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Site-Specific Simulation of Nutrient Control Policies: Integrating Economic and Water Quality Effects

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A watershed-based modeling system is developed to assess alternative nutrient abatement policies, including fertilizer taxes, application caps, and uniform reductions. A microeconometric model of nutrient use is estimated using farm-level data, prices, and spatially detailed soil and land characteristics. Results are interfaced with a physical watershed model to predict water quality changes. Simulations demonstrate differences in water quality effects across policies. For nitrate loads at the watershed outlet, an application cap provides slightly superior performance for small reductions, but a tax is more efficient under larger reductions. Phosphorus reductions at the sub-watershed level vary but provide information about policy tradeoffs.

Key words: nitrogen, nutrient policy, phosphorus, water quality

Introduction

Worsening surface water quality is an important and multifaceted issue encompassing problems such as hypoxic zones, fish kills, drinking water concerns, and diminished recreational opportunities. While regulating industrial and municipal point sources of water pollution has become common, non-point or diffuse sources, including agricultural sources, remain relatively uncontrolled. Agriculture's primary non-point source contribution to water quality problems is the use of fertilizers in the crop production process. Of the common fertilizer components, nitrogen and phosphorus are major nonpoint causes of impaired waters throughout most of the United States (U.S. Geological Survey, 1999). Public policy has yet to effectively address many of the concerns related to nonpoint source pollution and government bodies struggle to find the means to achieve changes in related pollution. Many of the difficulties associated with policy implementation arise from the need for solutions tailored to a specific watershed. This aspect of the problem is most acute in areas where a large proportion of water body impairment is due to nonpoint sources of pollution; each area has a unique distribution of nonpoint source pollutants that degrade water quality.

The goal of this study is to develop a framework for assessing policies designed to improve water quality in a given watershed; here, the Raccoon River watershed in Iowa. This watershed experiences some of the highest nitrate concentrations in the country and contains a number of nutrient-impaired lakes and waterways. Policy assessment requires examination of tradeoffs between water quality improvement and impact on net returns for farm operators. Policies examined here include a tax on each nutrient, a per-acre application cap, and a uniform reduction in application levels, following common policy options discussed by Griffin and Bromley (1982), Helfand and House (1995), and Shortle and Horan (2001). The analysis is conducted via the development and application of two complementary modeling frameworks. The first is a production model used to determine fertilizer input choice and farm net-return response to policy implementation. The second is a physical model, the Soil and Water Assessment Tool (SWAT), which predicts watershed-wide effects of changing

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nutrient application patterns. The output from econometric estimation of the production model is interfaced with the physical model and the resulting simulations used to determine changes in water quality and net returns under each policy.

Similar modeling frameworks have been implemented in a variety of contexts. The body of existing literature spans the fields of resource economics, hydrologic modeling, and agronomy. Related studies can be divided into two general approaches: those employing an economic model and those simulating land-use or land-management changes without reference to economic effects. Examples of the latter include Schilling and Wolter (2009), who simulate a variety of fertilizer and land-use reduction scenarios, and Jha, Gassman, and Arnold (2007), who establish a baseline scenario for the Raccoon watershed and then conduct sensitivity analysis involving long-term scenarios of land use.

Several studies have also employed SWAT or similar physical modeling frameworks in conjunction with an economic analysis. These might logically be classified by scale of modeling unit, from the farm level up to the state or regional level. At one end of this scale, analysis tends to involve aggregated data at a large scale and does not incorporate a micro-scale econometric model, instead relying on agricultural sector programming models like the Agricultural Sector Model (ASM). For examples, see Qiu and Prato (2001), Attwood et al. (2000), and Attwood et al. (2001). Projects on smaller units of analysis typically use economic models that rely on calculated technical coefficients (Osei et al., 2003) or other non-econometric approaches such as data envelopment analysis (Whittaker et al., 2003). In another approach, Huang and LeBlanc (1994) examine two extreme scenarios of farmer behavior: one in which farmers do not respond at all to input price changes, the other in which farmers fully adjust to optimal agronomic rates.

To our knowledge this paper presents the first implementation of an in-stream model joined to actual farm-level data using an econometric model of field-level decisions involving multiple nutrients. The modeling approach is also unique in that it incorporates detailed site-specific characteristics–including soil type, row-cropping intensity, slope, and weather–into the economic model rather than capturing these effects only in the watershed nutrient transport model.

This paper's more general contribution is to discussion of water-quality standards; information about the relative efficacy of policies and the costs associated with changes in row-crop management is essential to making efficient decisions about resource management. Policymakers are hesitant to make decisions without information on the effects of implementation, and we provide new details on the tradeoffs between water quality and returns to fertilizer use.

Modeling Framework

Studies addressing crop response to nitrogen and phosphorus input often report farmers applying amounts of these nutrients that exceed assumed profit-maximizing levels (Yadav, Peterson, and Easter, 1997) or assume that farmers apply at levels considered excessive when compared to a crop's nutrient intake requirements (Huang and LeBlanc, 1994; Abrahams and Shortle, 2004). Others explicitly incorporate risk considerations (Babcock, 1992; Rajsic, Weersink, and Gandorfer, 2009). With few exceptions, studies of farm or field-level choice base their assumptions on average agronomic conditions, ignoring heterogeneity in land characteristics. We assume that farmers are risk-neutral, have some information about appropriate nutrient levels for their fields, but may make mistakes in optimization with respect to nutrient use. The latter characteristic is part of the basis for assumptions about the meaning of the error term in the econometric analysis to follow. For a general discussion of nutrient application decisions, see Sheriff (2005).

Applying nutrients in excess of the crop's biological needs results in nutrients entering waterways through runoff, leading to the water quality issues discussed above. There are several requirements for a production model that will allow proper interfacing with the SWAT physical water quality model. Most important is the need for estimates of nutrient application rates that can respond to abatement policies. In addition, a means of comparing the effects of the policies on producers is necessary. A field-level model is sufficient as long as aggregation to the watershed level is possible; we use National Resources Inventory (NRI) data to perform this aggregation.

The unit of analysis is a single firm or farm that maximizes expected returns to nutrient application on corn through its choice of nutrient input levels. The model assumes a single output, so it does not allow farmers to react to policy changes by switching crops; this limitation is discussed in more detail below. The choice of nutrient input level depends on location-specific environmental characteristics, input prices, and the output price. The inputs focused on in this study are two commercial fertilizer components that tend to be heavily applied to corn crops: nitrogen and phosphorus. The general specification of the farmer's problem as outlined above is $\max_{\boldsymbol{x}} \pi(\boldsymbol{x};\boldsymbol{z})$, where π represents net returns to inputs $\boldsymbol{x}$ chosen by the farmer given site characteristics $\boldsymbol{z}$. A Cobb-Douglas production function is chosen to represent yield, as it requires the estimation of a relatively small number of parameters, an important consideration when limited instrumental variables are available. No additional restrictions beyond the general choice of functional form are assumed regarding the structural parameters of production. Two nutrient inputs, nitrogen and phosphorus, are considered here. Exogenous site-specific characteristics are modeled to enter through total factor productivity. The production technology is thus $y = A(\boldsymbol{z})x_1^{a_1}x_2^{a_2}$, where y is corn output measured in bushels per acre, x_1 is pounds per acre of nitrogen applied, x_2 is pounds per acre of phosphorus applied, $\boldsymbol{z}$ is a set of site-specific productivity variables that will be discussed below, a_1 and a_2 are parameters to be estimated, and $A(\boldsymbol{z})$ will require some assumption about functional form. This technology imposes constant returns to acreage, which is reasonable if farmers have already incurred most of their large capital costs in choosing to be in production.

The farmer's problem can now be expressed as $\max_{x_1,x_2}(pA(\boldsymbol{z})x_1^{a_1-1}x_2^{a_2} - r_1x_1 - r_2x_2)$, where r_1 and r_2 represent input prices and p represents the output price. The first-order conditions for a solution to this optimization problem are $A(\boldsymbol{z})pa_1x_1^{a_1-1}x_2^{a_2} = r_1$ and $A(\boldsymbol{z})pa_2x_1^{a_1}x_2^{a_2-1} = r_2$. This means that the farmer chooses x_1 and x_2 such that the value marginal product of each input is equated to the price of the input. These imply input demand expressions

$$x_1(r_1,r_2,p;\boldsymbol{z}) = \left(\frac{r_1}{pA(\boldsymbol{z})a_1}\left(\frac{r_1a_2}{r_2a_1}\right)^{-a_2}\right)^{\frac{1}{a_1+a_2-1}}$$

and

$$x_2(r_1,r_2,p;\boldsymbol{z}) = \left(\frac{r_2}{pA(\boldsymbol{z})a_1}\left(\frac{r_2a_1}{r_1a_2}\right)^{-a_1}\right)^{\frac{1}{a_1+a_2-1}}.$$

To jointly estimate these relations, it is assumed that there are some random errors associated with observed nutrient level choice. These could take the form of measurement error in the data, unobserved factors that influence application decisions, or errors on the part of the farmer in choosing the return-maximizing level of nutrient application. This implies that nutrients are applied, on expectation, at technically efficient rates and that farmers either cannot achieve the same yield using fewer nutrients or do not have sufficient information to do so. This and the general modeling framework preclude, for example, farmers adopting practices that increase efficiency in uptake, such as a reallocation of application from fall to spring.

There are a number of exogenous site-specific characteristics that might be used to model $A(\boldsymbol{z})$: weather, soil type, and slope, among other factors. We employ a single composite variable called the corn suitability rating (CSR). It is a spatially explicit measure that combines average weather conditions, soil type, drainage, and slope to create a relative ranking for sites statewide (Miller et al., 2010). The index runs from 5 for land poorly suited to corn production to 100 for ideal land.

The best fit of CSR in the econometric modeling framework was achieved under the assumption that total factor productivity is linear in CSR: $A(\mathrm{CSR}) = \alpha_0 + \alpha_1\mathrm{CSR}$, where CSR is unique to the farm location. In the following discussion this decomposition is suppressed for notational convenience and total factor productivity is simply represented by the symbol A. The estimable versions of the first-order conditions are then:

$$x_1(r_1,r_2,p;\mathbf{z}) = \left(\frac{r_1}{pA(\mathbf{z})a_1}\left(\frac{r_1a_2}{r_2a_1}\right)^{-a_2}\right)^{\frac{1}{a_1+a_2-1}} + v_1 \tag{1}$$

$$x_2(r_1,r_2,p;\mathbf{z}) = \left(\frac{r_2}{pA(\mathbf{z})a_2}\left(\frac{r_2a_1}{r_1a_2}\right)^{-a_1}\right)^{\frac{1}{a_1+a_2-1}} + v_2, \tag{2}$$

where v_1 and v_2 are (correlated) error terms. Input-demand functions (1) and (2) could be estimated alone, but without the production function it would be impossible to make any inference about changes in net returns associated with policy scenarios. If a production function were estimated separately there would be no guarantee that it would be consistent with the input demand functions unless the whole system is estimated simultaneously. Thus we also include the production function:

$$y = A(\mathbf{z})x_1^{a_1}x_2^{a_2} + v_3 \tag{3}$$

and assume correlated error terms $v_1,\ v_2,\ v_3 \sim N(0,\Sigma_v)$. Functions (1) through (3) cannot be consistently estimated by ordinary least squares due to cross-equation parameter restrictions and the correlation between the error components of each equation. Estimation using three-stage least squares is appropriate here (Amemiya, 1977; Gallant and Jorgenson, 1979).

The choice of a Cobb-Douglas production function is somewhat limiting in that it does not preserve a specific nutrient ratio: input demands depend on relative input prices and technical coefficients. This may not be a serious limitation if corn farmers apply N and P as part of a blended material but add more N later in the growing season in response to conditions. Additionally, while a specific nutrient ratio may be agronomically ideal for plant growth, N and P behave differently once introduced to the environment, so that the N/P ratio applied is not necessarily the same ratio taken up by the plant; farmers are aware of this and could be assumed to incorporate their expectations regarding uptake into their nutrient application decisions.

A potential limitation of the econometric model is that it does not incorporate data on non-nutrient/land-quality inputs such as capital and labor. For example, farmers may be able to achieve the same yield with less fertilizer if they use GPS-based variable rate technology or soil nitrogen tests. If these missing variables have a large influence on nutrient application rates, the model will underestimate the marginal impact of, e.g., reduced nitrogen on yields if nitrogen is negatively correlated with the omitted capital variable. In other words, what the model would suggest as the marginal impact of reducing N would actually be the impact of simultaneously reducing N and increasing capital or labor.

After obtaining parameter estimates for the system described above, it is necessary to obtain fitted values of the inputs to proceed with simulations of policy scenarios. For a given set of input and output prices, solutions for a range of CSR values can be obtained and the results used to perform the simulations needed for the physical water quality model. To accomplish this, the parameter estimates from the economic model are used in conjunction with each observation's input/output prices and CSR to determine the x_1 and x_2 that result from the estimated input demand equations.

Data and Estimation

There are three types of data used for estimation of the economic model: corn production input and output data, site-specific soil data and other exogenous variables to be used as instruments, and input and output prices. The USDA's Agricultural Resource Management Survey (ARMS), a survey of farm operators, provides the primary production data, including cropping practices, chemical application variables, and crop yields. The corn data available for this study runs from 1996 to 2001; the same operators are not surveyed each year. The primary variables of interest are output

Table 1. Summary of Data Used in Model Estimation (n = 821)

Variable	Mean	Standard Deviation	Minimum	Maximum
Yield (y), bushels/acre	144.5	27	2.5	224
Nitrogen input ($_1$), pounds/acre	128.6	42.1	8	300
Phosphorus input (x_2), pounds/acre	58.4	30.9	2.8	300
Residue, %	27.2	16.5	0	81
Corn-Soybean indicator	0.78	0.4	0	1
Corn Suitability Rating (CSR), index	66.9	21	5	100
Nitrogen price (r_1), \$/pound	0.22	0.04	0.17	0.28
Phosphorus price (r_2) \$/pound	0.27	0.03	0.23	0.31
Corn price (p), \$	1.98	0.42	1.46	2.81
Soybean price, \$	5.28	1.36	3.85	7.36

Table 2. Parameter Estimates for the Economic Model

Parameter	Estimate	Standard error	t-statistic	p-value
α_0	28.67	9.22	3.11	0.0019
α_1	0.68	0.14	4.93	< 0.0001
a_1	0.09	0.0014	68.11	< 0.0001
a_2	0.05	0.0011	51.59	< 0.0001

measured in bushels of corn per acre, application of nitrogen to the corn crop measured in pounds per acre (calculated from the commercial product description provided by the farmer), application of phosphorus to the corn crop in pounds per acre (also calculated from reported commercial product application), percentage of residue left on the field following tillage operations, and crop planted on the field the previous two seasons. Soil data via the CSR variable is sourced from the Iowa Soil Properties and Interpretation Database (ISPAID); see Miller et al. (2010) and the previous section for details. ARMS data point locations (latitude and longitude) were matched at the Iowa National Agricultural Statistics Service (NASS) site using an algorithm that assigned each site to a point on a high-resolution soil grid constructed from the ISPAID data. Base fertilizer prices were obtained from an annual USDA-NASS agricultural price compilation. Reported prices are based on specific fertilizer blends in the North Central region, which includes the study area. Since different blends are more prevalent in some areas, prices for every blend are not available for each region. The Iowa Department of Agriculture and Land Stewardship (IDALS) maintains fertilizer sales data that tracks statewide use by blend. This was used to construct a weighting scheme to approximate raw input prices on a per-pound basis. Output prices were obtained from the Iowa NASS office; prices used for estimation vary by year and county, the latter reflecting small spatial variations in prices received by farmers at different grain elevators. Soybean prices, used as an instrument in estimation, were also available from the same dataset. An overall summary of the dataset used for estimation appears in table 1.

The system of equations (1) through (3) is estimated using the R statistical programming language's nonlinear three-stage least squares package, nlsystemfit. The instruments used in estimation include the price of soybeans, proportion of residue left on the field (a measure of the tillage method used by the farmer), and two dummy variables indicating whether the farmer is following a corn-soybean or a continuous-corn crop rotation based on the previous year's crop. These variables are assumed to be correlated with profitability of corn production and/or fertilizer input usage, but not related to individual farmers' error terms. The dummy variables for crop rotation are likely to exhibit this behavior as long as they are exogenous in the long run. Residue also reflects at least previous-season, if not long-run, choices and the price of soybeans provides information about the opportunity cost of planting corn. The general assumption is that the error terms for the nutrient application choice and yield reflect current conditions and that the instruments are either long-run or otherwise decoupled from the error terms. For each independent variable in the estimated system of equations other than x_1, F tests reject at greater than the 99% level the null hypothesis that excluded instruments do not have explanatory power. For x_1, the same null hypothesis is rejected at greater than the 95% level. The impact of inconsistency arising from a possible weak correlation of instruments with errors can be reduced by a strong correlation between the instruments and the endogenous variables (Bound, Jaeger, and Baker, 1995).

Although it could be argued that the choice of crop rotation and tillage are endogenous, the assumption made here is that rotation and tillage choice are long-run decisions and are thus exogenous in any given year. Though fixed rotation is a theoretical limitation, observed farmer behavior and agronomic models suggest it may be difficult for operators to make a long-term switch to continuous soybeans or rotations heavier in soybeans. The ARMS dataset does not contain true panel data in that it does not survey the same farm operator each year, nor does it reveal information about the farmer's nutrient application choices in previous years or with different crops. Relevant information that is available are the farmer's crop choices for the previous two years. This variable is incorporated into the modeling framework as an instrument in the econometric estimation, so past behavior regarding crop choices are taken into account.

While some farmers might be induced to switch to soybeans from corn due to changes in output price, nutrient prices, or command-and-control policies, less than 2% of the sample preceded their corn crop with two years of soybeans, with that percentage remaining between 1.1% and 2.6% across the years of the data and under the various input and output price conditions. Continuous soybean cropping will rather quickly induce reductions in yield via increases in both soil erosion and pest pressure, among other factors. See Porter et al. (1997) and Stern, Doraiswamy, and Akhmedov (2008) for details on yield losses under continuous soybean cropping.

In the study area, continuous-corn and corn-soybean rotations are the most common, covering between 81% and 96% of the observations depending on the year. The importance of agronomic factors may dominate decision-making even under large policy changes, particularly in the medium to long term. It is conceivable that very large changes in the prices of inputs or severe restrictions on input use could induce switching in the long-run, but the data to resolve this issue would require further surveying of farm operators.

Another simplifying assumption that deserves some discussion is the fact that the modeling framework does not allow for farmer decisions about taking land into or out of production. This becomes a modeling problem if the policies considered would drive marginal land out of production. Given the limitations of the current dataset and the number of additional questions that would need to be explored–how to structure land retirement policy in this context, for example–this seems an excellent avenue for further research.

Parameter estimates and standard errors from estimation of the system of equations (1) through (3) appear in table 2. Yield elasticities with respect to nutrient inputs are positive and indicative of decreasing returns to nutrient input. CSR has a positive effect on yield and a negative effect on levels of nutrient input choice. Keeney and Hertel (2008) survey calculations of corn yield elasticities with respect to output price and find values ranging from 0.22 to 1.68; our parameter estimates indicate a value of approximately 1.17.

While not a direct comparison due to differences in model structure, our estimates of yield elasticity with respect to nutrient input (the a_1 and a_2 parameters) are somewhat similar to those of the mean effect identified by Love and Buccola (1991) in their primal system. The latter authors find a yield mean effect for nitrogen and phosphorus application of 0.02 and 0.07 compared to our results of approximately 0.09 and 0.05. We next proceed with simulation of policy scenarios through calculation of fitted values under baseline and policy-implementation conditions.

Water Quality Modeling

The Raccoon River watershed encompasses approximately 3,600 square miles of prime agricultural land, slightly more than 6% of Iowa's total surface area. The Raccoon River is the main river for the watershed and drains parts of seventeen counties. Most of the watershed contains very fertile soil. Approximately 75% of the watershed's surface area is used for corn and soybean production. Nitrogen and phosphorus fertilizers are applied at relatively high levels on the corn crop and constitute the primary non-point nutrient pollutant source in the watershed. There are several general water quality issues that make this watershed of primary importance in considering nonpoint pollution problems and possible policy solutions. This watershed provides an appealing testbed for simulating policy scenarios due to the multidimensionality of its nutrient-driven pollution. In addition, the SWAT model has previously been calibrated and validated for baseline conditions in this watershed (Jha, Gassman, and Arnold, 2007; Jha et al., 2010).

One important issue is nitrate levels at the Des Moines Water Works (DMWW), which provides drinking water for the Des Moines metro area, a population of nearly one-half million. It draws water from three sources: the Raccoon River, the Des Moines River, and a shallow aquifer associated with the riverbed. In 1990 the DMWW invested in a nitrate-removal system in response to nitrate levels that exceeded maximum safe drinking water standards. The nitrate removal facility is activated during periods of nitrate level increases. The costs of permanently removing nitrate from the water are much larger than the cost of disposal, so the removed nitrate is reintroduced to the river downstream from the DMWW. From there it continues on to the Mississippi river and eventually to the Gulf of Mexico. The facility cost $3.7 million to construct in 1990 and runs on average forty-five days per year. Additional effects of elevated nitrate levels can include negative effects on wildlife in the watershed (Camargo, Alonso, and Salamanca, 2005). Burkart and Jha (2007) provide a brief examination of tradeoffs between upstream nutrient reductions and the operation of the nitrate reduction facility.

Another impact of water quality degradation is related to recreational activities in the watershed. Phosphorus is the limiting factor in the excess growth of algae that is visually unappealing, results in offensive odors, creates hypoxic or anoxic conditions leading to fish kills, and which can contribute to dangerous levels of toxic cyanobacteria. Given these effects, phosphorus levels are a strong indicator of local freshwater quality. The Raccoon watershed contains seven lakes that offer recreational opportunities but that vary widely in water quality. For this reason, the impact of agricultural phosphorus use is an important factor in the quality of recreational opportunities available in the watershed.

SWAT is designed to simulate the effects of watershed management on water quality and water flow. It is primarily used for modeling non-point source contributions to nutrient and sediment loads within a watershed and is well suited to modeling the water quality effects of changes in agricultural nutrient application. The watershed under study is divided into many smaller parts, referred to as sub-watersheds or sub-basins. This is useful because different regions of the watershed often have unique combinations of many factors (e.g., land use, soil type) and must be considered separately while remaining related spatially. Each sub-basin has four general categories of characteristics: weather and climate; ponds, reservoirs, or other bodies of water within the watershed; groundwater and main channel routing; and land cover, soil, and land management. In our modeling framework, changes in land management will drive the differences in scenario results. The data used to populate sub-basins with the above data is derived primarily from the National Resources Inventory (NRI), which is linked to units in the economic model.

SWAT is a continuous-time model in that calculations are performed on a day-by-day basis. As it is not currently feasible to model scenarios that change by year, simulations use one target year's prices to determine nutrient application behavior. Since the 1997 NRI data is used for many of the model inputs, SWAT is run for several years before and after. SWAT provides three general categories of output: flow, sediment load, and nutrient load. Flow is of periphery interest here, as is

Table 3. Baseline Input Data

Mean N application (lbs./acre)	135.7
Mean P application (lbs./acre)	66.1
Mean yield (bu/acre)	150.85
Mean returns to nutrient application ($/acre)	296.19
Total N application (tons)	62,793
Total P application (tons)	30,566
Watershed returns ($)	301,847,307

Table 4. Tax Rates and Application Caps

Benchmark policy	Tax rate	N cap level (lbs./acre)	P cap level (lbs./acre)
10% N reduction	9.99%	132.43	
10% P reduction	10.45%		64.47
20% N reduction	22.34%	115.16	
20% P reduction	23.43%		56.06
10% N and P reductions	9.39%	132.28	64.59
20% N and P reductions	20.94%	115.02	56.16

sediment (except as it relates to phosphorus loads); nitrates and mineral phosphorus are of primary interest for this study.

Scenario Simulation and Results

This section catalogs the results of 10-year SWAT simulation runs (1994-2003) on the Raccoon watershed. These runs vary only by nutrient application rates: weather, land management, and other inputs are held at the baseline. Output values reported are for 1997, the year from which the NRI observations used to construct the land-use and other SWAT inputs are drawn. Driving the nutrient input levels are simulations of the economic model described above. Results from NRI-based economic simulations provide disaggregated farm-level information for each scenario and nutrient application rates that are used for SWAT runs. This farm-level information is aggregated through the NRI-point-specific expansion factor associated to arrive at watershed-level estimates of the economic impacts of each scenario.

A baseline scenario run is used as a reference to which each policy outcome can be compared. Ideally, the parameter(s) of each policy scenario (e.g., a tax rate) would be tailored to result in identical water-quality outcomes; policies could then be compared on the basis of implementation cost. Given the complexity of SWAT, this is an extremely difficult task that would require extensive trial-and-error testing. An alternative is to fix the watershed-scale cost (the change in aggregate net returns from nutrient application) and compare the relative water-quality changes associated with each scenario. We follow this alternative using one scenario as a benchmark: a fixed change in aggregate net returns to which other policies are set.

Six benchmark policies are considered at different combinations of nutrient reductions: 10% reduction in nitrogen application, 10% reduction in phosphorus, 10% reduction in both nitrogen and phosphorus, 20% reduction in nitrogen, 20% reduction in phosphorus, and 20% reduction in both nitrogen and phosphorus. These policies will serve as the benchmarks for the other two policy scenarios described below: a cap on per-acre application rates and a tax on the nutrient(s). A brief description of all scenarios follows.

- *10% Uniform reduction* Application of the nutrient(s) at each point is reduced by 10%. This scenario is used as a benchmark–the aggregate watershed net returns associated with it are used to determine the parameter(s) of the other scenarios. An implementation of this scenario and the one following might be considered the result of education or moral suasion as suggested by Shortle and Horan (2001).

- *20% Uniform reduction* Application of the nutrient(s) at each point is reduced by 20%. This scenario is used as a benchmark for a second set of larger reductions.
- *Application cap* A maximum per-acre allowed application of the nutrient is imposed. Farms applying at or below the cap are not affected relative to the baseline, but those who were applying above the cap in the absence of nutrient-control policy are constrained and suffer a loss in net returns. The cap is chosen such that resulting aggregate net returns equal those under the uniform reduction scenario. This policy would likely have some implementation issues, as there might be strong incentives to violate the policy and monitoring would be costly.
- *Nutrient tax* A per-pound tax is imposed on the nutrient(s). Tax revenues are included in the total for the change in watershed returns in order to make net returns comparable across policy scenarios. A tax rate resulting in this total being equal to the net returns associated with the uniform reduction scenario is used. This would be relatively straightforward to implement, given that Iowa already has a small tax on nitrogen fertilizer and thus a collection/enforcement infrastructure is in place.

Table 3 reports aggregate information related to the NRI corn points used to construct the baseline SWAT run. The aggregate measures (watershed returns and total nutrient application) are arrived at by multiplying the variables of interest at each NRI point by the point's expansion factor. Across the NRI-derived sample the average nutrient application rates are approximately 135 pounds per acre for nitrogen and 65 pounds per acre for phosphorus, roughly a two to one ratio of N to P. Average yield in the sample used for simulations is approximately 150 bushels per acre. These values are similar to those in the sample used for econometric estimation. Differences arise because the distribution of land types across the NRI are slightly different from those in the sample used for model estimation. The baseline SWAT run for this model is based on the calibration and validation of Jha, Gassman, and Arnold (2007), implementing the nutrient application information described above. Values are annual totals for one year in the middle of a ten-year run, at the watershed outlet. SWAT output from sub-watersheds is also of interest, particularly in terms of phosphorus output changes in areas with nutrient-impaired lakes. Figure 1 shows seven lakes that are listed as nutrient-impaired by the Iowa Department of Natural Resources. An accompanying comparison of phosphorus reductions at these sites appears in figures 2 and 3. Table 4 summarizes the tax rates and application caps associated with the menu of policies. At smaller reduction levels the required tax rates are of similar magnitude to the reductions themselves, but as the reductions tighten the required tax increases slightly. For example, a 10% P reduction requires a P tax of 10.45% while a 20% P reduction requires a tax in excess of 23%. The 10% application cap scenarios in general are not far below average baseline applications; the 132.4 pounds per acre cap on N is only slightly below the mean pre-policy application rate of 135.7 pounds per acre. Similarly the 10% P reduction scenario involves a cap of 64.5 pounds per acre imposed over a pre-policy rate of 66.1 pounds per acre. The distribution of policy impact therefore falls primarily on operations that would apply well above the cap in the absence of a control policy. At higher reduction levels the cap falls much further below pre-policy averages.

Discussion

Several characteristics emerge from the simulation results, which are summarized in table 5. We concentrate our discussion on two types of outcome: nitrate reductions at the watershed outlet

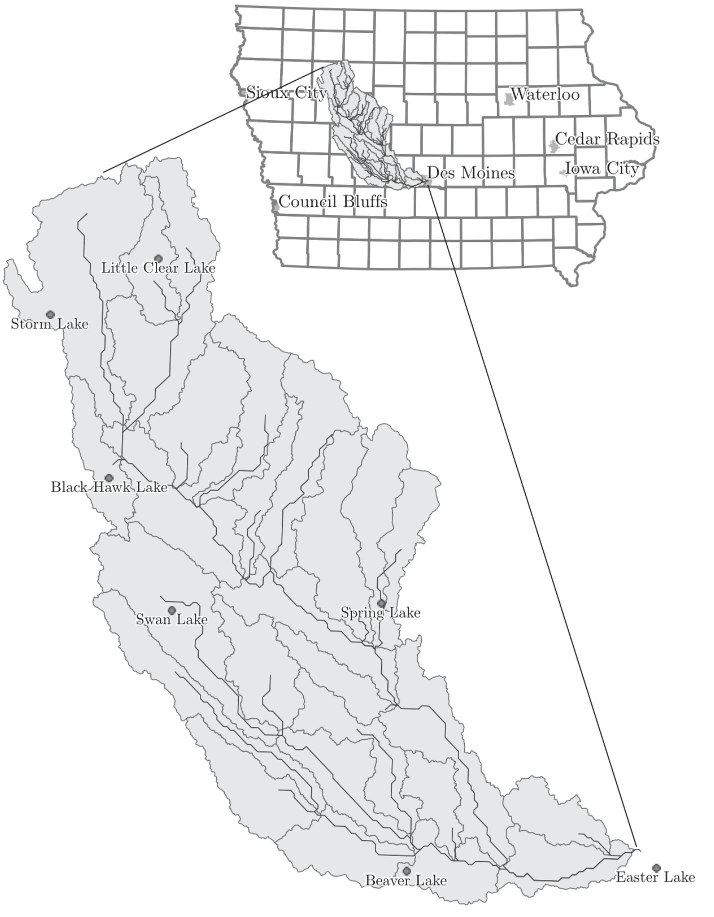

Figure 1. Impaired Lakes

and phosphorus reductions at the sub-watershed level. Both have implications for policy choice. As the economic effects within each set of policies are fixed, the differences across policies are driven by the spatial distribution, physical properties, and application rates at each site. In other words, it is the modeling of the physical environment that allows for differentiation between the effects of the policies. It may be useful to think of nitrate as driving "global" problems from a watershed standpoint. Drinking water and downstream issues such as hypoxia are driven by nitrate concentrations, so we concentrate on effects at the watershed outlet when discussing nitrates. Phosphorus, on the other hand, is believed to be the limiting factor in lake impairment, driving the presence of both cyanobacteria and eutrophication (see Carpenter (2008) and Schindler et al. (2008) for discussions of the relative effects of the two primary nutrients on lake water quality). Thus, for phosphorus scenarios we concentrate on effects in the sub-watersheds containing the impaired lakes identified in figure 1.

At the watershed outlet the differences across nitrogen-reduction policies are greater at low levels of reduction. This suggests that the choice of policy is less important if larger water quality improvements are desired. However, there is still some variability in simulation effects. Interestingly, the most efficient policy at the 10% reduction level–an application cap yielding 7.1% reduction in nitrate loading at the watershed outlet–becomes the least efficient policy at the 20% reduction level, where the tax is most efficient at reducing nitrate loading. At first glance one explanation seems straightforward: the less stringent cap catches the "low-hanging fruit" of inexpensive application reductions. As the reduction tightens, the inexpensive reductions (e.g., high nutrient application on

Table 5. Summary of Model Simulations

Scenario	Change in NO_3 at watershed outlet	Change in mineral P at watershed outlet	Loss in net returns	Cost/ton of N input reduction	Cost/ton of P input reduction
10% N reduction	−5.90%	0.10%	$161,280	$25.68	
N tax for 10% N reduction	−6.70%	−0.40%	$161,280	$25.61	
N cap for 10% N reduction	−7.10%	−0.20%	$161,280	$31.58	
10% P reduction	−0.20%	−2.40%	$96,804		$31.67
P tax for 10% P reduction	−0.60%	−2.10%	$96,804		$31.58
P cap for 10% P reduction	−0.20%	−1.90%	$96,804		$38.95
20% N reduction	−13.00%	−0.40%	$693,681	$55.24	
N tax for 20% N reduction	−13.20%	−0.10%	$693,681	$55.07	
N cap for 20% N reduction	−12.30%	−0.30%	$693,681	$63.80	
20% P reduction	0.30%	−4.40%	$417,035		$68.22
P tax for 20% P reduction	−1.00%	−4.50%	$417,035		$68.02
P cap for 20% P reduction	−0.50%	−3.90%	$417,035		$78.82
10% N and P reduction	−6.80%	−2.70%	$238,271	$37.95	$77.95
N and P cap for 10% reduction	−6.30%	−2.50%	$238,271	$37.95	$77.95
N and P tax for 10% reduction	−6.20%	−2.40%	$238,271	$46.20	$97.42
20% N and P reduction	−12.90%	−5.00%	$1,022,616	$81.43	$167.28
N and P cap for 20% reduction	−12.80%	−5.20%	$1,022,616	$81.43	$167.28
N and P tax for 20% reduction	−12.50%	−4.40%	$1,022,616	$93.60	$194.66

marginal land) are exhausted and the tax becomes more efficient. However, this explanation seems to run counter to the economic effects: the cap is the most costly of the three 10%-N policies on a cost per ton reduction basis at $31.58/ton of N input reduction versus approximately $26/ton for the other two scenarios. There is another effect at work, and that is the occurrence of high application levels on land that is particularly susceptible to runoff. The imposition of a cap reduces these and the spatial distribution of the contributors is such that water-borne nutrient levels are reduced by a larger amount than under other policies. Another way of stating this is that, for low tax rates, the places with the least expensive reductions happen to be on the least damaging land. This effect lessens as the cap tightens, thus the inversion of policy efficiency at the 20%-N reduction level where the cap becomes the least efficient, yielding a 12.3% reduction while the tax gives a 13.2% reduction. The nonlinearity of nutrient input effects inherent in the economic model translate through to the overall simulation results. Moving from a 10% benchmark reduction in N application to a 20% reduction gives an approximate twofold improvement in water quality on a percentage basis. For example, the N tax policies yield a 6.7% load reduction with the low tax rate and a 13.0% watershed outlet nitrate load reduction with the high tax rate. However, the loss in returns increases more than four times, from $161,280 to $693,681 and the cost per ton of reduction roughly doubles under all of the policies.

The policy effects on phosphorus loading at the watershed outlet vary, but as mentioned above it is lake water quality issues that are most relevant when discussing phosphorus control policy. Although SWAT does not simulate direct effects on individual lakes, the sub-watershed results provide a proxy for these effects. As can be seen from figures 2 and 3, the simulations show differences across both policies and locations.

This has important implications for policy design, particularly in areas like the test watershed where there are numerous impaired fresh-water bodies. For example, at Black Hawk Lake a tax yields the largest reductions under the 10%-P simulations, but for 20%-P simulations uniform reductions are more efficient for the same sub-watershed. Exactly the opposite is true at Spring Lake, where the tax is most efficient under large reductions but the uniform reduction policy is most

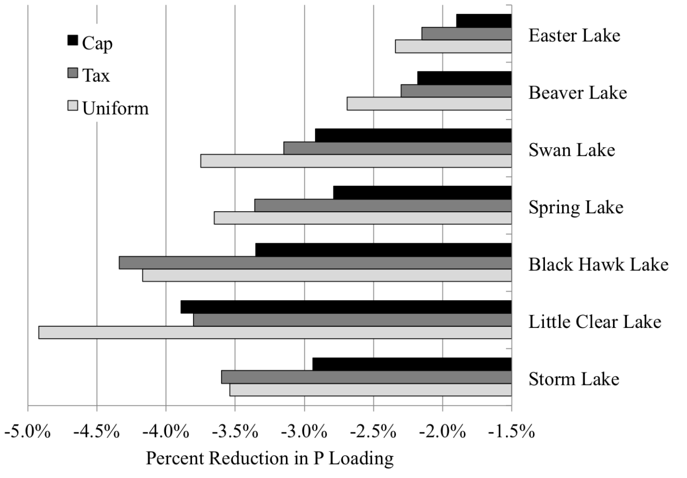

Figure 2. Phosphorus Reductions for 10%-P Benchmark

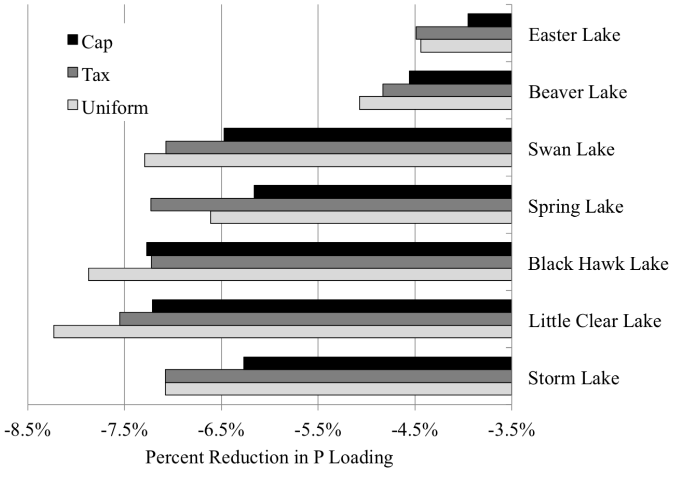

Figure 3. Phosphorus Reductions for 20%-P Benchmark

efficient if P reductions are smaller. For some lakes there is little to no difference among policies at the two levels of restriction. At Storm Lake, for example, the pattern of relative policy efficiency does not vary much across reduction levels.

Results at the sub-watershed level suggest that policies aimed at reducing nutrient-driven problems in lakes will require prioritization by location; the optimal choice for improving water quality in one lake may not be best for another. This may also suggest the need for more complex alternatives such as location-targeted reductions in phosphorus application.

Conclusion

As major nonpoint contributors to impaired waters, agricultural applications of nitrogen and phosphorus have important impacts on water quality. Policies designed to ameliorate nutrient-related water impairment are needed, but is difficult to move forward without information about the multidimensional effects associated with specific nutrient management policies. This article has presented a useful approximation of the effects of several possible policy avenues in the context of an actual watershed. The analysis employs both a hydrological model of nutrient transport in water and an economic model of policy impacts on returns to nutrient application in agricultural production.

Results of the analysis indicate that policies intended to reduce row crop production's contribution to nitrate at the watershed outlet vary in their impact depending on the degree of reduction. If large reductions are desirable, policy effects may not depend greatly on the choice of policy instrument, which might then be chosen based on other criteria such as ease of implementation. In the case of phosphorus loads–usually a limiting factor in localized water quality problems in lakes–sub-watershed results are of more importance. Results at that level indicate variation across policies, lakes, and reduction levels, suggesting that policy choice will necessarily involve prioritization based on analysis of the relevant tradeoffs. It is important to note that many of these conclusions are likely unique to this watershed.

Integrated economic and physical models of watershed outcomes are a useful tool; given sufficient data resources, the modeling framework is easily applied to other areas experiencing similar problems. The overall results highlight the importance of jointly modeling physical processes and economic choice to properly gauge policy effects. At the same time, the costs of various policies, particularly more aggressive policies, may be overstated because farmers are not modeled as being able to react by changing crop choice, timing of nutrient applications, or other management aspects. Future work could employ a more sophisticated economic modeling framework utilizing additional variables to more realistically simulate response to policy scenarios; this remains largely an issue of data collection and availability.

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