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Modeling Agricultural Production Considering Water Quality and Risk

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Modeling Agricultural Production Considering Water Quality and Risk[1]

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Abstract

Environmental goals often conflict with the economic goals of agricultural producers. The Cottonwood River in Minnesota is heavily polluted with nitrogen, phosphate and sediment from agricultural sources in the watershed. Goals of profit maximization for producers conflict with those of effluent alleviation. We incorporate water quality goals and risk into a mathematical programming framework to examine economically efficient means of pollution abatement while considering a wide range of alternative production practices.

Introduction

The impacts of agricultural production on the quality of water in our lakes, rivers and aquifers have been a long standing concern among environmental problems. In Southwestern Minnesota, intensive crop production has lead to deteriorating water quality in the Cottonwood River – a tributary of the Minnesota River, which flows, in turn, into the Mississippi. In this paper, farm modeling efforts involved in an ongoing study of best management practices for improving water quality in the Cottonwood River Watershed are discussed. In this study, results of a survey of production practices in the watershed are used along with experimental data and simulation to construct representative farm models. An economic analysis using a deterministic mathematical programming model of representative farms in the watershed is currently underway. The next phase of the study will focus on the extent to which risk in the economic and environmental consequences of agricultural production effect best management practices for improving water quality in the Watershed.

Following an overview of technical aspects of crop nutrient management and water quality and an overview of the economics literature on the topic, a deterministic, nonlinear programming model of crop farms in the area will be presented. Using the deterministic model as a frame of reference, a risk

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[1] Invited Paper; Institute for Operations Research and the Management Sciences Annual Meeting in Denver, Colorado; October 24-27, 2004.

[2] Jeffrey Apland is a Professor and Corbett Grainger is a Graduate Research Assistant, both in the Department of Applied Economics at the University of Minnesota. Jeffrey Strock is an Assistant Professor in the Department of Soil, Water, and Climate, also at the University of Minnesota

programming model will be presented. The model uses a discrete stochastic programming approach to incorporate a broad range of sources of risk important to production practices that influence nutrient and sediment loss. The risk model addresses variability in yields, market prices and nutrient loss in sub-objectives. Particular attention is given to sources of risk critical to environmental outcomes and the management practices used to improve water quality, including weather and field working days.

Overview of Agricultural Production, Crop Nutrient Management and Water Quality

Growth, development and yield of corn and soybean are all a function of the plants' potential to react to the environmental conditions under which they are grown. It is the producer's task to provide the best possible growing conditions by using management practices such as timely and effective weed and insect control, tillage and fertilization. Widespread adoption of commercial fertilizer use during the 1950's revolutionized agriculture by increasing farm productivity and farm income. Use of commercial fertilizers also increased the amount of farmed cropland because producers were no longer limited by the availability of animal manures for meeting crop nutrient demands.

Nitrogen is one of the most important elements required in agricultural systems for plant and animal production. Nitrogen fertilizer is known to increase yields of many crops. This is especially true for crops that take up large amounts of nitrogen such as corn. Generally, no nitrogen is applied for soybean production since the soybean plant is a legume and fixes nitrogen from the atmosphere. Yield response to nitrogen fertilizer varies depending on the amount of plant-available nitrogen in the soil at the beginning of the growing season (residual soil nitrogen), nitrogen supplied throughout the growing season by organic matter decomposition, and nitrogen in precipitation and irrigation water. The spatial and temporal response of corn yield to nitrogen is of prime interest in modeling the economics of crop production.

Phosphorus is an essential plant nutrient available from fertilizers and manure. The goal of phosphorus management is to balance inputs from commercial and manure sources with crop requirements so that no excess phosphorus is applied but that sufficient phosphorus fertilizer is applied for crop production with minimal environmental impact. After the introduction of commercial fertilizers, high rates of fertilization were encouraged to achieve greater yields Little consideration was given to the potentially adverse environmental impact of excess fertilizer use. Nitrogen from nonpoint sources such as agriculture is drinking water contaminant, where excessive levels of nitrogen cause blue baby syndrome. Excess nitrogen and phosphorus in lakes, rivers and streams causes algae blooms that deplete oxygen, killing fish and other aquatic life, and is a major contributor to hypoxia in the Gulf of Mexico; in this dead zone, aquatic life is unsupportable, which has had dramatic environmental and economic consequences.

In corn producing areas of Minnesota, more nitrogen is applied than any other nutrient. The correct amount of nitrogen use involves balancing farm profitability and the environmental qualities of lakes, rivers and ground water. Some factors leading to nitrogen loss are beyond the control of policymakers and managers. For example, climatic conditions and soil organic matter play critical roles in the loads of nitrogen in surface water [Randall and Mulla, 2001]. However, many factors leading to nitrogen pollution are due to factors within our control, such as management practices and agricultural policy. Nitrogen losses from the landscape are highly related to the system of crop production. Row crops such as corn and soybean, yield much greater nitrate-nitrogen concentrations than do perennial crops such as alfalfa and grass/legume mixes. The rate of nitrogen application affects nitrate loss more than any other nutrient management decision. Nitrate losses increase as the rate of nitrogen application increases. Nitrate loss as affected by the time of nitrogen application are influenced by distribution of precipitation, evapotranspiration demand, leaching, and source of nitrogen. Autumn application of nitrogen carries more risk of loss than spring application. Finally, tillage systems for row crops in the Northern US generally do not significantly affect the amount of nitrate lost.

Nitrogen requirements of corn vary spatially due to differences in soil and temporally due to variation in environmental conditions [Fiez et al., 1995], and since nitrogen is typically applied uniformly within a field, some areas will be under-fertilized and other areas will be over-fertilized. Under-application results in limited yields while over-application of nitrogen results in a higher probability of leaching [[Pan et al., 1997; Meisinger and Randall, 1991]. Mamo et al. (2003) examined the effect of field variability on the yield response of corn to nitrogen fertilization. They found that site-specific management of nitrogen increased profitability and decreased nitrogen fertilization when spatial and temporal variability were considered. Hanley (1990) provides an introduction to the economics of N, from the N cycle in soils to cost-benefit analysis of N management in agriculture. Soil tests are available to support fertilizer management decisions, but conducting tests and obtaining information regarding local nitrogen requirements is costly. Schmitt and Randall [1994] develop a soil test for nitrogen designed to reduce negative environmental externalities and to improve economic benefits. Use of the test by producers would substantially decrease the likelihood of over-application of nitrogen.

Decades of phosphorus fertilization at rates exceeding those of crop removal have resulted in widespread increases in soil test phosphorus. Test levels often exceed requirements for crop production. Accumulation of phosphorus near the soil surface increases the concentration and loss of phosphorus in surface runoff and erosion. Loss of phosphorus in runoff is influenced by the rate, method and time of phosphorus application, the source of phosphorus, the amount and duration of precipitation and vegetative cover. Increased phosphorus in runoff is frequently reported with increasing application rates of fertilizer phosphorous and animal manure. The length of time between phosphorus application and the first runoff event is also important, especially with phosphorus from manure. The major portion of annual phosphorus loss in runoff can often be attributed to one or two intense storms. Concern over phosphorus losses from commercial fertilizer and manure is primarily related to off-site transport of surface runoff, soil erosion and associated phosphorus-enriched sediment entering streams and lakes. Phosphorus is usually the limiting nutrient for the growth of algae in freshwater streams, rivers and lakes. Excess phosphorus in combination with nitrogen in freshwater promotes the growth of aquatic plants that consume oxygen as they decompose. Controlling erosion and runoff are critical to reducing phosphorus movement from agricultural landscapes. Phosphorus losses from erosion and runoff may be reduced by increasing residue cover on the soil surface through conservation tillage. Strategically placed and properly designed filter strips have also been shown to effectively reduce erosion and phosphorus movement. Other measures to reduce potential phosphorus movement by erosion and runoff include terracing, contour tillage, conservation tillage, cover crops and temporary darinage water storage basins.

Intensive cropping systems have produced surpluses of nitrogen and phosphorus and mobilized soil in field and stream banks that pollute surface and ground water. Field and watershed scale processes that affect the delivery of nutrients and sediment to surface water vary due to spatial and temporal variations in soil type, topography, climate and land use. Tillage practices, rate, time, and method of fertilizer and manure applications, and subsurface tile drainage on varying soil types, topography, and climatic conditions have major impacts on the pattern and magnitude of sediment and nutrient losses.

The factors influencing agricultural nutrient and soil losses can be uncontrollable or controllable. Uncontrollable factors include climate and soil mineralization. Controllable factors include management practices used by producers, such as crop rotation, tillage, nutrient and pest management. Management of the controllable factors is necessary in order to devise practical solutions to environmental problems.

Literature Review

Achieving abatement goals often requires economic and production tradeoffs. Researchers in many disciplines have sought solutions to alleviate pollution by recommending so-called best management practices and policy instruments such as input taxes or green payments. Various modeling techniques have been used to analyze and compare the effects of policies and the tradeoffs between environmental and economic goals. A primary focus of the economics literature is the efficiency of alternative policies and management practices which aim to achieve environmental goals. Mathematical programming methods are well-suited for analyses of the complex interactions between economic and environmental objectives. Although the information requirements of such models are complex, they can be developed to address a wide range of environmental and economic problems. Wossink and Renkema [1993] discuss the general data requirements for mathematical programs used to model the tradeoffs between environmental and economic goals in agriculture and provide an outline for the use of these models.

Often policies are aimed at watershed or statewide environmental goals.[3] Veith et al. [2003] use an integrated combinatorial optimization approach to solve for best management practice placement within a watershed. They address multiple pollutants, based on a prioritization scheme. Rejesus and Hornbaker [1999] use the EPIC model to compare environmental and economic outcomes under scenarios with and without site-specific management precision technology.[4] They find that site-specific management practices reduce the variability of net returns compared to the other management practices, but constant spring application of nitrogen actually reduces the mean and variability of nitrogen losses compared to site-specific management. Ribaudo et al. [2001] compare a nitrogen input tax and wetland restoration as policies to reduce nitrogen runoff in the Mississippi River. They integrate a multi-region, mathematical programming model of the US Agriculture Sector (USMP) and the EPIC biophysical model [House et al., 1999]. They find up until a critical level of pollution, the nitrogen tax is more cost effective; beyond the critical level of N, wetland restoration becomes relatively cost effective.

Skop and Schou [1999] use an integrated approach to model nitrogen leaching and targeting in Denmark. They use a heuristic spatial allocation procedure in a GIS model. Using seven farm types with two soils in their integrated model, they find that targeting farms with higher nitrogen leaching rates may not be cost effective. Brady [2003] employs a nonlinear programming approach with endogenous yield responses to fertilizer to study the effects of various policies to reduce the amount of nitrogen carried into the Baltic Sea. The model is spatially disaggregated, and includes a variety of crops in order

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[3] Other papers of interest but not discussed in this section include Fuglie and Bosch [1995], Schwabe [2000], and Swinton and Clark [1994].

[4] The EPIC model has also been linked to mathematical programming techniques by various authors to compare policies including Taylor et al., 1992; Mapp et al., 1994; Wu et al., 1994; Teague et al., 1995.

to compare the effects of various policies.[5] He finds that agricultural policy has a radical effect on the least-cost abatement practices.

Yang et al. [2003] use an integrated approach to identify land parcels that are most cost-effective for retirement under the Illinois Conservation Reserve Enhancement Program, with goals of sediment loss abatement. Their approach incorporates environmental, GIS, and economic models to determine the amount of abatement to undertake and to select the land parcels to be targeted for CREP enrollment in each of twelve watersheds. They find the most cost-effective strategy is to enroll land parcels that are adjacent to streams, sloping, erodible, less productive, and less profitable than other cropland.

Lintner and Weersink [1999] examine the cost-effectiveness of farming and abatement activities to meet water quality objectives by employing mathematical programming model in an agricultural watershed in Ontario.[6] They use endogenous nutrient transport coefficients.[7] The model recognizes individual farms and farm-level activities, and the emissions at the watershed level depend on the activities of each individual farm. While the individual farms emit different levels of pollution, they are characterized as nearly homogeneous in the model. Khanna, et al [2003] combine the spatial and biophysical attributes of land with an economic model and a hydrological model to identify cropland within a watershed for enrollment in the Conservation Reserve Enhancement Program. Transport coefficients are treated as endogenous. Their model employs GIS data and a hydrological model to simulate the flow process, and they analyze the cost-effectiveness of land retirement for land parcels in the watershed. They integrate the models by employing a social planner mathematical programming approach to meet environmental goals of various levels of abatement. They analyze the CREP and identify various approaches of modifying CREP to make the program more cost-effective.

Traditional optimization approaches to pollution problems yield results which ignor equity among agents. Önal et al. [1998] develop a mathematical programming model to determine spatial production activities, crop rotations, resource allocations and technology choices to maximize economic returns to the watershed subject to pollution standards, equity goals and resource constraints. By accounting for a measure of equity among producers, they seek to ensure support of all participants, because in a spatially diverse watershed, such as the Blue Creek watershed in Illinois, the environmental degradation caused by individual farms varies greatly.

Vatn et al. [1997] use an interdisciplinary modeling system, to analyze input taxes and BMPs aimed at nonpoint N, P, and sediment pollution abatement. The model is run for 20 years to capture the effects of stochastic weather variations. A nonlinear programming technique is used in the economic farm model. A deterministic hydrological model is run using weather, plant cover, and soil input data. N loss is modeled separately as a function of farm practices, plant growth, weather, and soil characteristics assuming homogenous fields. They models erosion as a function of farm practice, weather, and soil and

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[5] Spatial variations in the physical parameters, production costs, and the transport of nitrogen are accounted for.

[6] For environmental constraints, sediment-bound and soluble nitrogen, sediment-bound phosphorus, and soluble nitrogen in groundwater were used.

[7] Endogenous transport coefficients depend not only on the land characteristics and farm practices for that location, but also on the activities of farms between it and the outlet. Ignoring this relationship can create a positive externality at a watershed level.

topographical characteristics. Nitrogen leaching estimates are then aggregated to a watershed level, and sediment transport estimates are based on distance to surface water and topography.

Johnson et al. [1991] model groundwater pollution using a representative wheat, corn, and potato farm in the Columbia Basin in Oregon. They integrate a crop production simulation model, a dynamic optimization model, and a linear programming model to analyze practices to reduce N in groundwater. They find that changing the timing and application rates of N and water reduce N loss substantially without significantly impacting profit. After these practices are adopted, however, N pollution reduction is achieved only at increasing costs to producers.

Westra [2001] uses the ADAPT biophysical model [Chung et al.] to simulate phosphorus loading in the Minnesota River, and combines the results with a production and economic simulation to create a positive mathematical programming model. This model examines a corn-soybean rotation under various tillage and nutrient management practices, and tests various systems for phosphorus loading; each system is linked to P loss estimates, production costs, risk premiums, net returns, and spatial information. He then tests pollution standards, P effluent taxes, tillage taxes, and P fertilizer taxes for cost-effectiveness, finding that targeting regions and practices is more cost-effective than targeting all farms within the watershed. Westra et al. [2002] find that producers with land susceptible to erosion near surface water will significantly reduce P loading potential by switching to conservation tillage and by reducing P fertilization levels. Targeting these producers could reduce transactions costs and compensation compared to not targeting.[8]

The risk associated with agricultural production as it relates to environmental problems is receiving increasing attention in the literature. The effects of production and market risk on producer behavior have been widely studied and the notions that both the presence of risk and the risk attitudes of decision makers influence producer decisions is well supported. Some recent research has focused on how the presence of risk and various levels of risk aversion effect production decisions and in turn, water quality outcomes. Some risk analyses have included sources of uncertainty which influence environmental outcomes directly.

Lambert [1990] analyzes the impact of per-unit taxation on farm net returns and quantitative standards on nitrogen by addressing the role of uncertainty in determining input use. Using a Just-Pope production function fit to data from Arizona, he finds that analysts may not find efficient policy recommendations if uncertainty and the diversity of attitudes toward risk are not considered. The importance of attitudes toward risk in the design of environmental policy has also been demonstrated by Isik [2002]. Isik examines a risk-averse farmer's response to marginal changes in environmental and agricultural policies under uncertainty. He examines the impact of taxing profit, input, and output taxes under (output) price and production uncertainty. Depending on the degree of uncertainty and risk attitudes, production uncertainty, and risk-input relationships, the implications for policy design and implementation change.

Peterson and Boisvert [2004] propose a novel method to deal with asymmetric information on producer risk preferences in the design of environmental policies with voluntary participation. They use both a theoretical model and empirical evidence to show that, although the government's information regarding

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[8] In the analysis of policy instruments, transactions costs play a central role. For more on transactions costs and nonpoint source pollution, see McCann and Easter [1999].

risk preferences is limited, a voluntary environmental program can be successful. They simulate a policy in New York where the government would pay corn producers to reduce fertilizer use. The policy was found to require lower net payments than when transfers were tied to crop yields. Moreover, they allow for both risk neutral and risk averse firms in their model.

Chu et al. [1997] use an EV risk programming framework to study conpliance with and enforcement of environmental regulation. They use the model to design contracts aimed at reducing N leachingfor a representative southwestern Michigan farm. Among their results, they conclude that no contract design is dominant across risk preferences; therefore, knowledge of risk attitudes among growers is essential in contract design.

Risk is important to environmental goals as well as the economic goals of the producer. Uncontrolled random events, such as precipitation and temperature, are important determinants on environmental outcomes. Therefore, a policy or recommended management practice may meet water quality goals one year but fail the next. There are examples of studies which consider risk in environmental outcomes. Because the costs of abatement vary according to the stochasticity of variables, using the average cost of abatement to measure cost effectiveness may drastically understate the actual cost. McSweeny and Shortle use a farm-level model to examine pollution control rather than targeting individual practices.

Teague et al. [1995a] use a time series of environmental risk indices to capture the stochastic characteristics of environmental outcomes from agricultural production. Choosing a representative Oklahoma farm, they develop a risk-programming model that is a modification of the Target MOTAD approach [Tauer]. To capture the effect of environmental risk on decision-making, their model maximizes returns while constraining environmental risk to a target level. As a proxy for environmental risk, they use environmental indices to allow for the aggregation of multiple environmental factors. Using composite indices is a further simplification of reality, and the assigning of weights by the social planner inherently involves value judgments. Qiu et al. [2001] use a linear programming model that incorporates a stochastic inequality as a safety-first environmental constraint. In this application, a minimum probability of compliance with an environmental standard is set and the model endogenously determines the associated risk levels. Because the practices are constrained to strictly achieve the stated probability of compliance with the environmental goal, it is an especially attractive approach when the costs of violating the environmental standards are high.

Randhir and Lee [1997] use a direct expected utility risk programming model to optimize cropping systems over time; their approach is less reliant upon assumptions of the distribution of stochastic variables. They incorporate the EPIC biophysical simulation for the environmental results, and use the direct expected utility function as the objective function[9] They derive baseline production activities and pollutant loads, and analyze policies regulating input use. They find that policies have varied and multiple cross-effects on pollutant loads, income, and risk.

[9] The functional form used assumes Constant Absolute Risk Aversion (CARA).

A Deterministic Model of Farm Production

As a point of departure, a deterministic farm model designed to find best management practices for achieving improved water quality will be presented. This model will then be expanded to account for sources of risk which may be important to the efficient achievement of water quality goals. The model is a multiperiod mathematical program of a type widely used in studies of agricultural production. A simplified model of this type, in tableau format, appears in Table 1.

Consider a planning horizon in which land, labor and machine resources are fixed. Because of the critical implications of timeliness in the completion of field operations for both economic and environmental outcomes, the model is built with several intra-year time periods for which field operations and fixed resource constraints are defined. For simplicity, seven periods are used. Decision variables illustrated here include primary and secondary tillage, planting, post-plant and harvest operations. The number on the tillage, planting and post-planting variables indicates the time period in which the operation takes place. For harvest activities, the first number indicates the planting period and the second indicates the harvest period, thus allowing the resource requirements, yields, operating costs, and nutrient and sediment losses to reflect the joints impacts of planting and harvesting dates. Units of the tillage and production activities are acres. Net revenue is measured with coefficients on the tillage and production activities representing minus the per acre operating costs such as fuel, lubrication and repairs for field operations plus seed, chemical, grain drying and other operating costs assigned to the harvest variables. Revenue is generated by the grain sales activity with net selling price the coefficient on the net revenue equation.

A constraint on available arable land is applied to the harvest activities. Seven labor/machine constraints, one for each production period, are used to illustrate the structure of labor and machine resource restrictions – a set of such constraints is used for each type of labor and machine employed by the farm. Labor and machine requirements and availabilities are measured in hours. Thus the constraint coefficients are the resource requirements in hours per acre, placed in the constraint for the period in which the operation takes place. The righthand sides of these constraints are the hours of labor or machine time available in the period. These values are commonly measured as the product of the number of laborers or machines of a particular type, the hours the resource is used each day, and the number of days in the period. The later value is a function of the weather and soil conditions. Often referred to as field working days, this stochastic variable must be averaged in a deterministic model.[10]

Critical aspects of timeliness are expressed in the grain output constraint. The coefficients on the harvest activities represent minus the grain yield per acre – a function of the planting and harvest dates, operating input use, nutrient losses and other weather related factors. A later planting date typically results in lower yields, and delays in harvest beyond physiological maturity of the crop can lead to field losses. For a given planting date, the earliest feasible harvest periods will have greater costs for grain drying, reflected here in the objective function coefficients, than those associated with later harvest periods. Consequences of timeliness directly attributed to the harvest activities are influenced also by the timely completion of field operations which precede harvest. These relationships are captured in

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[10] Field working days as a source of risk is potentially an important determinant of the cost of improving water quality and will be discussed in more detail later in the paper. For a discussion of incorporating field working days as a constraint into a deterministic model, see Etyang et al.

Table 1: Tableau for a Simple Crop Farm Model.

	Tillage and Other Pre-Plant Activities									Crop Production Activities											
	Primary Tillage						Secondary Till			Planting		Post-Plant		Harvest							
	5	6	7	1	2	3	1	2	3	2	3	3	4	3802 1	3802 2	3805 0	3805 1	Grain Sales	Net Rev	N Loss	
Maximize: Obj																			1	-	RHS
Net Revenue	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	+	-1		= 0
Environmental Goals	+/-	+/-	+/-	+/-	+/-	+/-	+/-	+/-	+/-	+/-	+/-	+/-	+/-	+/-	+/-	+/-	+/-			-1	= 0
Land														1	1	1	1				≤ +
Labor/Machinery 1				+			+														≤ +
Labor/Machinery 2					+			+		+											≤ +
Labor/Machinery 3						+			+		+	+									≤ +
Labor/Machinery 4													+								≤ +
Labor/Machinery 5	+													+		+					≤ +
Labor/Machinery 6		+													+		+				≤ +
Labor/Machinery 7			+																		≤ +
Grain Output														-	-	-	-	1			≤ 0
Harvest-Till 5	1													-1		-1					≤ 0
Harvest-Till 6	1	1												-1	-1	-1	-1				≤ 0
Primary-Secondary Till 1	-1	-1	-1	-1			1														≤ 0
Prim-Second Till 2	-1	-1	-1	-1	-1		1	1													≤ 0
Prim-Second Till 3	-1	-1	-1	-1	-1	-1	1	1	1												≤ 0
Till-Plant 2							-1	-1		1											≤ 0
Till-Plant 3							-1	-1	-1	1	1										≤ 0
Plant–Post-Plant 2										1		-1									≤ 0
Plant–Post-Plant 3											1		-1								≤ 0
Plant-Harvest 2										-1				1		1					≤ 0
Plant-Harvest 3											-1				1		1				≤ 0

Non-Negativity

the model by constraints that impose the proper sequencing of field operations – primary tillage before secondary tillage, secondary tillage before planting, and harvest before fall primary tillage. The post-plant and harvest activities are linked to the timing of planting. Note that primary tillage may take place in the fall or spring – this is a convenient way of accounting for a particular type of inter-year linkage in an annual crop production model. It implies that the optimal solution is an intermediate-run equilibrium of sorts which could be repeated from one year to the next, given the available resources.

For the Cottonwood River study, the farm model has eighteen intra-year production periods. A two-year corn and soybean rotation system is discussed here although the study will consider other cropping systems. Details of the time periods and the schedule of field operations may be seen in Appendix Tables A1 and A2. Corn production begins with two custom fertilizer applications completed in the fall after soybean harvest by the fertilizer cooperative. The first application broadcasts phosphate and potassium. The second fertilizer application is of nitrogen in the form of anhydrous ammonia – the incorporation of anhydrous ammonia also serves a the primary tillage operation. As an alternative to anhydrous application in the fall, nitrogen may be applied in the form of urea in the spring before planting. Two secondary tillage operations, field cultivation, are completed in the spring prior to planting. Post plant operations include custom spraying and cultivation. Following corn harvest in mid-October, primary tillage for soybeans is completed with a multi-tool. Secondary tillage, field cultivation, procedes planting, and post-plant operations include two custom spraying operations.

As noted earlier, the effects of planting and harvest dates on costs of production and yields are captured by including harvest activities for each combination of planting and harvest period. Because the timing of fertilizer application also effects expected nutrient losses and yields, the sets of harvest activities are replicated for each alternative application period. In the absence of alternative application schedules and the resulting endogenous levels of nitrogen losses, rates of fertilizer application might be exogenous for a particular corn and fertilizer price. However, because the model is designed to estimate the tradeoffs between economic and environmental goals, rates of fertilizer application are endogenous. Thus the yield coefficients noted in Table 1 become yield response functions for fertilizer which reflect the timing of fertilizer application, planting and harvest. Correspondingly, per acre nitrogen losses, part of the environmental goal equations, are functions of the rates of fertilizer application.

A final aspect of the agricultural production/water quality problem in the Cottonwood River Watershed results from the heterogeneity of soil resources and topography. To address this, arable land for a particular farm is disaggregated into several fields. The land constraint shown in the tableau is replaced with an acreage constraint for each field. Field operation activities and fertilizer rate variables are replicated for each field. Consequently, optimal production practices are determined for each field. The production and environmental coefficients may, of course, reflect diversity of soils and topographies within each field.[11]

Bringing Risk into the Model

The effects of risk and the risk attitudes of producers have been studied using a variety of risk programming techniques. The agricultural economics literature is replete with applications of the EV and MOTAD models to analyses of producers' responses to changing markets, technologies and

[11] Taken to a much higher level, the disaggregation of land resources would serve an analysis of the economic and environmental implications of precision farming techniques.

policies. Applications of these models to problems of agricultural production and water quality were mentioned earlier. Examples of applications of discrete stochastic programming (DSP) are much less common, owing in large part to the relatively high complexity and cost of model construction, and the technique's formidable data requirements.[12] DSP is an attractive alternative among risk programming techniques, however, in its ability to account for risk in the constraint set and a sequential decision process – both typify agricultural production.[13] Alternative production practices important to both economic and environmental outcomes of crop farming fit the DSP framework quite nicely.

In the Cottonwood River Watershed, soybean and corn producers quite often apply nitrogen fertilizer in the fall after soybean harvest. As noted earlier, spring application is a desirable alternative to fall application in that nitrogen loss is generally reduced. However, particularly when spring weather is rainy, limited field working days may lead to delays in planting and thus lower crop yields – a problem that would be exacerbated by the need to complete additional field operations such as fertilizer application prior to planting. Corn producers in the Cottonwood River Watershed typically seek to plant in late April or early May. However, the number of days in April suitable for field work in Southwestern Minnesota is highly variable. Over the last ten years, there were on average about eight field working days in April with an average beginning date of April 20th for spring tillage and other preplant operations. The range of field working days in April was from zero (in three out of the last ten years) to 21 – the standard deviation of field working days in April was 7.4.[14] Given the uncertainty about the feasibility of completing spring field work in a timely way, the scheduling of fertilizer application in the fall as a strategy to avoid delays in planting is appealing to many farmers. The rates of fertilizer application, like the time of application, must be selected under uncertainty, also. When the rate of nitrogen application is selected in the fall, little is known about the growing conditions which will determine the actual yield response. Unknown, too, is how much of the applied fertilizer will be lost through leaching and therefore unavailable to the planted crop. Discrete stochastic programming is a modeling approach that can accommodate the sequence of crop nutrient management decisions and the uncertainties that characterize the feasibility, and economic and environmental outcomes of those choices.

In DSP, the decision process is characterized in a multistage framework. With the eighteen period, deterministic model described earlier, it would be tempting to use the eighteen time periods as decision stages. However, the implications for model size and the formidable data requirements make this option impractical. Consider the more modest characterization of the problem illustrated in Figure 1. Using a decision tree diagram to represent the problem, Figure 1 shows a two stage decision problem designed to characterize crop farms the the CRW. Stage one represents the production process beginning after harvest and continuing through the fall. Stage two represents the spring, pre-plant period through the growing season and harvest. Fall decision variables include the scheduling of tillage operations, and the schedules and rates of fertilizer application. Stage two decisions include spring

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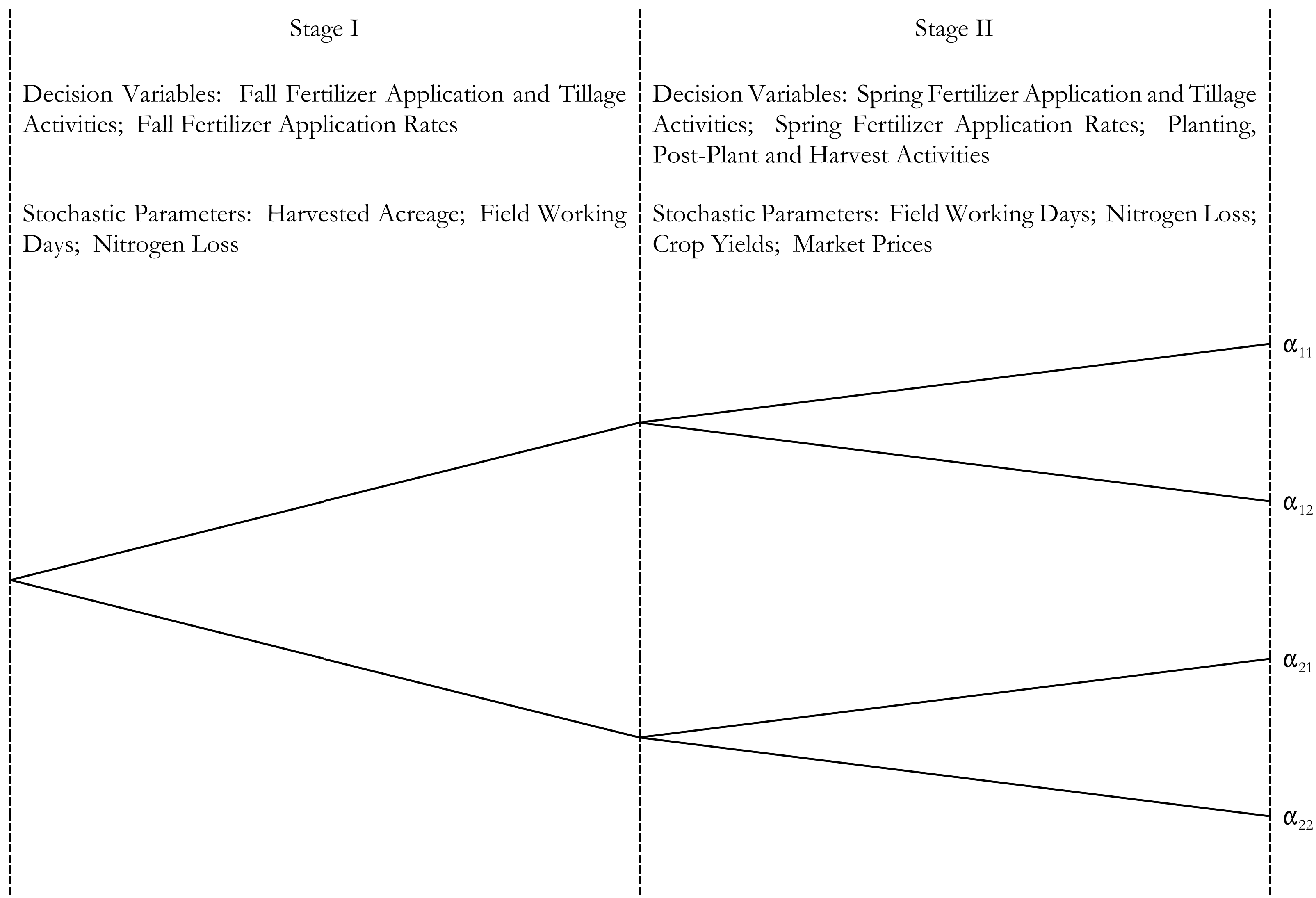
[12] For a review of applications of discrete stochastic programming, see Apland and Hauer.

[13] Details of DSP and other risk programming techniques are presented in Boisvert and McCarl.

[14] Based on unpublished data from the Southwest Research and Outreach Center in Lamberton, Minnesota. A table showing the observed field working days for time periods in the farm model appears in the Appendix of this paper.

Figure 1: Decision Tree for a Discrete Stochastic Programming Model.



tillage and fertilizer application, planting, post-planting and harvest operations. The stages are linked with the transfer of land with various crop histories, fertilizer levels and levels of preparation for planting – all decision variables completed under the prevailing states of nature.[15]

The decision tree in Figure 1 show two states of nature in each stage for purposes of illustration. In application, more states will be used to more thoroughly characterize the distributions of stochastic variables. Each fall state of nature defines a schedule of completed crop harvest by period, field working days by period, and levels of fall nutrient loss parameters characterizing nutrient loss as a function of the rate and schedule of application. Spring and growing season nutrient losses are among the stage two states of nature, which also include field working days, yields and crop prices.

Recall that for the deterministic model, the schedule of field operations was designed in an annual cycle described as an intermediate run equilibrium. When uncertainties such as field working days are brought into the model, it becomes necessary to account for year to year differences in the decision environment. The sequence of management decisions described here begins with a harvest schedule driven by earlier crop mix choices and the planting schedule. The model must also account for subsequent effects of management decisions by representing future demands for harvested land at the end of the crop year. Distributions of harvest schedules and the intrinsic values of harvest by period may be defined using historical patterns of harvest completion and shadow prices on the sequencing constraints from the deterministic analysis.

To support an analysis of efficient trade-offs between economic and environmental objectives, a multiple objective framework is used. In discrete stochastic programming, an objective is characterized as a function of a performance measure for each joint event or, referring to the decision tree in Figure 1, each terminal branch [Rae]. DSP can accommodate familiar risk programming objectives such as those used in the EV or MOTAD models, albeit with a richer characterization of the underlying risk than is possible in the more common versions of these models [for details, see Boisvert and McCarl, or Apland and Hauer]. But consider a more general depiction of producer behavior using expected utility maximization [Lambert and McCarl]. Let α_{ij} be the probability of an event history with state of nature i occurring in stage one and state of nature j occurring in stage two. Let Y_{ij}^* be the corresponding net revenue outcome, so expected utility can be expressed as follows:

$$\sum_i \sum_j \alpha_{ij} U\left[Y_{ij}^*\right]$$

With other relevant performance measures defined as functions of the DSP decision variables, a multiple objective framework emerges. For example, suppose two objectives, expected utility and nitrogen loss are to be included. Let V_{ij} be the total nitrogen loss for the farm given a particular event history. The expected nitrogen loss, then, can be written:

$$\sum_i \sum_j \alpha_{ij} V_{ij}^*$$

[15] The application of nitrgen to the growing crop, called side-dressing, is of interest both economically and environmentally. DSP is well-suited to an analysis of side dressing, also. To properly capture a side-dressing option, a third, post-plant decision stage could be added to the model.

By one common approach to multiple objective programming, an overall objective for the discrete stochastic programming farm model could be:

$$\text{Maximize:} \quad \sum_i \sum_j \alpha_{ij} \, U\left[Y_{ij}^*\right] - \gamma \sum_i \sum_j \alpha_{ij} \, V_{ij}^*$$

So the firm maximizes expected utility minus a penalty γ times expected nitrogen loss. γ can be set to zero, then parametrically increased to derive efficient production practices for achieving increasing levels of water quality. But the DSP framework will support a variety of other analyses. A dual to the approach just described may be employed by maximizing expected utility subject to an upper limit on expected nitrogen loss. The upper bound on expected nitrogen loss can then be decreased from a non-restrictive level to levels reflecting more favorable environmental outcomes. The dual of the expected nitrogen loss constraint becomes an implicit marginal cost, measured in expected utility, of achieving the given level of nutrient loss – an implicit γ. Building on the fact that nitrogen loss is now stochastic, it is possible to impose a maximum level of nutrient loss for each event history, say, $\bar{V}_{ij}$. By setting $\bar{V}_{ij}$ to be equal for all event histories, a policy which says the effluent must not exceed a given maximum under any state of nature is expressed. Along these lines, upper limits could be imposed on nutrient loads in the water over shorter periods of time by disaggregating V_{ij} temporally.

The use of a nonlinear penalty function on each effluent variable is appealing in that it would allow practices which exceed the average nutrient loss to be adopted if the economics offset the increased environmental cost. So the objective would become:

$$\text{Maximize:} \quad \sum_i \sum_j \alpha_{ij} \, U\left[Y_{ij}^*\right] - \gamma \sum_i \sum_j \alpha_{ij} \, C\left[V_{ij}^*\right]$$

The challenge, of course, would be to estimate function C[V] to satisfactorily capture the social costs associated with various levels of effluent.

As discussed earlier, the proposed risk programming model includes stochastic yields, market prices, field working days, and nutrient and soil losses. Alternative approaches to the estimation of yield and prices distributions are familiar to agricultural economists. The estimation of field working days, and nutrient and soil loss distributions is less common. Currently, nutrient loss parameters are being estimated for the deterministic farm model using a simulation model called ADAPT. ADAPT, which stands for agricultural drainage and pesticide transport, has been described as a daily time-step water table model [Davis, et al.]. It has been used for a variety of studies involving soil and crop nutrient loses, production practices, and water quality [Chung et al., 1992; Gowda et al., 2002; Gowda et al., 1998; Westra, 2001; Westra et al., 2002].

The levels of soil and nutrient loss are influences by soil type and topography as well as production practices. So the simulations are being completed for individual fields on the representative farms in the watershed. The representative farms were selected to characterize the range of soil types and topographies found in the watershed. ADAPT takes the schedule of field operations and the crop rotation as given and, using daily weather information, estimates water, soil and nutrient movements. Because the economic model presented here is a multi period model with the schedule of field operation determined endogenously, ADAPT is being run for several feasible schedules of field operations representing the ranges in the timing of fertilizer application, planting and harvest. By running the simulation over a ten year period for each production schedule, average annual values for nitrogen, soil and phosphate loss are estimated. By using the ADAPT results to estimate parameters on the yield response and nutrient and soil loss functions in the mathematical program, the implications of production choices, including timeliness fertilization rates, are expressed in the economic model. As noted earlier, field operations must be completed with fixed labor and machine resources, the availabilities of which are influenced by field working days. Average field working days may be estimated using records from the University of Minnesota's Southwest Research and Outreach Center in Lamberton Minnesota. These records provide daily field working days for the last years for this site within the watershed. For consistency, field working days are averaged over the same ten year period used in the ADAPT simulations. The risk analysis requires that states of nature be defined for soil and nutrient losses and field working days, as well as yields and prices. Because the simulations are run for a time series of weather, information about variation in the effluent levels is generated. Similarly, the time series data on field working days will readily support the definitions of states of nature for the DSP model.

Summary

This paper discusses on-going modeling efforts that are part of a study of best management practices for improving water quality in the Cottonwood River Watershed in Southwestern Minnesota. Following a general discussion of crop nutrient management and water quality for this corn and soybean producing area, the literature involving farm level economic analyses of water quality problems is reviewed. A deterministic nonlinear programming model of a crop farm is presented as a precursor to the development of a risk programming model. The proposed model focuses on sources of risk believed to be important to the economic and environmental outcomes of crop production. Using a discrete stochastic programming framework, the proposed model allows for stochastic yields, market prices, field working days, and nutrient and sediment losses. Importantly, the DSP model characterizes the sequence of decisons, including field operation and fertilizer application scheduling, which afford options for improving water quality outcomes, but involve uncertainties in field working days that are critical to the trade-off between profitability and water quality. The DSP framework accommodates environmental policies and regulations that account for uncertainty in nutrient and sediment losses, while reflecting the economic risks faced by farmers with diverse risk preferences.

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Appendix

Table A1: Schedule of Field Operations for Corn Following Soybeans.

	Length	First	Last	– Fertilizer Application[*] –		– Field Cultivation[**] –					
Period	Days	Day	Day	P & K	Nitrogen	First	Second	Plant	Spray[*]	Cultivate[***]	Harvest
1	21	Apr 03	Apr 23		X	X					
2	7	Apr 24	Apr 30		X	X	X	X			
3	7	May 01	May 07		X	X	X	X			
4	7	May 08	May 14			X	X	X			
5	7	May 15	May 21			X	X	X			
6	7	May 22	May 28			X	X	X	X		
7	7	May 29	Jun 04						X		
8	7	Jun 05	Jun 11						X	X	
9	7	Jun 12	Jun 18						X	X	
10	7	Jun 19	Jun 25						X	X	
11	49	Jun 26	Aug 13						X	X	
12	7	Sep 25	Oct 01	X	X						
13	7	Oct 02	Oct 08	X	X						
14	7	Oct 09	Oct 15	X	X						X
15	7	Oct 16	Oct 22	X	X						X
16	7	Oct 23	Oct 29	X	X						X
17	7	Oct 30	Nov 05	X	X						X
18	14	Nov 06	Nov 19	X	X						

[*] Fertilizer applications and spraying are custom operations. Nitrogen application serves also as primary tillage. Spraying occurs four to six weeks after planting.

[**] The second field cultivation is concurrent with the planting operation.

[***] Cultivation takes place six to eight weeks after planting.

Appendix, continued

Table A2: Schedule of Field Operations for Soybeans Following Corn.

Period	Length Days	First Day	Last Day	Tillage Multi-Tool	Field Cultivation	Plant	Spray 1*	Spray 2*	Harvest
1	21	Apr 03	Apr 23	X	X				
2	7	Apr 24	Apr 30	X	X				
3	7	May 01	May 07		X	X			
4	7	May 08	May 14		X	X			
5	7	May 15	May 21		X	X			
6	7	May 22	May 28		X	X			
7	7	May 29	Jun 04		X	X	X		
8	7	Jun 05	Jun 11				X		
9	7	Jun 12	Jun 18				X	X	
10	7	Jun 19	Jun 25				X	X	
11	49	Jun 26	Aug 13				X	X	
12	7	Sep 25	Oct 01						X
13	7	Oct 02	Oct 08						X
14	7	Oct 09	Oct 15	X					X
15	7	Oct 16	Oct 22	X					X
16	7	Oct 23	Oct 29	X					
17	7	Oct 30	Nov 05	X					
18	14	Nov 06	Nov 19	X					

* Spraying operations are custom. The first spraying occurs four to five weeks after planting and the second spraying occurs six to seven weeks after planting.

Appendix, continued

Table A3: A Summary of Field Working Days Data for Southwestern Minnesota.

Period	Length Days	First Day	Last Day	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	Mean	Std Dev
1	21	Apr 03	Apr 23	4	4	15	3	10	0	11	0	0	0	4.70	5.16
2	7	Apr 24	Apr 30	2	3	6	6	7	3	6	0	0	0	3.30	2.65
3	7	May 01	May 07	2.5	7	2	3	7	4	6	0	6	2.5	4.00	2.27
4	7	May 08	May 14	7	2	3.5	7	7	2	0	5	1.5	1	3.60	2.57
5	7	May 15	May 21	7	4	4	7	7	1	1	5	6	5	4.70	2.15
6	7	May 22	May 28	6	6	3	4	4	5	4	0	5	3.25	4.03	1.66
7	7	May 29	Jun 04	7	5	5	6	6	5	2	7	4	6	5.30	1.42
8	7	Jun 05	Jun 11	2.5	4	5	7	5	4	6	3	3	2	4.15	1.52
9	7	Jun 12	Jun 18	7	6.5	5	6	5	6	4	4	6.5	7	5.70	1.08
10	7	Jun 19	Jun 25	2.5	5.5	1	1	5	6	4	7	4	3	3.90	1.93
11	49	Jun 26	Aug 13	64.5	64.5	63	61	64	64	69	76.5	76	70	67.25	5.16
12	7	Sep 25	Oct 01	4	5	3	7	5	6	7	6	6	7	5.60	1.28
13	7	Oct 02	Oct 08	1	5	6	7	3	5	7	7	3	7	5.10	2.02
14	7	Oct 09	Oct 15	6	6	7	5	5	6	7	6	6	6	6.00	0.63
15	7	Oct 16	Oct 22	5	7	4	7	5	7	6.5	7	5	7	6.05	1.11
16	7	Oct 23	Oct 29	7	5	6	7	2	6	7	7	6	7	6.00	1.48
17	7	Oct 30	Nov 05	7	2	4	2	2	7	4.5	7	4	6	4.55	2.01
18	14	Nov 06	Nov 19	14	9	6	0	0	14	6.5	13	13	13	8.85	5.24