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Least-cost control of agricultural nutrient contributions to the Gulf of Mexico hypoxic zone

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Abstract. In 2008, the hypoxic zone in the Gulf of Mexico, measuring 20 720 km^2, was one of the two largest reported since measurement of the zone began in 1985. The extent of the hypoxic zone is related to nitrogen and phosphorous loadings originating on agricultural fields in the upper Midwest. This study combines the tools of evolutionary computation with a water quality model and cost data to develop a trade-off frontier for the Upper Mississippi River Basin specifying the least cost of achieving nutrient reductions and the location of the agricultural conservation practices needed. The frontier allows policymakers and stakeholders to explicitly see the trade-offs between cost and nutrient reductions. For example, the cost of reducing annual nitrate-N loadings by 30% is estimated to be US$1.4 billion/year, with a concomitant 36% reduction in P and the cost of reducing annual P loadings by 30% is estimated to be US$370 million/year, with a concomitant 9% reduction in nitrate-N.

Key words: agricultural conservation practices; evolutionary algorithm; Gulf of Mexico; hypoxia; nonpoint source pollution; Upper Mississippi River Basin, USA; water quality.

INTRODUCTION

In 2008, the hypoxic zone in the Gulf of Mexico, measuring 20 720 km^2, was one of the two largest reported since measurement of the zone began in 1985, and the five largest zones have all occurred within the last decade (Louisiana Universities Marine Consortium, *available online*).[8] The average size of the zone since that time now stands at >13 500 km^2 (Turner et al. 2008). While the scientific understanding of this phenomenon is still progressing, there is consensus that the cause of the Gulf's hypoxic zone is related to nutrients coming from the watershed of the Mississippi River. Specifically, nitrogen and phosphorous originating on agricultural fields in the upper Midwest, from wastewater treatment plants, and from urban runoff have been identified as important contributors to this seasonal hypoxic zone in the Gulf of Mexico (Turner et al. 2007, U.S. EPA-SAB 2007). There also exists new evidence (Donner and Kucharik 2008) that the federally mandated biofuels goals may further worsen the problems of nutrient export from agriculture to the Gulf.

In 2000, an Action Plan established a goal of reducing the hypoxic zone to 5000 km^2 by 2015 (U.S. EPA Mississippi River/Gulf of Mexico Watershed Nutrient Task Force 2008). Progress toward this goal has been limited for several reasons including lack of clear authority to undertake implementation and lack of funding to support control activities. Nonetheless, a number of control methods have been identified, particularly for nutrients coming from agricultural fields. Finding cost-efficient solutions for reducing nonpoint source pollution, such as nutrient reductions from agricultural fields, has been viewed as one of the most challenging problems to solve.

Here we focus on the control of nitrogen and phosphorous from the expansive agricultural sector of the Upper Mississippi River Basin. Recent estimates suggest that 43% of the N and 27% of the P flux to the Gulf originate in this region (Aulenbach et al. 2007). The goal of this research is to identify least cost combinations and placement of conservation practices in the region to achieve N and P reductions to the Gulf. To do so, we develop a simulation optimization framework combining water quality modeling with economic data and evolutionary algorithms to derive a

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three-dimensional frontier along which the least cost of obtaining reductions in N and P is identified. The development of a full frontier allows policy makers and stakeholders to explicitly see the trade-offs between cost and nutrient reductions as well as the potential trade-offs between the two nutrients. The specific set of conservation practices and their optimal location are also products of this research.

This task is unusually challenging for a number of reasons. First, numerous conservation options are potentially appropriate for any given agricultural field and several options can be used jointly. The options we assess include reduced fertilization of row crops, three reduced tillage options, contour farming, installation of grassed waterways, and retirement of land from row crop production with the addition of perennial cover. The cost and efficiency of these practices for reducing nutrient losses from fields depends on the specific land characteristics, weather, and crop rotation of the field on which they are adopted. The combinatorial nature of the problem creates an extremely large number of possible allocations of conservation practices to fields.

Beyond the sheer numbers is a second complicating factor that makes solving an optimal placement problem even more difficult: reduced nutrient export at the edge of agricultural fields is not the endpoint of interest. Rather, reduced nutrient loading into the Gulf is the goal. The relationship between the amount of nutrient reduction in the Gulf from a particular practice implemented in the watershed will depend on the location of the field within the watershed as well as the hydrology and land use at other locations in the watershed (including agricultural conservation practices).

A third complication is that conservation practices that are generally cost-effective for one nutrient, say, nitrogen, may have little or no beneficial effect on the other nutrient (even deleterious effects are possible). This implies that the optimal choice of conservation practices will depend on the degree to which control of each separate nutrient is desired.

Therefore, the cost-effective placement of conservation practices cannot be studied field by field or in isolation of the decisions made on all other fields in a watershed. This has at least two practical implications for modeling: (1) a watershed-based water quality model capable of modeling the relationship between detailed agricultural land use decisions such as cropping patterns, weather, tillage methods, nutrient inputs, and conservation practices and the water quality at the outlet of the watershed is needed and (2) simple optimization rules cannot be used to identify solutions to a least cost problem.

Historically, simplified representations of the biophysical process of water pollution were used so that optimization could be performed with conventional approaches. For example, early studies used a simplified model with fixed, exogenous pollution delivery coefficients (e.g., Montgomery 1972, Ribaudo 1986, 1989). Given such assumptions, it is straightforward to solve for cost-efficient allocations of pollution abatement using calculus-based constrained optimization techniques.

Incorporating, even partially, a more realistic hydrologic model into a spatial optimization framework typically greatly increases the complexity of the optimization. For example, Braden et al. (1989) separated a watershed into hydrologically independent flow paths and used a hydrologic model to estimate the impact of various management alternatives for the flow paths on the resulting sediment yield. As a result, a problem of finding cost-efficient sediment reduction solutions becomes a variant of the knapsack model in operations research. A study by Khanna et al. (2003) provides another good example of the ingenuity demonstrated by researchers to cope with the problem's complexity. The authors capture the interdependencies between upslope and downslope parcels by using coefficients derived from a hydrologic model. They restrict their attention to three parcels adjacent to a stream and to two alternatives on each parcel, crop production and land retirement, thereby keeping the combinatorial problem tractable.

A drawback to these approaches is that hydrologic models developed for the entire watershed are broken up, with only a few elements used; hence, one does not get the full benefit of a hydrologic simulation model. By contrast, many studies that incorporate the complete hydrologic simulation models do not attempt optimization of land use choices. Instead, alternative land use change scenarios that achieve the pollution reduction goals are evaluated (e.g., Secchi et al. 2007).

Here we develop an integrated simulation optimization framework that fully utilizes the biophysical simulation model and uses an optimization method (evolutionary algorithms) that is appropriate for dealing with this complex problem, yet itself is fairly straightforward to implement.

Methods

In this study, we combine the tools of evolutionary algorithms with the Soil and Water Assessment Tool (SWAT; Arnold and Fohrer 2005) and cost data to develop the frontier of least cost combinations and location of conservation practices to achieve various N and P reductions. Our application focuses on the Upper Mississippi River Basin in the central United States, a major contributor of nutrients to the Gulf of Mexico. Evolutionary algorithms (EAs) work with populations of candidate solutions iteratively applying stochastic operators of selection, recombination, and mutation in the hope of finding improvements with respect to the optimization objectives (loosely borrowing such operators and terminology from the theory of biological evolution). In general, EAs belong to a class of stochastic optimization methods and are well suited

FIG. 1. The Upper Mississippi River Basin (UMRB) and the watershed outlet at Grafton, Illinois, USA, with USGS eight-digit hydrologic unit code (HUC) watersheds outlined in gray and rivers in the UMRB outlined in white.

for approximating solutions to complex combinatorial problems (see e.g., Forrest 1993, Deb 2001). While tools that can be classified as EAs have been applied to integrated watershed modeling systems (Srivastava et al. 2002, Veith et al. 2003, Bekele and Nicklow 2005, Arabi et al. 2006), these studies have been done at a much smaller scale (e.g., smaller than 133 km^2 as in Bekele and Nicklow [2005] vs. 492 000 km^2 in the region studied here). (At the other end of the spatial spectrum, Whittaker et al. [2009] used field-level experimental data to consider optimal trade-offs between profit and nitrogen runoff in evaluating the effects of nitrogen fertilizer tax.) In addition, none of these studies examined the trade-offs between two different nutrients (N and P) and the consequences of meeting downstream targets (flow of nutrients into the Gulf) for upstream water quality (nutrient levels in the upstream watersheds).

Modeling efforts related to Gulf hypoxia include the work of Doering et al. (2001), who present an economic analysis of the sector-wide costs and benefits of policy alternatives. Their analysis considered aggregate agricultural regions, did not consider the fate and transport of nutrients, and did not include many of the conservation options studied here. The USGS SPARROW model (Alexander et al. 2000, 2008) has been extremely useful in identifying the sources of nutrients in the region, but that model does not currently have the capability of modeling the water quality changes occurring from implementation of agricultural conservation practices.

Here we briefly describe the Soil and Water Assessment Tool and its application to the Upper Mississippi River Basin (UMRB), the cost data, and the evolutionary algorithm used to construct the frontier and we illustrate its usefulness by discussing three policy-relevant questions: (1) What are the costs of achieving nutrient reductions to the Gulf? (2) What combination and location of practices can achieve a 30% reduction in both nitrate-nitrogen and phosphorous at the outlet of the UMRB? (3) What are the consequences for water quality (N and P) in each of the 131 subwatersheds (USGS eight-digit hydrologic unit codes [HUCs]) as a result of the 30% nutrient loading reduction at the outlet?

Study area

The Upper Mississippi River Basin extends from the source of the Mississippi River at Lake Itasca in Minnesota to a point just north of Cairo, Illinois. The total drainage area is nearly 492 000 km^2, which lies primarily in parts of Minnesota, Wisconsin, Iowa, Illinois, and Missouri. Fig. 1 contains a map of the Upper Mississippi River Basin and its position in the central United States. Cropland and pasture are the dominant land uses in the UMRB, which together are estimated to account for nearly 67% of the total area (NAS 2000). Nutrient inputs (nitrogen and phosphorus) are the primary agricultural sources of nonpoint source pollution in the UMRB stream system.

While the task force charged with assessing the causes of Gulf hypoxia in 2000 identified nitrogen (and, in particular, nitrate) contributions as the primary nutrient loading causing the problem, more recent assessments indicate that both nitrate and phosphorous loads from the UMRB region (and elsewhere) are responsible (U.S. EPA-SAB 2007). These assessments also affirm the role that the UMRB plays in contributing nutrients (Aulenbach et al. 2007, U.S. EPA-SAB 2007).

Nitrogen and phosphorous are also culprits of substantial local water quality problems within many areas of the UMRB. While phosphorous is more often a target in total maximum daily load programs in the UMRB, there are also many water bodies listed as impaired due to high nitrogen concentrations. In short, water quality problems in the UMRB are substantial and multifaceted. Nutrients from the region negatively affect water quality in lakes and streams locally throughout the basin, negatively affecting recreation opportunities, wildlife viewing, and ecosystem functioning. Additionally, these nutrients travel out of the watershed and flow to the Gulf of Mexico, where they contribute to the hypoxic zone.

TABLE 1. Cost estimates for conservation practices and land retirement for states in the Upper Mississippi River Basin, USA.

State	Annualized cost of GW (US$/protected ha)	Mean cash rental rate (US$/ha)	Cost of no-till (US$/ha)	Annualized cost of terraces (US$/protected ha)
Illinois	18.3	330.9	54.9	54.4
Iowa	13.1	370.4	23.7	127.5
Minnesota	13.1	212.0	26.7	99.3
Missouri	9.6	196.7	31.9	33.9
Wisconsin	32.4	198.9	128.2	59.3

Note: "GW" stands for grassed waterways.

Water quality modeling

The SWAT model (Arnold and Fohrer 2005) is a conceptual, physically based, long-term, continuous watershed-scale simulation model that operates on a daily time step. In SWAT, a watershed is divided into multiple subwatersheds, which are further subdivided into hydrologic response units (HRUs) that consist of homogeneous land use, management, and soil characteristics. Streamflow generation, sediment yield, and non-point source loadings from each HRU are summed, and the resulting loads are routed through channels, ponds, and/or reservoirs to the watershed outlet. Key components of SWAT include hydrology, plant growth, erosion, nutrient transport and transformation, pesticide transport, and management practices. Outputs provided by SWAT include streamflow and in-stream loading or concentration estimates of sediment, organic nitrogen, nitrate, organic phosphorous, soluble phosphorus, and pesticides. Previous applications of SWAT for streamflow and/or pollutant loadings have compared favorably with measured data for a variety of watershed scales (Gassman et al. 2007).

The UMRB SWAT simulation framework builds on the work of Arnold et al. (2000) and relies on numerous data sources to develop and execute the model. The source of cropping systems, non-agricultural land use, and conservation practice coverage is the 1997 Natural Resources Inventory Survey (Nusser and Goebel 1997). Climate data were obtained from the Illinois State Water Survey. SWAT calibration and validation results for the entire UMRB or subregions, as well as SWAT sensitivity analyses, are reported in Jha et al. (2003, 2004, 2006, 2007) and Reungsang et al. (2007).

Simulation optimization framework

Three major components were integrated to arrive at the final modeling framework. The first component is the logic and the fitness assignment method of a multi-objective evolutionary optimization algorithm, SPEA2 (Zitzler et al. 2002). The second component is a publicly available C++ library of genetic algorithms, GALib, version 2.4.6 (Wall 2006). The third component is the water quality model, the SWAT2005, coupled with a Windows-based database control system, i_SWAT (CARD 2009). SPEA2 provides the fundamental multi-objective optimization logic, while GALib provides the basis that is needed to implement an evolutionary search algorithm. Finally, SWAT and i_SWAT provide a means for modeling the different conservation practices and their watershed-level environmental impacts.

Conservation options

Several in-field conservation activities can reduce nitrogen and/or phosphorus loadings from agricultural fields. In this study, we include conservation tillage (mulch, ridge, and no till), contour farming, grassed waterways, terraces, and complete retirement of land from crop production in favor of perennial cover. In addition, nitrogen loadings can be controlled by reducing its application. With the exception of land retirement, all other practices are modeled in conjunction with the cropping system currently in place. Conservation practices and cropping systems observed in the baseline are preserved: we allow the algorithm to add, but not subtract, conservation practice options. In total there are 32 sensible combinations of these conservation practices. These 32 combined with no conservation activity at all results in 33 possible land use options for each HRU (Appendix: Table A2).

Land retirement is modeled by assigning a permanent grass cover to the HRU, fertilizer reductions are modeled by reducing nitrogen fertilizer applications by 20% for all crop rotations where nitrogen fertilizer is used, and the in-field practices (tillage, grassed waterways, contour farming, and terraces) are modeled by adjusting the SWAT model parameters (Secchi et al. 2007, Arabi et al. 2008).

Detailed information on the costs of all the options was obtained from multiple sources. State-level costs of terraces, no-till, and contouring were gathered from the USDA Natural Resource Conservation Service website (Kling et al. 2007, Rabotyagov 2007; USDA NRCS *available online*).[9] The costs of grassed waterways were obtained from the Conservation Reserve Program office and converted to a per hectare protected, annualized basis using a 5% discount rate and a 20-year useful life term (Table 1).

The costs of land retirement are proxied by the cash rental rates (Table 1), and the costs of nitrogen fertilizer reductions were developed using the yield curves inferred from Iowa State University Extension's N-

[9] ⟨http://www.economics.nrcs.usda.gov/cost/nrcscost.html⟩

TABLE 2. Estimates of cost of 20% nitrogen fertilizer application reduction.

Yield zone	State	N application (kg/ha)	20% reduced	C–C yield drag (m^3)	C-C cost (US$/yr)	C–SB yield drag (m^3)	C–SB cost (US$/yr)
1	Illinois (north)	176.5	141.2	0.24	15.2	3.2	0.11
2	Illinois (central)	176.5	141.2	0.20	12.8	5.4	0.19
2	Missouri (north)	172.3	137.8	0.25	15.6	3.4	0.12
3	Illinois (south)	176.5	141.2	0.23	14.1	4.9	0.17
3	Missouri (central)	172.3	137.8	0.21	13.4	5.6	0.20
4	Iowa	140.7	112.6	0.29	17.9	3.1	0.11
5	Minnesota	128.2	102.5	0.11	6.7	2.5	0.09
6	Wisconsin	98.6	78.9	0.22	13.8	4.4	0.16

Notes: The assumed corn (C) price is US$0.078/$m^3$ (US$2.2/bushel; a historical price was selected to match the crop rotation data period). Yield reduction is computed based on implied yield response curves found at ⟨http://extension.agron.iastate.edu/soilfertility/nrate.aspx⟩. The cost for the corn–soybean (C–SB) rotation is divided by 2 to get the annual cost.

Rate Calculator information for geographic zones and corn–soybean crop sequences for Iowa, Minnesota, Illinois, and Wisconsin. Reduced profits predicted by the yield reduction multiplied by the price of corn served as the cost estimate (Table 2).

Algorithm initialization

The algorithm was initialized with a population of 40 individuals (scenarios). In order to efficiently exploit prior domain-specific knowledge, and in contrast to the earlier studies (e.g., Bekele and Nicklow 2005, Arabi et al. 2006), the initial population was not created completely at random. First, the initial population was seeded with an individual representing the baseline allocation of conservation practices and an individual representing a scenario of all cropland in the UMRB being retired from production and placed under permanent grass cover. These individuals represent the boundary points on the trade-off frontier: the baseline individual results in the lowest cost and the highest nutrient loadings, while the "all cropland retired" individual results in the highest cost and lowest nutrient loadings. To further cover the search space, an additional 32 individuals, each of which represents a uniform application of each of the conservation practice combinations, were included in the initial population. The purpose (and the payoff) of such seeding is twofold: (1) a good coverage of the objective space is achieved and (2) the land use options that are immediately judged to be "good" help define the direction of the stochastic search and improve the algorithm's efficiency. The rest of the initial population was generated by randomly assigning one of the 33 options to each cropland HRU in the watershed (subject to the baseline constraint).

Formal statement of the multi-objective problem

The evolutionary algorithm is used to develop a conservation frontier that provides an approximate solution to the multi-objective optimization of minimizing (1) the cost of nonpoint source pollution control; (2) the mean annual nitrate-N loadings at the assumed UMRB watershed outlet (Grafton, Illinois), and (3) the mean annual total phosphorus loadings at the UMRB outlet. That is, the algorithm solves

$$\min[c(\mathbf{X}), y(\mathbf{X})^1, y(\mathbf{X})^2, \ldots, y(\mathbf{X})^N]$$

subject to $(\mathbf{X}, \mathbf{Y}) \in T$, where $\mathbf{X}$ is a collection of conservation actions planned for the watershed. The environmental impact of $\mathbf{X}$ is denoted as $\mathbf{Y}$, where $\mathbf{Y}$ is a vector with N elements, i.e., $\mathbf{Y} = (y^1, y^2, \ldots, y^N)$. Here, $N = 2$, and the relevant environmental indicators are the loadings of nitrate-nitrogen and phosphorus. T is the set of all $(\mathbf{X}, \mathbf{Y})$ combinations that are technically feasible given the existing state of conservation technology and subject to the physical constraints imposed by the environmental processes. The cost of a conservation plan is represented by a cost function, $c(\mathbf{X})$.

The set of solutions consists of all conservation plans that are Pareto-optimal. A conservation plan $\mathbf{X}$ is Pareto-optimal if there is no $(\mathbf{X}', \mathbf{Y}') \in T$ such that $y(\mathbf{X}')^n \leq y(\mathbf{X})^n$ and $c(\mathbf{X}') \leq c(\mathbf{X})$, for all $n \in \{1, 2, \ldots, N\}$, and such $m \in \{1, 2, \ldots, N\}$, such that $y(\mathbf{X}')^n < y(\mathbf{X})^n$ or $c(\mathbf{X}') < c(\mathbf{X})$. In other words, the solutions to the problem represent efficient nutrient control scenarios: i.e., once a solution is found, it is not possible to improve on any one objective without hurting another. All the efficient solutions found make up the three-dimensional (nitrates–phosphorus–cost) trade-off frontier given T and $c(\cdot)$.

RESULTS

A set of Pareto-nondominated configurations surviving after several hundred generations (iterations of the evolutionary algorithm) provides an approximation to the true frontier. Figs. 2 and 3 provide two-dimensional projections and a three-dimensional visualization of the empirical frontier.

Fig. 4 presents nitrate-N loadings in terms of the percentage of baseline loadings (>423 000 Mg of nitrate-N) on the horizontal axis and control costs in terms of the percentage of baseline cost of conservation practices (estimated to be just over $416 million per year) on the vertical axis and contains cost curves for nitrate-N reductions for two different scenarios. For the first scenario, the cost curve is developed in the absence of any constraint on phosphorus levels (as a lower envelope

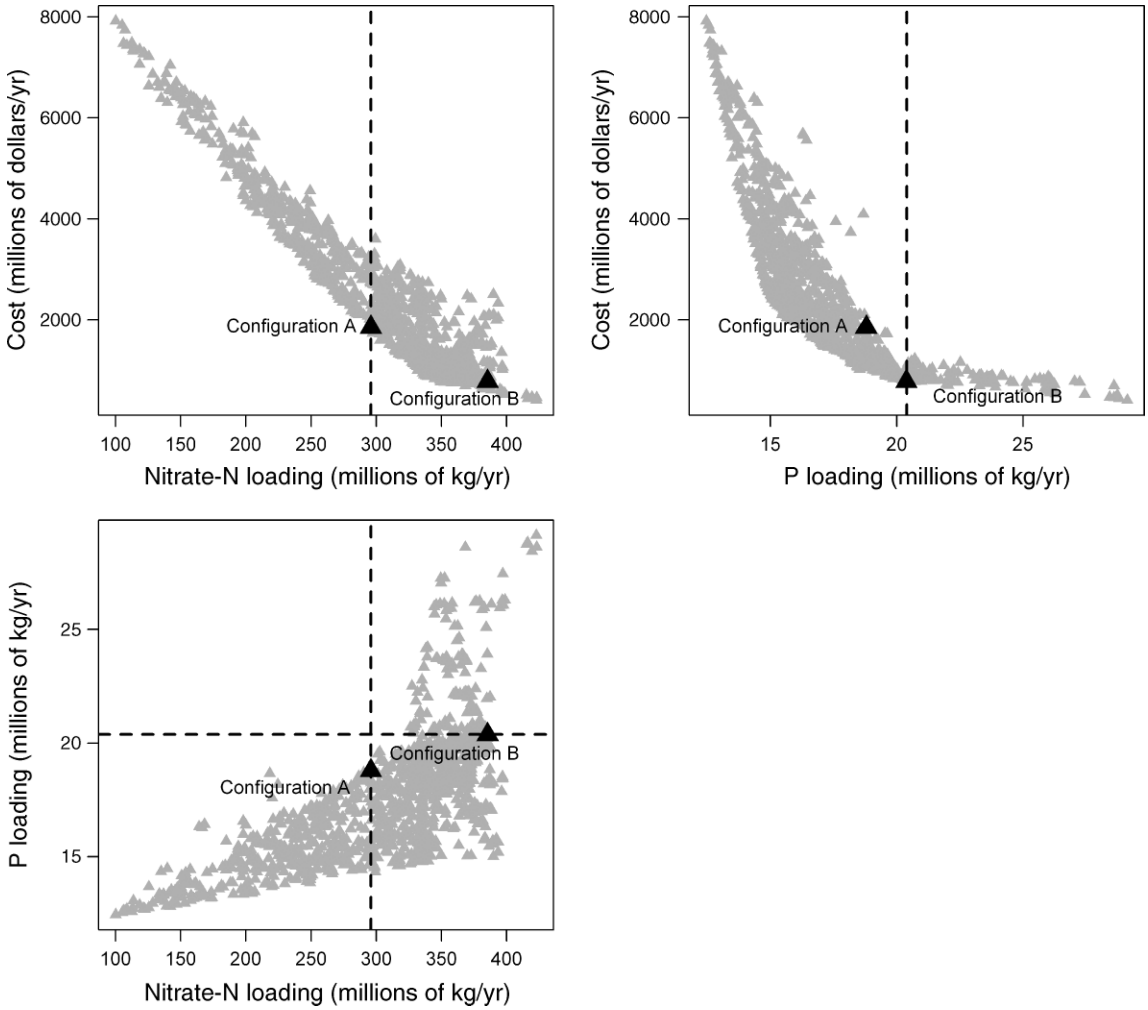

FIG. 2. Two-dimensional projections of the empirical trade-off frontier. Dashed lines represent 30% nutrient reduction targets. Configuration A (achieving a 30% NO_3, 36% P reduction) and configuration B (achieving 9% NO_3, 30% P reduction) are labeled.

of the trade-off frontier in nitrate-cost space). For an alternative scenario, a 30% concomitant reduction in phosphorus loadings is imposed as a constraint. As theory suggests, the constrained cost curve can be no lower than the unconstrained one, and that is indeed the case.

Fig. 4 provides interesting insight into the interactions between the conservation practices considered and the two nutrients. Note that while the unconstrained cost curve begins at the baseline level of nitrate loadings, imposing a phosphorus constraint forces the curve to start at a level of nitrate loadings that is ~9% lower than the baseline. In other words, given the set of practices considered, once phosphorus loadings are reduced by 30%, an automatic reduction of ~9% in nitrate loadings follows. Further evidence of such interactions is revealed by the fact that the phosphorus constraint is only binding up to approximately a 20% reduction in nitrate-N. Greater reductions in nitrates lead to simultaneous reductions in phosphorus, suggesting complementarities in the set of practices used to achieve greater nitrate reductions. Also, as illustrated in Fig. 4, the extra cost of achieving a 30% phosphorus target is relatively small. Over the range of nitrate reduction values at which the phosphorus constraint is binding (from 9% to 20% reduction in nitrate-N), average extra cost is just over \$168 million per year.

Interestingly, such complementarities are not evident in the case of modest phosphorus reduction targets. Fig. 5 depicts an unconstrained phosphorus cost curve and a constrained phosphorus cost curve, subject to the 30% constraint on nitrate-N loadings. Baseline phosphorus loadings in the UMRB were estimated to be over 29 000 Mg of total P per year. In this case, imposing a nitrate constraint automatically reduces phosphorus loadings by ~35%, and a nitrate-N constraint is binding up to a 40% reduction in phosphorus and is not binding thereafter. Furthermore, in contrast to the case above, the average extra cost of achieving a nitrate target over the range at which the nitrate constraint is feasible and

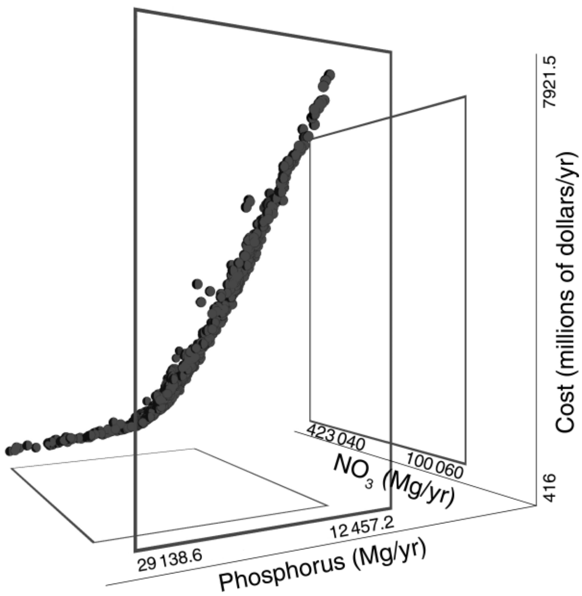

FIG. 3. Three-dimensional visualization of the empirical trade-off frontier. Boxes outline the ranges of nutrient loadings and cost.

binding is estimated to be over $805 million per year. These findings suggest an asymmetry between the impact of a set of practices used to achieve moderate nitrate reductions on phosphorus loadings and the impact of practices achieving moderate phosphorus reductions on nitrate loadings. In particular, for this watershed, a set of practices that achieves moderate nitrate reductions appears to be effective in controlling outlet phosphorus loadings, while the converse turns out to be false. Thus, if water quality policy in the UMRB targets outlet nitrate-N, then a sizeable (30%) reduction in outlet phosphorus loadings comes at no extra cost if the nitrate policy seeks reductions in excess of 20% and comes at a very moderate cost if the nitrate reduction targets fall between 9% and 20%. However, a policy seeking exclusively phosphorus loadings reductions at the outlet will not be effective in simultaneously controlling nitrates, unless an ambitious (in excess of 50%) phosphorus reduction target is specified.

Least cost practices to achieve 30% nitrate-N and P reductions

Each point on the frontier corresponds to a unique watershed configuration, i.e., a prescription for the application of conservation practices in the watershed. Thus, a policy maker could select nutrient reduction targets and then identify the particular configuration meeting these targets.

For illustrative purposes, suppose a policy maker wishes to reduce nitrate-N loadings by 30% at the lowest possible cost. Each configuration (which corresponds to a point on the frontier) is encoded with a unique identification number. The watershed configuration (referred to as configuration "A") that achieves this goal is located at the intersection of the lower envelope of the frontier in nitrate-cost space and the line specifying the loadings target in Fig. 2. This configuration lies on the unconstrained cost curve for nitrates identified in Fig. 4. As noted above, as a result of reducing nitrates by 30%, phosphorus loadings are in fact reduced by more than 30%.

Alternatively, if the policy maker were to identify the least cost watershed configuration to reduce phosphorous by 30%, configuration "B" would be chosen. (Configurations "A" and "B" have identification numbers 4715 and 3812, respectively.) This configuration

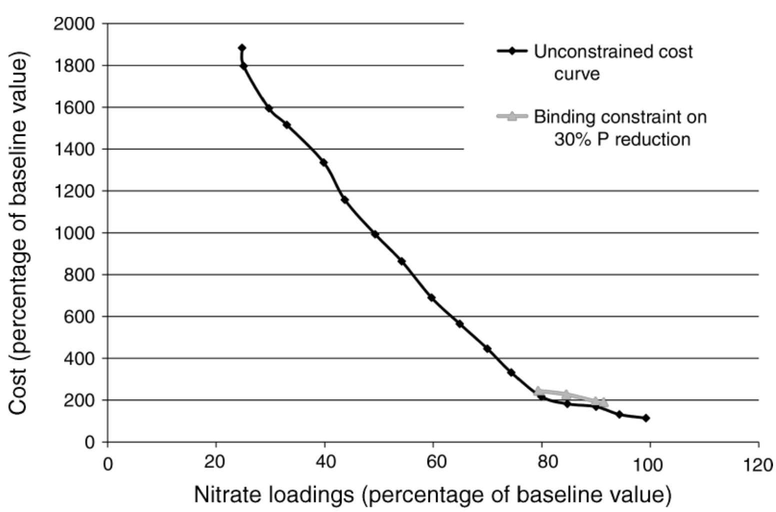

FIG. 4. Cost–pollution trade-off for NO_3 loadings as a percentage of the baseline values for cost and NO_3 loading at the Upper Mississippi River Basin (UMRB) outlet. The lower curve reflects the unconstrained nitrogen abatement cost curve. The abatement cost curve reflecting a constraint of simultaneously achieving a 30% P reduction lies no lower than the unconstrained abatement cost curve (strictly higher where the constraint is binding).

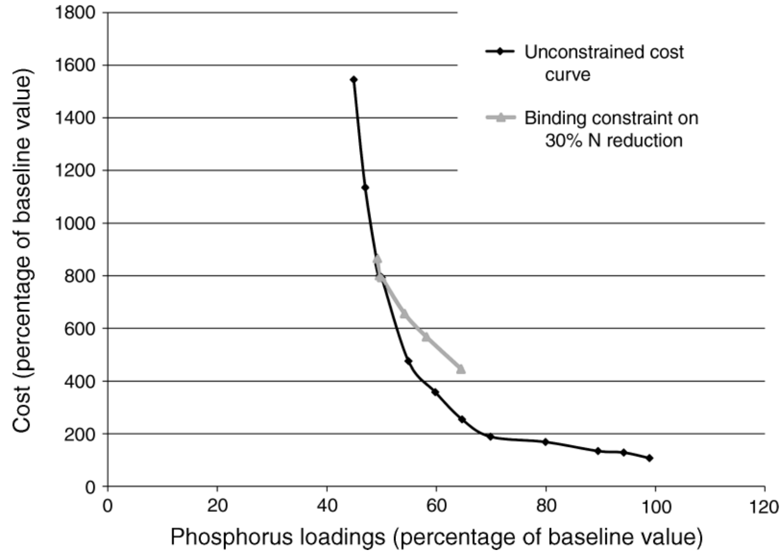

FIG. 5. Cost–pollution trade-off for phosphorus loadings as a percentage of the baseline values for cost and phosphorus loading at the Upper Mississippi River Basin (UMRB) outlet. The lower curve reflects the unconstrained phosphorus abatement cost curve. The abatement cost curve reflecting a constraint of simultaneously achieving a 30% NO_3 reduction lies no lower than the unconstrained abatement cost curve (strictly higher where the constraint is binding).

results in nitrate loadings that are far from meeting the 30% reduction goal. For the UMRB, striving for a 30% reduction in nitrates only also, as a by-product, (over)achieves a 30% phosphorus reduction goal, but seeking to reduce phosphorus alone produces only slight reductions in nitrate-N loadings. Table 3 presents the estimated cost and nutrient loading consequences for the two configurations.

Further examination of the conservation practices chosen in these two watershed configurations sheds light on this finding. With a control cost of more than $1.4 billion per year, configuration A achieves a 30% reduction in nitrates and almost a 36% reduction in phosphorus. This is almost four times as costly as configuration B, whose cost runs at approximately $370 million per year and achieves a 30% phosphorous reduction, but only about a 9% nitrogen reduction.

The detailed allocation of practices for these two watershed configurations is contained in Table 4. Configuration A allocates most of the cropland to an option combining grassed waterways with nitrogen fertilizer reductions, terraces combined with nitrogen fertilizer reductions, and land retirement. In contrast, application of grassed waterways is the main vehicle of achieving phosphorus reductions for configuration B.

Sensitivity of solutions to cost assumptions

We expect that the solutions obtained might be sensitive to the (relative) costs of conservation practices. In fact, economic theory suggests that the algorithm should be responsive to relative "prices" of conservation practices, much like a cost-minimizing firm is responsive to changes in relative prices of its inputs. (Strictly speaking, quasi-concavity of the production function is required, which in this context would imply the quasi-concavity of the SWAT-described relationships between conservation practices and water quality. Given that the latter has not been established, we cannot directly apply economic theory results in our context.) We assess the sensitivity of solutions by obtaining the trade-off frontier for eight cost scenarios, one of which is the baseline cost scenario presented above and the rest are based on the following factorial design with respect to the costs of practices identified as most likely to be chosen in the baseline solution.

We expect that the algorithm will tend to shift away from practices that become relatively more costly (e.g., grassed waterways in scenario 3 in Table 5) and toward practices that in turn appear relatively less costly (e.g., grassed waterways in scenario 6 or land retirement in scenario 7). Also, proportionately inflating all conservation practice costs should affect the minimum cost

TABLE 3. Consequences of targeting nutrients for a 30% reduction.

Configuration	NO_3 loadings (Mg/yr)	Total control cost (million US$/yr)	Net control cost (million US$/yr)	P loadings (Mg/yr)	NO_3 (% of baseline)	Cost (% of baseline)	P (% of baseline)
A	295 720	1854	1438	18 792	70	445.7	64.5
B	385 360	786	370	20 379	91.2	188.8	69.9

TABLE 4. Scenarios for conservation practice cost sensitivity analysis (scenario 1 is baseline).

Scenario	Fertilizer reduction costs†	Grassed waterways costs‡	Land retirement cost‡
1	baseline	baseline	baseline
2	baseline	baseline	high
3	baseline	high	baseline
4	baseline	high	high
5	high	baseline	baseline
6	high	baseline	high
7	high	high	baseline
8	high	high	high

† Assumed baseline price of corn is US\$0.078/m^3 (\$2.2/bushel) vs. the higher price of \$0.211/m^3 (\$6/bushel).
‡ Baseline costs vs. doubled baseline cost.

discovered but not the optimal practice selection. Overall, our intuition is confirmed: the algorithm tends to reallocate conservation effort toward relatively less costly practices, and a proportional inflation of costs does not affect the baseline cost solution. Fig. 6 provides an illustration for scenario 5 (for the solution found to reduce nitrate-N by 30%), in which fertilizer reductions are relatively more expensive than in the baseline cost scenario. As can be seen in the figure, the algorithm shifts away from conservation practice options containing fertilizer reductions (RF) and toward other options: from combination of grassed waterways and fertilizer reductions toward grassed waterways without fertilizer reductions and land retirement.

Consequences for upstream water quality

The analysis above was conducted under an objective of simultaneously reducing nitrate and phosphorus loadings at the outlet of the UMRB, corresponding to a water quality goal of reducing hypoxia in the Gulf of Mexico. Thus, in principle, the evolutionary algorithm only rewards those solutions that reduce nutrient loadings at the outlet subbasin and does not directly seek reductions occurring in other subbasins in the watershed. This may have important implications for local water quality (subbasin-level nutrient loadings). To illustrate, we again consider the watershed configurations just discussed.

Achieving a 30% nutrient reduction goal at the outlet of the UMRB has profound implications for local water

TABLE 5. Distribution of conservation practices for the selected watershed configurations.

		Configuration A			Configuration B		
Option number	Option description	Area (km^2)	Percentage of total area	Change from baseline (km^2)	Area (km^2)	Percentage of total area	Change from baseline (km^2)
1	CT	0	0	−78 071	0	0	−78 071
2	RT	0	0	−40 485	0	0	−40 485
3	MT	0	0	−78 144	0	0	−78 144
4	NT	0	0	−35 413	0	0	−35 413
5	CT + contour	0	0	−1074	0	0	−1074
6	RT + contour	0	0	−52	0	0	−52
7	MT + contour	0	0	−2189	0	0	−2189
8	NT + contour	0	0	−576	0	0	−576
9	CT + GW	0	0	−2299	76 154	31	73 855
10	RT + GW	0	0	−444	38 806	16	38 362
11	MT + GW	0	0	−4087	78 376	31	74 289
12	NT + GW	0	0	−3330	33 532	13	30 201
13	CT + terraced	0	0	−75	75	0	0
14	RT + terraced	0	0	0	0	0	0
15	MT + terraced	0	0	−2875	2875	1	0
16	NT + terraced	0	0	−210	210	0	0
17	CT + RF	262	0	262	5289	2	5289
18	RT + RF	172	0	172	2175	1	2175
19	MT + RF	1136	0	1136	6044	2	6044
20	NT + RF	205	0	205	5787	2	5787
21	CT + contour + RF	0	0	0	0	0	0
22	RT + contour + RF	0	0	0	0	0	0
23	MT + contour + RF	63	0	63	0	0	0
24	NT + contour + RF	0	0	0	0	0	0
25	CT + GW + RF	77 296	31	77 296	0	0	0
26	RT + GW + RF	36 219	15	36 219	0	0	0
27	MT + GW + RF	73 007	29	73 007	0	0	0
28	NT + GW + RF	31 029	12	31 029	0	0	0
29	CT + terraced + RF	825	0	825	0	0	0
30	RT + terraced + RF	1429	1	1429	0	0	0
31	MT + terraced + RF	3683	1	3683	0	0	0
32	NT + terraced + RF	1035	0	1035	0	0	0
33	Land retirement	22 962	9	22 962	0	0	0

Notes: Configuration A is 30% NO_3, 36% P reduction; configuration B is 9% NO_3, 30% P reduction. RF denotes a simulated 20% reduction in nitrogen fertilizer application. Abbreviations are: CT, conventional till; RT, ridge till; MT, mulch till; NT, no till; GW, grassed waterway.

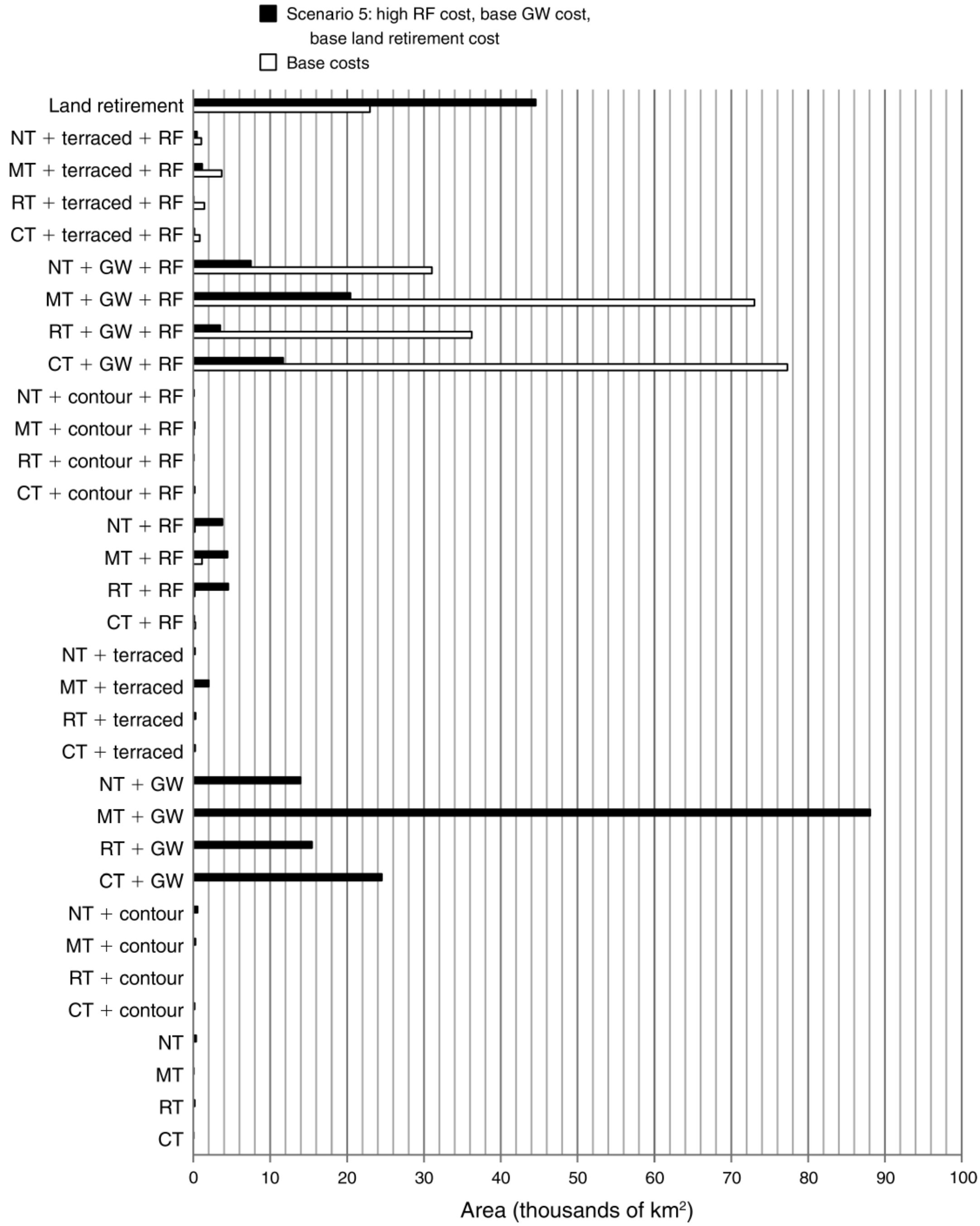

FIG. 6. Algorithm response to a relatively high cost of fertilizer reductions (RF; 20% N fertilizer reduction). Abbreviations are: CT, conventional till; RT, ridge till; MT, mulch till; NT, no till; GW, grassed waterway.

quality. For configuration A, there are only a few subbasins in which reductions are dramatic (over 90%), while many of the subbasins experience very modest nitrate loading reductions, if at all. In contrast, for configuration B, approximately 20 subbasins out of 131 experience small reductions in nitrate loadings, with the remaining subbasins seeing no reductions at all or even an increase in nitrate loadings. This is consistent with the nature of configuration B, which has been selected for its ability to reduce phosphorus alone, regardless of the consequence for nitrate loadings.

Figs. 7 and 8 contain a visual representation of this information for configurations A and B. Many subbasins experiencing notable nitrate loading reductions follow the flow path of the Mississippi River (especially evident in Minnesota) and the Illinois River. That is, the

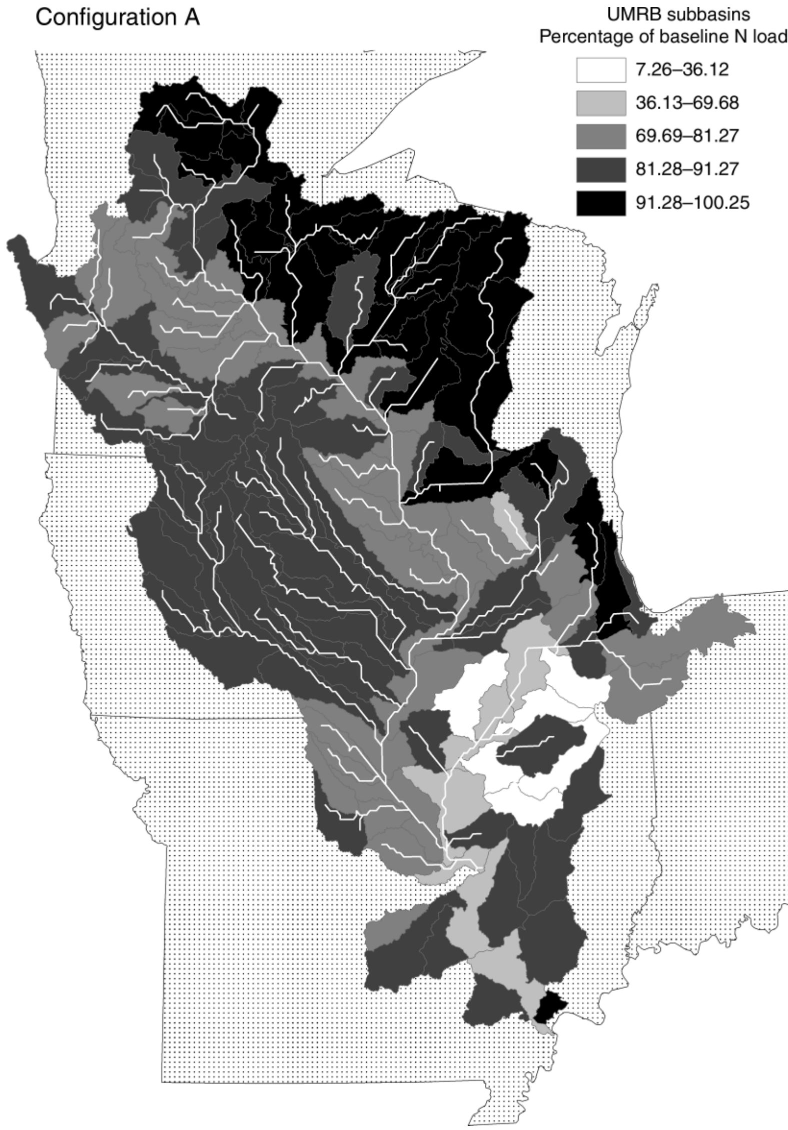

FIG. 7. Distribution of subbasin nitrate loadings in the Upper Mississippi River Basin (UMRB) as a percentage of the baseline value (configuration A, 30% NO_3, 36% P reduction).

evolutionary algorithm allocates conservation practices to induce nitrate loading reductions to the major waterways. This is what one would expect the algorithm to do, given its objectives. Widespread application of grassed waterways (for both configurations) and land retirement (in the case of A) serves to produce a surprisingly uniform spatial distribution of sizeable phosphorus loading reductions.

In particular, the mix of conservation practices describing configuration A produces a spatial pattern of reductions in which only 16 subbasins do not experience phosphorus loading reductions. For configuration B, loadings in 25 subbasins either do not decrease or increase (Appendix: Figs. A2 and A3).

Thus, for the UMRB, the mix of conservation practices that efficiently reduces outlet phosphorus and nitrate loadings also produces large local water quality gains in terms of phosphorus loading reductions. Local nitrate loading reductions, on the other hand, are concentrated in a few select subbasins of the watershed.

DISCUSSION

While computationally intensive, integration of a simulation (water quality modeling with economic data) and optimization (an evolutionary algorithm) is capable of producing very detailed information on least cost approaches for the implementation of conservation practices, even with a large number of locations and options. We have used these tools to estimate a frontier containing watershed configurations that provide the least cost of control for alternative levels of nutrients from agricultural sources for a region of the country that

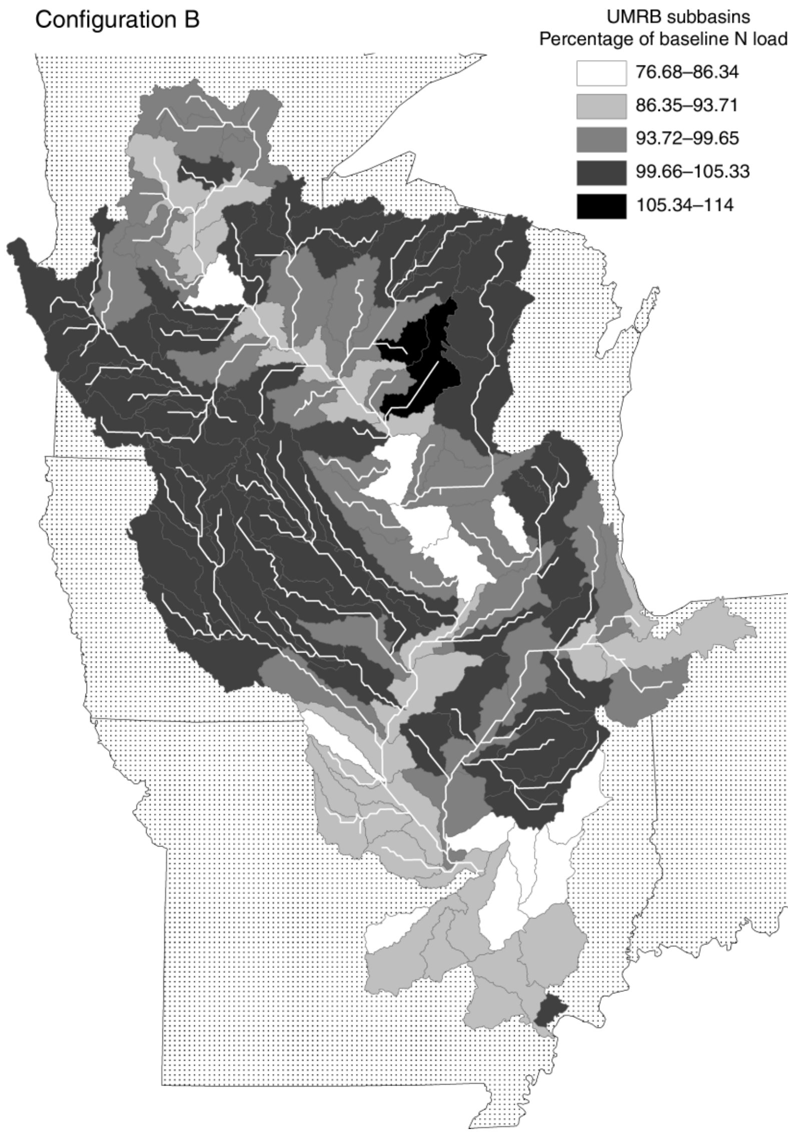

FIG. 8. Distribution of subbasin nitrate loadings in the Upper Mississippi River Basin (UMRB) as a percentage of the baseline value (configuration B, 9% NO_3, 30% P reduction).

has significant water quality impairments and has been identified as a major contributor to hypoxia in the Gulf of Mexico: the Upper Mississippi River Basin in the central United States.

A priori, one expects that whether nitrates and phosphorus at the outlet are targeted separately or jointly may have dramatic implications for which set of conservation practices should be used and where they should be located within the watershed. Further, this highlights the importance of careful planning of nutrient reduction goals. If a plan meant to control only nitrates (or phosphorus) is quite different from a plan controlling both pollutants, then implementing water quality policy in a piecemeal fashion (e.g., control nitrates first, then focus on phosphorus) may be socially costly and inefficient. Careful empirical analysis is needed to assess the validity of these concerns. For the case of UMRB, we find that if nitrate reduction of 20% or more is the goal, then at least 30% phosphorus reductions follow. Interestingly, we also find that if a phosphorus reduction strategy is implemented first, then, in order to achieve a nitrate target, no large-scale redistribution of conservation practices would be required. Additional conservation practices, implemented in conjunction with a phosphorus-reducing strategy, would be capable of achieving a nitrate reduction goal. This is an important finding, as nothing, in principle, guarantees that it should hold. The makeup of the two solutions could be quite distinct, which would then imply that choosing an initial nutrient reduction target is extremely important. However, for the UMRB, for the targets considered, it appears that if a policymaker gets the distribution of conservation practices right for one nutrient reduction goal, the other goal can subsequently be achieved with little to no spatial redistribution of conservation practices.

Several caveats should be mentioned. First, the enormity of the search space precludes one from claiming with certainty that the solutions obtained are the most efficient possible. Second, the results are indeed tied to the set of conservation practices and cost estimates. Although an effort was made to evaluate a wide variety of conservation practices discussed in the water quality literature, inclusion of other possibly relevant practices may alter the results. Both wetlands and conservation buffers are important omitted options that the SWAT model is not yet capable of reliably simulating. Nonetheless, many more options are considered here and at a much finer spatial scale than previous analyses. Improvements in the water quality models and better availability of detailed spatial land use and conservation practices data can drastically increase the level of detail and realism of the obtained solutions. Considerations of additional or alternative environmental objectives (e.g., nutrient concentrations or a specific quantile of the loadings distribution) may be in order to better address the nature of nutrient pollution. Increased computational capacity may allow for better characterizations of uncertainty imbedded in the input data and/or the water quality model parameters.

Economists have long been able to point out that trade-offs are ever-present in all of environmental policy and in particular in nonpoint source pollution control. The strength of the models and use of the evolutionary algorithm is that the empirical magnitude of these trade-offs can be assessed so that decision makers are better informed about the true costs and benefits of the policies they promote.

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APPENDIX

Algorithm description and additional results (*Ecological Archives* A020-058-A1).