Using a coupled simulation-optimization approach to design cost-effective reverse auctions for watershed nutrient reductions.

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Abstract: In many watersheds, water quality is degraded by nutrients and sediment from row crop agriculture. The continued development of watershed process models on one hand and optimization tools on the other hand places today's decision-makers in a position where the problems of cost-effective assignment of conservation activities can be solved for a variety of landscapes and environmental objectives.

At the same time, reverse auctions have received significant attention from researchers and policymakers, and involve private landowners submitting bids for activities thought to provide environmental benefits. The agency administering the auction then evaluates the bids in terms of cost and the likely environmental benefit and decides on which bids to accept, given its limited budget. We demonstrate how models and solution algorithms that can solve the problem of the cost-effective allocation of conservation actions in a watershed can be directly integrated within a reverse auction. Many reverse auctions include a bid selection mechanism which attempts to increase the cost-effectiveness of the program. The optimality and effectiveness of such ranking methods is an empirical question, especially in the settings where water quality improvements are concerned. We demonstrate here how the simulation-optimization tools can be used to inform the design of a reverse auction for the Raccoon River Watershed in west central Iowa, and we evaluate the magnitude of the potential gains from using the simulation-optimization approach relative to a simpler ranking method for selecting bids. We also consider that simple ranking schemes may not yield sufficient nutrient reductions to achieve water quality goals.

We consider bid ranking methods based on the Universal Soil Loss Equation (USLE) and the Modified USLE (MUSLE). The USLE full enrollment solution is dominated by sixteen Pareto-optimal solutions in N-P-Cost space, while the USLE partial enrollment solution is dominated by five Pareto-optimal solutions (e.g, there exists a Pareto-optimal solution, which, relative to USLE full enrollment case, offers additional 1.4% reductions in N and 0.4% reduction in P at a cost saving of $2.8 million/year). Relative to USLE-based partial enrollment, we can find a solution which offers additional 0.2% reductions in N and 0.9% reductions in P at an additional cost savings of $1.4 million/year. The MUSLE ranked solutions, in spite of being dominated in the N-Cost space, are not dominated in P-Cost space and remain a part of the final Pareto frontier set.

Ranking-based approaches are relatively ineffective in reducing either of the nutrients, compared to the feasible nutrient reductions predicted by the simulation-optimization system. In other words, if a reverse auction program in the watershed had a mandate to achieve greater than 10% reductions in N and greater than 32% reductions in P, it would not be able to do so using a based bid ranking and acceptance method even if it enrolled every cropland unit in the watershed. A simulation-optimization approach provides the agency with the way to reach a wide range of pollution reduction goals optimally.

1. Introduction

In many agricultural watersheds in the Upper Mississippi River Basin (UMRB), USA, water quality is degraded by nutrients and sediment from row crop agriculture. Despite the presence of market failures in this situation, there seems to be little support for regulatory reform that would directly regulate agriculture entities. One approach to addressing the suboptimal environmental performance in this situation is for public agencies and/or NGOs to provide incentives for landowners to undertake activities consistent with water quality improvements.

To cost-effectively provide a given level of environmental performance, it is necessary to equate the marginal costs of environmental improvement across all pollution sources and abatement activities. However, in the case of water pollution from agricultural sources, it can be quite difficult to uniquely identify the marginal cost of abatement for a particular conservation practice on the landscape since the ultimate contribution of such a "source" to ambient environmental quality may depend in highly nonlinear ways on the choices made at other "sources" on the landscape. The continued development of watershed process models capable of capturing such nonlinearities and interactions on one hand (e.g., Gassman et al., 2007; Collins and McGonigle, 2008; Silgram et al., 2008) and optimization techniques (e.g., Srivastava et al., 2002; Muleta and Nicklow, 2002; Whitaker et al., 2003; Arabi et al., 2006; Rabotyagov et al., 2010a; Cools et al., 2011) on the other hand places today's decision-makers in a position where the problems of cost-effective assignment of abatement (conservation) activities can be solved for a variety of landscapes and environmental objectives.

At the same time, competitive bidding mechanisms, which we refer to as "reverse auctions", have recently gained a foothold among researchers as well as policymakers (Latacz-Lohmann and Schilizzi, 2005 provide a comprehensive review). Internationally, major examples include the Conservation Reserve Program in the U.S. (USDA-FSA, 2011), the BushTender program in Victoria, Australia (DSE, 2012), and the Challenge Funds program in the U.K. (CJC Consultants, 2004).

In general, such auctions (also known as procurement auctions) involve private landowners submitting bids for undertaking a particular activity thought to provide an environmental benefit. The agency administering the auction then evaluates the bids in terms of cost and the likely environmental benefit and decides on which bids to accept, given its limited budget or the desired environmental objective. The main attraction of reverse auctions lies in introducing competition among the landowners, inducing them to submit bids close to their opportunity costs and thus increase the degree of budgetary cost-effectiveness by stretching the available conservation funds. In addition to the budgetary cost-effectiveness (which is a function of reducing the amount of overpayment beyond the true opportunity costs of the landowners), a question of allocative efficiency (targeting those locations and conservation actions which achieve the desired environmental objectives at the lowest cost to society) is clearly of high importance. Under some conditions, auctions yield results which achieve both budgetary cost-effectiveness and allocative efficiency (Chan et al., 2003). In the realm of reverse auctions for conservation, a substantial gap between theory and practice remains (Latacz-Lohmann and Schilizzi, 2005), and auction design has the potential to influence both the allocative and budgetary performance of the program.

In this paper, we focus on the question of allocative efficiency of reverse auctions and demonstrate how models and solution algorithms that can solve the problem of the cost-effective allocation of conservation actions in a watershed can be directly integrated within a reverse auction program[1]. This integration is likely to have two sets of benefits. First, many reverse auctions attempt to include a bid selection mechanism which serves to increase the cost-effectiveness of the program. In the conservation realm, a large body of research focuses on bid ranking (Ribaudo 1989; Wu and Babcock, 1996; Smith 1995; Feng et al., 2006), and the largest active reverse auction program in the U.S., the Conservation Reserve Program, relies on a specific ranking tool called the Environmental Benefits Index (USDA-FSA, 2011). The optimality of such ranking methods is an empirical question, especially in the settings where water quality improvements are concerned. Theory suggests that bid selection based on optimization cannot do worse than bid selection based on simplified rules. Discovering such gains is a major, but not the only, policy-relevant benefit of integrating simulation-optimization tools in reverse auction programs.

The second set of benefits is related to using the results of optimization to improve the reverse auction process after the bids on the costs of adopting conservation actions have been collected. We argue that the proposed integration is indeed an “integration”, where the modeling and optimization results can be used to provide feedback, to refine the reverse auction process, and to highlight opportunities and limitations, as opposed to only serving as a more sophisticated bid ranking mechanism (which may prove to be quite valuable in and of itself). In practice, the extent to which such benefits could be capitalized on by the auction-administering agency

[1] We do not take up the issue of incentive compatibility properties of various reverse auction designs—that is, the extent to which landowners reveal their true opportunity costs. Latacz-Lohman and Schillizzi (2005) or Cason and Gangadharan (2005) provide excellent treatments of the issue. For simplicity, we assume that different bid ranking approaches we propose lead to the same set of cost bids. This may not be true, as bid evaluation rules may have an effect on bidding strategies. To the extent that the proposed reverse auction format is a more complicated bid evaluation approach, research suggests that bidding in this context may be closer to true opportunity costs (Cason et al., 2003; Vukina et al., 2008). This would provide an additional (budgetary cost-effectiveness) rationale for adopting the proposed reverse auction approach over simple bid scoring rules. Further, we note that if bids do not represent true opportunity costs, both optimization and ranking approaches will lead to second-best watershed configurations in terms of allocative efficiency of conservation practice assignments (we thank an anonymous reviewer for this observation).

depends on the policy environment, stakeholder attitudes and cooperation, and the overall agency flexibility.

We demonstrate here how the simulation-optimization tools can be used to inform the design of a reverse auction for the Raccoon River Watershed in west central Iowa, which is located in the URMB, and we evaluate the magnitude of the potential gains from using the simulation-optimization approach relative to a simpler ranking method for selecting bids and show the implications of using ranking methods for the environmental effectiveness of a reverse auction program.

We begin by describing how an optimal (cost-effective) reverse auction would work and how stakeholders and policy makers could both learn from the auction before implementing payments and how they could adjust the details of the auction payments in response. We then describe the key features of the watershed followed by details concerning all of the modeling components and the results associated with potentially applying an optimal reverse auction using the methods outlined. Since we are not modeling the actual implementation of such an auction, but rather are evaluating the potential for such an auction to achieve nutrient reduction goals and cost effectiveness, we must make some assumptions about the compensation that landowners will be willing to accept to participate in these auctions. Conditional on assumptions about those costs, we demonstrate the potential empirical gains associated with an optimal reverse auction relative to the use of simpler, but not necessarily optimal, ranking schemes. We also consider that simple ranking schemes may not yield sufficient nutrient reductions to achieve water quality goals.

2. Comparison of Alternative Reverse Auction Systems

2.1. Optimal reverse auctions

First, we briefly describe the steps in an optimal reverse auction process, followed by a discussion of potential benefits of using optimal reverse auctions as compared to the more traditionally employed bid ranking methods, focusing on the potential inefficiencies (not achieving a target at the lowest cost) and ineffectiveness (failing to meet a target even in the extreme case of accepting all bids) of the latter approaches.

In implementing the proposed optimal reverse auction, the agency starts with identifying a potential set of conservation practices that it will consider funding in an auction and announces this list to potential participants. The agency makes clear that multiple conservation practices and/or combinations of practices at different cost levels are encouraged from landowners.[2] Next, bids from landowners in the watershed are elicited providing the implementing agency, for each decision-making unit (DMU) in the watershed, a set of bids that encompass all of the conservation practices applicable. These bids then serve as the cost data for the implementing agency.

Using these costs as inputs to an integrated simulation-optimization system, the implementing agency creates the full frontier of (approximately) optimal tradeoffs between program costs, environmental objectives, and potentially between separate environmental objectives. Visualizing the entire set of tradeoffs presents is valuable for decision-makers. In particular, as the tradeoff frontier can be interpreted directly as the watershed-level total

[2] In practice, a significant effort in educating landowners and building trust is required. Failure on the part of the agency to do so may result in a situation where no landowners express the desire to participate (such a negative outcome was observed in 2007 in Washington State, where the Dept. of Ecology attempted, unsuccessfully, to run a reverse auction for improving water quantity available in streams): http://www.ecy.wa.gov/programs/wr/cro/yrtrwra.html

abatement cost curve (Rabotyagov et al., 2010a), it presents to the decision-makers the marginal costs of environmental improvements at relevant margins. Should the shape of the frontier suggest that the marginal costs of improvements at the level of cost matching the available budget are low, this may provide justification for attempting to increase the program budget to capture low-marginal cost improvements. The agency and the stakeholders can evaluate the tradeoffs and, depending on funding sources and program flexibility, make the decisions involving 1) auction budget (using information on marginal costs of environmental improvements); 2) environmental targets; and 3) set of accepted bids representing a particular allocation of conservation practices which achieve the specified objectives in a cost-efficient manner.

2.2. Evaluating reverse auctions involving bid ranking

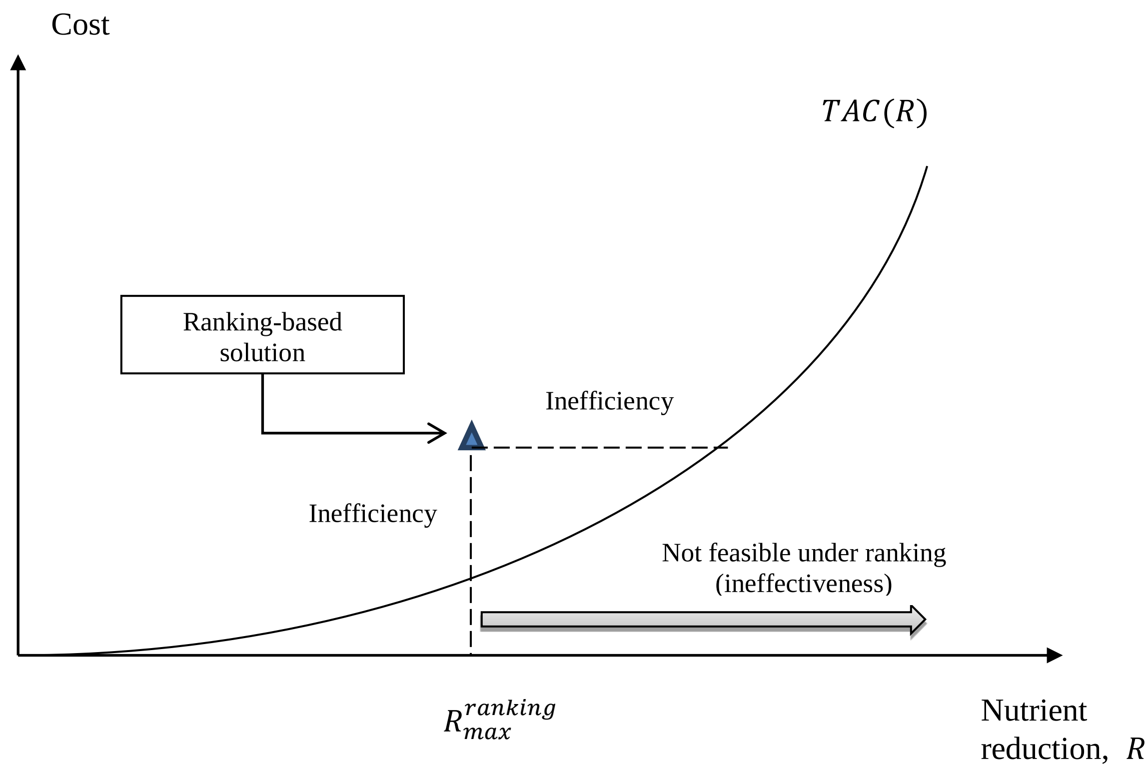
Consider the total abatement cost curve as in Figure 1, derived using optimization methods. Note that this refers to a two-dimensional tradeoff between a single environmental objective (nutrient abatement) and the cost of conservation practices. In the empirical section below, we extend this to three dimensions by considering two environmental objectives in addition to the cost.

Suppose that the shaded triangle represents a point in abatement-cost space arising from the *full enrollment* of the DMUs in the watershed using a ranking method, which involves computing some kind of benefit/cost ratio for each DMU and each practice and accepting, for each DMU in the watershed, the bid for the practice with the largest benefit/cost ratio. Such ranking rules are common in real-world reverse auctions such as CRP or the recent reverse auction for water quality improvements in the state of Kansas (Smith et al., 2009). Two things should be considered. First, depending on how accurately the benefits assignment rule represents the actual environmental process, there are likely to be inefficiencies associated with using a simplified ranking rule as opposed to full-on optimization using the best available modeling tools. This means that the decision-maker could find alternative ways to allocate conservation practices on the landscape which would result in a larger abatement for the same level of cost, or a lower cost for the same level of abatement, or both.

Second, even if no inefficiency is discovered (which means that the ranking-based solution is a part of the total abatement cost curve), committing to selecting bids based on a benefit/cost ratio introduces the possibility of insufficient effectiveness of such an approach. Decision-makers need to be aware of this potential pitfall in using simple ranking approaches based on benefit/cost ratios. For example, if the ecological considerations require that nutrients in the watershed should be reduced by more than $R_{max}^{ranking}$, alternative bid selection mechanisms need to be utilized, as selecting the practice with the biggest benefit per dollar for each DMU results in omission of practices which are more effective in terms of nutrient reductions but don't have the highest benefit/cost ratio.

Such pitfalls of simple benefit-cost ratios have, of course, been recognized previously, both in the context of general benefit-cost analyses (e.g., Boardman et al., 2006, pp. 464-470) and in the context of selecting conservation practices in agriculture-dominated landscapes (Feng et al. 2006; Rabotyagov 2010). The recommended remedy usually involves a move to more sophisticated ranking methods based on explicit optimization results.

Figure 1. Potential ineffectiveness and inefficiency of simplified ranking methods



2.3. Optimization method

The solution of optimal allocation of conservation practices to decision-making units in the watershed is non-trivial, but can be approximated closely by using the simulation-optimization system. Note that if there are, e.g., 10 mutually exclusive conservation practices that could be applied to 1,000 DMUs in the watershed, there are 10^{1000} possible assignments of conservation practices to the DMUs in the watershed which then would have to be evaluated for their environmental impacts using a watershed water quality model.

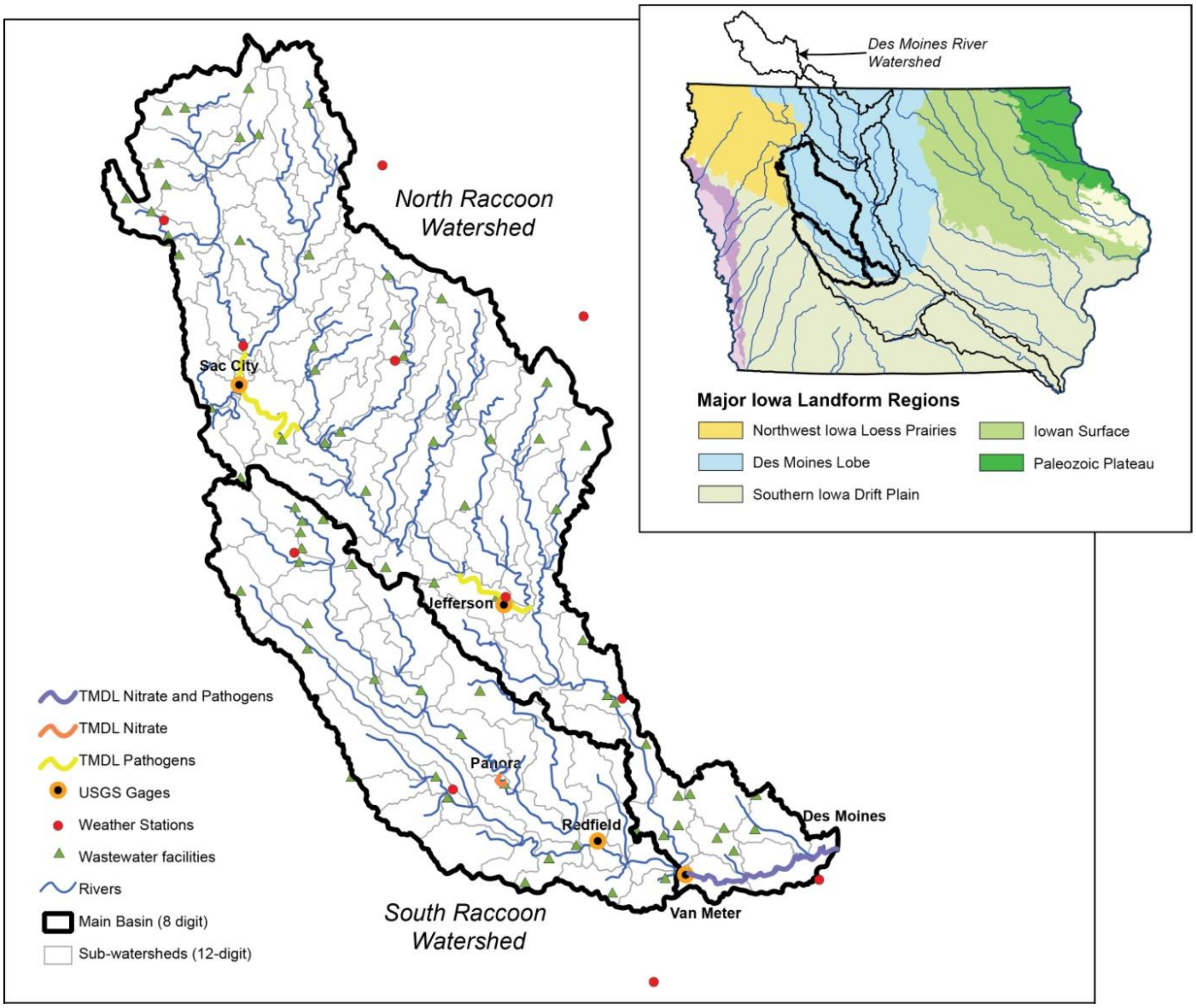
However, recent advances in evolutionary computation (Deb, 2001) have allowed researchers to closely approximate solutions to similarly difficult problems. The basic idea of evolutionary computation borrows heavily from the theory of natural evolution and is centered around iteratively evaluating multiple candidate solutions ("individuals") in terms of their performance (here, it is water quality impacts as well as program cost), selecting solutions which solve the problem well compared to other candidate solutions, discarding suboptimal solutions, and creation of new solutions from solutions which appear to perform well. This "survival of the fittest" logic, along with a stochastic search component, provides for an attractive optimization heuristic, well suited to problems such as the choice of optimal conservation practices. Evolutionary algorithms provide the basis for the optimization component of the simulation-optimization system, while the Soil and Water Assessment Tool (SWAT) water quality model (Arnold and Fohrer, 2005; Gassman et al., 2007; Tuppad et al., 2011) is used to simulate the performance of numerous alternative solutions (configurations of conservation practices in the watershed). Arabi et al. (2006) and Rabotyagov et al. (2010a, 2010b, 2010c) discuss in detail coupling the SWAT water quality simulation model with a multiobjective evolutionary algorithm.

Following the approach described in Rabotyagov et al. (2010a, 2010b, 2010c), we use a simulation-optimization system using SWAT for simulation and an evolutionary algorithm for optimization to approximate the solution to the 3-objective minimization problem, where we wish to simultaneously minimize total mean annual nitrogen loadings, total mean annual phosphorus loadings, and the cost of conservation practices for the study watershed. That is, we minimize *(N, P, Cost)* by selecting from a set of mutually-exclusive combinations of conservation practices for each cropland DMU in the watershed. The solution to the 3-objective problem can be visualized as a set of Pareto-nondominated points in *(N, P, Cost)* space, where each solution (“individual”) is a specific watershed configuration, prescribing a particular allocation of conservation practices to DMUs.

3. The Raccoon River Watershed: Characteristics and Data

The Raccoon River Watershed, drains a region covering over 9,400 km^2 in portions of two major landforms in west central Iowa and is a major tributary of the Des Moines River (Figure 2). The North Raccoon subwatershed (Figure 2) drains an area lying in the recently glaciated (<12,000 years old) Des Moines Lobe landform region, which is dominated by low relief and poor surface drainage and thus managed with an extensive network of subsurface tile drains (Schilling et al., 2008). In contrast, the South Raccoon River subwatershed mainly drains an older (>500,000 years old) Southern Iowa Drift Plain landscape region characterized by higher relief, steeply rolling hills, and well-developed drainage (Schilling et al., 2008). Agricultural row crop production is the predominant land use, with roughly 73% of the area planted almost exclusively to corn and soybeans. There are two key sources of nitrogen and phosphorus applied to cropland, mainly corn, in the watershed: inorganic fertilizer and land-applied livestock manure. The primary point sources of nutrients to the stream system are 77 wastewater treatment facilities (Figure 2). The location of climate stations and subwatershed boundaries used in the water quality modeling are also shown in Figure 2, as well as the stream network, the location of U.S. Geological Survey (USGS) streamflow gauges used for establishing baseline streamflows and for model testing, and

Figure 2. Location of the Raccoon River Watershed relative to major Iowa landform regions, and location of climate stations, USGS streamflow gauges, wastewater treatment plants, and stream segments requiring TMDLs within or near the watershed.



impaired stream segments requiring the establishment of Total Maximum Daily Loads (as described in Schilling et al. (2008) and Jha et al. (2010)).

4. Modeling Components

4.1. SWAT Model: Description and Baseline Testing

In SWAT, a watershed is divided into multiple subbasins, which are then 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 in a subbasin 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. Previous applications of SWAT for streamflows and/or pollutant loadings have compared favorably with measured data at a variety of watershed scales in many regions across the globe (Gassman et al., 2007; Tuppad et al., 2011).

The SWAT (version 2005) modeling framework used in this study follows the model used to support a TMDL assessment for the Raccoon River Watershed (Schilling et al., 2008; Jha et al., 2010), in which the watershed was subdivided into 112 subbasins and 3,640 HRUs. Strong baseline calibration and validation results were reported for this application, (Schilling et al., 2008; Jha et al., 2010), based on comparisons with USGS streamflow data and periodic pollutant grab samples collected near Van Meter, Iowa (Figure 2). The SWAT modeling framework used in this study is identical to the improved model, which was used to support the development of a Raccoon River Watershed Master Plan, which included additional baseline testing, as described in detail in Gassman and Jha (2011) and Ridgely (2011).

4.2. The Costs of Conservation Practices

Theoretically, the minimum willingness-to-accept (WTA) of compensation for adoption of a practice is a function of the direct costs of adoption (building of structures, purchase of new inputs, etc.), plus any lost profits via reduced yield (or minus any increase in profits from lower input usage and costs), and any compensation needed for increased risk or to cover increased labor time associated with new management practices. The WTA for adopting conservations practices may vary with hydrology, soil types, weather, and other physical variables, crops grown and history of land use, as well landowner preferences and sociodemographic characteristics.

A large component of WTA can be expected to be based on the direct costs of adopting and maintaining a practice and on lost yield (profits from such adoption). Thus, for an empirical demonstration of the approach, a reasonable proxy for the costs of conservation (WTA) are estimates of direct costs of adoption. This approach may be missing important variation in WTAs across HRUs based on the risk attitudes of farmers and perceived opportunity costs of time or other factors that make the actual WTAs vary (Lynne et al., 1988)[3]. Nonetheless, since the principal purpose of this paper is to evaluate the effectiveness of such an auction, we assign the WTAs (which are assumed to be equivalent to the bids) based on estimates of the direct costs of conservation practices.[4] The following conservation practices are considered: land retirement, cover crops, no-till, contour farming, N fertilizer reductions, terraces, and grassed waterways. The descriptions of these practices as well as the costs used in this study and their sources are provided in Tables A2 and A3 of the Supplementary material. Since not all of the conservation practices are mutually exclusive, we create a set of 23 mutually exclusive combinations of conservation practices. Table A4 of the Supplementary material presents this set of 23 mutually exclusive options (decision variables) which can be applied to each cropland HRU, along with the SWAT-predicted consequence of applying each of the options in a uniform fashion to each

[3] HRU represents the basic unit of the SWAT model and serves as the DMU in the optimization process.

cropland HRU (e.g., treating all cropland HRUs with a combination of no-till and grassed waterways).[5]

4.3. Ranking-based reverse auctions

In our empirical demonstration, we compare the proposed optimal reverse auction with two ranking-based reverse auction designs. Both ranking approaches compute the benefit to cost ratio for each practice and accept bids in the descending order of this ratio until the budget is exhausted (or all bids are accepted). The two approaches differ in terms of the method by which they compute the environmental benefit. The first ranking scheme, referred to as the "USLE-based ranking", uses the Universal Soil Loss Equation (USLE; Wischmeier and Smith, 1978) to estimate the HRU-level benefits, measured in terms of soil loss reductions. The second ranking scheme, referred to as "MUSLE-based ranking", uses the Modified USLE (MUSLE; Williams and Berndt, 1977) to estimate the benefits used in the ranking process.The DMU-level benefit is defined as the change in sediment load for a particular conservation practice combination applied to the DMU. In this application, we use HRUs as the decision-making units (DMUs).

In terms of real-world examples, an USLE-based ranking, modified by SWAT-derived transport ratios, was used in the real reverse auction in Kansas (Smith et al., 2009). We are not aware of reverse auctions employing a MUSLE-based ranking. Conceptually, any alternative ranking scheme (e.g., one proposed in Bechmann et al., 2009) can be evaluated using the proposed simulation-optimization approach.

The soil loss and the sediment load values are estimated using the SWAT model for a variety of scenarios and the baseline, where a scenario is defined as the watershed configuration

[5] Most conservation practices are modeled in a manner described in Arabi et al. (2008). Table A2 of Supplementary material describes the specific SWAT parameter adjustments.

where each field (HRU) is assigned the same conservation practice. Hence, we are able to obtain soil loss and sediment loads field level values for each conservation practice including the baseline. The benefit values for each HRU are computed as the differences between the values of the above mentioned indicators under the baseline case and their counterpart values under each scenario. Next, using the assumed per-acre costs and HRU areas, we compute the area-weighted cost for each HRU and for each conservation practice, and determine the benefit-cost ratios under the two approaches: USLE and MUSLE. Finally, we sort the HRUs in a decreasing order according to their maximum benefit-cost ratio.

Next, we simulate the behavior of a reverse auction agency by "accepting" the bids according to the highest benefit-cost ratio HRUs until the budget is exhausted. We consider two budget scenarios. The first scenario is deliberately chosen to be somewhat extreme in order to speak to the effectiveness of ranking-based reverse auctions. Under this scenario, ("full enrolment"), we assume that the size of available budget is sufficient to enroll all HRUs in the watershed.[6] Under the second scenario, ("partial enrolment"), we consider that the available budget equals one half of the budget size required for a full watershed enrollment. Under each ranking approach and budget scenario, we create the implied configuration of agency-accepted conservation practices for the watershed. In order to assess the watershed-level impacts of these configurations, we use SWAT to determine the environmental outcomes of the reverse auctions based on these ranking schemes.

[6] Although accepting bids from all auction participants may appear extreme, this is sometimes the experience of the Conservation Reserve Program, where all willing farmers may be enrolled.

Table 1. Simulated outcomes of reverse auctions based on bid ranking schemes

Ranking	Cost, $/year	N reduction at watershed outlet (%)	P reduction at watershed outlet(%)
USLE (full enrollment)	19,460,735	10.17	31.93
USLE (partial enrollment)	9,727,643	8.24	25.12
MUSLE (full enrollment)	15,595,966	9.84	31.52
MUSLE(partial enrollment)	7,764,808	8.05	25.61

Table 1 summarizes the results for the two budget scenarios. Note that the full enrollment case indicates the maximum level of nutrient reductions at the outlet that can be achieved under these ranking schemes (i.e., the maximum effectiveness of a ranking approach to achieve water quality goals).

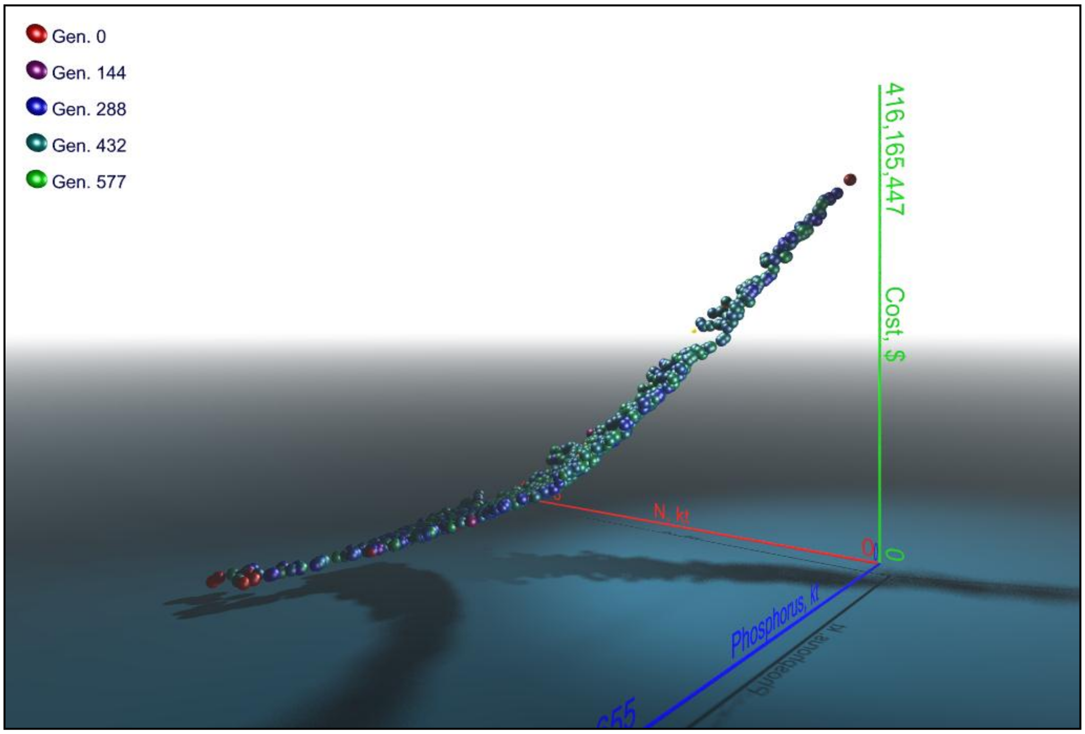
The total enrollment with USLE-based ranking reduces total N by 10.2 % and total P by 31.9 %, at an expense of 19.5 million dollars. A total enrollment with a MUSLE-basedranking, while only slightly less effective in reducing total N and total P, results in a cost of 15.6 million dollars (i.e. more than 20% cost savings).

5. Results

5.1. Efficient frontier

We generate approximate optimal tradeoff frontiers for the Raccoon River watershed by running the evolutionary multi-objective algorithm for 300 generations (iterations). We then add the watershed configurations created using the two bid ranking approaches described above to the set of Pareto non-dominated watershed configurations and run the evolutionary algorithm for an additional 275 iterations. This allows us to “challenge” the ranking-based watershed configurations within the simulation-optimization framework. The outcome can be visualized in the N-P-Cost space by a cloud of Pareto-optimal points, where each point represents a specific watershed configuration in terms of allocating conservation practices to HRUs (Figure 3).

Figure 3. Visualization of the 3-dimensional tradeoff frontier



5.2. Optimization compared to ranking-based bid selection

As part of the "challenging" process", ranking-based watershed configurations were made to compete with the configurations discovered by the evolutionary algorithm. The configurations generated using USLE-based ranking method did not withstand the challenge. The USLE-based full enrollment configuration is dominated by sixteen Pareto optimal configurationsin N-P-Cost space, while the USLE-based partial enrollment configuration is dominated by five Pareto optimal configurations. For example, there exists a Pareto-optimal configuration, which, relative to USLE-based full enrollment case, offers additional 1.4%

reductions in N and 0.4% reduction in P at a cost saving of 2.8 million dollars per year. Relative to USLE-based partial enrollment, we can find a configuration which offers additional 0.2% reductions in N and 0.9% reductions in P at an additional cost savings of $1.4 million per year.[7] The MUSLE-based ranking configurations, in spite of being dominated in the N-Cost space, are nondominated in the P-Cost space. Thus they remain a part of the final Pareto frontier set.

Table 2. Ranking vs. Pareto-Optimal Individuals

Ranking method used, extent of cropland enrollment	Cost, $/yr	N reduction (%)	P reduction (%)	Pareto-dominated in the final frontier/ number of dominating configurations	Dominating configuration with the largest cost savings/cost savings/increase in N reductions/increase in P reductions (percentage points)
USLE, full enrollment	19,460,735	10.18	31.93	Yes/16	#105974/$2.8 mil/1.4/0.4
USLE, partial enrollment	9,727,643	8.25	25.13	Yes/5	#107059/$1.4 mil/0.2/0.9
MUSLE, full enrollment	15,595,966	9.8	31.50	No/0 Dominated by 110 in N-Cost space	--
MUSLE, partial enrollment	7,764,808	8.0	25.60	No/0 Dominated by 9 in N-Cost space	--

There are several important implications of the result that configurations generated using a relatively simple MUSLE equation remain a part of the optimal tradeoff frontier even when “challenged” by the optimization algorithm. First, it implies that, when reductions in P are desired, watershed configurations resulting from the use of simple bid ranking tools may perform

[7] In the frontier, these individual configurations are encoded as #105974 and #107059, respectively. Such numbers can be seen in the Figures as, e.g., “Individual 105974”.

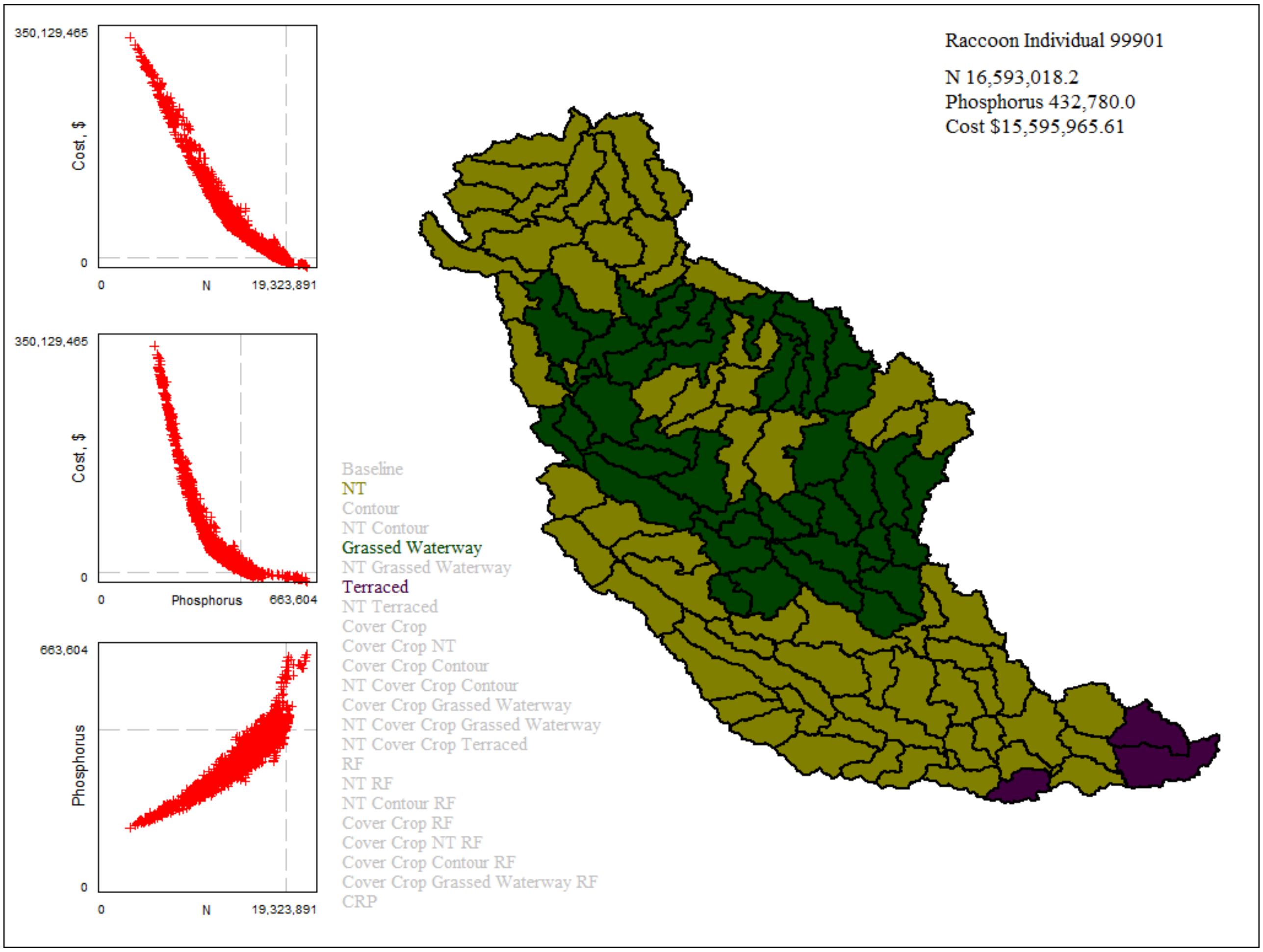
no worse than the configurations generated using the optimal reverse auction approach. The likely reason for such a result is that both the ranking-based configuration and the SWAT model use the MUSLE equation to model sediment transport, which is tightly linked to P reductions. In essence, the ranking-based configuration is using the same kind of scientific information incorporated into the SWAT model. However, when USLE is used, which is not used in the SWAT model because MUSLE offers improved sediment yield prediction (SWAT2005 Theoretical Document, p. 225), the algorithm quickly discovers the inefficiencies associated with modeling sediment inherent in USLE-based configurations and discovers better watershed configurations.

Second, although the MUSLE-based bid ranking procedure may be appropriate for auctions for watershed P reductions, the fact that *all* MUSLE-based ranking configurations are dominated in N-Cost space immediately suggests the obvious point that the choice of the bid evaluation procedure must be accurately tied to the environmental goal. If N improvements are of primary importance, a ranking that is well suited for P reductions is inefficient.

Third, although we find that a relatively simple ranking-based method for bid evaluation may not be inefficient for P reductions, the issue of potential ineffectiveness of any ranking procedure remains. Figure 4 demonstrates this for the case of all landowners submitting bids and all those bids accepted according the MUSLE-based ranking. The full enrollment is shown by the subbasin-level map, where every cropland HRU is assigned to the conservation practice options with the highest benefit-cost ratio.[8]

[8] Although we discuss allocation of conservation practices to DMUs (HRUs) as a spatial optimization problem, in this case we can only present spatial distribution of conservation practices at the subbasin level due to the nature of the data used to create the SWAT model. However, if field-level data is available, HRUs can be mapped back to the underlying fields (see, e.g., Rabotyagov et al. 2010b,c).

Figure 4. Efficiency and effectiveness of a MUSLE-based ranking configuration.



The three panes on the left in Figure 4 provide an empirical (3-dimensional) counterpart to Figure 1 by presenting the 2-dimensional projections of the tradeoff frontier. The lower envelopes of the frontier in nutrient-cost space can be interpreted as total abatement cost curves for the corresponding nutrients (where the consequences for the other nutrient are ignored). We can note that the ranking-based configuration is Pareto-nondominated in P-Cost space (the configuration, lying at the intersection of dashed lines is at the lower envelope of the tradeoff frontier), and dominated (inefficient) in N-Cost space (the configuration is above the envelope).

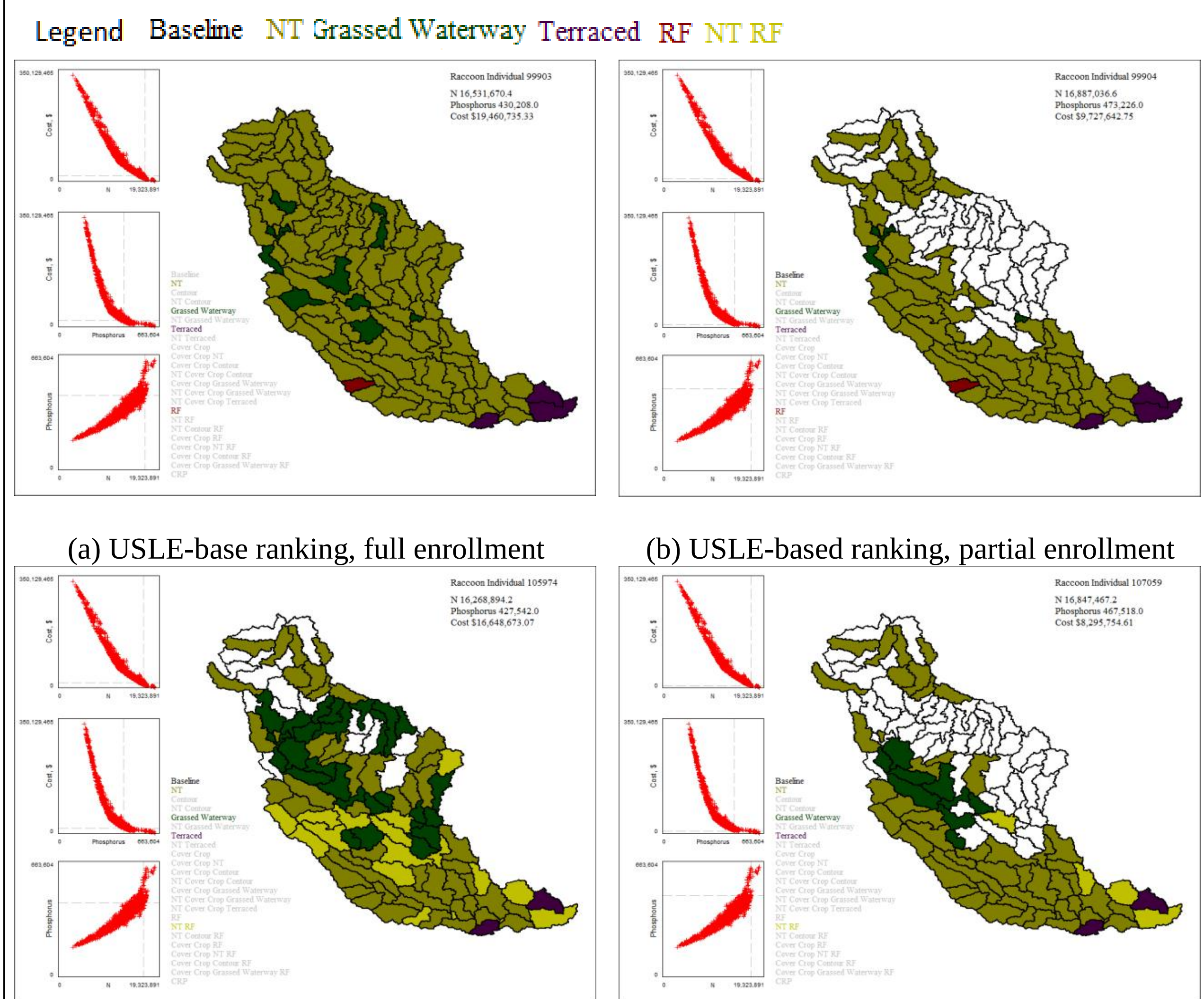
However, it is mostly noticeable that the ranking-based configuration is relatively ineffective in reducing either of the nutrients, compared to the feasible nutrient reductions predicted by the simulation-optimization system. In particular, all the watershed configurations lying to the southwest of the intersection of the dashed lines in the lower pane are feasible (and Pareto-optimal) under the simulation-optimization system, but are not feasible under the ranking system. In other words, if a reverse auction program in the watershed had a mandate to achieve greater than 9.8% reductions in N and greater than 31.5% reductions in P, it would not be able to do so using a MUSLE-based bid ranking and acceptance method even if the program enrolled every cropland unit in the watershed. A simulation-optimization approach provides the agency with the way (should funds be available) to reach a much wider range of nutrient reduction goals optimally.

5.3. Inefficiencies in practice allocation

No-till and grassed waterways represent the most commonly accepted practices under any type of enrollment, while the configurations that dominate the USLE-based ranked individuals make use of a broader array of conservation practices (Figure 5). Table A6 of the Supplementary material summarizes the conservation practices used and the percentage of watershed area allocated to them.

Next, we provide the visual descriptions of the watershed configurations under the optimal reverse auction process and the USLE-based bid ranking in order to compare the inefficient mix and location of conservation practices (prescribed by USLE-based ranking) with the solution generated by the algorithm which achieves higher water quality while costing less (Figure 5).

Figure 5. Ranking-based vs. efficient configurations



(a) USLE-base ranking, full enrollment (b) USLE-based ranking, partial enrollment

(c) Pareto-optimal configuration (#105974) (d) Pareto-optimal configuration (#107059)

An interesting result that emerges is that, for the chosen configurations, a large number of subbasins are targeted by the same set of conservation practices. For example, the subbasins located at the southern part of the watershed are targeted by terraces in all configurations presented in Figure 5. At the same time, the subbasins located in the central part of the watershed are repeatedly targeted by grassed waterways. The algorithm discovers a way to enroll fewer

HRUs into the reverse auction program than under the USLE-based ranking, but the many of the same subbasins left un-enrolled under USLE-based partial enrollment are left un-enrolled in the optimal reverse auction.

Finally, we also note that the current set of conservation practices incorporated in the simulation framework may not be ideal for addressing nutrient loadings, especially nitrate losses. In addition, the current reliance on a P factor approach to approximate grassed waterway effects (Table A2), due to the inability to more directly simulate grassed waterways in SWAT2005, may result in over-estimates of the effectiveness of that practice. Other practices—including expanded use of perennials in row crop systems, and adaptive nutrient management that includes adjustment of fertilizer application timing as well as fertilizer rates (outlined in the Raccoon Master Plan (Ridgeley, 2011))—may, with the improvements in modeling capability, be found to be more cost-effective for nutrient reductions for the watershed.

6. Final Remarks and Policy Implications

Diffuse pollution from agricultural landscapes continues to be a daunting problem in many countries and across many landscapes. At the same time, conservation program funding is being curtailed and reconsidered. The combination of frustration over the lack of progress and increased budgetary pressure has lead policy makers and analysts to look for alternative approaches.

In this paper we have presented a method for using advanced modeling tools to support the design and implementation of reverse auctions which can be used to address nutrient reductions. In addition to describing the approach, we demonstrate the gains from an “optimal” reverse auction relative to a simpler ranking of bids for the Raccoon River Watershed in Iowa.

Our results suggest that in some cases, substantial improvements can be made using the more efficient allocation mechanism of the optimal reverse auction, but that there are some cases in which the prescribed configuration of conservation practices in the watershed are quite similar. We further find that simple ranking of bids may only lead to relatively small nutrient reductions even in the extreme case where every landowner submits a bid and every landowner's bid is accepted.

Based on these findings, a number of additional aspects of reverse auctions merit consideration including whether omitting difficult-to-measure practices would alter the findings significantly, whether there are other ranking methods besides USLE or MUSLE that could better approximate the optimal reverse auction, and whether the costs of N and P reductions observed in this watershed will be typical of other watersheds in the region. While much work remains, advances in watershed modeling and computational methods promise to continue to improve our ability to target conservation practices and achieve nutrient reductions at low cost.

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