sum of the normalized objectives is maximized. The expression in (33) is identical to the preference structure implied by (26) with the weighting parameter λ_i being equal to the scaling constant c_i^{*} and is same as maximizing the linear sum of the weighted objectives (30).

By scaling the objectives with nonnegative weights, such that $\lambda_i \neq \lambda_j$, we get the modern welfare economist's version of SWF (a weighted sum of utilities with different relative weights). Therefore, the "weights" approach—that is solving (33) through repeated and systematic variation of the weight vector—can be used to trace out the noninferior set N^d. Note, if the weights $\lambda_i = \lambda_j \; \forall \; i,j$ then the expression in (32) is analogous to the utilitarian type SWF suggested by Bentham (1948), which implicitly assigns a value judgment that utilities of individuals in society should be weighed equally. Similarly, note the parallel between (33) and the extreme egalitarian type SWF provided by Rawls (1971) principle of social justice, which states that society is no better off than its worst-off member. Utilizing the concept of production possibility frontier it was demonstrated that the utility maximization solution, where the multiattribute utility function is represented by an L_p-metric, will be in the noninferior set bounded by L_1 and L_∞ metrics (Ballestero and Romero 1991; pp. 421-427).

Clearly, several efficient noninferior solutions will be generated by varying the weights. The number of solutions and the complexity of the problem is stupendous if the problem has more than three objectives. Therefore, the problem of identifying the best-compromise solution is solved in two steps. In the first stage, alternative efficient solutions are generated, corresponding to the parametric variation of the weight vector for a given metric. In the second stage, these solutions are evaluated to identify the best solution as some compromise of the first-stage solutions. One of the following two methods can be used to find the best-compromise solution.

The first method is a more systematic, but time consuming, interactive (learning by doing) technique, where the DM evaluates and ranks interim (provisional) solutions and express how far off or close those solutions are to the true preferences. In the next iterative phase the additional information that is given by the DM is incorporated into the mathematical programming method by way of new constraints to improve the provisional solutions. An optimal stopping rule ends the search. By this interactive technique we try to identify, at least approximately, the true preferences.

The second method chooses the best-compromise solution from the several alternative efficient solutions generated in stage one, where the problem of choice is now specified as an expected utility maximization problem. This technique is computationally faster and simple to implement but it requires specific structure to be imposed on the expected utility function. Suppose X(i) are the noninferior solutions, max E u(X(i);τ), where τ is the scale parameter. By imposing a particular structure on u, such as the Cobb-Douglas structure, this problem can be solved for the best-compromise solution.

CHAPTER IV. EMPIRICAL MODELS AND METHODS

Integrated analysis of alternative NPS pollution policies, to achieve both economic feasibility and environmental sustainability, requires multidisciplinary models and methods. As described in the conceptual framework, three major modules— environmental, economic, and policy— constitute the overall integrated framework. In this chapter, a brief description of each of the modules along with a description of various data needs and sources is presented. Economic data, including data on production and management, are available from published sources. However, the environmental data are not readily available. These data gaps are filled by outputs from biogeophysical simulation models, where the simulation experiment is performed according to a well designed plan similar to the agronomic field experiments. At present, mathematical simulation models are the only hope for a timely evaluation of alternative policies, *ex ante*. The plan starts at the homogenous spatial unit, soil. The outputs from the physical process models simulated at the spatially disaggregated level must be aggregated to the level of enumeration of the economic model, which is the regional (watershed) level. Therefore, a brief outline of method of aggregation and its implications and underlying assumptions also forms a section in this chapter.

This chapter is organized into four major sections. First section describes the simulation plan including a description of the physical process model. The agricultural economic model is described in section two. Section three describes the aggregation process including the metamodeling procedure and economic, environmental, and policy model interface. Finally, the empirical multicriteria decision making model is outlined with a brief explanation of the choice and relevance of various environmental criteria and their reference values (standards / benchmarks).

Biogeophysical Simulation Plan

Agricultural NPS pollution is a significant source of water quality problem. Alternative best management practices are being developed to combat the NPS pollution threat. Proper management of any system requires estimates of the impacts of alternatives being considered. This is particularly true with NPS pollution control as decision maker's are faced with conflicting objectives. The decision space of environmental component is multidimensional which compounds the analytical task. For instance, to adequately address the water quality problem several water quality constituents have to be measured simultaneously. Therefore, the data requirements for comprehensive resource quality assessments are extensive. An effective plan can be developed only from good data.

Monitoring and simulation modeling are two approaches to assessing water quality information and evaluating the effectiveness of alternative BMPs. Water quality monitoring can be defined as any effort to obtain an understanding of the biophysical and chemical characteristics of water via statistical sampling (Dillaha and Gale 1992). Monitoring is the first best option to assess water quality, but the usefulness of monitoring data depends on the design and implementation of the monitoring effort. The scale of resource quality assessments where we are called upon to perform the analysis is usually regional scale. The heterogeneity of soil, topography, hydrology, and weather factors within a region calls for a large network of monitoring stations, which makes monitoring impractical because of the time and resource limitations. These are also the factors that make it difficult to implement monitoring programs whose results can be generalized across the spectrum of spatial and temporal factors.

An alternative approach for assessing resource quality impacts is to use biogeophysical simulation models.[14] These are mathematical models that describe and simulate the physical, chemical, and biological processes impacting the real-life system being modeled. In recent years there has been a great interest among the research community in using these models to answer NPS pollution control issues. These models consider site-specific attributes including land use patterns and management practices. The availability of superior computing capabilities has enabled these models to simulate the real-life processes in significant detail.

The simulation modeling approach, however, does not eliminate the problem of aggregation from field-scale to regional and watershed-scale. The heterogeneity of physical and hydrological factors as well as the regional production practices are so important in evaluating resource quality impacts, and that the aggregation has to be done carefully considering all these heterogenous factors. Antle and Capalbo (1991) show that the heterogeneity problem can be suitably addressed by defining the aggregate unit of analysis as a function of the problem context; for instance, the drainage area for which these process models are fabricated could represent the homogenous micro-unit of analysis. Joint statistical distributions for the production

[14] Biogeophysical models are becoming an increasingly important tool in applied agricultural economics research. Particularly, in research involving multidisciplinary efforts these are handy tools to capture the biogeophysical process impacts ex ante.

and pollution can be developed from this micro-unit, which can be integrated to the desired level of aggregation.

Suppose the homogenous physical and hydrological factors of a site-specific simulation, which is usually the drainage area of the process model, is represented by the vector $\underline{\epsilon}$. Assume that these physical and hydrological factors are fixed at a given point in time but are distributed across sites according to a distribution Ω_ϵ. Associated with the distribution of these environmental factors is a joint distribution of production practices Q and related resource impairments R. Represent this joint distribution as

$$\Theta = \Theta(Q,R \mid \text{prices, policy, technology, and } \Omega_\epsilon), \tag{1}$$

which then provides a statistical basis for aggregation at the same time retaining the heterogenous impacts from micro-units.

EPIC\WQ simulation model

A consistent statistical framework for aggregation of resource quality impacts, from assessments at the micro-unit level to watershed scale was discussed at the outset. The next step is to choose a mathematical simulation model that is comprehensive in its treatment of various biogeophysical processes. That is, the chosen model must be able to assess simultaneously the impacts of management and environmental factors on crop production and soil and water quality. To our knowledge, the most comprehensive model available to date is the EPIC\WQ (Erosion Productivity Impact Calculator and Water Quality) model developed by a multidisciplinary team of USDA. It is a time-tested model that has proved to be quite useful, economical, and realistic in several applications, including evaluating impacts on water quality and soil erosion, both in US and around the world (Jones et al. 1991).

The specific applications for which EPIC\WQ has been used include crop production, soil degradation, crop yield response to varying input levels and management practices, response to climate and soils, climate change and global warming, and water quality. It was originally designed to help DM's analyze alternative cropping systems, and project their socioeconomic and environmental sustainability with specific reference to soil erosion and productivity. The current version of EPIC\WQ includes a water quality component, namely the GLEAMS (Groundwater Leaching Effects on Agricultural Management Systems) water quality model, which allows simulation of pesticide degradation and movement in the soil. So, EPIC\WQ can simulate the movement of pesticides and nutrients toward ground and surface waters, both in solute, and as applicable, sediment phases.

Specific design goals of EPIC\WQ were: (1) to simulate the relevant biogeophysical processes simultaneously using readily available data and, where possible, accepted methodologies; (2) to simulate these processes , if necessary, over a long-term (100 years) as most of them are relatively slow processes; and (3) to be applicable to a wide range of soils, climates, crops, and chemicals. The design objectives of EPIC\WQ are consistent with the current research objectives and it is clearly the most comprehensive tool to assess simultaneously the impacts of physical, hydrological, and management factors on crop production and soil and water resources. Furthermore, EPIC\WQ has been calibrated to the site-specific parameters of the study area for the 1985 RCA analysis. Rural Clean Water Program (RCWP) experiences suggest that the models must be carefully calibrated for site-specific parameters. EPIC\WQ is composed of the following ten major components: weather, hydrology, erosion, nutrient cycling, pesticide fate, soil temperature, tillage, crop growth, crop and soil management, and economics. Figure 4 is a schematic of the various components, their interactions, and input requirements.

Sampling design

On a regional and watershed-scale, the analysis using physical models is still unmanageable because of extensive simulations required to cover different soil, climate, hydrology, management, crop, chemical, and policy options. For instance, it is estimated that a quarter of a million simulation runs are required to cover 1200 soil types recorded in the SOILS5 (Soil Interpretation Records [SIRS]) database, 3 different weather stations, 8 major tillage and conservation practices, and 7 crops prevalent in the study watershed. This extensive coverage is required to capture the heterogeneity of the physical environment as well as the agricultural production practices so that a meaningful aggregation of site-specific assessments is possible. Because of resource limitations, time and money, such an extensive simulation plan is impracticable. Alternatively, a spatial-sampling design which will reduce the simulation runs considerably, and at the same time retain the statistical validity of aggregation and extrapolation into the population (the word *population* is used to denote the aggregate from which the sample is chosen) is suggested here.

The results from sample simulation are, however, subject to some uncertainty because only part of the population has been simulated and because of errors of

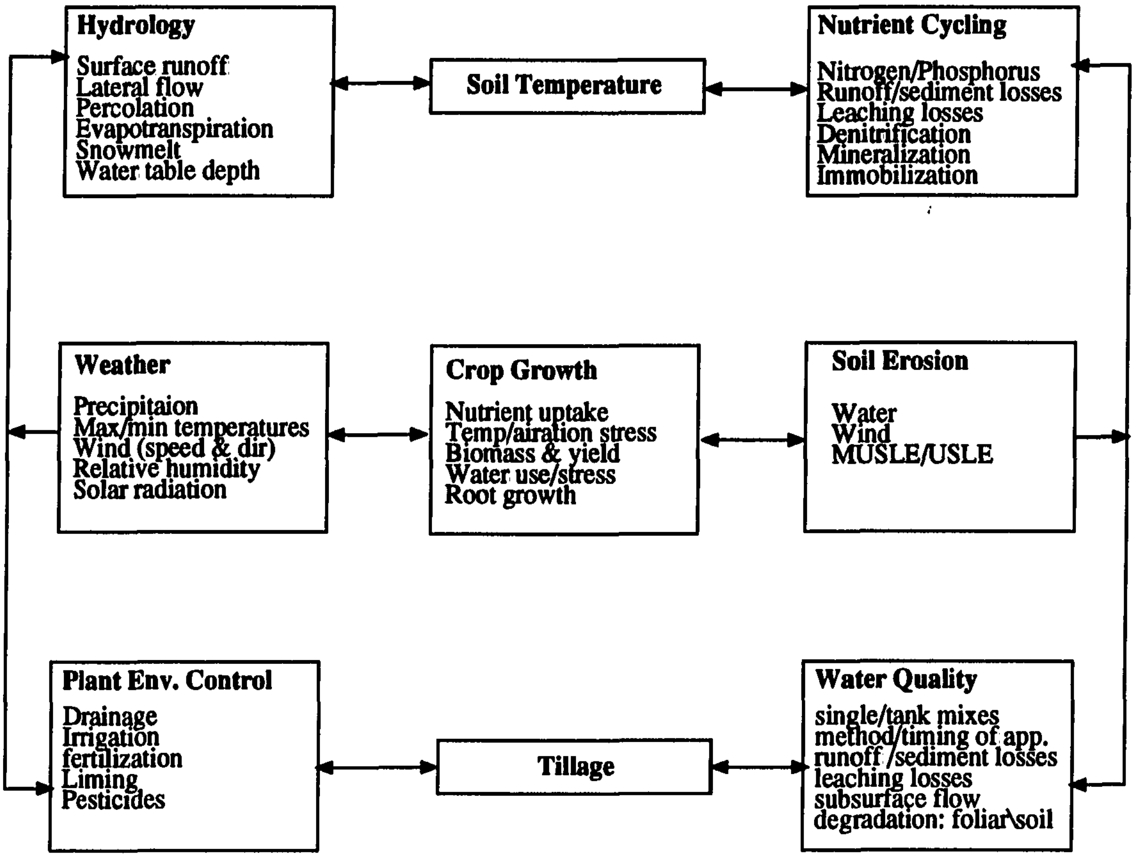

Figure 4. An outline of the EPIC\WQ simulation model

measurement. This uncertainty can be reduced by increasing the sample size, which usually costs time and money. There is a tradeoff between the degree of precision needed and resources that could be spent. The fact that the sample simulation results will be used for analytical rather than descriptive evaluation is also recognized in choosing the sampling design. The design is based on probability sampling so that the frequency distribution of the estimates, if repeatedly applied to the same population, can be observed. A schematic outline of the simulation plan development is shown in Figure 5. A brief description of the major components in this plan is what follows.

The SOILS5 database used to sample soil is the same database used to calibrate EPIC. For the watershed, this database has layered (soil profile) information for [1200*p] soil\USDA-texture types, where p is the number of soil profiles. A straight forward sampling method is to use a simple random sampling, that is selecting n units out of the N such that every one of the ${}_{N}C_{n}$ distinct samples has an equal chance of being selected. For our purpose this method is less precise[15] because the soil information is layered with properties of each profile varying both within and across the soil types. A typical soil is characterized by soil profiles; physical factors, such as clay, sand, silt, permeability, organic matter content, pH, and bulk density; erodibility factors, such as k-factor, k_f-factor, and slope; hydrological factors, such as hydrologic groups A to D (classified based on the rate of infiltration, with soils in A group having the maximum infiltration and soils in D group having the minimum infiltration) and available water. EPIC requires, at a minimum, layered information on

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[15] The precision of any estimate made from a sample depends both on the method by which the estimate is calculated from the sample data and on the plan of sampling.

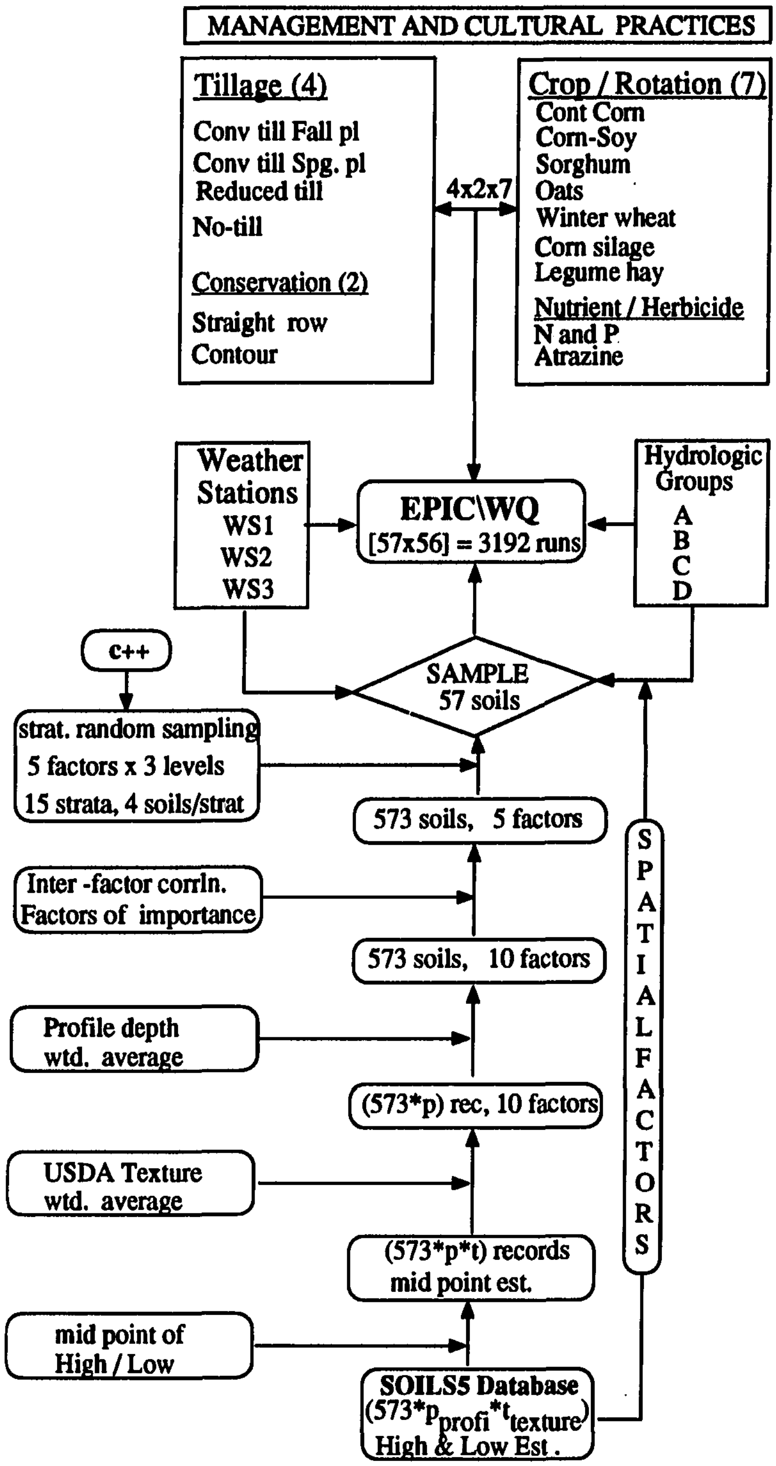

Figure 5. A schematic of the simulation plan for spatial and management factors

the following soil properties: clay, silt, organic matter, bulk density, permeability, available water, pH, and k-factor. Therefore, stratified random sampling with a complete factorial design was used. If intelligently used, stratification nearly always results in a smaller variance for the estimated parameters compared to a simple random sample (Cochran 1977).

The [1200*p] soil/texture types were aggregated into [573*p] soil types by taking a weighted average across USDA texture classes, with proportion of each texture class acreage as the weight. This is further aggregated across soil profiles into 573 unique soil types using profile-depth as weights. The next step is to limit the number of factors (soil properties) that will be considered in the sample allocation thought to be most important.[16] Simple correlation estimates between the factors were used as a guide to restrict the set of factors that will be used to determine the allocation. Important EPIC soil inputs was also used as guide in limiting the soil factors to be considered for sample allocation. Five soil factors, namely clay, bulk density, permeability, pH, and k-factor were identified. The selected factors were stratified into three levels, as high, medium, and low, and 4 units were sampled from each of the 15 strata (3 levels and 5 factors) *without replacement.* This stratification, where the sampling fraction is the same in all strata, is described as stratification with proportional allocation. It gives a *self-weighting* sample. The sampling proportion is 10 percent in terms of soil types and 56 percent in terms of arable land. Soil selection within each stratum was such a way that the probability of selection was proportional

[16] Since the best allocation for one factor will not in general be best for another, some compromise must be reached in a sampling design with several factors.

to the number of acres of arable land. The distribution of hydrologic groups in the sample parallels the population distribution.

In summary, the resulting sample of soil types was *self-weighting* (soils in all levels of each property are represented at similar proportions), *balanced* (each cultivable acre in the watershed had equal probability of selection), and *representative* of the population of soils in the watershed. The relative frequency distribution of the sampled soil factors in the sample vis-a-vis population is shown in Figure 6. The sample and population means and standard deviations are also reported. Table 1 shows the major sample and population attributes. The summary statistics and the frequency distributions confirm uniform and representative allocation.

Table 1. The sampling proportion and the distribution of hydrologic groups

Item	Population		Sample	
	Number	Percent	Number	Percent
Sampling Proportion				
Unique soil types	573		57 (10%)	
Area in million acres	34		19 (56%)	
Hydrologic Groups				
Group A	34	6%	1	2%
Group B	402	70%	46	81%
Group C	98	17%	8	14%
Group D	39	7%	2	3%

Note: Figure in parenthesis is the sampling proportion.

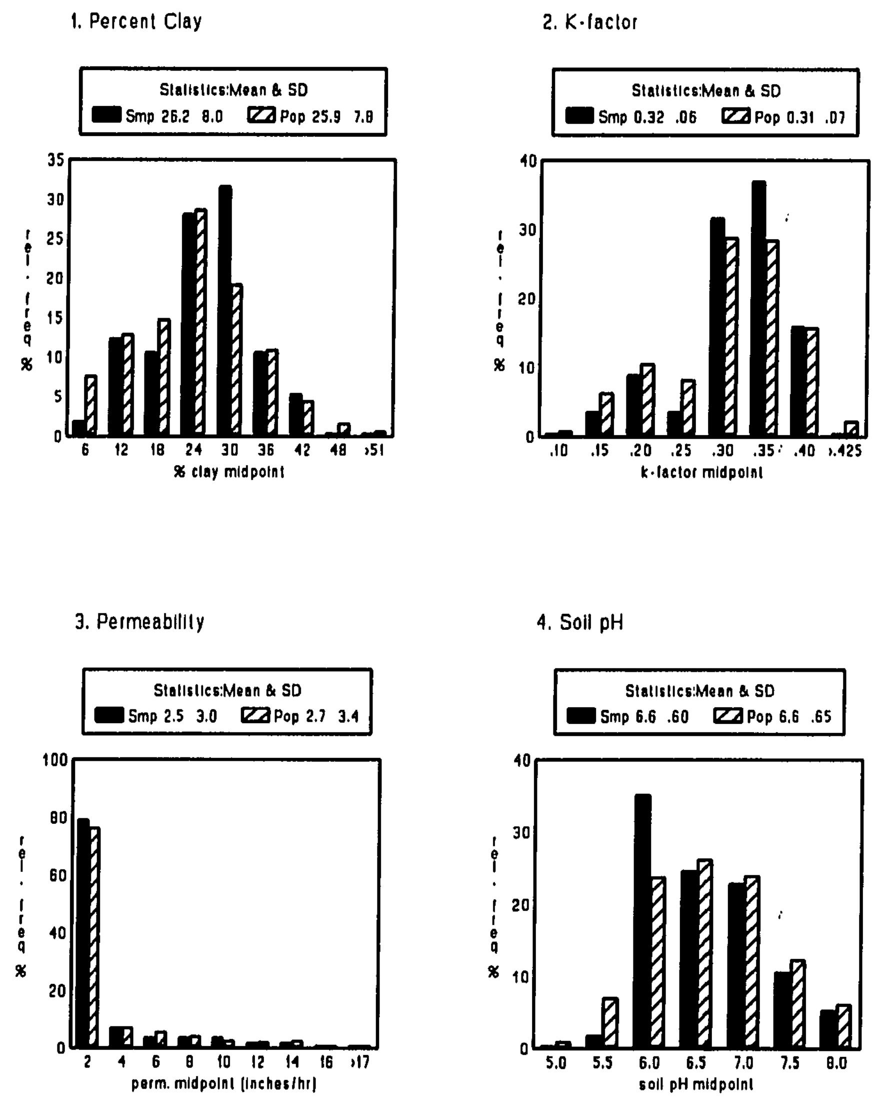

Figure 6. The frequency distribution of selected soil properties in the sample and in population

Table 2 lists the complete set of soils sampled and their properties, coverage, and also the associated weather station.

Another major component that needs consideration in sampling design and allocation for the EPIC simulation plan is weather. Daily precipitation amounts, maximum and minimum temperatures, solar radiation, wind velocity and direction, and relative humidity are the important weather factors used in EPIC simulation. Based on historically observed meteorological data, the watershed can be grouped into iso-climatic zones. Since a given soil type may be in more than one zone it becomes necessary to do as many simulations for as many climatic zones in the watershed. This approach precipitates our objective of reducing the number of simulation runs. Therefore, an alternative approach of allocating the sampled units to one of the two or more climatic zones, where the allocation is based on the area of each soil type in each of the zones. The EPIC model has the option of reading actual daily weather data or generate weather data using internally built stochastic weather generators or a combination of both. For actual weather data we have the option of choosing from EPIC weather stations (Des Moines, Dubuque, and Madison) or major land resource area (MLRA) weather stations. Since the model has been calibrated for EPIC weather stations and since the three dominant MLRA's in this watershed fall in the "EPIC climatic zones" we distributed the soil sample based on the EPIC weather station's location and coverage. A soil type may fall in more than one EPIC weather station. In such cases the following scheme was adopted. Weather station assigned for the soils appearing in more than one location is the one in which the soil has maximum acreage.

Table 2. List of sampled soils, hydrology, acreages, and selected properties

Soil Type	Hydrol. Group	Area ac.	Clay %	Bulk dens gms/cc	Permeab in/sec	Org.Mat %	k-factor	pH	Avl.water inches	Weather Station
CHELSEA	A	126925	10.6	1.53	13.0	0.8	0.17	6.45	0.12	DBU
COLWOOD	B	13499	14.3	1.50	1.0	5.5	0.40	7.44	0.18	MDS
SEATON	B	150708	17.4	1.35	3.8	0.7	0.32	6.12	0.18	DBU
CLARION	B	1672141	20.3	1.56	1.3	1.0	0.35	7.29	0.19	DSM
KENYON	B	606390	23.6	1.54	1.3	1.4	0.29	6.52	0.19	DBU
WACOUSTA	B	57993	26.0	1.31	1.3	2.7	0.37	7.58	0.21	MDS
STORDEN	B	208244	23.8	1.49	1.3	0.6	0.36	7.90	0.18	DSM
DOWNS	B	876052	25.0	1.35	1.5	0.7	0.40	6.20	0.20	DBU
MUSCATINE	B	446134	27.8	1.33	2.2	2.0	0.38	6.46	0.19	DBU
WEBSTER	B	1044075	27.7	1.49	1.3	3.5	0.30	7.40	0.18	DSM
COLO	B	709936	31.1	1.32	1.3	3.8	0.29	6.51	0.20	DSM
ROCKTON	B	108270	28.7	1.40	4.7	4.0	0.28	5.90	0.20	DBU
NICOLLET	B	1120691	27.5	1.33	1.3	6.0	0.30	7.09	0.18	DSM
TAMA	B	1504595	23.9	1.33	3.4	1.1	0.35	6.17	0.18	DBU
NIRA	B	90900	32.0	1.35	1.3	0.9	0.41	5.86	0.20	DSM
DUBUQUE	B	483630	36.1	1.38	0.8	0.9	0.35	6.04	0.17	MDS
FAYETTE	B	1853921	25.3	1.42	2.2	0.5	0.39	5.83	0.18	DBU
COLAND	B	243829	28.1	1.48	1.8	4.1	0.25	6.76	0.20	DSM
KENDALL	B	20961	26.2	1.42	1.3	0.6	0.37	6.23	0.19	MDS
CANISTEO	B	1019591	27.4	1.43	1.3	6.0	0.30	7.90	0.17	DSM
BOLAN	B	40775	13.2	1.54	6.0	1.3	0.22	6.37	0.14	DBU
ARMSTRONG	C	143939	39.8	1.54	0.4	0.7	0.32	5.97	0.15	DSM
CLYDE	B	627483	24.3	1.56	1.7	3.1	0.33	6.98	0.19	DBU
UDOLPHO	B	40275	14.4	1.55	6.2	2.9	0.25	6.43	0.13	DBU
SEYMOUR	C	29035	39.4	1.44	0.4	1.0	0.35	6.14	0.18	DSM
GARA	C	354570	31.1	1.64	0.4	0.6	0.33	6.10	0.17	DSM
TAINTOR	C	164851	33.4	1.38	0.6	2.2	0.36	6.46	0.20	DSM
DUNBARTON	D	73952	37.7	1.34	1.0	2.0	0.34	6.78	0.20	DBU
DINSDALE	B	426103	27.6	1.49	1.3	1.4	0.40	6.57	0.19	DBU
SAWMILL	B	146304	29.3	1.35	1.3	2.3	0.28	7.01	0.20	DBU
ELY	B	190869	28.6	1.35	1.3	3.0	0.37	6.75	0.20	DBU
NODAWAY	B	263277	24.6	1.31	1.3	1.3	0.39	6.70	0.21	DSM
PLANO	B	232413	24	1.39	2.5	1.3	0.37	6.57	0.18	MDS
RINGWOOD	B	41662	20.7	1.45	2.4	1.2	0.33	7.17	0.16	MDS
GARWIN	B	99942	25.2	1.35	3.4	2.2	0.3	6.79	0.18	DBU
CLINTON	B	434178	32.7	1.41	0.9	0.6	0.37	5.77	0.19	DSM
LADOGA	B	422206	32.6	1.36	0.9	0.9	0.41	5.83	0.20	DSM
SHARPSBURG	B	262883	32.7	1.39	1.1	1.3	0.41	6.00	0.20	DSM
LAWLER	B	113064	14.9	1.56	9.8	1.9	0.19	6.17	0.12	DBU
READLYN	B	231766	22.7	1.57	1.3	2.7	0.30	6.43	0.19	DBU
EDMUND	D	66389	38.6	1.44	0.9	2.2	0.31	6.70	0.18	DBU
NORDNESS	B	192902	24.2	1.38	0.4	1.4	0.33	6.58	0.17	DBU
FLOYD	B	403604	20.4	1.56	1.8	2.1	0.30	7.00	0.17	DBU
WARSAW	B	51954	15.6	1.49	8.9	1.3	0.21	6.99	0.12	MDS
OSSIAN	B	17671	24.9	1.33	1.3	3.4	0.28	7.14	0.22	DBU
SAYBROOK	B	107066	27.4	1.49	1.1	0.8	0.36	7.03	0.17	MDS
SAUDE	B	137782	11.0	1.54	12.0	1.3	0.17	5.92	0.11	DBU
DICKINSON	B	204654	9.7	1.59	9.5	0.6	0.18	6.10	0.08	DBU
SHAFFTON	B	20184	14.9	1.62	8.6	1.2	0.22	5.96	0.12	DBU
DRUMMER	B	241551	27.4	1.35	1.4	1.7	0.28	6.91	0.20	MDS
HARPS	B	273072	26.0	1.48	1.3	2.4	0.30	8.06	0.19	DSM
ADAIR	C	124236	40.6	1.58	0.3	0.8	0.32	6.27	0.15	DSM
OTTOSEN	B	71341	31.2	1.53	0.8	2.4	0.31	7.30	0.19	DSM
KESWICK	C	110494	38.7	1.58	0.4	0.7	0.37	5.73	0.14	DSM
FRANKLIN	B	43277	25.4	1.55	1.3	1.3	0.36	6.19	0.19	DBU
THERESA	C	41865	18.5	1.68	0.9	2.0	0.37	7.47	0.14	MDS
GRUNDY	C	125095	35.2	1.38	0.3	0.9	0.37	6.34	0.17	DSM

To evaluate the environmental impacts of alternative BMPs the simulation plan should include alternative and feasible management and cultural practices. The following are the major crops grown in this watershed: corn grain, soybeans, sorghum, winter wheat, oats, corn silage, legume hay, and nonlegume hay. The four common tillage practices are: conventional tillage with fall plow, conventional tillage with spring plow, reduced tillage, and No-till. The two conservation practices evaluated are the straight row and contour cropping practice. The tillage practices are defined as follows. Fall plow is a clean conventional tillage which leaves no residue cover. Spring plow leaves 30 percent residue cover in the field after harvest and the soil is tilled in the spring months following the harvest. Reduced or ridge till leaves 30-70 percent residue cover on the soil surface after planting. No-till refers to zero tillage with more than 70 percent residue cover and planting is completed by only disturbing a narrow seed bed of 1 to 3 inches.

The strategy followed in simulating the cultural practices is a combination of single crop and crop rotation systems. Specifically, continuous corn, corn-soybean rotation, small grains (oats and winter wheat), legume and nonlegume hay, corn silage and sorghum are the alternative cultural practices simulated. The crop rotational impact is particularly significant for nutrient cycling and to some extent on soil loss. There is no demonstrated evidence of impacts of crop rotation and herbicide use. The crop growth component of the EPIC was fertilized with optimum nitrogen (N) and phosphorus (P) application rates. These rates were taken from Tillage Update published by the Resource and Technology Division, Economic Research Service, USDA. The data on the amount of residue left in the field under alternative tillage systems was also obtained from the same source.

The schedule of operations— management, tillage, and harvest— were taken from FEDS (Firm Enterprise Data System) budget. Most of the crops grown in this watershed are rainfed, therefore, irrigation practice is not simulated. Atrazine application in corn and sorghum, applied as early preplant and postemerge, was simulated. An application rate of 1 kilogram per hectare (kg/hac) was used. Preliminary sensitivity analysis of EPIC with different application rates suggest that the atrazine loading was linear in application rate. Atrazine is the most widely used herbicide for corn and sorghum production and the most commonly encountered in ground and surface waters. Atrazine is also the most compatible herbicide for conservation tillage systems. In 1989, 40 percent of the corn acres was treated with atrazine, with more than 80 percent of which being applied as preplant and postemerge (Duffy and Thompson 1991). Atrazine is detected in surface and groundwater samples monitored across the United States (USEPA 1990). Tables 3 to 6 presents a complete description of the management operations for the alternative crops.

The Economic Model: A Regional LP Model

The agricultural economic decision system is described at the environmentally meaningful level, namely the watershed. Specifically, the hydrologic unit representing the water resources aggregate sub area 703 (PA 41) is the model's regional delineation. The political and the major land resource area configuration of the study area, is shown in Figure 7.

Table 3. The management and harvest schedule for corn grain by tillage systems

Date	Machinery / Field operation	Conv.till fall plow	Conv.till spg.plow	Reduced till	No-till
4-15	Shredder		x		
4-15	Moldboard Plow		x		
4-15	Tandem Disk	x	x	x	
5-1	Tyne Harrow	x	x	x	
5-1	Field Cultivator	x	x		
5-1	Atrazine Application	x	x	x	x
5-5	Row Planter	x	x	x	x[a]
5-5	N-fertilizer (lbs/ac)[b]	120	120	132	129
5-5	P-fertilizer (lbs/ac)[b]	55	55	58	55
6-5	Rotary Hoe	x	x		x[c]
6-5	Row Cultivator	x	x	x	
11-10	Combine Corn	x	x	x	x
11-10	Shredder	x			
11-15	Moldboard Plow	x			
11-15	Chisel Plow			x	
	Crop Residue[b]	2%	15%	37%	61%

[a]Mini-till planter. [b]"RTD Updates- Tillage Systems". [c]Rolling cultivator.

Note: An x indicates use of that machinery / operation under that tillage.

Table 4. The management and harvest schedule for soybeans by tillage systems

Date	Machinery / Field operation	Conv.till fall plow	Conv.till spg.plow	Reduced till	No-till
4-15	Shredder		x		
4-15	Moldboard Plow		x	x	
4-16	Tandem Disk	x	x		
4-16	Chisel Plow	x	x		
4-20	Field Cultivator	x	x		
4-20	Spike Harrow	x	x	x	
5-1	Tandem Disk	x	x	x	
5-1	Spike harrow	x	x		
5-5	Row Planter	x	x	x	x[a]
5-5	N-fertilizer (lbs/ac)[b]	18	18	27	26
5-5	P-fertilizer (lbs/ac)[b]	42	42	48	52
6-15	Rotary Hoe	x	x		x[c]
6-15	Row Cultivator	x	x		
10-15	Combine Beans	x	x	x	x
10-15	Shredder	x			
11-1	Moldboard Plow	x			
	Crop Residue[b]	2%	14%	39%	68%

[a]Mini-till planter. [b]"RTD Updates- Tillage Systems". [c]Rolling cultivator.

Note: An x indicates use of that machinery / operation under that tillage.

Table 5. The management and harvest schedule for sorghum, oats, and winter wheat

Date	Machinery / Field operation	Conv.till fall plow	Conv.till spg.plow	Reduced till	No-till
SORGHUM					
4-15	Moldboard Plow		x	x[a]	
5-1	Tandem Disk	x	x	x	
6-1	Field Cultivator	x	x		
6-1	Atrazine Application	x	x	x	x
6-5	Planter	x	x	x	x[b]
6-5	N-fertilizer (lbs/ac)	88	88	101	101
6-5	P-fertilizer (lbs/ac)	35	35	40	40
7-5	Row Cultivator	x	x	x	x
10-10	Combine Grain	x	x	x	x
11-15	Moldboard Plow	x			
OATS					
4-1	Tandem Disk		x		
4-1	Offset Disk	x	x	x	
4-15	Spike Harrow	x	x		
4-15	Grain Drill	x	x	x	x
4-15	N-fertilizer (lbs/ac)	34	34	34	39
4-15	P-fertilizer (lbs/ac)	18	18	18	18
8-15	Combine Small Grain	x	x	x	x
9-15	Shredder	x			
9-15	Tandem Disk	x			
WINTER WHEAT					
6-15	Combine Small Grain	x	x	x	x
9-1	Tandem Disk	x	x		
10-1	Tandem Disk	x	x	x	
10-5	Small Grain Drill	x	x	x	x
10-5	N-fertilizer (lbs/ac)	69	69	48	61
10-5	P-fertilizer (lbs/ac)	34	34	27	38
	Residue	2%	14%	39%	56%

[a]Chisel plow. [b]Mini-till planter.

Table 6. The management and harvest schedule for corn silage and hay by tillage

Date	Machinery / Field operation	Conv.till fall plow	Conv.till spg.plow	Reduced till	No-till
Corn Silage					
4-15	Shredder		x		
4-15	Moldboard Plow		x		
4-15	Tandem Disk	x	x	x	
5-1	Tyne Harrow	x	x	x	
5-1	Field Cultivator	x	x		
5-1	Atrazine Application	x	x	x	x
5-5	Row Planter	x	x	x	x[a]
5-5	N-fertilizer (lbs/ac)[b]	129	129	141	139
5-5	P-fertilizer (lbs/ac)[b]	71	71	74	71
6-5	Rotary Hoe	x	x		x[c]
6-5	Row Cultivator	x	x	x	
11-10	Silage Harvester	x	x	x	x
11-10	Shredder	x			
11-15	Moldboard Plow	x			
11-15	Chisel Plow			x	
	Residue[b]	2%	14%	39%	68%
Legume Hay					
4-1	N-fertilizer(lbs/ac)	13	13	13	13
4-1	P-fertilizer(lbs/ac)	47	47	47	47
6-1	Sickle Mower	x	x	x	x
6-1	Harvester	x	x	x	x
7-1	Sickle Mower	x	x	x	x
7-1	Harvester	x	x	x	x
7-15	Moldboard Plow	x			
8-15	Tandem Disk		x	x	
9-1	Harrow Spike	x	x		
9-1	Grain Drill	x	x	x	x

[a]Mini-till planter. [b]"RTD Updates- Tillage Systems". [c]Rolling cultivator.

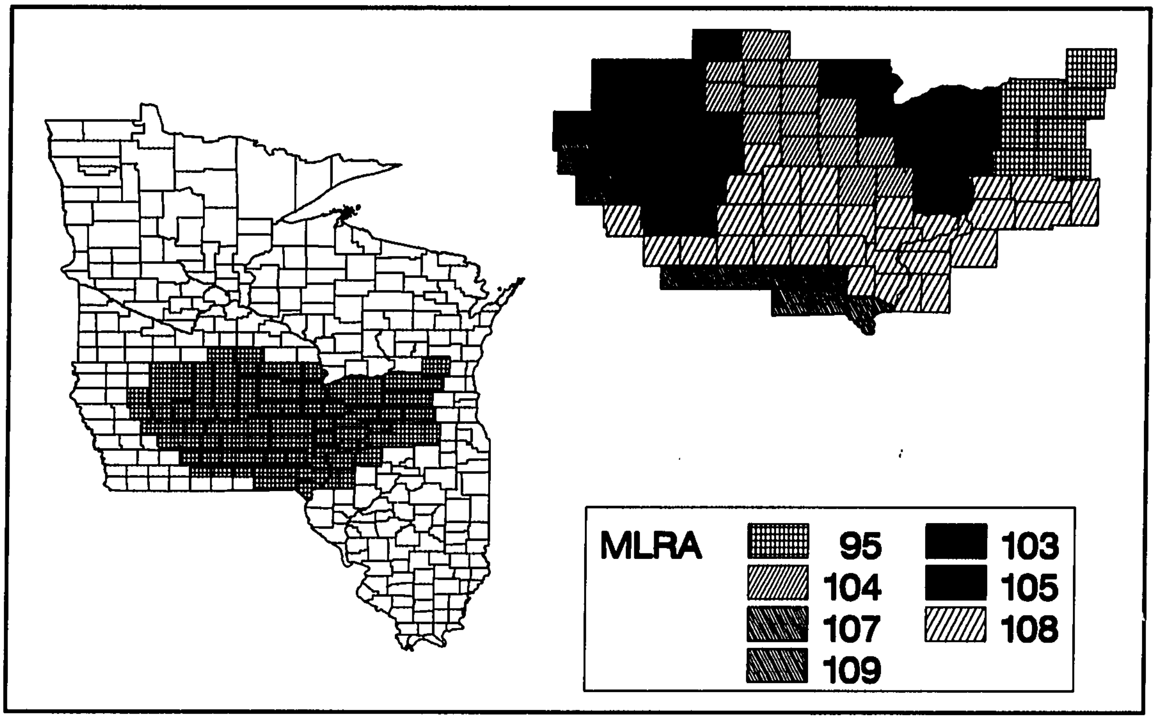

Figure 7. The political and major land resource area configuration of the study area

The Resource Adjustment Modeling System (RAMS) developed by the CARD to provide the economic interface for CEEPES, constitute the basic agricultural economic decision unit (Bouzaher et al. 1991). RAMS is a regionally delineated linear programming, comparative static, and partial equilibrium model. Since RAMS provides significant production and management detail with government program and a weed control subsector, it has become a vital model for evaluating agricultural chemical policy impacts on crop mix and other production decisions. The crop production relationships in RAMS are modeled to capture crop rotation, tillage, and conservation effects. The model is useful for short and medium term analysis. Besides having applications in corn herbicide policy analysis it is also used to simulate a cover crop scenario for carbon sequestration project. A nutrient sector is added to simulate fate and transport of nitrogen and phosphorus in groundwater and surface water.

The linear programming model is a set of mathematical relationships incorporating characteristics most relevant to agricultural production, resource use, and response to economic factors and policy options (Hazell and Norton 1986). RAMS is a short-run, static profit maximizing model with exogenous input and output prices. The objective function measures short-run total net profit, which is equal to the difference between total returns from the government programs and marketing, and the total costs from production, weed control, and buy-inputs sub-sectors. RAMS is developed to determine optimal patterns of resource use and production practices, following traditional regional LP models (Burton and Martin 1987). A detailed weed control subsector linked to crop production through herbicide management practices, productivity response, resource use, and chemical cost is incorporated to simulate substitution between the chemical and mechanical weed control methods.

Constancy of technology through the planning period is assumed in RAMS. This justifies holding input and output prices and basic resource levels constant. The resource and production levels are assumed to be representative of a large number of relatively homogenous farms, so that they are aggregated over a geographically homogenous area. Not withstanding this, the RAMS model is open to aggregation bias. Aggregation bias exists when the microeconomic behavior of the RAMS modeling structure is transformed into aggregate market behavior. In general, the set of conditions for exact aggregation are highly stringent. Given that aggregation bias is a pervasive problem with regional modeling systems, RAMS is designed to minimize the aggregation bias to the extent possible.

Geographically defined production areas are the basic unit of production. Within a PA, a unique land group definition representing aggregated MLRA is used. That is, an MLRA is aggregated over eight major RCA (Resource Conservation Act) land groups defined according to USDA land capability classes and subclasses. This aggregation process was carried through and reflected in the technological coefficients of RAMS, and most importantly in the yield effects of weed control alternatives. RAMS treats highly and nonhighly-erodible land separately for modeling conservation compliance. RAMS activities are grouped under the following four sub-sectors:

1. **The crop production** activities are defined as acres of nonirrigated crop rotations, on highly and nonhighly erodible land, and under one of four tillage practices (conventional till fall plow, conventional till spring plow, reduced till, and no till) and two conservation practices (straight row and contour). Since the study watershed (PA-41) is a fully nonirrigated agricultural area, irrigation practice is not included. Eighteen major crop rotations covering 8 major crops (corn grain, corn silage, soybeans, oats, winter wheat, sorghum, legume hay, and nonlegume hay) are included in RAMS. These activities represent the complete set of current practices in this watershed; therefore, they are associated with base input use, yields, and production costs and returns, derived from cropping practices survey (USDA 1993).

2. **The government program** activities are defined in relation with the production activities. Conservation reserve, deficiency payment, base-loss penalty are the program activities defined.

3. **The buy-inputs and marketing** activities are defined for principal variable inputs labor, fertilizer, and chemical and for all crops including program crops. Thus, except for land, which is physically constrained, all other major input levels are endogenously determined through the buy-input activity.

4. **The weed control** activities are modeled as acres of herbicide treated acres and chemical activities, representing amounts of individual chemicals. These activities are defined by tillage and soil type (sand or clay). Each weed control activity is defined as a strategy, which is a set of information on primary and secondary herbicide treatments including nonchemical control, effectiveness, yield loss, and cost (Bouzaher et al. 1992). Totally, there are 488 weed control strategies for corn and 148 strategies for sorghum, which allows for substitution between herbicides and between herbicide and mechanical weed control.

The four major sectors described above are interrelated through the use of resources and physical constraints defining RAMS. Physical constraints define availability of total land, highly erodible land, CRP land, and commodity program base acreage. Besides the physical constraints, flexibility constraints are incorporated for calibration purposes. The flexibility constraints enable the model to determine resource and management practice levels to conform to historical levels. It also helps to diversify herbicide use conforming to current use levels. This is particularly useful because it eliminates the model's tendency to choose only one weed control strategy that is relatively cheap and effective. A complete mathematical description of the RAMS model is shown in Appendix 2.

System Integration

There are two levels of *integration* that needs to be achieved to integrate the diverse economic and environmental models. The first level of integration concerns bringing together the multidisclplinary models through some unification technique. A novel and efficient unification technique is provided by *metamodeling* (Blanning 1975 Bouzaher et al. 1993). The word *meta* meaning derived, and the metamodels are models derived from another model in the hierarchy. Metamodels are reduced form response functions fitted to the outputs of complex mathematical models to ease the computational burden of integrated analysis of diverse models. The second level of integration concerns the *aggregation* of parameters of the biogeophysical process models, which are mostly at the homogenous soil level in a field, to the level desired by the multicriteria decision making model. This is a very crucial process in NPS pollution measurement because of extensive spatial heterogeneity. Ignoring spatial heterogeneity will bias the results and policy conclusions.

Metamodeling

Ideally, water quality monitoring should provide policy analysts with the needed information. But due to high monitoring costs, mathematical models are generally used to simulate the physical processes that describe the agricultural chemical movement in soil and predict their concentrations in groundwater and surface water (Wagenet and Hutson 1991). Use of these process models is economical and practical for site-specific problems only (Evans and Myers 1990). To use these field-scale models for regional water quality assessments we have to simulate them for the area-wide distribution of soil and weather parameters. But it is costly and time consuming to do area-wide simulation for all combinations of crop, chemical, management practice, and technology. Therefore, building metamodels from process model outputs is a viable and manageable option, which is statistically valid.

Furthermore, to evaluate a new policy within a regional integrated modeling system, we have to repeat the simulation runs for all combinations of factors used in the baseline evaluation. For instance, a policy scenario in an integrated modeling system requires a mutually consistent combination of policy, environmental, chemical, management, and technological parameters and behavioral equations. Integrated systems analysis requires both timely integration of diverse process models and integration of outcomes over a distribution of diverse input sets. Therefore, a simplified technique to ease the computational burden while abstracting the key process characteristics is needed. Metamodels are simple, but statistically validated, analytical tools capable of addressing both of these difficulties.

Metamodeling is a statistical method to abstract away from unneeded detail for regional analysis by approximating outcomes of a complex process model through statistically validated parametric forms. The simplification provided by metamodels allows us to evaluate the consequences of alternative policies without the need for additional simulations. If the complex simulation model is a tool to approximate the underlying real-life system, the analytic metamodel attempts to approximate and aid in the interpretation of the simulation model and ultimately the real-life system. Empirical application of metamodels in industrial, computer, and management fields is documented in Kleijnen (1987). To our knowledge, use of metamodels in agriecological systems simulation and, particularly, the simulation of real processes describing the fate of agricultural chemicals, is fairly new.

A metamodel is a regression model explaining the input-output relationship of a complex simulation model, which is a mathematical model structured to mimic the underlying real-life process. Let Φ be the unknown function which characterizes the underlying real phenomena relating the response y to the input vector **v**:

$$y = \Phi(\mathbf{v}). \quad (2)$$

Most simulation models mimic outcomes for a variety of possible response variables, and specification of the response of interest may not be trivial matter.

A simulation experiment is a set of executions of the simulation models intended to approximate the values of y associated with a specified set of input vectors. The output of a simulation experiment is a data set consisting of specified input vectors and their associated responses, as determined by the simulation model. Choice of the number and values of input vectors for which the simulation model will be executed is the subject of experimental design. For statistical purposes, it would be preferable to experiment with the real-life system rather than a simulation model of the system. In that case we would have a statistical model of the system rather than a metamodel. This approach is not adopted because it would mean incurring the cost and delay of waiting, in this case for 15 years of weather to present itself to the real-life system.

Given the output of a simulation experiment, we can specify an analytic metamodel with relatively few inputs, x_1 through x_k. Let the metamodel explaining the simulated outcome be represented as:

$$y = \phi(x_1, x_2, \ldots, x_k, u), \quad (3)$$

where u is the stochastic disturbance term. We can use statistical procedures to identify and estimate the function ϕ describing the metamodel. Because of their simple and precise representation of the complex mathematical model, simulation practitioners are favoring metamodels for purposes such as validation, sensitivity analysis, estimation of interactions among inputs, control, and optimization, without the need for additional simulation runs (Kleijnen 1987).

The long-term average values (average over 15 years of simulation) of environmental indicators, such as soil erosion, nitrate-N in runoff, leaching losses of nitrate-N, soluble P in runoff, atrazine in runoff, and leaching losses of atrazine, predicted by EPIC are at the micro-unit level. Fifteen years of simulation was considered to be long enough to capture the long-term average, because empirical evidence suggest that the time series values of these parameters reach a steady state after 10 years. To capture the spatial and production heterogeneity within the multicriteria decision model the following aggregation scheme was adopted. Metamodels are very essential part of this aggregation, without which timely evaluation of NPS pollution policies is not possible. The estimated metamodels are extrapolated to the *population* of soils in the study area to get predictions for each of the environmental indicators. This is the novel and the challenging aggregation technique attempted so far in analytical works involving environmental models, with the exception of CEEPES. The superiority of the CEEPES integrated modeling framework lies in its ability to capture the spatial heterogeneity. These population estimates can be used to target hot-spots for prescribing site-specific resource quality standards.

Because the decision making unit is configured at the PA level, these predictions are aggregated to the PA level by taking a weighted average. The weights are the amount of arable acres under each of those soil types. A major assumption is that the different production and management practices and crops are supported in each and every soil in the same proportion.

The Empirical Multicriteria Decision Model

The multicriteria decision making model is a mathematical programming model, which finds a best-compromise solution simultaneously given a set of economic and environmental objectives. Five environmental objectives representing (1) soil loss from water erosion (EROSI), (2) nitrate-N in runoff (NRUF), (3) nitrate-N in percolate below soil profile (NLCH), (4) atrazine in runoff (ARUF), and (5) atrazine in percolate below soil profile (ALCH), are included in the multicriteria decision making model. These are the principal NPS pollution indicators related to crop production in this study area, which are of concern to the society at present. The economic objective measures short-run net profit defined as total returns, including returns from CRP and deficiency payments, net of cost of crop production activities, which includes cost of weed control activities. The full specification of the multiobjective model is:

MAX: Profit =

$$-\sum_{v=1}^{1}\sum_{m=1}^{2}\sum_{l=1}^{4}\sum_{k=1}^{18} CPRD_{vmlk} * XPRD_{vmlk} \qquad \textit{[Cost of Production Activities]}$$

$$+ \quad RCRD * XCRP \qquad \text{[Return from CRP]}$$

$$+ \quad \sum_{q=1}^{q1} RDP_q * XDP_q \qquad \text{[Deficiency Payment]}$$

$$+ \quad \sum_{q=1}^{q1} RSELL_q * XSELL_q \qquad \text{[Return from Marketing]}$$

MIN: Soil Loss =

$$\sum_{v=1}^{1} \sum_{m=1}^{2} \sum_{j=1}^{4} \sum_{k=1}^{18} XPRD_{vmjk} * EROSI_{vmjk}$$

MIN: Nitrate-N in Runoff =

$$\sum_{v=1}^{1} \sum_{m=1}^{2} \sum_{j=1}^{4} \sum_{k=1}^{18} XPRD_{vmjk} * NRUF_{vmjk}$$

MIN: Nitrate-N Leaching =

$$\sum_{v=1}^{1} \sum_{m=1}^{2} \sum_{j=1}^{4} \sum_{k=1}^{18} XPRD_{vmjk} * NLCH_{vmjk}$$

MIN: Atrazine in Runoff =

$$\sum_{v=1}^{1} \sum_{m=1}^{2} \sum_{j=1}^{4} \sum_{k=1}^{18} XPRD_{vmjk} * ARUF_{vmjk}$$

MIN: Atrazine Leaching =

$$\sum_{v=1}^{1} \sum_{m=1}^{2} \sum_{j=1}^{4} \sum_{k=1}^{18} XPRD_{vmjk} * ALCH_{vmjk}$$

The summation index v is irrigation practice, m is conservation practice, j is tillage practice, and k denotes crop rotation. The definition of the variables and indices in the economic criterion function are the same as in Appendix 2. The coefficients of the environmental indicators will be derived as explained in the previous section on system integration using baseline production levels. For this purpose the baseline is carefully simulated and calibrated to the actual production reported in extension publications.

CHAPTER V. RESULTS AND DISCUSSION

This chapter is organized into two major sections. The first section summarizes the EPIC\WQ model results of long term average values of environmental indicators, briefly describes metamodel development process and the estimated metamodels for each of the environmental indicators. The results from extrapolating these metamodels to the population of soils in the study region are also shown. These results are summarized as cumulative frequency distribution of nonpoint pollution indicators for alternative tillage and conservation practices, for the two major crop rotation systems—continuous corn and corn-soybean cropping system. The method of aggregation of environmental indicators, from soil-space scale to watershed scale, to get the coefficients for the environmental indicators for the economic-environmental decision model is also discussed. The second section elaborates the alternative policy scenarios and the economic and environmental impacts and tradeoffs as indicated by the multiple objective scenario analysis. The scenario results are used to develop tradeoff relationships between economic returns, soil quality, groundwater quality, and surface water quality. The implication of these tradeoffs from a general welfare stand point is also discussed.

EPIC and Metamodel Results

Summary of simulation results from EPIC

Using the EPIC\WQ model, which was calibrated to the study region based on a comparison of simulated and historical crop yields, the soil erosion and chemical and nutrient runoff / leaching processes were simulated for seven different crop and crop rotations—continuous corn, corn-soybean, oats, winter wheat, sorghum grain, corn silage, and legume hay. Four alternative tillage practices—conventional tillage with fall plow, conventional tillage with spring plow, reduced tillage, and no-till— and two types of conservation practices the straight row and contour were simulated for each of the crop and crop rotations. The physical process model was simulated over 15 years using actual historical weather data from three representative weather stations in the study watershed. Preliminary calibration runs suggested that the environmental indicators reached steady state after 8 to 10 years, therefore by simulating over 15 years we are fully capturing the impact of different weather cycles and hence predict the long term average values.

The long term average soil loss and chemical and nutrient emissions were recorded for the 57 representative soil types sampled from the watershed. This is a novel procedure which allows us to capture the spatial heterogeneity of physical processes by expending reasonable amount of time and computer resources. The model was simulated using optimal fertilization rates where the rates are obtained from a Resource and Technology Division survey of cropping practices. Only preemerge and postemerge application of atrazine to corn and sorghum was simulated using an application rate of 0.9 pounds active ingredient (lbs. a.i.) per acre. Sensitivity test runs of EPIC to alternative application rates of atrazine showed linear relationship between atrazine emission and the rate of application. Therefore, we assume this linear relationship to hold in our estimated metamodel predictions.

The summary statistics—mean, standard deviation, minimum, and maximum—of EPIC simulated soil loss for alternative cropping and management practices is shown in Table 7. Soil erosion as measured by the modified universal soil loss equation (MUSLE) is reported here.[17] The amount of soil erosion is significantly smaller for no-till and reduced till compared to conventional till. The mean soil loss for no-till corn and corn-soybean rotation was lower by 90 and 70 percent, respectively. Contouring reduced soil loss by 40 to 50 percent under all tillage and cropping practices. Simulated soil erosion indicate that corn-soybean rotation is the most erosive cropping system followed by sorghum, continuous corn, oats and winter wheat. Soil erosion from a corn-soybean rotation is often greater than from a continuous corn because of loss of residue cover after soybean harvest, exposing the top soil to the impact of raindrops and the deterioration of the soil aggregate stability associated with soybean cropping (Corak and Kaspar 1990). Since oat is an important cover crop with root structure anchoring surface residues and soil it is the least erosive crop.

The simulated nitrate-N emissions in runoff and percolate are summarized in Table 8 and 9, respectively. The mean concentration of nitrate-N in runoff is lower under no-till and reduced till practices compared to conventional till, while the concentrations in percolate were higher for reduced and no-till systems than the conventional tillage. This result is supported by the actual measurements at the Iowa

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[17] The MUSLE uses runoff variables to simulate erosion and sediment yield. The equation is specified as: $Z = (R*K*LS*C*P) * \phi$, where R is the coarse fragment factor, K is the soil erodibility factor, LS is the slope length factor, C is the crop management factor, P is the erosion control practice factor, and ϕ is a function of runoff volume and peak runoff rate.

Table 7. Simulated long term average soil erosion (tons/ha) by cropping systems

Cropping System	Conservation Practice	Tillage Practice	Mean	Standard Deviation	Minimum	Maximum
Continuous Corn	Straight Row	Fall Plow	69.28	93.27	0.58	670.26
		Spring Plow	64.55	85.30	0.47	609.39
		Reduced Till	48.27	101.78	0.20	761.92
		No-Till	6.49	22.51	0	156.34
	Contour	Fall Plow	34.33	88.61	0.06	639.27
		Spring Plow	29.43	74.92	0.05	548.48
		Reduced Till	19.47	53.65	0	385.96
		No-Till	3.05	11.34	0	80.26
Corn-Soybeans	Straight Row	Fall Plow	90.05	103.83	0.99	721.27
		Spring Plow	80.13	89.65	0.88	614.37
		Reduced Till	70.80	113.02	0.61	842.89
		No-Till	26.71	51.22	0.16	382.50
	Contour	Fall Plow	41.07	93.38	0.13	685.10
		Spring Plow	37.29	87.80	0.11	647.06
		Reduced Till	28.71	65.58	0	476.26
		No-Till	11.56	33.43	0.02	246.27
Oats	Straight Row	Fall Plow	20.85	23.96	0.11	162.63
		Spring Plow	17.96	21.23	0.09	145.95
		Reduced Till	12.89	17.29	0.06	123.07
		No-Till	5.06	8.03	0.01	57.82
	Contour	Fall Plow	12.66	19.55	0.04	138.68
		Spring Plow	10.94	17.35	0.04	123.86
		Reduced Till	7.98	14.51	0.02	105.88
		No-Till	3.11	6.51	0	48.03
Winter Wheat	Straight Row	Fall Plow	14.78	30.56	0.09	227.07
		Spring Plow	12.21	23.97	0.07	177.78
		Reduced Till	9.37	17.34	0.05	127.17
		No-Till	4.87	10.09	0.01	73.84
	Contour	Fall Plow	9.67	26.93	0.04	202.14
		Spring Plow	7.87	20.58	0.03	154.23
		Reduced Till	5.99	14.69	0.02	109.20
		No-Till	3.11	8.64	0.01	64.48
Sorghum Grain	Straight Row	Fall Plow	83.05	105.19	0.62	736.65
		Spring Plow	79.04	100.37	0.60	703.47
		Reduced Till	87.49	103.68	0.64	718.28
		No-Till	67.15	109.38	0.35	807.90
	Contour	Fall Plow	39.28	103.18	0.07	762.74
		Spring Plow	35.50	86.21	0.07	630.34
		Reduced Till	39.98	95.79	0.08	704.27
		No-Till	28.43	70.30	0.04	514.32

Table 8. Simulated long term average nitrate-N in runoff (mg/L) by cropping systems

Cropping System	Conservation Practice	Tillage Practice	Mean	Standard Deviation	Minimum	Maximum
Continuous Corn	Straight Row	Fall Plow	7.37	3.44	2.00	14.00
		Spring Plow	7.14	3.39	2.00	14.00
		Reduced Till	6.05	3.39	2.00	13.00
		No-Till	1.66	1.65	0	10.00
	Contour	Fall Plow	5.49	3.25	2.00	12.00
		Spring Plow	5.28	3.03	2.00	12.00
		Reduced Till	4.60	3.04	0	13.00
		No-Till	1.21	1.37	0	9.00
Corn-Soybeans	Straight Row	Fall Plow	5.86	2.42	2.00	11.00
		Spring Plow	5.74	2.36	2.00	11.00
		Reduced Till	5.77	2.56	2.00	12.00
		No-Till	4.79	2.71	1.00	11.00
	Contour	Fall Plow	3.98	2.29	2.00	10.00
		Spring Plow	3.88	2.23	2.00	10.00
		Reduced Till	4.04	2.38	0	11.00
		No-Till	3.47	2.34	1.00	9.00
Oats	Straight Row	Fall Plow	3.42	1.72	1.00	7.00
		Spring Plow	3.20	1.64	1.00	7.00
		Reduced Till	3.14	1.59	1.00	7.00
		No-Till	3.12	2.00	0.95	7.00
	Contour	Fall Plow	3.21	1.54	1.00	7.00
		Spring Plow	3.11	1.59	1.00	7.00
		Reduced Till	2.93	1.53	1.00	6.00
		No-Till	2.96	1.91	0.94	7.00
Winter Wheat	Straight Row	Fall Plow	2.67	0.83	1.00	5.00
		Spring Plow	2.63	0.79	1.00	4.00
		Reduced Till	2.54	0.78	1.00	4.00
		No-Till	3.09	1.17	1.00	5.00
	Contour	Fall Plow	2.63	0.82	1.00	5.00
		Spring Plow	2.60	0.75	1.00	4.00
		Reduced Till	2.46	0.71	1.00	4.00
		No-Till	3.00	1.18	1.00	5.00
Sorghum Grain	Straight Row	Fall Plow	4.79	2.31	1.00	9.00
		Spring Plow	4.88	2.44	1.00	10.00
		Reduced Till	6.14	2.79	2.00	12.00
		No-Till	5.88	2.82	2.00	11.00
	Contour	Fall Plow	3.21	2.03	1.00	9.00
		Spring Plow	3.25	2.07	1.00	9.00
		Reduced Till	4.02	2.55	1.00	11.00
		No-Till	3.89	2.48	1.00	10.00

Table 9. Simulated long term average leaching losses of nitrate-N by cropping systems

Cropping System	Conservation Practice	Tillage Practice	Mean	Standard Deviation	Minimum	Maximum
Continuous Corn	Straight Row	Fall Plow	2.12	3.99	0.22	23.00
		Spring Plow	2.05	3.68	0.20	20.00
		Reduced Till	2.87	3.70	0.28	19.00
		No-Till	2.36	2.67	0.46	16.00
	Contour	Fall Plow	2.43	3.61	0.23	18.00
		Spring Plow	2.46	3.79	0.21	21.00
		Reduced Till	3.26	3.81	0.31	19.00
		No-Till	2.31	2.45	0.46	14.00
Corn-Soybeans	Straight Row	Fall Plow	1.73	2.28	0	13.00
		Spring Plow	1.84	2.13	0.34	11.00
		Reduced Till	2.19	2.37	0.42	15.00
		No-Till	9.43	10.72	0.60	42.00
	Contour	Fall Plow	2.12	2.57	0.42	18.00
		Spring Plow	2.21	2.47	0.42	17.00
		Reduced Till	2.80	2.77	0.48	19.00
		No-Till	9.85	11.22	0.63	43.00
Oats	Straight Row	Fall Plow	2.08	1.28	0.27	5.00
		Spring Plow	2.10	1.22	0.29	5.00
		Reduced Till	2.03	1.22	0.24	4.00
		No-Till	2.13	1.27	0.38	5.00
	Contour	Fall Plow	2.16	1.29	0.29	5.00
		Spring Plow	2.21	1.27	0.30	5.00
		Reduced Till	2.10	1.22	0.26	4.00
		No-Till	2.18	1.27	0.39	5.00
Winter Wheat	Straight Row	Fall Plow	2.26	2.05	0.17	13.00
		Spring Plow	2.21	1.94	0.16	12.00
		Reduced Till	2.11	1.65	0.16	9.00
		No-Till	2.65	1.91	0.30	10.00
	Contour	Fall Plow	2.27	1.96	0.18	12.00
		Spring Plow	2.24	1.88	0.18	11.00
		Reduced Till	2.13	1.68	0.18	9.00
		No-Till	2.78	1.93	0.32	10.00
Sorghum Grain	Straight Row	Fall Plow	1.86	3.33	0.09	16.00
		Spring Plow	1.92	3.47	0.10	18.00
		Reduced Till	3.60	5.36	0.09	26.00
		No-Till	3.25	4.59	0.10	22.00
	Contour	Fall Plow	1.80	2.64	0.10	14.00
		Spring Plow	1.84	2.70	0.11	14.00
		Reduced Till	3.44	4.09	0.11	19.00
		No-Till	3.27	3.89	0.12	19.00

Sate University experimental sites in Nashua watershed in northeast Iowa. Surface runoff measurements at this site reveal that the average concentration of nitrate-N in runoff was greatest under the moldboard plowing plots than the reduced and no-till plots. However, no-till plots had the greatest total nitrate-N and herbicide losses to groundwater (Kanwar et al. 1990). The concentrations in runoff decreased under contour system compared to straight row. For continuous corn, under straight row cropping system with fall plow, the mean simulated concentration of nitrate-N in runoff was 7.37 mg/L (ppm), which is close to the actual annual measurements. Average annual measurements (actual) of nitrate-N in runoff in the Roberts Creek watershed in northeast Iowa, with 49 percent row crop, mostly corn under fall plow, was 8 ppm (Seigley et al. 1993).

Assuming nitrate-N concentration in runoff as a measure of concentration in the major river system we estimate a 5.3 ppm weighted long term average concentration of nitrate-N in surface water. The weights are the historical proportions of alternative tillage and cropping practices. Keeney and DeLuca (1993) report a eleven year (1980-91) average flow of nitrate-N in Des Moines river system, based on actual annual measurements, as 5.6 ppm. Leaching losses of nitrate-N under conventional cropping practices ranged from 0 to 23 ppm, while for no-till it ranged from 0.12 to 43 ppm. Measurements of nitrate-N from several well samples in the region showed concentrations to range from 0 to 30 ppm (Vander Zee et al. 1990; Blanchard et al. 1993). An USGS (1993) monitoring study of near-surface aquifers in Iowa, testing 40 sampled wells, showed nitrate-N concentrations in the range of less than 0.05 to 12 ppm. The simulated long term average leaching losses of nitrate-N is inside this range.

In Table 10 we report the long term average runoff values of soluble P. The phosphorous emissions are generally low in all cropping systems, which confirms with the USGS findings (USGS 1993). The reason for low detection of phosphorous is that the two major crops grown in this region, corn and soybeans, require relatively less phosphorous application. In view of the low detection and limited concern from phosphorus pollution this indicator is not included in further analysis.

Long term average values of atrazine in runoff and percolate are summarized in Table 11. As mentioned previously, atrazine is the most widely used herbicide in corn production in Iowa with nearly 40 percent of corn acres being treated with atrazine. Therefore, the economic ramifications of regulating atrazine use based on water quality standards will be severe requiring a careful evaluation of alternative policies. The concentration of atrazine in runoff from corn production decreases with conservation tillage but for sorghum the impact of tillage was marginal. The mean annual concentration of atrazine in runoff from corn ranged from 37 μg/L (ppb) with conventional tillage to 12 ppb with no-till (a reduction of 68 percent), while contouring reduced runoff losses by 33 to 55 percent. Fawcett et al. (1993) who reviewed over 100 published studies to assess the effectiveness of various BMPs in reducing herbicide runoff conclude that conservation tillage systems have usually reduced runoff. Their summary of averaging natural rainfall study area data indicate that atrazine in runoff decreased by as much as 70 percent with no-till, and contouring reduced herbicide runoff by 60 percent. Reductions of this magnitude are the result of large reductions in erosion and increased infiltration.

Table 10. Simulated long term average soluble-P in runoff (mg/L) by cropping systems

Cropping System	Conservation Practice	Tillage Practice	Mean	Standard Deviation	Minimum	Maximum
Continuous Corn	Straight Row	Fall Plow	1.09	0.47	0.53	2.00
		Spring Plow	0.80	0.32	0.31	2.00
		Reduced Till	0.05	0.06	0	0.31
		No-Till	0.25	0.38	0	2.00
	Contour	Fall Plow	0.87	0.28	0.44	2.00
		Spring Plow	0.68	0.36	0.23	2.00
		Reduced Till	0.04	0.05	0	0.25
		No-Till	0.21	0.36	0	2.00
Corn-Soybeans	Straight Row	Fall Plow	0.87	0.22	0.48	2.00
		Spring Plow	0.72	0.21	0.35	1.00
		Reduced Till	0.29	0.15	0.11	0.86
		No-Till	1.02	0.46	0.39	2.00
	Contour	Fall Plow	0.79	0.27	0.00	2.00
		Spring Plow	0.60	0.22	0.28	1.00
		Reduced Till	0.22	0.13	0.00	0.71
		No-Till	0.83	0.36	0.32	2.00
Oats	Straight Row	Fall Plow	0.33	0.14	0.13	0.58
		Spring Plow	0.27	0.14	0.07	0.52
		Reduced Till	0.24	0.12	0.06	0.48
		No-Till	0.36	0.17	0.05	0.66
	Contour	Fall Plow	0.31	0.13	0.13	0.56
		Spring Plow	0.25	0.13	0.07	0.51
		Reduced Till	0.23	0.11	0.06	0.45
		No-Till	0.35	0.17	0.05	0.66
Winter Wheat	Straight Row	Fall Plow	0.57	0.13	0.35	1.00
		Spring Plow	0.57	0.13	0.35	1.00
		Reduced Till	0.35	0.11	0.19	0.94
		No-Till	0.52	0.15	0.21	1.00
	Contour	Fall Plow	0.55	0.12	0.35	1.00
		Spring Plow	0.55	0.12	0.34	1.00
		Reduced Till	0.34	0.11	0.18	0.94
		No-Till	0.51	0.16	0.21	1.00
Sorghum Grain	Straight Row	Fall Plow	0.55	0.20	0.25	1.00
		Spring Plow	0.44	0.21	0.16	1.00
		Reduced Till	0.76	0.18	0.36	1.00
		No-Till	0.68	0.18	0.32	1.00
	Contour	Fall Plow	0.49	0.18	0.23	1.00
		Spring Plow	0.36	0.18	0.11	0.94
		Reduced Till	0.70	0.19	0.34	1.00
		No-Till	0.62	0.18	0.29	1.00

Table 11. Simulated long term average atrazine concentrations (µg/L) in runoff and percolate by cropping systems

Cropping System	Conservation Practice	Tillage Practice	Mean	Standard Deviation	Minimum	Maximum
Runoff						
Continuous Corn	Straight Row	Fall Plow	36.58	16.66	0.35	69.00
		Spring Plow	35.96	16.59	0.25	70.00
		Reduced Till	29.88	15.84	0.23	60.00
		No-Till	11.97	25.18	0	109.00
	Contour	Fall Plow	24.76	15.05	0.07	57.00
		Spring Plow	23.99	15.69	0.13	64.00
		Reduced Till	19.37	14.04	0	53.00
		No-Till	5.43	15.96	0	94.00
Sorghum Grain	Straight Row	Fall Plow	27.10	13.26	0.31	50.00
		Spring Plow	27.37	13.45	0.33	53.00
		Reduced Till	28.61	13.41	0.40	52.00
		No-Till	27.68	13.36	0.40	52.00
	Contour	Fall Plow	16.84	12.10	0.08	49.00
		Spring Plow	16.49	11.54	0.09	49.00
		Reduced Till	17.36	12.05	0.08	51.00
		No-Till	16.86	11.72	0.06	47.00
Leaching						
Continuous Corn	Straight Row	Fall Plow	1.67	6.84	0.00	44.00
		Spring Plow	1.39	5.35	0.00	34.00
		Reduced Till	1.55	6.78	0.00	49.00
		No-Till	5.75	22.73	0.01	62.00
	Contour	Fall Plow	2.75	12.70	0.00	93.00
		Spring Plow	2.80	15.57	0.00	117.00
		Reduced Till	2.43	12.41	0.00	93.00
		No-Till	5.12	18.60	0.01	129.00
Sorghum Grain	Straight Row	Fall Plow	2.55	11.09	0.00	64.00
		Spring Plow	2.33	10.39	0.00	67.00
		Reduced Till	2.36	10.18	0.00	60.00
		No-Till	2.29	12.06	0.00	89.00
	Contour	Fall Plow	2.18	10.05	0.00	72.00
		Spring Plow	2.56	13.14	0.00	97.00
		Reduced Till	2.52	12.69	0.00	93.00
		No-Till	2.45	13.12	0.00	98.00

The leaching losses of atrazine are in general several magnitude smaller than runoff losses. The concentration of atrazine in percolate increased under conservation tillage, ranging from 1.67 ppb with conventional tillage to 5.75 ppb with no-till. Contouring increased leaching losses of atrazine. Baker and Boddy (1990) examined the conservation tillage effects on nitrate-N and atrazine leaching in actual field sites with three different tillage systems: moldboard plow, chisel plow, and no-till. The results from this study show that conservation tillage, with the likely existence of more macropores at the soil surface, may influence chemical leaching depending on rainfall patterns.

Regression metamodels

Metamodeling is a novel econometric procedure that helps to abstract away unneeded detail of the complex process model by estimating reduced form response functions for the environmental indicators. These response functions will enable us to make statistically valid prediction of the dependent variable for complete set of soil, weather, and hydrologic parameters, within the study area, without the need for additional simulation runs. Furthermore, they allow economic and environmental model integration for an endogenous evaluation of environmental policies, which is not possible if one were to use the process model directly. Metamodels were fitted for the following environmental indicators: soil erosion, nitrate-N in runoff, nitrate-N in percolate, atrazine in runoff, and atrazine in percolate.

Regression model development requires thorough examination of data so that the prior information contained in the data is fully utilized. Data diagnosis is necessary to avoid model mis-specification and bias, which generally result if the classical assumptions of regression such as normality and constant variance of the stochastic disturbance term are violated. Therefore, it is a good practice to examine the distributions and residual scatter plots from the ordinary least squares (OLS) estimation of a simple linear regression model and decide weather the data requires any transformation. Experience with constructing metamodels for herbicide leaching and runoff for CEEPES analysis strongly suggest the need for data transformations. The details of transformation that was carried out after examining the distribution and OLS results for each indicator will be elaborated as we explain the individual metamodels.

A simple linear model for soil erosion indicated that the error term is not randomly distributed suggesting heteroskedasticity (nonconstant variance). By fitting a weighted least squares model or estimating the regression model for transformed data homoskedasticity can be ensured.[18] A simple linear regression model fitted to the cube-root transformation of the dependent variable gave a good fit as judged by adjusted R-square and root mean squared error (RMSE). The estimated metamodel is:

$$\widehat{(\text{soil loss}_{ji})}^{1/3} = \hat{\alpha}_0 + \hat{\alpha}_1 \text{ slope} + \hat{\alpha}_2 \text{ K}_f\text{-factor} + \hat{\alpha}_3 \text{ org.mat} + \hat{\alpha}_4 \text{ pH} + \hat{\alpha}_5 \text{ rainfall}$$
$$+ \hat{\alpha}_6 \text{ RCN} + \hat{\alpha}_7 \text{ c-prac} + \hat{\alpha}_8 \text{ residue}, \quad j = \text{crop and } i = 1 \text{ to } 456 \quad (1)$$

Note, for notational parsimony the subscript i on the independent variable is dropped. K_f-factor is the soil erodibility factor, RCN is the runoff curve number which captures

[18] A variance stabilizing transformation for dependent variable Y can be found by using the generalized power transformation, Y^{λ}, with $\lambda < 1$ for contracting transformation or $\lambda > 1$ for expanding transformation.

the effect of hydrology and soil cover complexes in controlling runoff, and c-prac is a (0,1) dummy variable to capture the difference between the straight row and contour practices. The residue cover is included to capture the tillage effects. Table 12 shows the parameters of the above model. The model gave a good fit to the data as indicated by the signs on the estimated parameters, adjusted R^2, and the coefficient of correlation between the dependent variable and its predicted value.

The signs on the independent variables are consistent with theory. Soil erosion increases with slope and k_f-factor. Higher organic matter content of the soil implies greater microbial activity reducing soil compaction and thereby increasing erosion. Soil pH has a negative sign implying reduced erosion of alkaline soils because of high compaction of soils with higher pH. Rainfall increases soil erosion so does the runoff curve number. Runoff curve number increases for soils with lesser infiltration capacity, which explains the positive sign on this coefficient. As explained previously, contour practice reduces soil erosion; and the residue cover, which captures the intensity of conservation tillage, also reduces soil erosion as indicated by the negative signs.

Nitrate-N concentrations in runoff and percolate are influenced by several factors, including soil, weather, hydrology, and agronomic factors. Identifying a simple relationship explaining nitrate-N in runoff or percolate is very useful for modeling purposes. A simple linear regression model fitted to the untransformed data on nitrate-N in runoff gave a good fit. The estimated metamodel for nitrate-N in runoff is:

$$\widehat{(\text{nitrate-N in runoff}_{ji})} = \hat{\beta}_0 + \hat{\beta}_1 \text{ slope} + \hat{\beta}_2 \text{ clay} + \hat{\beta}_3 \text{ org.mat} + \hat{\beta}_4 \text{ permeab} + \hat{\beta}_5 \text{ rainfall} + \hat{\beta}_6 \text{ RCN} + \hat{\beta}_7 \text{ c-prac} + \hat{\beta}_8 \text{ residue}, \quad j = \text{crop}, i = 1 \text{ to } 456 \quad (2)$$

Table 12. Parameters of the estimated metamodels for soil erosion (in tons/ha) by cropping system

Independent Variables	Cont. Corn	Corn-Soybeans	Sorghum Grain	Oats	Winter Wheat	Corn Silage	Legume Hay
Intercept	-5.789	-5.866	-7.431	-3.910	-5.184	-6.593	-6.117
Soil Slope %	0.196	0.228	0.243	0.141	0.137	0.236	0.179
K_f-Factor[a]	3.858	5.228	5.866	1.374	2.894	5.848	2.278
Organic Matter %	0.069	0.072	0.104	0.053	0.034	0.067	0.057
Soil pH	-0.245	-0.204	-0.224	-0.151	-0.047	-0.166	-0.226
Rainfall (mm)	0.004	0.004	0.004	0.001	0.002	0.004	0.003
Runoff Curve No.[b]	0.061	0.055	0.062	0.066	0.043	0.056	0.079
Conservation Dummy[c]	-0.252	-0.531	-0.528	-0.249	-0.248	-0.538	-0.429
Residue Cover (t/ha)[d]	-0.117	-0.060	-0.012	-0.082	-0.054	-0.064	-0.421
Adjusted R^2	0.82	0.91	0.90	0.90	0.90	0.93	0.83
RMSE	0.68	0.43	0.47	0.27	0.24	0.39	0.47
$\hat{\rho}$	0.87	0.94	0.93	0.94	0.93	0.94	0.73

[a] This variable is a measure of soil erodibility potential.
[b] Runoff curve number is an index to capture the hydrologic soil-cover complexes.
[c] This is a (0,1) variable, taking a value of 0 if straight row and 1 if contour.
[d] This variable captures the differences caused by alternative tillage practices.

Note: All variables are significant at 5 percent level, RMSE is root mean squared error, N=456, and $\hat{\rho}$ is the coefficient of correlation between the actual (simulated) and predicted values of the dependent variable.

The explanation for the independent variables are as in equation (1). The estimated parameters of the above model are shown in Table 13. This model gave a good fit to the data as indicated by the signs on the estimated parameters, adjusted R^2, and RMSE, and the coefficient of correlation between the dependent variable and its predicted value. The sign on the independent variables are consistent with theory. Factors that influenced runoff such as slope, clay content, organic matter, permeability, and RCN have positive signs implying increased nitrate-N runoff. Increased residue cover reduces runoff, therefore nitrate-N in runoff is negatively related to residue cover.

A simple linear regression model fitted to the untransformed data on nitrate-N in percolate did not produce a good fit. The distribution of error term was skewed suggesting heteroskedasticity. We tried weighted least squares and transformation procedure, but the data did not give a good fit to any of these methods. A close examination of the data revealed that it has large number of observations that are zero or close to zero showing a skewed exponential distribution. It is quite common to have such a distribution for leaching values of nutrients and chemicals. Therefore, we fitted a simple nonlinear model ($Y=\exp^{X\tau}$) to the leaching data. The estimated metamodel for nitrate-N in percolate is:

$$\begin{aligned}(\widehat{\text{nitrate-N in percolate}_{ji}}) = \exp(&\hat{\tau}_0 + \hat{\tau}_1 \text{ slope} + \hat{\tau}_2 \text{ clay} + \hat{\tau}_3 \text{ org.mat} + \hat{\tau}_4 \text{ permeab} \\ &+ \hat{\tau}_5 \text{ bulk density} + \hat{\tau}_6 \text{ rainfall} + \hat{\tau}_7 \text{ RCN} + \hat{\tau}_8 \text{ c-prac} \\ &+ \hat{\tau}_9 \text{ residue}),\ j= \text{crop},\ i=1 \text{ to } 456. \qquad (3)\end{aligned}$$

The explanation for the independent variables are as in equation (1). The estimated parameters of the above model are shown in Table 14. The sign on the independent

Table 13. Parameters of the estimated metamodels for nitrate-N in runoff (in mg/L) by cropping system

Independent Variables	Cont. Corn	Corn-Soybeans	Sorghum Grain	Oats	Winter Wheat	Corn Silage	Legume Hay
Intercept	^{ns}-1.213	-3.929	-7.509	4.670	2.044	-0.222	-10.655
Soil Slope %	0.071	0.071	0.079	0.029	^{ns}0.001	0.060	^{ns}-0.038
Clay %	0.081	0.053	0.092	0.064	^{ns}0.002	0.016	^{ns}0.007
Organic Matter %	0.292	0.307	0.340	0.431	0.291	0.362	0.102
Permeability (in/hr)	0.182	0.117	0.197	0.111	0.039	0.061	^{ns}0.050
Rainfall (mm)	-0.014	-0.012	-0.010	-0.010	-0.005	-0.020	-0.002
Runoff Curve No.[a]	0.222	0.223	0.214	0.053	0.054	0.308	0.204
Conservation Dummy[b]	1.060	0.779	0.705	^{ns}-0.084	^{ns}0.050	1.336	^{ns}0.272
Residue Cover (t/ha)[c]	-0.246	-0.033	-0.002	-0.026	0.032	-0.084	-0.458
Adjusted R^2	0.73	0.84	0.77	0.70	0.64	0.87	0.55
RMSE	1.88	1.04	1.20	0.93	0.54	1.30	4.26
$\hat{\rho}$	0.86	0.92	0.88	0.84	0.80	0.93	0.73

[a] Runoff curve number is an index to capture the hydrologic soil-cover complexes.
[b] This is a (0,1) variable, taking a value of 0 if straight row and 1 if contour.
[c] This variable captures the differences caused by alternative tillage practices.

Note: All variables, except the ones marked (ns), are significant at 5 percent level, RMSE is root mean squared error, N=456, and ρ is the coefficient of correlation between the actual (simulated) and predicted values of the dependent variable.

Table 14. Parameters of the estimated metamodels for leaching losses of nitrate-N (in mg/L) by cropping system

Independent Variables	Cont. Corn	Corn-Soybeans	Sorghum Grain	Oats	Winter Wheat	Corn Silage	Legume Hay
Intercept	-18.112	7.786	-17.587	[ns]-0.422	-7.050	-7.195	-12.252
Soil Slope %	0.236	[ns]-0.003	0.187	0.022	0.078	0.193	0.214
Clay %	0.214	0.032	0.152	0.039	0.031	0.130	0.134
Organic Matter %	0.510	0.205	0.353	0.189	0.169	0.278	0.512
Permeability (in/hr)	0.238	0.068	0.149	[ns]0.009	[ns]-0.004	0.139	0.227
Bulk Density (g/cc)	4.194	1.661	3.578	0.700	0.863	[ns]0.501	3.286
Rainfall (mm)	0.006	-0.009	0.007	0.001	0.005	0.003	-0.828
Runoff Curve No.[a]	-0.032	-0.078	[ns]-0.004	-0.026	[ns]-0.000	-0.030	0.045
Conservation Dummy[b]	-0.286	-0.903	-0.210	[ns]-0.016	[ns]0.009	-0.208	0.143
Residue Cover (t/ha)[c]	-0.116	0.179	0.014	-0.001	[ns]0.008	0.025	-0.135
Adjusted R^2	0.72	0.64	0.72	0.31	0.50	0.93	0.69
RMSE	1.84	4.04	1.88	1.03	1.33	0.39	1.94
$\hat{\rho}$	0.87	0.82	0.86	0.57	0.73	0.94	0.84

[a] Runoff curve number is an index to capture the hydrologic soil-cover complexes.
[b] This is a (0,1) variable, taking a value of 0 if straight row and 1 if contour.
[c] This variable captures the differences caused by alternative tillage practices.

Note: All variables, except the ones marked (ns), are significant at 5 percent level, RMSE is root mean squared error, N=456, and ρ is the coefficient of correlation between the actual (simulated) and predicted values of the dependent variable.

variables are consistent with theory. This nonlinear model gave a good fit as judged by the estimated parameter values and their signs, adjusted R-square, root mean squared error (RMSE), and the coefficient of correlation between the dependent variable and its predicted value.

For atrazine in runoff, a simple linear model estimated using OLS indicated that the error term is not randomly distributed suggesting heteroskedasticity (nonconstant variance). A simple linear regression model fitted to square-root transformation of the dependent variable gave a good fit. The estimated metamodel for atrazine in runoff is

$$\begin{aligned}(\widehat{\text{atrazine in runoff}_{ji}})^{1/2} &= \hat{a}_0 + \hat{a}_1 \text{ slope} + \hat{a}_2 \text{ org. mat} + \hat{a}_3 \text{ avl. water} + \hat{a}_4 \text{ rainfall} \\ &+ \hat{a}_5 \text{ RCN} + \hat{a}_6 \text{ c-prac} + \hat{a}_7 \text{ residue}, \; j = \text{crop}, \; i = 1 \text{ to } 456. \qquad (4)\end{aligned}$$

The explanation for the independent variables are as in equation (1). The estimated parameters of the above model are shown in Table 15. This model gave a good fit to the data as indicated by the signs on the estimated parameters, adjusted R^2, and RMSE. The sign on the independent variables are consistent with theory. The RCN has a positive sign suggesting higher concentrations in runoff for soils with less infiltration capacity. The negative sign on residue implies less concentration in runoff as the cover factor is increased, therefore no-till should result in less emissions into runoff as reported in field studies.

A simple linear regression model fitted to the untransformed data on atrazine in percolate did not produce a good fit. The distribution of error term was skewed suggesting heteroskedasticity. We tried weighted least squares and transformation procedure, but the data did not gave a good fit to any of these methods. A close

Table 15. Estimated metamodels for atrazine runoff and leaching losses (in μg/L)

Independent Variables	Cont. Corn	Sorghum Grain	Cont. Corn	Sorghum Grain
	Atrazine in Runoff		Leaching Losses of Atrazine	
Intercept	-5.621	-3.170	-5.719	-30.490
Soil Slope %	^{ns}-0.000	-0.035	0.392	0.810
Clay %			0.217	0.542
Organic Matter %	0.434	0.506	^{ns}0.078	1.096
Permeability (in/hr)			0.413	1.080
Available Water (in/in)	5.299	5.573		
Bulk Density (g/cc)			-5.001	^{ns}0.873
Rainfall (mm)	-0.004	-0.005	0.003	0.003
Runoff Curve No.[a]	0.172	0.143	-0.027	-0.057
Conservn. Dummy[b]	0.762	0.377	-0.216	-0.767
Residue Cover (t/ha)[c]	-0.180	-0.017	0.034	0.004
Adjusted R^2	0.60	0.76	0.88	0.95
RMSE	1.60	0.80	4.87	2.55
$\hat{\rho}$	0.72	0.87	0.94	0.97

[a] Runoff curve number is an index to capture the hydrologic soil-cover complexes.
[b] This is a (0,1) variable, taking a value of 0 if straight row and 1 if contour.
[c] This variable captures the differences caused by alternative tillage practices.

Note: All variables, except the ones marked (ns), are significant at 5 percent level, RMSE is root mean squared error, N=456, and ρ is the coefficient of correlation between the actual (simulated) and predicted values of the dependent variable.

examination of the data revealed that it has large number of observations that are zero or close to zero showing a skewed exponential distribution. It is quite common to have such a distribution for leaching values of herbicides (Bouzaher et al. 1993). Therefore, we fitted a simple nonlinear model ($Y=\exp^{X r}$) to the leaching data. The estimated metamodel for atrazine in percolate is:

$$(\widehat{\text{atrazine in percolate}}_{ji}) = \exp(\hat{b}_0 + \hat{b}_1 \text{ slope} + \hat{b}_2 \text{ clay} + \hat{b}_3 \text{ org.mat} + \hat{b}_4 \text{ permeab} + \hat{b}_5 \text{ bulk density} + \hat{b}_6 \text{ rainfall} + \hat{b}_7 \text{ RCN} + \hat{b}_8 \text{ c-prac} + \hat{b}_9 \text{ residue}), \; j = \text{crop}, \; i = 1 \text{ to } 456. \tag{5}$$

The explanation for the independent variables are as in equation (1). The estimated parameters of the above model are shown in Table 15. The sign on the independent variables are consistent with theory. This nonlinear model gave a good fit as judged by the estimated parameter values and their signs, adjusted R-square, root mean squared error (RMSE), and the coefficient of correlation.

Prediction, spatial distribution, and aggregation

Using the estimated metamodels rate of soil erosion and nutrient and chemical runoff/leaching rates were predicted (extrapolated) for every soil in the watershed. Thus the estimates account for site-specific variations in soil properties, weather, and hydrologic parameters. These site-specific estimates are summarized as cumulative frequency distributions for each of the environmental indicators. The distribution gives a measure of spatial probability that a given soil under a given technology will exceed the appropriate reference value for that indicator. This measure, "probability that a soil is at-risk," is more intuitively interpreted as a measure of the spatial distribution of risk, and its usefulness is to target vulnerable soils and areas.

Figure 8 shows the cumulative frequency distribution of soil erosion for continuous corn and corn-soybean rotation under straight row and contour system. The distributions are shown separately by tillage. Suppose we pick a reference value of 50 tons per hectare (20 tons/acre) or less soil erosion, then the distributions in Figure 8.1. tells that only 40 percent of the soils grown with straight row continuous corn will meet this criteria under conventional till fall-plow cropping system. The percent of soils that will meet this criteria increases as we move towards conservation tillage. That is, the farther the curve from the origin and closer to upper left-hand corner the smaller is the proportion of erosive soils. Comparing between straight row and contouring, the later reduces soil erosion and the proportion of at-risk soils considerably. Likewise between continuous corn and corn-soybean rotation, the former is less erosive cropping system reiterating the field study results. Note, the differences in erosion impacts of tillage is narrowed as we switch from straight row cropping to contouring suggesting that the gains, in terms of preserving top soil, to conservation tillage under straight row cropping system is significant.

Figures 9 and 10 shows the cumulative frequency distributions for nitrate-N in runoff and percolate. The proportion of at-risk soils for nitrates in runoff decreases considerably as we move from conventional till fall-plow to no-till. In a corn-soybean rotation the tillage impacts are not profound. This could be explained by the smaller difference in tillage impacts on soil erosion (Figure 8). Contrary to this, the tillage impacts are more profound in the case of nitrate-N leaching from corn-soybean rotation

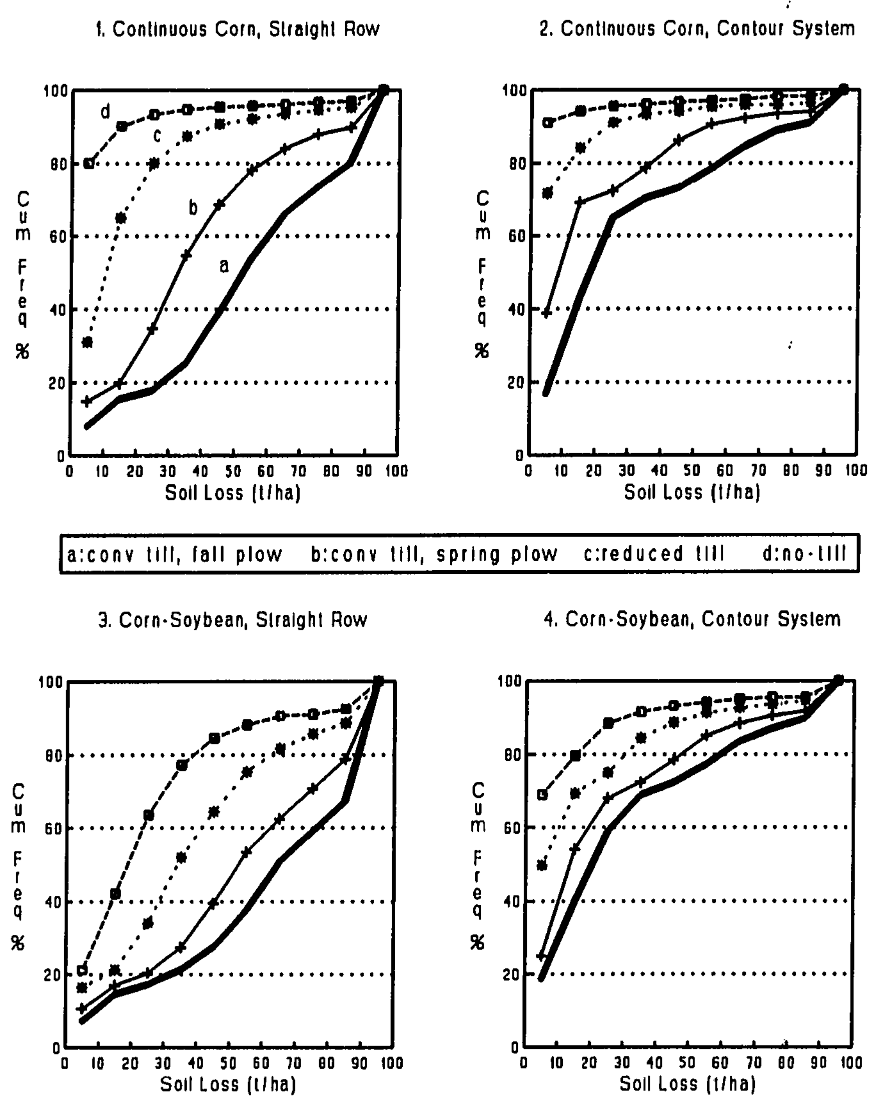

Figure 8. The cumulative distribution of soil erosion for continuous corn and corn-soybean rotations under straight row and contour

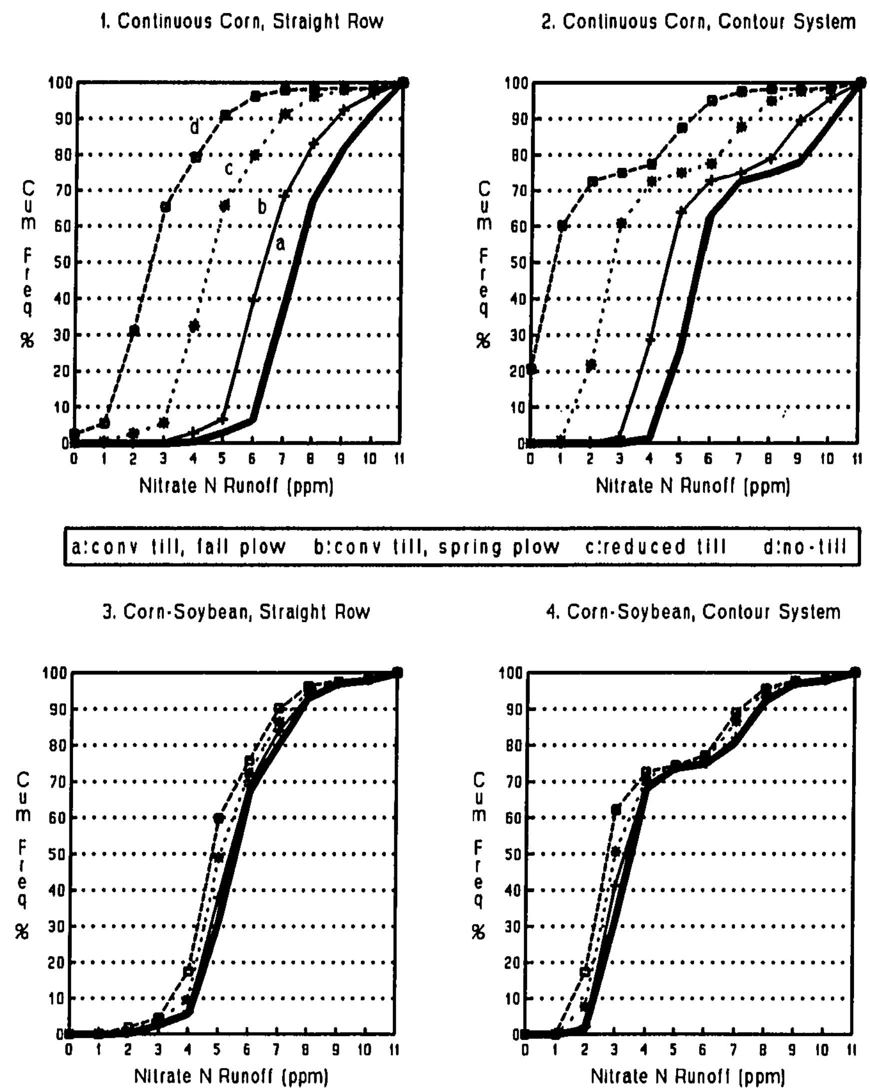

Figure 9. The cumulative distribution of nitrate-N in runoff for continuous corn and corn-soybean rotations under straight row and contour

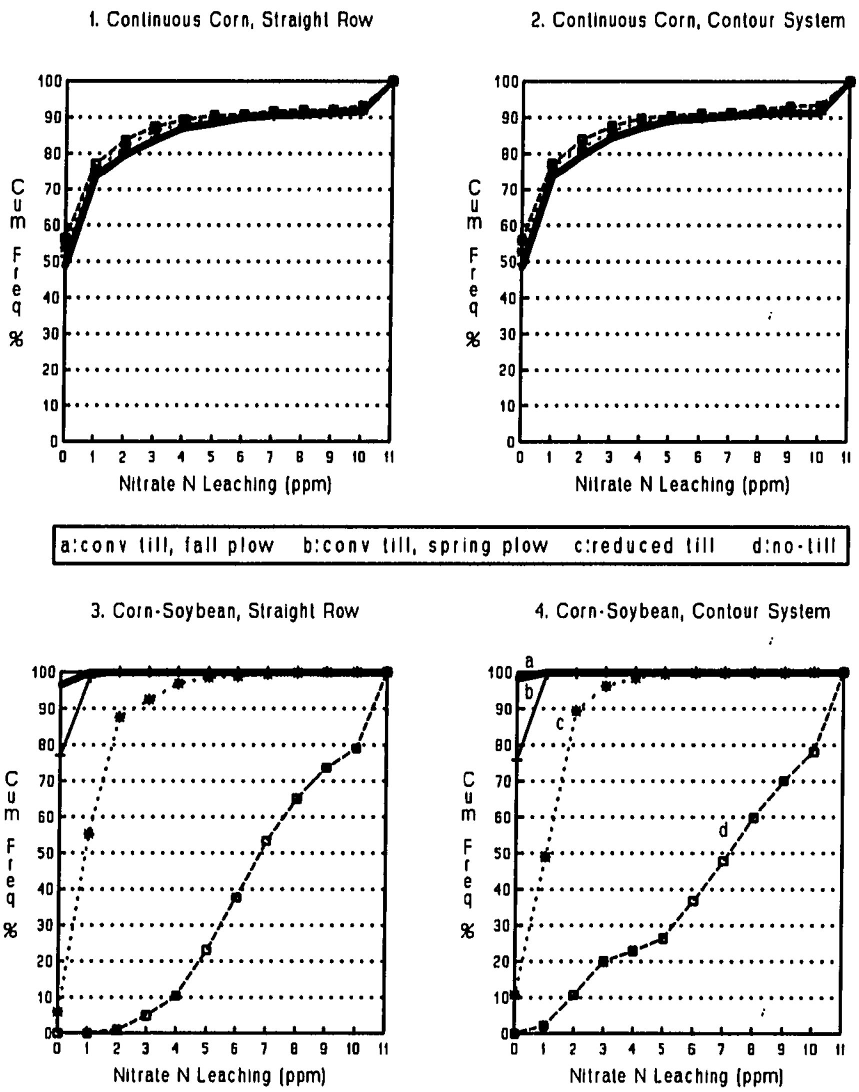

Figure 10. The cumulative distribution of nitrate-N in percolate for continuous corn and corn-soybean rotations under straight row and contour

than continuous corn, see Figure 10. This is an interesting finding because it asserts that conservation tillage for continuous corn is environmentally sound agricultural practice that can simultaneously protect both soil and water resource. The higher leaching of nitrates under corn-soybean rotation could be explained partly by the nitrogen fixing capacity of soybean. Therefore, by developing a BMP that gives proper credit for crop fixed nitrogen and reduces fertilizer supplied N, the potential leaching problem could be controlled.

Figure 11 shows the cumulative distribution of atrazine in runoff and percolate for continuous corn. The probability of at-risk soils in terms of atrazine runoff is greater for conventional tillage, while the probability of at-risk soils in terms of atrazine leaching is greater for conservation tillage. The difference between tillage systems is significant as far as runoff of atrazine is concerned than the leaching losses. Similar trends can be seen under contour system, but the probabilities of at-risk soils are generally smaller compared to straight row.

Policy Scenario Results

The integrated economic-environmental model allows evaluation of alternative environmental resource protection policies and its impact on economic efficiency and environmental quality and sustainability. By integrating the economic decision model with the physical process model outputs, through metamodeling and spatial aggregation, such policy evaluations can be performed. This is the most advanced modeling technique to date that accounts for spatial heterogeneity of the underlying processes in a scientific way. Due to the uncertainty introduced by stochastic weather events exercise caution in using the absolute numbers. The merit of this analysis,

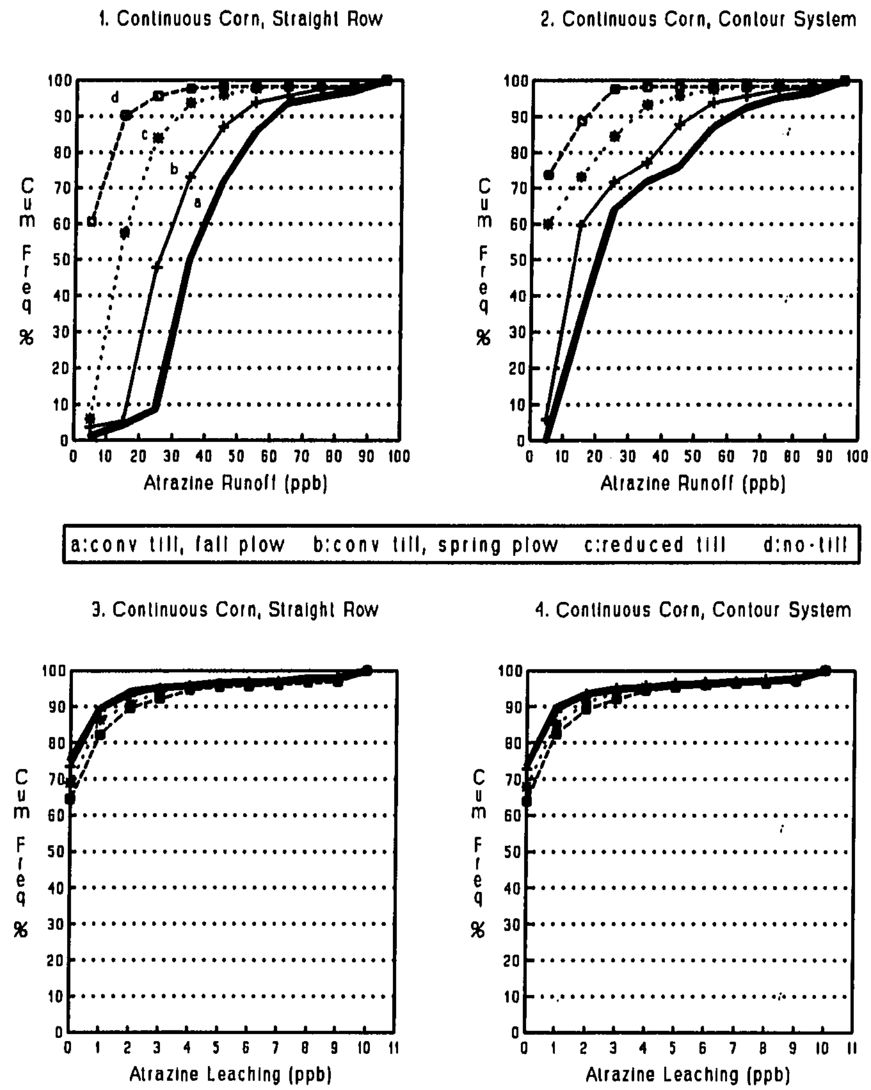

Figure 11. The cumulative distribution of atrazine in runoff and percolate for continuous corn under straight row and contour

however, is its results indicating the direction of changes, tradeoffs, and relative shifts of various economic and environmental indicators in response to alternative policy scenarios. Furthermore, it allows evaluation of alternative scenarios simultaneously as opposed to the traditional piecemeal policy evaluation. This section briefly discusses results from alternative policy scenarios including the potential tradeoffs and gains.

Piecemeal policy scenarios

Preserving top soil from erosion and protecting ground and surface waters from chemical pollution has been receiving tremendous attention as is evident from various voluntary and regulatory policies. To understand the tradeoffs between soil conservation and water quality policies three alternative scenarios were evaluated. Three scenarios representing soil quality, surface water quality, and groundwater quality protection policies, respectively, were evaluated. The scenarios are, S1— a 50% reduction in soil erosion with minimum deviation of profits from the level achieved in the baseline scenario; S2— a 25% reduction in nitrate-N concentration and 50% reduction in atrazine concentration in surface runoff; and S3— a 50% reduction in leaching losses of nitrate-N and atrazine. Scenarios S2 and S3 also required minimum deviation of profit from baseline. It is assumed that the leaching losses and surface runoff are indicators of potential ground and surface water contamination.

The baseline scenario is calibrated to the historical crop acreage, production, resource use, and the levels of soil conserving technologies observed in the study area. According to this baseline, corn and soybeans are produced in 13 and 8 million acres out of a total of 25 million acres. Conventional, reduced, and no-till systems are adopted in 63, 34, and 3 percent. The net returns to marketing and government program payments determined by the baseline model is $2.58 billion for this watershed. The baseline is modeled to account for CRP and CCP participation. To know the influence of CRP and CCP on the baseline scenario, and consequently on the three soil and water quality scenarios, two additional scenarios, namely baseline without CRP and baseline without CCP were evaluated. It is important to note that these two scenarios, analyze the impacts of allowing commercial crop production and waiver of conservation plan on CRP and CCP lands. This is counter to the traditional approach, but it is justifiable on the basis of recent debates. Table 16 shows the baseline results without CRP and CCP provisions. In general the economic impacts are smaller and the resource use adjustments are minimal. The impacts on environmental indicators are mixed. Soil erosion and runoff increases while leaching losses decrease.

The policy scenario S1 aims at reducing soil loss by 50% or equivalently to achieve a 2T (twice the soil loss tolerance limit) standard. T is basically the natural rate of growth of soil. This policy will not only sustain soil productivity, but also minimize off-site sediment transport problem. The results of S1 are summarized in Tables 17 through 19. Table 17 shows the shifts in economic and environmental indicators including the input use changes, relative to baseline. Scenario S1 reduces net returns by 21% in trying to achieve a 2T standard or $22 per acre. The estimated loss in revenue of $1.88 per ton of soil saved is comparable to Barbarika and Dicks (1988) estimate of $1.90 for the Corn Belt and Setia and Osborn's (1989) estimate of $2.38 per ton. By limiting soil erosion, nutrient and chemical runoff were reduced by about 20%, but leaching losses increased by 40% for nitrate-N and 18% for atrazine. Herbicide use increases by 80%, while there was marginal reduction in N and P use.

Table 16. CRP and CCP: Shifts in economic-environmental indicators and input use

Indicator/Input	Baseline	Absolute change	
		no-CRP	no-CCP
Net Returns, $/ac	102.40	-4.80	-1.65
Soil loss, tons/ac	23.40	+0.70	-1.51
Nitrate-N runoff, mg/L	5.15	+0.02	+0.15
Nitrate-N leaching, mg/L	1.67	-0.12	-0.21
Atrazine runoff, µg/L	25.91	+0.01	-2.54
Atrazine leaching, µg/L	0.60	-0.06	-0.05
Nitrogen fert., lbs/ac	76.46	unchg	unchg
Phosphorous, lbs/ac	47.28	unchg	unchg
Herbicides, lbs a.i./ac	0.90	unchg	unchg

Note: CRP is the Conservation Reserve program and CCP is the Conservation Compliance Program.

Table 17. Scenario—S1[a]: Shifts in economic-environmental indicators and input use

Indicator/Input	Baseline	S1	Abs.change	% change
Net Returns, $/ac	102.40	80.45	-21.95	-21.4
Soil loss, tons/ac	23.40	11.77	-11.63	-49.7
Nitrate-N runoff, mg/L	5.15	4.15	-1.00	-19.3
Nitrate-N leaching, mg/L	1.67	2.49	+0.82	+49.1
Atrazine runoff, µg/L	25.91	21.64	-4.27	-16.5
Atrazine leaching, µg/L	0.60	0.71	+0.11	+18.3
Nitrogen fert., lbs/ac	76.46	70.44	-6.02	-7.9
Phosphorous, lbs/ac	47.28	43.15	-4.13	-8.7
Herbicides, lbs a.i./ac	0.90	1.65	+0.75	83.3

[a] Soil quality (2T soil erosion reduction) scenario.

Table 18. Scenario—S1: Crop production acreage and tillage shifts from baseline

Crop/Tillage	% share to total		Baseline acreage (mil ac)	% change from baseline
	Baseline	S1		
Corn grain	50.9	41.7	12.83	-18.0
Corn silage	2.1	1.4	0.53	-33.8
Legume hay	10.1	15.2	2.55	+50.2
Nonlegume hay	1.2	1.2	0.31	-0.0
Oats	2.9	9.9	0.74	+237.5
Soybeans	32.2	21.6	8.12	-32.9
Winter wheat	0.6	9.0	0.14	+1541.5
Tillage				
Conventional till	62.8	50.0	15.82	-25.4
Reduced till	34.3	41.2	8.65	+16.7
No-till	2.9	8.8	0.74	+66.7

Table 19. Scenario—S1: Crop rotation adjustments

Crop Rotation	Baseline		S1	
	mil ac	% share	mil ac	% share
CRN	2.14	8.5	0.05	0.2
CRN-CRN-SOY	7.00	27.7	8.21	32.6
CRN-CRN-SOY-OTS-NLH	1.53	6.1		
CRN-CRN-SOY-WWT	0.50	2.0		
CRN-CRN-CRN-OTS-HLH-HLH			0.75	3.0
CRN-OTS-WWT	0.04	0.1	6.80	27.0
CRN-SOY	10.29	40.8	4.71	18.7
CSL-SOY			0.71	2.8
CSL-CSL-OTS-HLH	0.66	2.6		
CSL-SOY-HLH-HLH-HLH-HLH	1.22	4.8		
OTS-HLH-HLH-HLH	1.02	4.1		
OTS-NLH-NLH-NLH			0.41	1.6
HLH-HLH-HLH-HLH	0.80	3.2	3.58	14.2

Note: CRN-corn, CSL-corn silage, HLH-legume hay, NLH-nonlegume hay, OTS-oats, SOY-soybeans, and WWT-winter wheat.

The increased herbicide application is explained by the increase in conservation tillage acreage (reduced and no-till), see Table 18. The crop acreage distribution under the baseline and S1 scenarios are shown in Table 18. The reductions in corn grain, corn silage, and soybean acreage by 18%, 34%, and 33%, respectively, were offset by increased acreage of small grains (oats and winter wheat) and legume hay. The decrease in corn acreage explains the decline in fertilizer use. Table 19 shows the distribution of various crop rotations. The soil loss reduction scenario reduces corn-soybean rotation from 10.3 million acres to 4.7 million acres and increases legume hay rotation from 0.8 million acres to 3.6 million acres, and takes most of the acreage out of continuous-corn rotation. Bringing in more rotational cropping systems than continuous cropping systems is a better sustainable agricultural practice as it reduces pesticide use and also commercial fertilizer use.

The policy scenario S2 aims at 25% reduction in nitrates and 50% reduction in atrazine in runoff. Nitrates is more of a problem for groundwater than surface waters, therefore the reference (goal) value is set at only 25% reduction. The results of S2 are summarized in Tables 20 through 22. Table 20 shows the shifts in economic and environmental indicators including the input use changes, relative to baseline. Scenario S2 reduces net returns by 8% in trying to achieve the stipulated runoff standard. Reducing runoff reduces soil erosion from 23 tons/acre in baseline to 15 tons/acre. Limiting runoff losses of nutrients and chemical, however, increases the leaching losses of nitrates by 35% and atrazine by 15%. The increase in leaching is, however, smaller compared to that caused by the soil reduction scenario (S1). The N and P fertilizer use decreases by 17% and 9%, respectively, while herbicide use remain unchanged.

Table 20. Scenario—S2[a]: Shifts in economic-environmental indicators and input use

Indicator/Input	Baseline	S2	Abs.change	% change
Net Returns, $/ac	102.40	93.74	-8.66	-8.4
Soil loss, tons/ac	23.40	14.87	-8.53	-36.4
Nitrate-N runoff, mg/L	5.15	3.99	-1.16	-22.6
Nitrate-N leaching, mg/L	1.67	2.24	+0.58	+34.5
Atrazine runoff, μg/L	25.91	16.82	-9.09	-35.1
Atrazine leaching, μg/L	0.60	0.69	+0.09	+15.0
Nitrogen fert., lbs/ac	76.46	63.78	-12.68	-16.6
Phosphorous, lbs/ac	47.28	43.00	-4.28	-9.1
Herbicides, lbs a.i./ac	0.90	0.91	+0.01	+1.1

[a] Surface water quality (nitrates and atrazine runoff reduction) scenario.

Table 21. Scenario—S2: Crop production acreage and tillage shifts from baseline

Crop/Tillage	% share to total		Baseline acreage (mil ac)	% change from baseline
	Baseline	S2		
Corn grain	50.9	42.06	12.83	-17.4
Corn silage	2.1	1.4	0.53	-35.5
Legume hay	10.1	30.4	2.55	+200.0
Nonlegume hay	1.2	1.2	0.31	-0.02
Oats	2.9	2.9	0.74	+0.11
Soybeans	32.2	21.5	8.12	-33.3
Winter wheat	0.6	0.5	0.14	-0.00
Tillage				
Conventional till	62.8	51.8	15.82	-21.2
Reduced till	34.3	41.2	8.65	+16.6
No-till	2.9	7.0	0.74	+58.3

Table 22. Scenario—S2: Crop rotation adjustments

Crop Rotation	Baseline		S2	
	mil ac	% share	mil ac	% share
CRN	2.14	8.5	1.05	4.2
CRN-CRN-SOY	7.00	27.7	11.10	44.0
CRN-CRN-SOY-OTS-NLH	1.53	6.1	1.53	6.1
CRN-CRN-SOY-WWT	0.50	2.0	0.55	2.2
CRN-OTS-WWT	0.04	0.1		
CRN-SOY	10.29	40.8	2.53	10.0
CSL-CSL-OTS-HLH	0.66	2.6	0.69	2.7
CSL-SOY-HLH-HLH-HLH-HLH	1.22	4.8		
OTS-HLH-HLH-HLH	1.04	4.1	1.05	4.2
HLH-HLH-HLH-HLH	0.80	3.2	3.58	26.6

Note: CRN-corn, CSL-corn silage, HLH-legume hay, NLH-nonlegume hay, OTS-oats, SOY-soybeans, and WWT-winter wheat.

The crop acreage distribution under the baseline and S2 scenarios are shown in Table 21. The reductions in corn grain, corn silage, and soybean acreage by 17%, 36%, and 33%, respectively, were offset by increased acreage of oats (11%) and legume hay (200%). The decrease in corn acreage explains the reduction in average fertilizer use. Scenario S2 reduces conventional tillage by 21% and increases reduced and no-till by 17% and 58%, respectively. Table 22 shows the distribution of various crop rotations. The runoff scenario reduces continuous-corn rotation from 2.1 million acres to 1.1 million acres and increases legume hay rotation from 0.8 million acres to 3.6 million acres.

The policy scenario S3 aims at 50% reduction in leaching losses of nitrate-N and atrazine. The results of S3 are summarized in Tables 23 through 25. Table 23 shows the shifts in economic and environmental indicators including the input use changes, relative to baseline. Scenario S3 reduces net returns by about 10% in trying to achieve the stipulated percolation standard. Groundwater quality scenario S3 increases soil erosion by more than 8 tons per acre per year, which is a 35% increase from baseline. Limiting leaching losses of nutrients and atrazine increases runoff of nitrate-N by 9% and that of atrazine by 37%. N and P fertilizer use decreased by 17% and 7%, respectively, while average herbicide use doubled.

The crop acreage distribution under the baseline and S3 scenarios are shown in Table 24. The reductions in corn grain and corn silage acreage by 16% and 31%, respectively, were offset by increases in soybeans (15%), nonlegume hay (82%), and legume hay (32%). The decrease in corn acreage explains the reduction in average fertilizer use. Scenario S3 increases the proportion of conventional tillage from 63% in

Table 23. Scenario—S3[a]: Shifts in economic-environmental indicators and input use

Indicator/Input	Baseline	S3	Abs.change	% change
Net Returns, $/ac	102.40	92.70	-9.70	-9.5
Soil loss, tons/ac	23.40	31.60	+8.20	+35.1
Nitrate-N runoff, mg/L	5.15	5.63	+0.47	+9.2
Nitrate-N leaching, mg/L	1.67	0.83	-0.84	-50.0
Atrazine runoff, μg/L	25.91	35.58	+9.67	+37.3
Atrazine leaching, μg/L	0.60	0.33	-0.02	-50.0
Nitrogen fert., lbs/ac	76.46	63.27	-13.19	-17.3
Phosphorous, lbs/ac	47.28	44.15	-3.13	-6.6
Herbicides, lbs a.i./ac	0.90	1.87	+0.97	+107.8

[a] Groundwater quality (nitrates and atrazine leaching reduction) scenario.

Table 24. Scenario—S3: Crop production acreage and tillage shifts from baseline

Crop/Tillage	% share to total		Baseline acreage (mil ac)	% change from baseline
	Baseline	S3		
Corn grain	50.9	42.6	12.83	-16.3
Corn silage	2.1	1.5	0.53	-31.0
Legume hay	10.1	13.3	2.55	+31.8
Nonlegume hay	1.2	2.2	0.31	+81.5
Oats	2.9	2.9	0.74	-0.1
Soybeans	32.2	36.9	8.12	+14.8
Winter wheat	0.6	0.5	0.14	+0.1
Tillage				
Conventional till	62.8	96.6	15.82	+35.0
Reduced till	34.3	3.4	8.65	-917.9
No-till	2.9	0.0	0.74	

Table 25. Scenario—S3: Crop rotation adjustments

Crop Rotation	Baseline		S3	
	mil ac	% share	mil ac	% share
CRN	2.14	8.5		
CRN-CRN-SOY	7.00	27.7	2.20	8.7
CRN-CRN-SOY-OTS-NLH	1.53	6.1	2.77	11.0
CRN-CRN-SOY-WWT	0.50	2.0	0.55	2.2
CRN-OTS-WWT	0.04	0.1		
CRN-SOY	10.29	40.8	15.78	62.6
CSL-CSL-OTS-HLH	0.66	2.6	0.74	2.9
CSL-SOY-HLH-HLH-HLH-HLH	1.22	4.8		
OTS-HLH-HLH-HLH	1.02	4.1		
HLH-HLH-HLH-HLH	0.80	3.2	3.17	12.6

Note: CRN-corn, CSL-corn silage, HLH-legume hay, NLH-nonlegume hay, OTS-oats, SOY-soybeans, and WWT-winter wheat.

baseline to 97%, while the proportion of reduced tillage drops significantly from 345 to 3% and no-till acreage is totally shifted into conventional tillage. Table 25 shows the distribution of various crop rotations. The percolation reduction scenario eliminates continuous-corn rotation and increases legume hay rotation from 0.8 million acres to 3.2 million acres.

The results from theses three scenarios clearly suggest that there is tradeoff between the economic and the environmental objectives. There is also tradeoff between the environmental objectives, that is, soil resource and groundwater quality protection objectives are in conflict with one another. If the piecemeal policy emphasis is on soil conservation then one can not avoid impairing groundwater quality. Therefore, the S1 and S3 scenarios must be jointly evaluated by imposing soil and groundwater quality standards simultaneously. On the other hand scenarios S1 and S2 are complementary to each other. Note that the soil erosion scenario, which is restrictive than the runoff scenario, also achieves the desired runoff water quality standards. Therefore, in the ensuing multiple objective evaluation for multimedia (soil and water) quality we considered soil erosion and groundwater quality protection objectives only. Reducing the elements of the multiple objective vector will greatly speed up the solution procedure and also reduces the number of alternative noninferior solutions to be evaluated.

Multi-objective scenario

An additively linear sum of deviation of profits, soil loss, and leaching losses of nitrates and atrazine from the respective targets was minimized. The target for profit was set at the baseline level. The target for soil erosion was set at 2T level and the groundwater quality target is the baseline leaching losses of nitrates and atrazine. Since the objectives are noncommensurable the normalized percentage deviations of the objectives from their targets are minimized. A normalized weight vector was also used to generate the tradeoffs.

The multiobjective scenario (S4) is a comprehensive economic and environmental policy scenario, therefore it requires compromising between the objectives. The results of this scenario are summarized in Tables 26 through 28. In Table 26 the changes in economic and environmental indicators including input use changes, relative to the baseline, are shown. Scenario S4 reduces net returns by about 43% in trying to achieve the stipulated soil loss goal and simultaneously protect groundwater from further impairment. Soil erosion decreases by 48% bringing the annual soil loss level within 2T standard. The leaching losses of nitrates and atrazine were below the baseline levels of 1.67 ppm and 0.6 ppb, respectively. The runoff losses of nitrates and atrazine were reduced to 3.37 ppm and 21.96 ppb from the baseline levels of 5.15 ppm and 25.91 ppb, respectively. Note, the piecemeal soil erosion scenario S1 increased leaching losses of nitrates by about 50% and atrazine by 18%, while the piecemeal groundwater quality scenario S3 increased soil erosion by more than 8 tons per acre per year, which is a 35% increase from baseline.

In this multiobjective scenario, the N and P fertilizer use decreases by 19% and 10%, respectively, while average herbicide use doubled. Since this scenario imposes standards for atrazine it is likely that the concentrations of other herbicides may increase in ground and surface waters. A future evaluation should consider including

Table 26. Scenario—S4[a]: Shifts in economic-environmental indicators and input use

Indicator/Input	Baseline	S4	Abs.change	% change
Net Returns, $/ac	102.40	57.50	-44.90	-43.4
Soil loss, tons/ac	23.40	12.30	-11.10	-48.0
Nitrate-N runoff, mg/L	5.15	3.37	-1.77	-34.5
Nitrate-N leaching, mg/L	1.67	1.58	-0.10	-5.5
Atrazine runoff, µg/L	25.91	21.97	-3.94	-15.2
Atrazine leaching, µg/L	0.60	0.56	-0.04	-6.6
Nitrogen fert., lbs/ac	76.46	62.03	-14.42	-18.9
Phosphorous, lbs/ac	47.28	42.34	-4.93	-10.4
Herbicides, lbs a.i./ac	0.90	1.80	+0.90	+100.0

[a] Soil erosion reduction to 2T and groundwater quality protection scenario.

Table 27. Scenario—S4: Crop production acreage and tillage shifts from baseline

Crop/Tillage	% share to total		Baseline acreage (mil ac)	% change from baseline
	Baseline	S4		
Corn grain	50.9	42.0	12.83	-17.6
Corn silage	2.1	1.5	0.53	-31.0
Legume hay	10.1	30.3	2.55	+200.0
Nonlegume hay	1.2	1.2	0.31	-0.0
Oats	2.9	2.9	0.74	-0.1
Soybeans	32.2	21.5	8.12	-33.1
Winter wheat	0.6	0.5	0.14	+0.0
Tillage				
Conventional till	62.8	45.4	15.82	-38.0
Reduced till	34.3	42.9	8.65	+20.4
No-till	2.9	11.7	0.74	+74.5

Table 28. Scenario—S4: Crop rotation adjustments

Crop Rotation	Baseline		S4	
	mil ac	% share	mil ac	% share
CRN	2.14	8.5	4.59	18.2
CRN-CRN-SOY	7.00	27.7		
CRN-CRN-SOY-OTS-HLH			2.08	8.2
CRN-CRN-SOY-OTS-NLH	1.53	6.1		
CRN-CRN-SOY-WWT	0.50	2.0		
CRN-OTS-WWT	0.04	0.1	0.41	1.6
CRN-SOY	10.29	40.8	10.03	39.8
CSL-CSL-OTS-HLH	0.66	2.6	7.39	2.9
CSL-SOY-HLH-HLH-HLH-HLH	1.22	4.8		
OTS-HLH-HLH-HLH	1.02	4.1		
HLH-HLH-HLH-HLH	0.80	3.2	7.05	28.0
NLH-NLH-NLH-NLH			0.31	1.2

Note: CRN-corn, CSL-corn silage, HLH-legume hay, NLH-nonlegume hay, OTS-oats, SOY-soybeans, and WWT-winter wheat.

the water quality standards of other herbicides. The crop acreage distribution under the baseline and S4 scenarios are shown in Table 27. The reductions in corn and soybean acreage by 18% and 33%, respectively, were offset by increases in legume hay production. The decrease in corn acreage explains the reduction in average fertilizer use. The increase in herbicide use is explained by the increase in conservation tillage. The proportion of reduced and no-till acreage to total acreage increases 34% and 3% in baseline to 43% and 12%, respectively. Table 28 shows the distribution of crop rotation. The share of continuous corn increases from 9% in baseline to 18%, while corn-soybean rotation remained unchanged. The share of Legume hay rotation and corn-soybean-oats-legume hay rotation increased significantly, also some nonlegume hay rotations were introduced.

By varying the elements of the normalized weight vector we traced the tradeoff between returns, soil loss, groundwater quality, and surface water quality. The results are summarized in Figure 12. The tradeoff between net returns and soil loss (relative to soil loss tolerance) is shown in quadrant I. The level of groundwater quality, as measured by the leaching losses of nitrate-N and atrazine, relative to different levels of soil loss tolerance is shown in quadrant IV. The tradeoff between groundwater and surface water quality (measured as runoff of nitrate-N) is shown in quadrant III. The level of surface water quality as influenced by soil loss reduction is shown in quadrant II, which shows the tradeoff between the economic goal and surface water quality.

Comparing quadrants I and IV, it is clear that to achieve higher groundwater quality (that is, lower concentrations of nitrate-N in groundwater) one must be willing to accept increased soil loss. The alternative best management practices, however, will have a role to play in minimizing this tradeoff. Likewise, there is a tradeoff between surface and groundwater quality. Given this information on tradeoffs and the range of viable BMPs, it is up to the decision maker to find the best compromise solution.

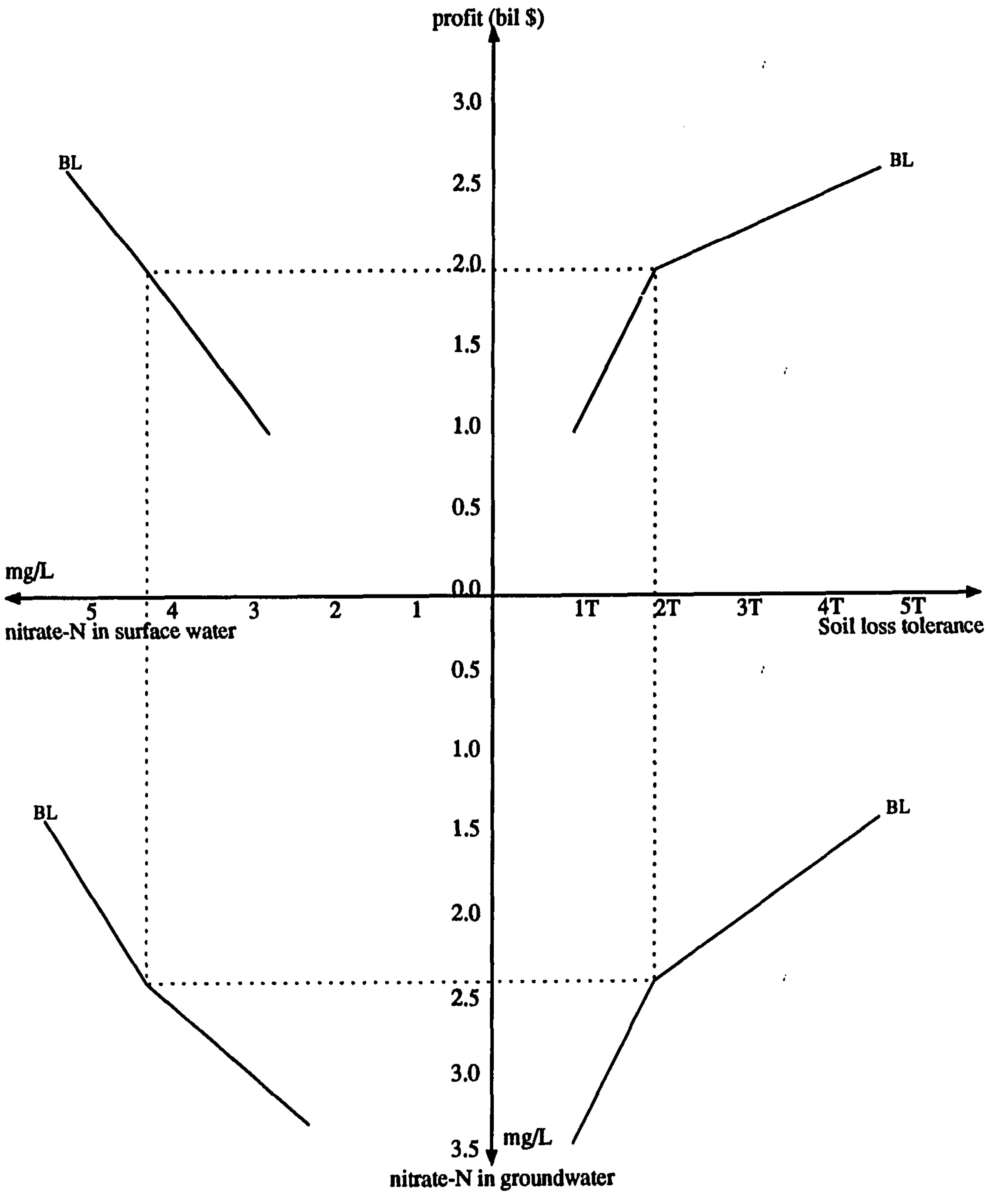

Figure 12. The economic-environmental tradeoffs

CHAPTER VI. SUMMARY AND CONCLUSIONS

The task of integrated modeling of economic and environmental policies, to address agricultural nonpoint source pollution, is confounded by a novel method that integrates multidisciplinary models in a consistent multiple objective framework. The need for integrated assessment in a multiobjective framework is motivated by the physical process interactions. In the past the agricultural nonpoint source pollution problem is mostly addressed on a piecemeal basis as a result, even after 20 years of research and regulation, the problem is still at large. A primary reason for this is the inherent tradeoff between the economic and environmental objectives and a lack of comprehensive policy.

There are several approaches to modeling the economic and environmental integration. In practice, however, many researchers have adopted the simple and piecemeal approach. Such simplistic approach fails to give a holistic treatment to the NPS pollution problem and hence gives *ad hoc* solutions. Another drawback of these studies is that they have mostly ignored the spatial variability of the environmental indicators. The spatial variability is so pervasive in agricultural NPS evaluations, that ignoring them will bias the results and lead to erroneous policies. The attention paid to develop a theory for the integrated modeling method and a statistically consistent approach to integrate spatial variability, distinguishes the present study from other studies on economic-environmental modeling.

Realizing the need for an empirical modeling approach, derived explicitly from economic theory, that integrates the multidisciplinary models—economic and environmental models— and spatial variability, the study had three main objectives. The first objective is to derive theoretical structure for the empirical multiobjective decision problem invoking social welfare and utility theoretic principles. The second objective is to state the multidimensional resource quality problem as a multiple objective problem and state the relevant resource quality attributes. The third objective is to verify the empirical applicability of the method for a representative watershed.

Chapter I gives a general background and sets out the objectives and scope of the study. Chapter II reviews issues concerning agricultural NPS pollution assessment and multicriteria optimization principles and techniques. A theoretical model was developed in Chapter III based on social welfare arguments and multiattribute utility theory. The concept of separating hyperplane theorem (second welfare theorem) was invoked to show the existence of noninferior solution to the multicriteria problem. An appropriate solution method to solve the vector optimization problem is presented. Based on the principles of multidisciplinary integration, a conceptual framework is suggested to integrate the economic and environmental models.

In Chapter IV description of the empirical tools, sampling procedures and simulation experiment design, data and technology sets, and spatial aggregation procedures are provided. A consistent and comprehensive biogeophysical model EPIC/WQ was used to spatially simulate the prevalent crop production practices over a long term (15 years) using actual historical weather. A watershed level resource adjustment modeling system constituted the basic agricultural economic decision model. The linkage between the physical simulation model outputs and the economic behavioral model parameters was provided by the empirical metamodels.

The crops and cropping systems prevalent in the study area, which is a major watershed in the Midwest comprising most of central and eastern Iowa and western Illinois, were modeled. The crops included in the analysis are corn, soybeans, oats, winter wheat, hay, and sorghum. The environmental indicators modeled are soil erosion, nitrate-N in runoff and percolate, and atrazine in runoff and percolate. Besides conventional tillage, soil conserving tillage systems, such as reduced till and no-till were modeled to study the tillage / residue impacts on environmental loading.

Chapter V summarizes the results of the present study in two sections. The first section summarizes the EPIC\WQ model results of long term average values of environmental indicators, briefly describes metamodel development process and the estimated metamodels for each of the environmental indicators. The results from extrapolating these metamodels to the population of soils in the study region are also shown. The second section elaborates the alternative policy scenarios and the economic and environmental impacts and tradeoffs as indicated by the multiple objective scenario analysis. The scenario results are used in quantifying the tradeoffs between economic returns, soil quality, groundwater quality, and surface water quality.

The spatial distribution of various environmental indicators are valuable information for targeting the policies to problem areas. The impacts differentiated by conservation and tillage systems for alternative crop / rotations will serve as a guide for evaluating the alternative BMPs. The response functions (metamodels) for soil loss and nutrient and chemical loading can be used to make spatial forecasts within similar geographic regions. Long term average nitrate-N concentration in surface water is estimated at 5.3 ppm is close to the actual measurements in the region, 5.6 ppm.

Likewise, the predicted long term average leaching losses of nitrate-N is within the range of actual measurements from sample wells and near surface aquifers. The mean annual concentration of atrazine in surface runoff and percolate were also estimated.

The results from simulating four different policy scenarios, representing soil quality (S1), surface water quality (S2), groundwater quality (S3), and a comprehensive scenario addressing soil and water quality jointly (S4) are presented in the second section of Chapter V. Major findings and conclusions of the policy simulation exercise are: (i) there is significant tradeoff between the economic and environmental goals and, even between the environmental goals, therefore a comprehensive analysis with reasonable compromise will give an ideal solution; (ii) to achieve a soil loss reduction goal of not exceeding 2T soil loss tolerance level, a 21% reduction in net returns is inevitable, or equivalently a loss in revenue of about $1.88 per ton of soil saved from erosion, however, this policy resulted in increased impairments to groundwater quality; and (iii) a multiobjective scenario minimizing soil loss to 2T levels and not allowing nitrate-N and atrazine leaching to exceed the baseline resulted in 43% decrease in returns, but both surface and groundwater quality improved relative to baseline.

The model and the results are subject to following limitations. The model ignores uncertainty and dynamics, inclusion of uncertainty will produce a more realistic tradeoff. Because the data on soil, hydrology, weather, and production practices are specific to this watershed, the results are not directly applicable to other areas. But, the results could be generalized to areas with similar spatial attributes. Furthermore, the results should reflect, in general, sustainable agricultural practices in controlling soil erosion and chemical pollution.

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APPENDIX 1. THE SOLUTION ALGORITHM

The *goal* programming technique proposed by Charnes and Cooper (1961) has wide spread application for private and public sector problems. Romero (1991) has supplied a detailed review of *goal* programming applications. The application of goal programming for public policy problems, specifically the environmental management problems, is demonstrated in Charnes et al. (1976) and Panagiotakopoulos (1975). The former develops a multidimensional goal programming model to aid resource allocation decisions in the U.S. Coast Guard's Marine Environmental Protection program, and the later develops a multiobjective framework for regional environmental management using goal programming. The goal programming technique is often of value in modeling and analyzing multiobjective problems, and it provides a reasonable analytical structure to such problems, although it is far from a panacea. Goal programming is related to the multiattribute utility theory in that it embodies additively separable preference structure (Hannan 1984).

In goal programming the objective is to achieve certain conditions characterized as "meeting the goals as closely as possible", and each such condition is specified in a function which penalizes for deviations from the specified target (goal) for the i^{th} objective. In particular, goal programming uses a minimum-distance (from the specified goals) notion of best. The goal programming formulation as conceived originally for the industrial applications, minimizes the weighted sum of the absolute deviations from the specified goals. That is, both positive and negative deviations from the goal are minimized based on weights reflecting the relative importance attached to the deviations.

A major weakness of this traditional goal programming formulation is that a "good" becomes a "bad" at a critical threshold level. For example, for a profit maximization objective penalizing positive deviation of profit from the goal is equivalent to saying that more profit is bad, does not express a rational behavior of economic agents. Let the goal for the i^{th} objective be denoted as G_i, then the traditional weighted goal programming formulation is:

$$\min d = \sum_i \lambda_i \mid G_i - f_i(\underline{x}) \mid \quad \text{s.t. } \underline{x} \in X \tag{1}$$

where the objective function minimizes the weighted sum of the absolute deviations of the outcomes from the specified goals for each objective. Note,

$$\begin{aligned} \partial f / \partial d &= -\lambda_i \ \text{ if } f_i(\underline{x}) < G_i \\ &= +\lambda_i \ \text{ if } f_i(\underline{x}) > G_i. \end{aligned} \tag{1.1}$$

Thus, the formulation in (1) is identical to the L_p-metric with $p = 1$ and the goals G_i replacing the ideal values f_i^*. The f_i^* is the optimal solution to the following single objective optimization problem,

$$\underline{f}^* = \max \{f^i(\underline{x}) \mid x \in X, \forall i\}.$$

The formulation in (1), however, is not an intuitive representation of public policy problems involving economic and environmental objectives. Rational agents should consider it as "good" if the realized profit exceeded the goal. That is, the agent would be concerned only if the profit fell below the goal. For environmental pollution the agent would likely consider it as "good" if the realized level of pollution were less than the goal, and would be concerned only if the level of pollution realized exceeded the goal. In this sense the formulation in (1) is not an appropriate approximation of rational decision making, at least for economic-environmental policy problems. At the same time, this formulation is apparently used for quality control and design problems, where the consequences of even a small + or - deviation from the desired goals (targets) are not permitted.

We can develop a piecewise linear approximation for the nonlinear goal programming problem, and specify the *Lagrangean* for this problem, deriving appropriate first-order conditions. A rationalization of the formulation for environmental management problems and the mathematical representation of alternative scenarios will conclude this annex. Before specifying the linear approximation, we introduce notation defining the negative and positive deviations from the goals. Let the variables d_i^- and d_i^+ represent the negative and positive deviations, respectively, of the i^{th} objective from its goal G_i.

If $f_i(\underline{x}) < G_i$ meaning we have less than the desired level of i^{th} objective, then we have a negative deviation, d_i^-, such that

$$d_i^- = (G_i - f_i(\underline{x})) \text{ if } f_i(\underline{x}) < G_i \qquad (2.1)$$

$$= 0 \text{ otherwise.}$$

This can be more compactly stated as

$$d_i^- = \max\,[G_i - f_i(\underline{x});\ 0] \;=\; -\min\,[0;\ f_i(\underline{x}) - G_i]. \tag{2.2}$$

Similarity, if $f_i(\underline{x}) > G_i$ meaning we have more than the desired level of i^{th} objective, that is we have a positive deviation, d_i^+, then,

$$\begin{aligned} d_i^+ &= (f_i(\underline{x}) - G_i) \text{ if } f_i(\underline{x}) > G_i \\ &= 0 \text{ otherwise.} \end{aligned} \tag{3.1}$$

This can be more compactly stated as

$$d_i^+ = \max\,[f_i(\underline{x}) - G_i;\ 0]. \tag{3.2}$$

Substituting the definition for the d_i's given in (3.1) and (3.2) into (1) obtain an expression for the weighted goal programming problem, that minimizes absolute deviations from the stipulated goals,

$$\begin{aligned} &\min \textstyle\sum_i (\lambda_i^- \max\,[f_i(\underline{x}) - G_i;\ 0] + \lambda_i^+ \max\,[0;\ G_i - f_i(\underline{x})]) \\ &\text{s.t. } \underline{x} \in X. \end{aligned} \tag{1.1}$$

The piecewise linear approximation for this problem is

$$\min \textstyle\sum_i (\lambda_i^- d_i^- + \lambda_i^+ d_i^+), \tag{4}$$

s.t.

$$f_i(\underline{x}) + d_i^- - d_i^+ = G_i,$$

$\underline{x} \in X$, and the nonnegativity.

The d_i's are associated with positive coefficients in the objective function, which guarantees their status as structural variables, and not the slack variables. Therefore, the first line in the "constraint block" is a set of *equations*, such that their corresponding dual variables are *not* constrained to be nonnegative. Charnes and Cooper verify this by solving the dual for a simple goal attainment problem for machine-loading example (1961; pp. 219-221). The *Lagrangean* for this minimization problem is

$$\min \mathscr{L} = [\lambda_i^- d_i^- + \lambda_i^+ d_i^+] + \Phi_i [G_i - f_i(\underline{x}) - d_i^- + d_i^+]. \tag{5}$$

The solution follows from Khun-Tucker theorem (Varian 1984). The Khun-Tucker conditions are:

$$x_k: \quad -\Phi_i (\partial f_i / \partial x_k) = 0 \tag{5.1}$$

$$d_i^-: \quad (\lambda_i^- - \Phi_i) \geq 0 \text{ and } d_i^-(\lambda_i^- - \Phi_i) = 0 \tag{5.2}$$

$$d_i^+: \quad (\lambda_i^+ + \Phi_i) \geq 0 \text{ and } d_i^+(\lambda_i^+ + \Phi_i) = 0 \tag{5.3}$$

if $d_i^- > 0 \Rightarrow \lambda_i^- = \Phi_i$ from (5.2), then,

$d_i^+ = 0$[19] and $(\lambda_i^+ + \Phi_i) > 0$; substituting for Φ_i from above get $\lambda_i^- > -\lambda_i^+$.

Thus the solution to (5) requires $\lambda_i^- > -\lambda_i^+$ and that the product of the deviation variables is equal to zero holds for all i ($d_i^- d_i^+ = 0 \ \forall \ i$). The later condition, however, need not be imposed for all iterations in the solution of the goal programming problem since only equivalence at an optimum is required.

In (5) λ_i (-/+) is the relative weight reflecting the importance of the objective, and the significance of the positive or negative deviations, that is it penalizes the

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[19] The deviational variables will never both be positive for the same goal since the vectors associated with the deviational variables are the negatives of each other.

deviations from the goal. In the special case when λ_i^- or λ_i^+ is set to zero the formulation is consistent with the formulation of numerous environmental management problems. For instance, if λ_i^- is set to zero it implies the minimization of positive deviations. It makes sense, for the profit objective, to let $\lambda_j^+ = 0$ meaning profits that exceed the goal are not penalized. And for the environmental pollution objective, likewise $\lambda_k^- = 0$ means that the environmental pollution level less than the goal is not penalized.

A simple algebraic proof demonstrating the equivalence of (5) and (1) is shown below (Charnes and Cooper 1977). To simplify the notation let $\lambda_i = 1 \; \forall \; i$. Define,

$$d_i^- = \tfrac{1}{2}[\,|G_i - f_i(\underline{x})| + (G_i - f_i(\underline{x}))] \tag{6.1}$$

$$d_i^+ = \tfrac{1}{2}[\,|G_i - f_i(\underline{x})| - (G_i - f_i(\underline{x}))]. \tag{6.2}$$

Adding and subtracting the above expressions yields,

$$d_i^- + d_i^+ = |G_i - f_i(\underline{x})| \tag{7.1}$$

$$f_i(\underline{x}) + d_i^- - d_i^+ = G_i. \tag{7.2}$$

Hence, the above results confirm that the formulation in (1) can be equivalently stated as a piecewise linear approximation (5), along with the nonnegativity conditions for the negative and positive deviation variables.

For many of the modern environmental management problems this piecewise linear goal programming formulation, is ideal. It is not that hard to articulate goals for the environmental objectives. Environmental policy includes threshold limits for resource degradation. Therefore, it is reasonable to have a target that the potential for resource degradation is within threshold limit. For example, in the soil erosion the T-value (the soil loss tolerance value) specifies that a natural rate of growth of soil is a reasonable goal. This approach is consistent with the resource degradation problem that is being addressed. Taking the soil erosion example, if erosion exceeds the natural rate of growth of soil (T-value) then long term sustainability may be in jeopardy. Accordingly, a typical goal might be keep soil losses within the threshold limit. For profits, however, it is desirable to achieve more than that stipulated as the goal.

Consider two objectives the profits, π, and the environmental pollution, z. Let the profit goal be, π^*, and the pollution goal be, z^*. The piecewise linear formulation of the goal programming problem is:

$$\text{Min } [\, \lambda_\pi^- d_\pi^- + \lambda_\pi^+ d_\pi^+ + \lambda_z^- d_z^- + \lambda_z^+ d_z^+ \,] \tag{8}$$

s.t.

$$\begin{aligned}
&\pi(\underline{x}) + d_\pi^- - d_\pi^+ && = \pi^* \\
&z(\underline{x}) \qquad\qquad + d_z^- - d_z^+ && = z^* \\
&A\underline{x} && = b \\
&\underline{x},\, d_\pi^-,\, d_\pi^+,\, d_z^-,\, d_z^+,\, (\lambda_\pi^- + \lambda_\pi^+),\, (\lambda_z^- + \lambda_z^+) && \geq 0,
\end{aligned}$$

where the condition three is the feasibility condition in matrix notation, and the last condition is for nonnegativity. It is desirable to have profits higher than the goal, and pollution lower than the goal, which can be ensured by not penalizing the positive deviation from π and the negative deviation of z. The problem in (8) can be equivalently stated as maximizing the negative of (8) subject to the conditions stated in

(8). Therefore, if the domain (feasible region) is a closed, bounded, and convex set and the constraint functions are smooth and concave then there exists unique solution.

The *Lagrangean* for the constrained optimization problem in (8) is:

$$\mathcal{L} = [\lambda_\pi^- d_\pi^- + \lambda_\pi^+ d_\pi^+ + \lambda_z^- d_z^- + \lambda_z^+ d_z^+] + \mu_\pi [\pi^* - \pi(\underline{x}) - d_\pi^- + d_\pi^+]$$

$$\mu_z [z^* - z(\underline{x}) - d_z^- + d_z^+] + \tau [\mathbf{b} - \mathbf{Ax}]. \qquad (9)$$

The solution to this constrained optimization problem follows from Khun-Tucker theorem (Varian 1984). The Khun-Tucker conditions are,

x_k: $\quad -\mu_\pi (\partial\pi/\partial x_k) - \mu_z (\partial z/\partial x_k) - \tau A' = 0 \qquad (9.1)$

d_π^-: $\quad (\lambda_\pi^- - \mu_\pi) \geq 0$ and $d_\pi^-(\lambda_\pi^- - \mu_\pi) = 0 \qquad (9.2)$

d_π^+: $\quad (\lambda_\pi^+ + \mu_\pi) \geq 0$ and $d_\pi^+(\lambda_\pi^+ + \mu_\pi) = 0 \qquad (9.3)$

if $d_\pi^- > 0 \Rightarrow \lambda_\pi^- = \mu_\pi$ from (9.2), then,

$d_\pi^+ = 0$[20] and $(\lambda_\pi^+ + \mu_\pi) > 0$; substituting for μ_π from above get $\lambda_\pi^+ > -\lambda_\pi^-$.

d_z^-: $\quad (\lambda_z^- - \mu_z) \geq 0$ and $d_z^-(\lambda_z^- - \mu_z) = 0 \qquad (9.4)$

d_z^+: $\quad (\lambda_z^+ + \mu_z) \geq 0$ and $d_z^+(\lambda_z^+ + \mu_z) = 0 \qquad (9.5)$

if $d_z^+ > 0 \Rightarrow \lambda_z^+ = -\mu_z$ from (9.4), then,

$d_z^- = 0$ and $(\lambda_z^- - \mu_z) > 0$, substituting for $-\mu_z$ from above get $\lambda_z^- > -\lambda_z^+$.

Solution requires that the conditions on the weighting parameter λ, on the positive and negative deviations from the goal for each objective, hold.

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[20] The deviational variables will never both be positive for the same goal since the vectors associated with the deviational variables are the negatives of each other.

For this two dimensional problem, the feasible region, "level sets" for the alternative assumptions on λ_i (+/-), and the goals can be represented graphically, Figure 13. The level set is the locus of points which returns the same value for the objective function, and equivalent of the idea of an isoquant in production. Profits are shown on the vertical axis, with π^* denoting the goal. Pollution is shown on the horizontal axis, with z^* denoting the goal. Point G represents the "bliss" point. The locus of points that satisfy the typical goal programming formulation in (1) is drawn in Figure 13 as the parallelogram with dotted lines. The locus of points that satisfy the piecewise linear formulation in (8) is the dashed line, and the solid line represents the locus of points that satisfy the objective function in which λ_π^+, λ_z^- are set to zero.

The piecewise linear formulation of the alternative scenarios examined in the empirical evaluation is shown below.

<u>Scenario S1</u>: (soil erosion)

$$\text{Min } [\, \lambda_\pi^- d_\pi^- + 0\, d_\pi^+ + 0\, d_{eros}^- + \lambda_{eros}^+ d_{eros}^+ \,] \qquad (10)$$

s.t.

$$\begin{aligned} &\pi(\underline{x}) + d_\pi^- - d_\pi^+ && = \pi^* \\ &eros(\underline{x}) \quad + d_{eros}^- - d_{eros}^+ && = eros^* \\ &A\underline{x} && = b \end{aligned}$$

where eros denotes soil erosion and eros* the goal.

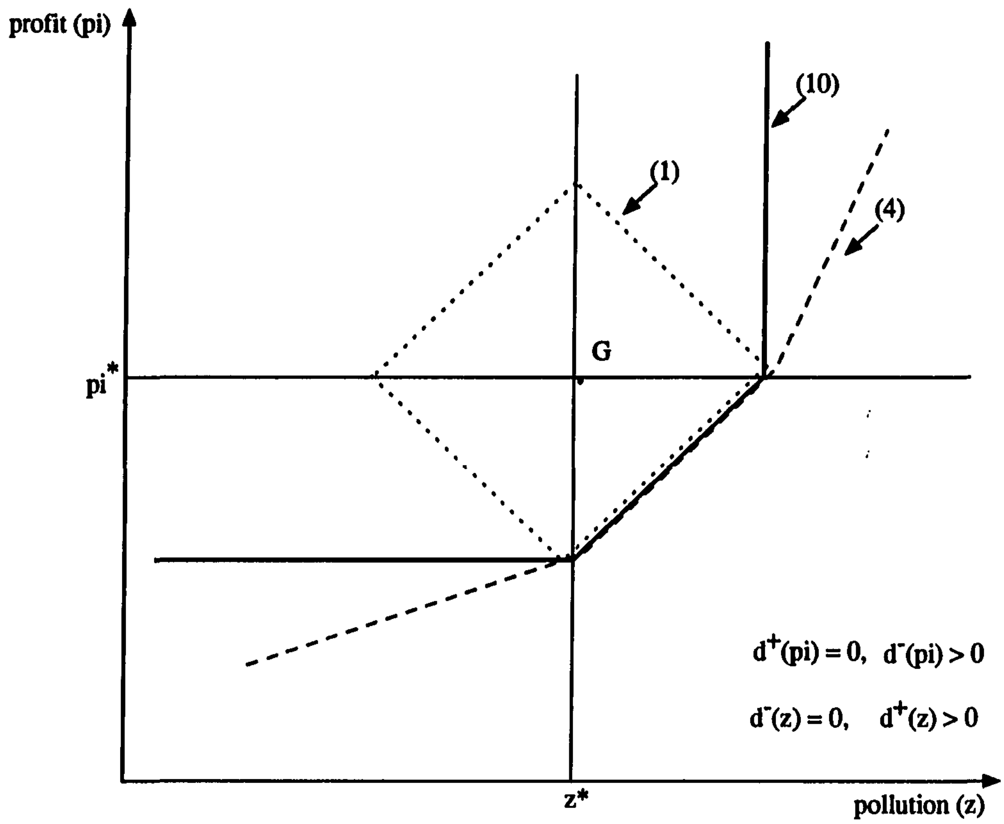

Figure 13. A graphical representation of level sets for alternative formulations

Scenario S2: (surface water quality)

$$\text{Min } [\, \lambda_{\pi}^{-} d_{\pi}^{-} + 0\, d_{\pi}^{+} + 0\, d_{nruf}^{-} + \lambda_{nruf}^{+} d_{nruf}^{+} + 0\, d_{aruf}^{-} + \lambda_{aruf}^{+} d_{aruf}^{+} \,] \qquad (11)$$

s.t.

$$\begin{array}{llllc} \pi(\underline{x}) + d_{\pi}^{-} - d_{\pi}^{+} & & & = & \pi^{*} \\ nruf(\underline{x}) & + d_{nruf}^{-} - d_{nruf}^{+} & & = & nruf^{*} \\ aruf(\underline{x}) & & + d_{aruf}^{-} - d_{aruf}^{+} & = & aruf^{*} \\ A\underline{x} & & & = & b \end{array}$$

where nruf and aruf are runoff of nitrate-N and atrazine, respectively.

Scenario S3: (groundwater quality)

$$\text{Min } [\, \lambda_{\pi}^{-} d_{\pi}^{-} + 0\, d_{\pi}^{+} + 0\, d_{nlch}^{-} + \lambda_{nlch}^{+} d_{nlch}^{+} + 0\, d_{alch}^{-} + \lambda_{alch}^{+} d_{alch}^{+} \,] \qquad (12)$$

s.t.

$$\begin{array}{llllc} \pi(\underline{x}) + d_{\pi}^{-} - d_{\pi}^{+} & & & = & \pi^{*} \\ nlch(\underline{x}) & + d_{nlch}^{-} - d_{nlch}^{+} & & = & nlch^{*} \\ alch(\underline{x}) & & + d_{alch}^{-} - d_{alch}^{+} & = & alch^{*} \\ A\underline{x} & & & = & b \end{array}$$

where nlch and alch are leaching losses of nitrate-N and atrazine, respectively.

APPENDIX 2. MATHEMATICAL STRUCTURE OF THE REGIONAL LP MODEL

MAX: OBJ = PROFIT =

$$= - \sum_{v=1}^{1} \sum_{m=1}^{2} \sum_{j=1}^{4} \sum_{k=1}^{18} CPRD_{vmjk} * XPRD_{vmjk} \quad \text{[Cost of Production Activities]}$$

$$\left. \begin{aligned} & -\sum_{f=1}^{f3} \sum_{q=1}^{q2} \sum_{s=1}^{s1} HCNT_s * X2HNT_{fqs} \\ & -\sum_{f=1}^{f3} \sum_{q=1}^{q2} \sum_{s=1}^{s2} HCRT_s * X2HRT_{fqs} \\ & -\sum_{f=1}^{f1} \sum_{q=1}^{q2} \sum_{s=1}^{s3} HCCT_s * X2HCT_{fqs} \end{aligned} \right\} \quad \text{[Weed Control Cost]}$$

$$+ \quad RCRD * XCRP \quad \text{[Return from CRP]}$$

$$+ \quad \sum_{q=1}^{q1} RDP_q * XDP_q \quad \text{[Deficiency Payment]}$$

$$- \quad RIRRA * XIRRA \quad \text{[Irrigation Water Delivery Costs]}$$

$$- \quad \sum_{g=1}^{3} RFERT_g * XF_g \quad \text{[Fertilizer Cost]}$$

$$- \quad \sum_{n=1}^{7} RLABO * XL_n \quad \text{[Labor Cost]}$$

$$+ \quad \sum_{q=1}^{q1} RSELL_q * XSELL_q \quad \text{[Return from Marketing]}$$

The CONSTRAINT SET

a. Corn and corn silage production, for q = 1,2,...,q2

$$\sum_{v=1}^{1}\sum_{m=1}^{2}\sum_{j=1}^{4}\sum_{k=1}^{18} YLD_{vmjkq} * XPRD_{vmjk} - \sum_{f=1}^{f3}\sum_{s=1}^{s1} YLDLNT_{sq} * X2HNT_{fsq}$$

$$-\sum_{f=1}^{f3}\sum_{s=1}^{s2} YLDLRT_{sq} * X2HRT_{fsq} - \sum_{f=1}^{fs}\sum_{s=1}^{s3} YLDLCT_{sq} * X2HCT_{fsq} - XSELL_{q} \geq 0$$

b. Other Crop Production, for q = 1,2,...,q3

$$\sum_{v=1}^{1}\sum_{m=1}^{2}\sum_{j=1}^{4}\sum_{k=1}^{18} YLD_{vmjzq} * XPRD_{vmjk} - XSELL_{q} \geq 0$$

c. Total Land Constraint

$$\sum_{v=1}^{1}\sum_{m=1}^{2}\sum_{j=1}^{4}\sum_{k=1}^{18} XPRD_{vmjk} - LAND * DUMMY \leq 0$$

d. Surface and Ground Irrigation Constraint, for w = 1

$$\sum_{m=1}^{2}\sum_{j=1}^{4}\sum_{k=1}^{18} XPRD_{mjkw} - LANDIRR_{w} * DUMMY \geq 0$$

e. Highly Erodible Land Constraint

$$\sum_{v=1}^{1}\sum_{m=1}^{2}\sum_{j=1}^{4}\sum_{k=1}^{18} XPRD_{vmjk} * PRDCOMP_{vmjk} - HLD * DUMMY \geq 0$$

f. Weed Control Treatment, for $q = 1,2,\ldots,q_2$

(1) No Till Land

$$\sum_{v=1}^{1} \sum_{m=1}^{2} \sum_{j=1}^{j1} \sum_{k=1}^{18} XPRD_{vmjk} * B_{1qk} - \sum_{s=1}^{s1} X2HNT_{qs} = 0$$

(2) Reduced Till Land

$$\sum_{v=1}^{1} \sum_{m=1}^{2} \sum_{j=1}^{j1} \sum_{k=1}^{18} XPRD_{vmjk} * B_{1qk} - \sum_{s=1}^{s2} X2HRT_{qs} = 0$$

(3) Conventional Till Land

$$\sum_{v=1}^{1} \sum_{m=1}^{2} \sum_{j=1}^{j3} \sum_{k=1}^{18} XPRD_{vmjk} * B_{1qk} + \sum_{v=1}^{3} \sum_{m=1}^{4} \sum_{j=1}^{j4} \sum_{k=1}^{2600} XPRD_{vmjk} * B_{1qk} - \sum_{s=1}^{s3} X2HCT_{qs} = 0$$

g. Herbicide Accounting, for $e = 1,2,3$

$$\sum_{f=1}^{f3} \sum_{q=1}^{q2} \sum_{s=1}^{s1} X2HNT_{fqse} * RHNT_{se} + \sum_{f=1}^{f3} \sum_{q=1}^{q2} \sum_{s=1}^{s2} X2HRT_{fqse} * RHRT_{se}$$

$$+ \sum_{f=1}^{f3} \sum_{q=1}^{q2} \sum_{s=1}^{s3} X2HCT_{fqse} * RHCT_{se} - XCHAC_{e} = 0$$

h. Herbicide Bounds, for $e = 1,2,3$

(1) Upper Bounds

$$XCHANC_{e} \leq CHEMMAX$$

(2) Lower Bounds

$$XCHANC_{e} \geq CHEMMIN$$

i. Weed Control Strategy

(1) Sand

$$\sum_{f=1}^{f3} \sum_{q=1}^{q2} \sum_{s=1}^{s1} X2HNT_{fq1} * SNNT_s + \sum_{f=1}^{f3} \sum_{q=1}^{q2} \sum_{s=1}^{s2} X2HRT_{fqs} * SNRT_s$$

$$+ \sum_{f=1}^{f3} \sum_{q=1}^{q2} \sum_{s=1}^{s3} X2HCT_{fqs} * SNCT_s - XTEX * SNPCT \geq 0$$

(2) Clay and Silt

$$\sum_{f=1}^{f3} \sum_{q=1}^{q2} \sum_{s=1}^{s1} X2HNT_{fq1} * CLNT_s + \sum_{f=1}^{f3} \sum_{q=1}^{q2} \sum_{s=1}^{s2} X2HRT_{fqs} * CLRT_s$$

$$+ \sum_{f=1}^{f3} \sum_{q=1}^{q2} \sum_{s=1}^{s3} X2HCT_{fqs} * CLCT_s - XTEX * CLPCT \geq 0$$

j. Commodity Program, for q = 1,2,...,q1

$$\sum_{v=1}^{1} \sum_{m=1}^{2} \sum_{j=1}^{4} \sum_{k=1}^{18} B_{4kq} * XPRD_{vmjk} - (1 - ARPFLEX_q) * XDP_q \geq 0$$

k. Conservation Reserve

$$XCRP - CRPL * DUMMY = 0$$

l. Government Program, for q = 1,2,...,q_1

$$XDP_q - RBASE_q * DUMMY \leq 0$$

m. Irrigation Water Requirement, for w = 1

$$\sum_{m=1}^{2} \sum_{j=1}^{4} \sum_{k=1}^{18} XPRD_{mjkw} * - WR_{mjkw} XIRRA_w * WDR_w \leq 0$$

n. Fertilizer Requirement, for g = 1,2,3

$$\sum_{v=1}^{1} \sum_{m=1}^{2} \sum_{j=1}^{4} \sum_{k=1}^{18} FR_{vmjkg} \ * \ XPRD_{vmjk} - XF_g \quad \leq 0$$

o. Conservation Tillage Requirement

$$\sum_{v=1}^{1} \sum_{m=1}^{2} \sum_{j=1}^{j1} \sum_{k=1}^{18} XPRD_{vmjk} - MXKT \ * \ DUMMY \quad \leq 0$$

p. No Till Requirement

$$\sum_{v=1}^{1} \sum_{m=1}^{2} \sum_{j=1}^{j1} \sum_{k=1}^{18} XPRD_{vmjk} - MXZT \ * \ DUMMY \quad \leq$$

q. Soil Erosion Accounting

$$\sum_{v=1}^{1} \sum_{m=1}^{2} \sum_{j=1}^{4} \sum_{k=1}^{18} XPRD_{vmjk} \ * \ EROSI_{vmjk} - XEROSION \quad = 0$$

r. Labor Requirement, for n = 1,2,...,7

$$\sum_{q=1}^{q1} LBDR_n \ * \ (1-ARPFLEX_{q1}) \ * \ XDP_{q1} + \sum_{f=1}^{f3} \sum_{q=1}^{q2} \sum_{s=1}^{s1} X2HNT_{fqs} \ * \ LBWCNT_{ns}$$

$$+ \sum_{f=1}^{f3} \sum_{q=1}^{s2} \sum_{s=1}^{s2} X2HRT_{fqs} \ * \ LBWCRT_{ns} \quad + \sum_{f=1}^{f3} \sum_{q=1}^{q2} \sum_{s=1}^{s3} X2HCT_{fqs} \ * \ LBWCCT_{ms}$$

$$+ LBCRP_n \ * \ XCRP - XL_n \quad = 0$$

s. Flexibility Constraints on Production Levels, for q = 1,2,...,18

(1) Upper Bound

$$XSELL_q - MAXPROD_q \ * \ DUMMY \quad \geq 0$$

(2) Lower Bound

$$XSELL_q - MINPROD_q \ * \ DUMMY \quad \geq 0$$

t. Crop Acreage Accounting, for q = 1,2,...,18

(1) No Till

$$\sum_{v=1}^{1} \sum_{m=1}^{2} \sum_{j=1}^{j1} \sum_{k=1}^{18} B_{5qk} * XPRD_{vmjk} - XCROPACNT_q = 0$$

(2) Reduced Till

$$\sum_{v=1}^{1} \sum_{m=1}^{2} \sum_{j=1}^{j2} \sum_{k=1}^{18} B_{5qk} * XPRD_{vmjk} - XCROPACRT_q = 0$$

(3) Conventional Till

$$\sum_{v=1}^{1} \sum_{m=1}^{2} \sum_{j=1}^{j3} \sum_{k=1}^{18} B_{5qk} * XPRD_{vmjk} + \sum_{v=1}^{3} \sum_{m=1}^{4} \sum_{j=1}^{j4} \sum_{k=1}^{2800} B_{5qk} * XPRD_{vmjk}$$

$$- XCROPACCT_q = 0$$

u. Nonnegativity Requirements

$XPRD_{vmjkl}$	≥ 0	$XSELL_q$	≥ 0	$XCROPACNT_q$	≥ 0
$X2HNT_{fqs}$	≥ 0	XCRP	≥ 0	$XCROPACRT_q$	≥ 0
$X2HRT_{fqs}$	≥ 0	XDP_q	≥ 0	$XCROPACCT_q$	≥ 0
$X2HCT_{fqs}$	≥ 0	XIRRA	≥ 0	XDP_q	≥ 0
XCRP	≥ 0	XF	≥ 0	XL_n	≥ 0

INDICES, VARIABLES, AND TABLES

(i) Index Sets

a	-	Producing areas
e	-	Chemicals
f	-	Rotational restrictions on weed control strategies
g	-	Fertilizers
y(i)	-	Current policy
j	-	Tillage practices
k	-	Crop rotations
m	-	Conservation practices
n	-	Labor purchasing periods
q	-	Endogenous crops
s	-	Weed control strategies
v	-	Irrigation practice

(ii) Variables

$XPRD_{vmjk}$ methods, and j	:	Production activities by k rotations, m conservation practices, v irrigation tillage practices (acre)
$X2HNT_{fqs}$	:	No till weed control strategy activities (acres)
$X2HRT_{fqs}$	:	Conservation till weed control strategy activities (acres)
$X2HCT_{fqs}$	:	Conventional till weed control strategy activities (acres)
XCRP	:	CRP enrollment activity (acres)
XDP_q	:	Deficiency payment activities (acres)
XCHAC	:	Chemical constraining activity (lbs. active ingredient)
XIRRA	:	Irrigation water supply activities (units)
XF	:	Purchasing activity for fertilizer (lbs)
XL_n	:	Labor supply activities (hrs)
$XSELL_q$	:	Crop sell activity for endogenous crops (crop units)
$XCROPACNT_q$	:	No till crop acreage accounting activities
$XCROPACRT_q$	:	Reduced till crop acreage accounting activities
$XCROPACCT_q$	:	Conventional till crop acreage accounting activities

(iii) Tables

$CPRD_{vmjkn}$	:	Cost of production activities by k rotations, m conservation practices, v irrigation methods, and j tillage practices ($/acre)
$HCNT_{s1n}$	:	Cost of no till herbicide strategy ($/acre)
$HCRT_{s2n}$	:	Cost of no till herbicide strategy ($/acre)
$HCCT_{s3n}$	:	Cost of reduced till herbicide strategy ($/acre)
$RSELL_{qn}$	:	Return per unit of selling crop
$RCRP_n$	:	Returns per acre from enrollment in CRP ($)
RDP_{pn} program crop p	:	Deficiency payment from enrollment on acre of established base for each ($)
$RFERT_{gn}$	:	Fertilizer prices ($/lb)
$RIRRA_{wz}$	:	Costs of water and water delivery ($/acre foot)
$RLABO_n$	:	Costs of purchased labor ($/hour)

YLD_{qvmjka}	:	Crop yield for crop q, rotation k, under conservation practice m, irrigation practice v, and tillage practice j. Pre-adjusted for relative share of crop in rotation (bu/ac)
$YLDLNT_{s1a}$	:	Cost of production activities by k rotations, m conservation practices, v irrigation methods and j tillage methods ($/acre)
$YLDLRT_{s2a}$	:	Yield loss under conservation till weed control strategy s2 (bu/ac)
$YLDLCT_{s3a}$	:	Yield loss under conventional till weed control s3 (bu/ac)
$RHNT_{es1a}$	:	Application rate of chemical e under no till weed control strategy s1 (lbs of active ingredient)
$RHRT_{es2a}$	:	Application rate of chemicals under reduced till weed control strategy (chemicals, weed control strategies under no till, current pa) application rate of chemical e under no till weed control strategy s1 (pounds of active ingredient)
$RHCT_{es3a}$	:	Application rate of chemical e under conventional till weed control strategy s3 (lbs of active ingredient/ac)
$SNNT_{a}$	:	Sand texture indicator, one if weed control activity s is specified for use on sandy soils only, zero if specified for silt or clay soils only and % of sandy soil acres in PA if specified for sand, silt, or clay
$SNRT_{s2a}$	:	Sand texture indicator, one if weed control activity s is specified for use on sandy soils only, zero if specified for silt or clay soils only and % of sandy soil acres in PA if specified for sand, silt, or clay
$SNCT_{s3a}$	:	Sand texture indicator, one if weed control activity s is specified for use on sandy soils only zero if specified for silt or clay soils only and % of sandy soil acres in PA if specified for sand, silt, or clay
$CLNT_{s1a}$	:	Clay texture indicator, one if weed control activity s is specified for use on clay or silty soils only, zero if specified for sandy soils only and % of silt and clay soil acres in PA if specified for sand, silt, or clay
$CLRT_{s2a}$	:	Clay texture indicator, one if weed control activity s is specified for use on clay or silty soils only, zero if specified sandy soils only and % of silt and clay soil acres in PA if specified for sand, silt, or clay
$CLCT_{s2a}$	:	Clay texture indicator, one if weed control activity s is specified for use on clay or silty soils only, zero if specified for sandy soils only and % of silt and clay soil acres in PA if specified for sand, silt, or clay
$SNPCT_{a}$	:	Acres of clay or silty soils as a percent of total acres in PA a
$CLPCT_{a}$	:	Acres of clay or silty soils as a percent of total acres in PA a
$CORNCHPCT_{ea}$	:	Use of herbicide e on corn and corn silage expressed as a minimum % of total herbicides (lb a.i.) applied on corn and corn silage

$SORGCHPCT_{ea}$	:	Use of herbicide e on sorghum and sorghum silage expressed as a minimum % of total herbicides (lb a.i.) applied on sorghum and sorghum silage
$SEQNROT_{cckz}$	:	% of rotations occupied by cover crop sequences
$CHEMMAX_{ea}$	:	Use of herbicide e on corn and corn silage expressed as an absolute maximum (lbs a.i.)
$CHEMMIN_{ea}$	:	Use of herbicide e on corn and corn silage expressed as an absolute minimum (lbs a.i.)
$B1_{q2ka}$	:	Percent of corn, corn silage, sorghum and sorghum silage in each rotation k followed by two or more years of corn, corn silage, sorghum, sorghum silage or soybeans
$B2_{q2ka}$	:	Percent of corn, corn silage, sorghum silage in each rotation k followed by one year only of corn, corn silage, sorghum, sorghum silage, or soybeans
B_{3q2ka}	:	Percent of corn, corn silage, sorghum and sorghum silage in each rotation k followed by some other crop
$B4_{q1ka}$	:	Percent of program crop q in each rotation k
$B5_{qka}$	:	Percent of crop q in rotation k
$ARPFLEX_{q1a}$	:	Acreage reduction program set aside rate (%)
$PRDCOMP_{hvmjkz}$	:	One if the combination of tillage practice j, conservation practice m, and irrigation type v is in compliance on land in highly erodible land group h, 0 otherwise
$EROSI_{vmjkz}$	:	Erosion levels caused by production activities (tons/acre)
$LAND_a$	:	Total land in producing area, available for production and government programs (acres)
$LANDIRR_{wa}$	:	Land irrigated with surface water and groundwater (acres)
HLD_{ha}	:	Land in each of the h highly errodible land groups (acres)
$CPRL_a$	:	Conservation reserve retirement level (acres)
$RBASE_{pa}$	:	Base acreage level of program crop p (acres)
WR_{akmvj}	:	Water rate for production activities (acre feet)
WDR_{wz}	:	Acre feet of water delivered to cropland per acre feet removed from source -reflects delivery losses
FR_{gakmvj}	:	Fertilizer rate for production activity (lbs/ac)
$MXRT_a$	:	Maximum conservation tillage (acres)
$MXZT_a$	:	Maximum no till acres

$MXCSTIL_z$	:	Minimum acres of no till and conservation till for carbons tillage runs
$TERR_a$	:	Minimum terraced (acres)
$COVCRAC_a$	:	Target acreage of cover crops (acres
$LBDP_{na}$	:	Labor usage rate during month n for cover cost component of def. payment activities (hrs/ac)
$LBWCNT_{ns1a}$	:	Labor usage rate during month n for weed control activities
$LBWCRT_{ns2a}$	:	Labor usage rate during month n for weed control activities
$LBWCCT_{ns3a}$	:	Labor usage rate during month n for weed control activities (hrs/ac)
$LBCRP_{an}$	:	Labor usage rate during month n for cover cost component of conservation reserve program activities (hrs/ac)
$MAXPROD_{qz}$	:	Upper limit on crop production (cwt, bu, tons, or bales)
$MINPROOD_{qz}$	:	Lower limit on crop production (cwt, bu, tons, or bales
$MAXCACRE_{qz}$	:	Upper limit on crop acreage (acres)
$MINCACRE_{qz}$	:	Lower limit on crop acreage (acres)
$DUMMY_{zysn}$	:	PA and policy and scenario dummy dimensions