Good Seeds Bear Good Fruit: Using Benefit-to-Cost Ratios in Multiobjective Spatial Optimization under Epistasis

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ABSTRACT *Many biophysical models exhibit epistasis (interdependence), where a conservation action impacts the effectiveness of another elsewhere. At the same time, ranking conservation actions according to the independent benefit-to-cost ratios is cost-efficient when epistasis is absent. We use benefit-to-cost rankings as starting points for an evolutionary algorithm employing an epistatic biophysical model. We model a variety of conservation actions to assess trade-offs for sediment reduction and wildlife conservation in the study watershed. We find that despite the presence of epistasis, the weighted benefit-to-cost ratio-derived solutions perform remarkably well in the decision space, but effects in objective space need the model evaluation.* (JEL Q25, Q52)

1. Introduction

Optimizing the mix and location of conservation actions within a watershed, which considers the spatial heterogeneity in conservation effectiveness and cost across the agricultural landscape, can bring significant gains in terms of stretching conservation funds and is a necessary component for any effort aiming to fully assess or maximize the net social benefit of managed landscapes. Effectiveness of conservation actions is, among other factors, highly dependent on their spatial arrangement within a watershed. The structure of many biophysical models captures such effects, and models are often used in optimization applications within a simulation-optimization paradigm. A sizeable body of literature on agricultural landscape optimization using evolutionary algorithm (EA) simulation-optimization approaches has been developed, with perspectives emphasizing agricultural systems engineering (Veith, Wolfe, and Heatwole 2003; Arabi, Govindaraju, and Hantush 2006; Maringanti et al. 2011), agricultural and environmental economics (Bostian et al. 2015; Rabotyagov, Valcu, and Kling 2013), and hydrology (Wu et al. 2018). In the context of cost efficiency, where environmental objectives are not monetized, the task is generally to find a spatial pattern of conservation actions that attains a specific environmental objective with the lowest cost (or a pattern that attains the largest desirable environmental change for a limited budget). Often, multiple noncommensurate environmental objectives are of importance, and the cost-effectiveness problem is generalized into multiobjective optimization, where the principle of Pareto efficiency is used to generate solutions (i.e., one cannot attain any improvement in a desirable objective, e.g., lower cost, without a sacrifice of another desirable objective, e.g., water quality). In other words, such optimi-

Land Economics • November 2020 • 96 (4): 531–551
ISSN 0023-7639; E-ISSN 1543-8325

Appendix materials are freely available at http://le.uwpress.org and via the links in the electronic version of this article.

zation exercises aim to construct frontiers of production possibilities with respect to (1) nonmonetized goods and services represented by environmental objectives and (2) monetized goods and services represented by the costs of conservation actions.

In some cases, conservation budgets or environmental targets represent stringent real-world requirements, and constrained optimization becomes of primary importance. In other cases, the question of interest is not specifically tied to a precise water quality goal or budget constraint; rather, the primary interest lies in understanding the trade-offs between cost and one or more environmental objectives or in assessing the degree of synergistic relationships among environmental objectives. Synergies may be present among those environmental objectives, which can be produced simultaneously by some conservation actions and/or a particular spatial arrangement of conservation actions. We do not impose strict constraints on costs or environmental objectives and estimate the full scope of cost-efficient trade-offs and potential synergies.

In this paper, we focus on estimating efficient trade-offs between multiple environmental and economic objectives using a hybrid simulation-optimization approach. Sediment reduction, a common nonpoint source water pollution management problem, constitutes the first environmental objective, with wildlife production (represented by estimates of duck hatchlings) being the second. We use highly spatially resolved data for the study region, an area of intensive crop production, aiming to estimate trade-offs and to present the solutions in a spatially explicit way. We employ a multiobjective EA heuristic to estimate the set of Pareto-efficient landscape management configurations. On the environmental benefits side, we use an ecohydrologic sediment model tailored to the study region and a simple empirical model of duck production. On the costs side, we use a mix of engineering, econometric, and real options estimates to arrive at costs associated with conservation actions to be used in optimization.

Our landscape-level watershed optimization problem is formulated with many decision variables corresponding to small spatial units and coupled with a complex biophysical simulation model. Due to the "curse of dimensionality," it is not feasible to solve such simulation-optimization problems exactly (see, e.g., Kollat, Reed, and Kasprzyk 2008). Consequently, we explore an alternative. We combine approaches used in exact optimization (a "greedy" ranking based on a weighted benefit-to-cost ratio) with a simulation-optimization EA heuristic that can further challenge and improve the solutions and estimate trade-off frontiers, which may be satisfactory in terms of policy discussion and decisions. Intuitively, there is a trade-off in errors to be considered in choosing the optimization approach. Heuristic simulation-optimization approaches represent the consequences of landscape actions in a manner exactly consistent with process model assumptions, but we cannot be assured of the optimality of solutions obtained. Exact approaches assure us of optimality of the solutions obtained, yet introduce error due to the simplification of the underlying process (model). By combining approaches we seek to reduce the overall error associated with optimization (of course, any errors associated with the process model and its assumptions still propagate to any solutions discovered). At a minimum, such frontiers can provide an estimate of how well a specific watershed policy proposal compares to the solutions such hybrid approaches can feasibly discover.

2. Materials and Methods

Multiobjective Optimization

We estimate the efficient trade-offs by conducting a multiobjective optimization search using the EA heuristic. The objective is formulated similarly to that of Rabotyagov et al. (2010): we aim to approximate the Pareto frontier associated with simultaneously minimizing (1) the annual cost of conservation actions affecting sediment and duck production, (2) the mean annual sediment load at the watershed outlet, and (3) the (negative of) total annual duck hatchling production. That is, the algorithm solves the following:

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

subject to $(X,Y) \in \mathbf{T}$, where $\mathbf{X}$ is a set of conservation actions. The environmental benefits of $\mathbf{X}$ are denoted by $\mathbf{Y}$, where $\mathbf{Y}$ is a vector with N elements, namely, $\mathbf{Y} = (y^1, y^2, \ldots, y^N)$. Here, $N = 2$, and the relevant environmental indicators are the sediment loadings and duck hatchlings. $\mathbf{T}$ defines implicit constraints represented by the environmental models. The total cost of a particular pattern of conservation actions is represented by $c(\mathbf{X})$.

The set of solutions consists of all watershed conservation plans that are Pareto optimal. A conservation plan $\mathbf{X}$ is Pareto optimal if there is no $(\mathbf{X'}, \mathbf{Y'}) \in \mathbf{T}$ such that $y(\mathbf{X'})^n \leq y(\mathbf{X})^n$ and $c(\mathbf{X'})^n \leq c(\mathbf{X})^n$, for all $n \in \{1, 2, \ldots, N\}$, and such that $m \in \{1, 2, \ldots, N\}$, such that $y(\mathbf{X'})^m \leq y(\mathbf{X})^m$ or $c(\mathbf{X'})^m \leq c(\mathbf{X})^m$. In other words, once such a solution is found, it is not possible to improve on any one objective without trading off another. All the (approximate) efficient solutions found make up the three-dimensional trade-off frontier, which we denote as $F(\mathbf{X})$.

The EA used is an elitist (nondominated solutions are maintained in the archive) (Rabotyagov et al. 2010) modification of a SPEA2 algorithm (Zitzler, Laumanns, and Thiele 2001). In our application, we assume that the K decision variables are binary, the cost objective is linear and separable ($c(\mathbf{X}) = \sum_{k=1}^{K} c_k x_k$), and the duck population objective is also linear and separable ($y^{\text{duck}}(\mathbf{X}) = \sum_{k=1}^{K} g_k x_k$). The sediment objective is represented by the sediment simulation model, which is not easily written down in a compact form: $y^{\text{sed}}(\mathbf{X}) = S(\mathbf{X})$.

Epistasis

In many problems where simulation models are used, effectiveness of a specific decision variable depends on the state of other decision variables. Such issues often arise in biological conservation and other environmental management problems. For example, the survival probability of a species depends on the overall habitat size, the configuration of sites, and the distance and connectivity between sites (Fahrig 2003). Everything else being equal, neighboring sites tend to have a higher ecological value than isolated ones because species can migrate between sites, facilitating recolonization of sites in which a population has become extinct (Hanski 1998). As Murdoch et al. (2007, 377) pointed out: "In virtually all cases of interest, conservation actions are not independent of each other, and conservation planning is, therefore, a 'portfolio allocation' problem rather than a simple ranking problem: the benefits or costs of an action depend upon what other actions are taken."

As a result, one of the challenges in cost-effective policy design for biodiversity conservation is that the ecological value of habitat patches for the survival of species is space dependent, in other words, it depends on the presence and location of other habitat patches (Drechsler and Wätzold 2009). A recent study by Taylor (2019) highlighted that policies for wildfire risk mitigation depend on the character of the spatial dependencies between neighboring homeowners' investments. Murdoch et al. (2007, 377) write: "The number of species protected by purchase of a particular parcel of habitat may well depend on whether the parcel is connected to other parcels of habitat or is relatively isolated. When returns are not independent across actions, the complete allocation across all actions needs to be considered jointly rather than considering the return on each action in isolation."

In nonpoint source water pollution problems, this is driven largely by hydrologic interactions, and previous work variously referred to such effects as "endogeneity" (Carpentier, Bosch, and Batie 1998; Khanna et al. 2003), "nonlinearity" (Rabotyagov et al. 2014; Shortle and Horan 2013), "interdependence" (Randhir, Lee, and Engel 2000; Murdoch et al. 2007), and "nonseparability" (Rabotyagov et al. 2014) or "epistasis" (Maier et al. 2014; Kollat, Reed, and Kasprzyk 2008). As an example, in Appendix section 0.6, we provide a derivation of the gamma-distributed routing hydrographs in a cascade of linear reservoirs system. From the derivation, one can see that the effect of placing a reservoir is dependent on the presence or absence of other reservoirs in the cascade. We discuss the similar underpinnings of interdependence in our sediment model below and present a simulation example demonstrating the magnitude of these effects in our model in the Appendix.

Given EAs' inspiration by biology, and following Kollat, Reed, and Kasprzyk (2008), we adopt the term "epistasis" to refer to the potential interdependence across actions, since the term is used to describe "a phenomenon whereby the effects of a given gene on a biological trait are masked or enhanced by one or more other genes" (Moore 2005, 13). More broadly, one can speak about epistasis in terms of positive or negative externalities resulting from an action that affects the production possibilities elsewhere. Strong epistasis can drastically complicate market-based schemes for water quality trading (e.g., Shortle and Horan 2013). Rabotyagov et al. (2014) discuss this issue but suggest that a nonpoint source water quality trading scheme can still be useful when epistasis is ignored, while Kuwayama and Brozović (2013) present a more complicated trading mechanism explicitly designed to deal with epistasis present in trading groundwater, as hydrology provides for strong interdependence between decisions in the system.

Epistasis (interdependence) across decision variables has received a fair amount of attention in the broader field of evolutionary computation (Chen and Rajewsky 2007; Kollat, Reed, and Kasprzyk 2008; Li et al. 2016). Sun (2017) suggests new methods of identifying interactions and improving optimization algorithms. Undoubtedly, such approaches may prove very useful, but in the current application, we essentially treat the objective function represented by a biophysical model as a "black box" (but see Wu et al. [2018] for an example of trying to "unpack" the structure of an ecohydrologic model).

In general, the presence of epistasis results in situation where the environmental benefit is not well represented by aggregating incremental changes, even when the - incremental changes account for the differential impact of individual actions on the environmental objective. For instance, in this application, outlet sediment is not characterized by the sum of incremental reductions in sediment: $S(X) \neq S_0 - \sum_{k=1}^{K} b_k x_k$, where S_0 represents the sediment baseline and $b_k = S_0 - S(x_k = 1,; x_{-k} = 0)$ represents the estimated incremental sediment reduction benefit obtained by running the sediment model selecting one conservation action at a time, keeping all other candidate conservation sites at their baseline values.

Weighted Benefit-to-Cost Ranking

At the same time, consider a simple multiobjective optimization problem, where the decision-maker wishes to choose n binary decision-making units $\mathbf{X}_k$ in order to

$$\min\left(-\sum_{i=1}^{n} b_i x_i, -\sum_{i=1}^{n} g_i x_i, \sum_{i=1}^{n} c_i x_i\right), \qquad [2]$$

subject only to the requirement that all $x \in \{0,1\}$, where b_i represents an independent sediment reduction ability benefit from a candidate site, and g is the duck hatchling coefficient. Suppose one were to construct an index, for each x_i where λ is the weight place on the sediment objective, $r(x_i) = \lambda(b_i / c_i) + (1-\lambda)(g_i / x_i), \lambda \in [0,1]$, and sort this index in a descending fashion to obtain an ordered list and a corresponding ordered list of decision-making units $x_{r(k)}$, where, for example, $x_{r(2)}$ denotes the decision-making unit with the second-largest index r. A corresponding decision vector

$$\mathbf{X}_k = \{x_{r(1)}, x_{r(2)}, \ldots, x_{r(k)}, \ldots, x_{r(n)}\} = \{1, 1, \ldots, 1, 0, 0\}$$

is then created. It has been known for some time (Cohon and Marks 1975) and it is easy to show (see the Appendix) that $\mathbf{X}_k$ is a member of the Pareto front associated with the objective function. In other words, one can show that there does not exist another decision vector that Pareto-dominates $\mathbf{X}_k$ (although other Pareto-efficient solutions may exist). We refer to this procedure as the weighted benefit-to-cost ranking(wBCR). Note that such procedures are referred to as "greedy," especially in relation to single- and multiobjective knapsack problems (see, e.g., Lust and Teghem 2012; Schulze 2017). Existence of hard constraints (e.g., with respect to cost) distinguishes knapsack problems from the problem we are considering, where the "granularity" of decision variables (potential conservation sites) is small enough that going down the list of wBCR solutions presents a fairly dense trade-off frontier, and watershed planners can either find a point on the frontier that fits their budget (or attains the environmental goals) closely enough or alternatively are only really concerned with identifying optimal trade-offs. Duke, Dundas, and Messer (2013) confirmed the optimality of simple benefit-to-cost ratio ranking for two-objective problems of landscape optimization with high granularity and linear and separable objective functions.

It is easy to imagine that the presence of epistasis may invalidate the efficiency of the wBCR procedure. For example, consider a "benefit" function such that $B(x_j = 1; x_k = 1,\ldots) = B(x_j = 0,; x_k = 1,\ldots)$ but $b_j / c_j > b_k / c_k$ (where incremental benefits are estimated using the 'one-at-a-time' procedure), so that x_j gets selected first according to the benefit-to-cost ranking. Yet, if a decision-maker decides to proceed down the list of ranked decision variables so that x_k is selected, unselecting x_j would represent a strict Pareto improvement, meaning that a wBCR solution cannot be efficient. In other words, an action that was best given that some other action was not selected may no longer be efficient. A connection with hysteresis, or path dependence, can clearly be made in this case, but we leave the discussion of path dependence in watershed optimization for future work.

Three potentially important questions emerge. First, to what degree is the simulation model epistatic in the sense that "the whole is not the sum of its parts"? In the applied watershed management or policy context, the interest is often in assigning *separable* benefits associated with a particular conservation action. As discussed by Kling (2011) and Shortle and Horan (2013), separating the 'abatement' benefits in such a manner facilitates the design and implementation of the traditional policy tools such as taxes, subsidies, or trading systems. However, the presence of epistasis may lead to such policies being inefficient or ineffective in the sense that pollution reduction may be either under- or overestimated. If epistasis is present, is there a consistent pattern that may be used in subsequent policy design? Is the nature of interdependence essentially one of negative interactions, or is there a possibility of positive interactions (which can be thought about as synergies in conservation effort)?

Second, although the presence of epistasis can invalidate the Pareto efficiency of wBCR approaches, it need not do so. In that case, wBCR approaches (and the particular case of wBCR in two dimensions) as presented in numerous existing research (Feng et al. 2006; Murdoch et al. 2007; Ran et al. 2013; Duke, Dundas, and Messer 2013) may still hold significant optimization, interpretability, and policy design value, even when complex (and epistatic) simulation models are used.[1]

Third, what is the relationship between wBCR and EA approaches? Does the use of wBCR have the potential to improve the performance of EA in realistic applications with very large search spaces? And, in turn, can the EA build upon the optimization logic embedded in wBCR but improve upon wBCR solutions by exploiting the epistatic structure of the simulation model? The first part of the question relates to the notion of "seeding" the EA with a priori known or otherwise obtained members of the Pareto front. Recent examples of using "good seeds" in multiobjective EAs are provided by Hernandez-Diaz et al. (2008), Truemper (2016), and Friedrich and Wagner (2015). The basic intuition is that EAs are in a sense "blind," and the human researcher can use logic, specific domain knowledge, and other mathematical approaches to pass to the EA an "intelligent paradigm" (see Truemper 2016) that can steer the EA in the right direction and improve its performance. The consensus in the literature is that if one is able to provide a good set of initial solutions as seeds in the EA population, the EA performance is typically improved by a nontrivial amount (Friedrich and Wagner 2015), with Bi, Dandy, and Maier (2015) showing it in an applied water resources context.

The answer to the first question (on the nature of epistasis) in large part guides the likely answers to the questions on whether wBCR approaches can still be directly useful for optimization and policy design (second question),

[1] For an applied conservation example, see trade-offs developed in wBCR fashion by B. Bryant and C. Weil at https://charlottegiseleweil.github.io/webviz_natcap/intro.html.

or whether the construction of solutions based on wBCR can be useful as starting values for EA optimization (third question). Although the simulation models may be complex and not lend themselves easily to comparative static analyses, the domain of these models and their theoretical underpinnings can provide a great deal of insight. As a thought experiment, consider a somewhat contrived example of selecting household chemicals for cleaning. Both bleach and vinegar can be used separately (and could be assigned separate benefit-to-cost ratios), yet one should never choose one of these chemicals given that the other one is being used, in order to avoid the production of noxious gas.[2] In this case, the magnitude of the interaction is large enough to turn the benefit of an isolated option negative. In such cases, constructing benefit-to-cost ratios based on separate estimates of benefits is not useful. Most interaction effects in conservation or nonpoint source pollution problems are expected to be bounded so that the main effect of a conservation action could potentially be driven to zero but is not likely to be negative. Exceptions could be envisioned in cases where the site of a conservation action may become a pollution source depending on other actions in the watershed (examples may include the changes in production of greenhouse gas methane [Zhang et al. 2017] or toxic methylmercury in restored wetlands [Strickman and Mitchell 2018; Metcalfe, Nagabhatla, and Fitzgerald 2018]). Such possibilities should be elucidated at the outset by biophysical component modelers and should help guide the expectations regarding the utility of wBCR approaches.

In our application, the model structure does not allow for either "catastrophes" or "magic bullet" solutions for either sediment or wildlife. The scale of locations represented by decision variables is small and we do not expect any one location to have a major impact on the effectiveness of actions at other locations. Given these considerations, we conjecture that the nature of individual-level epistatic effects in our application is small, so the wBCR procedure is likely to prove useful. Given the number of decision variables and the structure of the simulation model, we expect that adopting the intelligent paradigm of seeding the EA with wBCR-derived solutions is likely to improve the performance of the simulation-optimization heuristic. At the same time, it is not a priori clear whether the wBCR-derived solutions can withstand the challenge by EA iterations, so the direct policy relevance of wBCR is a more open question.

[2]As explained, for example, at https://www.goodhousekeeping.com/home/cleaning/tips/a32773/cleaning-products-never-mix/. Of course, many other examples of fairly dramatic epistatic effects can be offered. The common feature is the degree of importance of taking the whole-system perspective.

3. Empirical Application

Study Area

The Le Sueur River watershed, located in southcentral Minnesota, is one of the 12 major watersheds in the Minnesota River Basin. Ecological health and aesthetics of the Minnesota River and its tributaries are affected by excess suspended sediment, measured as total suspended solids (TSS) (Belmont et al. 2011; Schottler et al, 2014). An increased TSS results in higher water turbidity, lower light penetration, and, consequently, bloom of undesirable floating algae, causing degradation of aquatic habitats, loss of biodiversity, and impairment of aesthetic quality. The water quality issues have been exacerbated in the past 150 years due to an ongoing expansion of cropland and altered watershed hydrology (Belmont et al. 2011; Gran, Belmont, and Day 2011). For example, sediment in Lake Pepin, a naturally dammed lake on the mainstem Mississippi River, downstream from its confluence with the Minnesota River, has increased by an order of magnitude since 1830 (Engstrom, Almendinger, and Wolin 2009), with 90% of the loads originating from the Minnesota River. Further, the Le Sueur watershed, as part of the Prairie Pothole Region, is an important habitat for waterfowl, but with the expansion of cropland and conversion of habitat to agricultural fields, the populations of some species have suffered a decline (Reynolds et al. 2001).

There are over 30 lakes in the Le Sueur River watershed with 1,200 miles of streams, including the Maple, Cobb, and Little Le

Sueur Rivers (Kudelka 2010). The Le Sueur River watershed is mostly rural, with 82% of the land under agricultural cultivation (Gran et al. 2011). The watershed is the largest contributor of sediment to the Minnesota River, delivering up to 30% of the river's annual sediment load, although it drains only 6% of the basin area (about 1,112 square miles) (Boettcher 2015).

Sediment Model

To model the effect of conservation actions on sediment reductions, we use a watershed simulation model, the management options simulation model (MOSM), developed by Cho et al. (2019). The MOSM simulates the movement of water and sediment across a watershed and evaluates the effects of various management options on sediment delivery and loading. It is a reduced-complexity model in which many components (i.e., spatial and temporal grids, and number of interacting state variables) and the degree of complexity (i.e., range of physical, chemical, and biological processes) have been reduced to include only those processes essential to represent the sediment transport and surface water routing. MOSM is data driven, such that it distributes the results of the physical processes from observed data, and its structure and predictions are constrained by the best-available existing information, including stream gaging records, an integrated watershed sediment budget, historical trends in watershed processes, and independent measures of outputs, such as sediment fingerprinting and a suite of geomorphic change detection outputs.

The MOSM consists of two computational modules: hydrologic routing, and sediment delivery and loading with a set of management options addressing agricultural field erosion, water conservation, and near-channel sediment loading (Appendix Table A1).

First, the hydrologic routing module simulates the changes in the time and magnitude of peak river discharge, resulting from the water conservation management option (WCMO) and the in-channel management option (ICMO). Hydrologic routing consists of a level-pool routing procedure to calculate the outflow hydrograph from the WCMO and ICMO, and a river routing procedure to evaluate the downstream river hydrology. With the simulated river discharge, the MOSM applies the near-channel sediment supply (NCSS) model (Cho et al. 2019) to estimate the sediment loading reduction in the incised river corridors of the Le Sueur River basin, where near-channel sources (e.g., streambanks and bluffs) are dominant.

Second, the MOSM utilizes high-resolution topography through TopoFilter simulation (Cho, Wilcock, and Hobbs 2018) to estimate the on-field and in-stream sediment delivery ratios (SDRs) and loading across the watershed by integrating spatially distributed information about soil loss to the integrated sediment loading at the watershed outlet. The sediment delivery and loading module evaluates the effects on sediment delivery and loading from (1) reducing soil erosion with the tillage management option (TLMO); (2) reducing on-field sediment delivery with the agricultural field management option (AFMO), WCMO, and buffer management option (BFMO); and (3) reducing near-channel source erosion with the ravine management option (RAMO) and near-channel bluff management option (NCMO) (Appendix Table A1). For more information about the MOSM, refer to Cho et al. (2019).

The MOSM, although a reduced-complexity model, is nevertheless expected to exhibit epistatic behavior in relation to the management options that affect water storage. As described by Cho et al. (2019), daily peak flow control is key to reducing in-channel-generated sediment, and field and in-channel water storage can accomplish this goal by both direct attenuation and delay (e.g., Appendix section 0.6).[3]

The conceptual source of epistasis in our sediment model is hydrologic interdependence of water-storing features along hydrologic flow-paths in the watershed, especially as it manifests itself in reductions in peak flows (the main physical driver of near-channel sediment in our model). In Appendix section 0.6, as an example of how sequential water reservoirs reduce (and delay) peak flows,

[3] See also NRCS hydrology at https://www.wcc.nrcs.usda.gov/ftpref/wntsc/H&H/NEHhydrology/ch17.pdf.

we include a "classic derivation" (in the words of Hansen et al. [2003]) in hydrology that shows that the effect of placing a reservoir in a flow-path depends on the presence of other reservoirs upstream or downstream.

Wildlife Model

For the wildlife conservation objective of increasing waterfowl populations, we use a modification of the model recently used by the U.S. Department of Agriculture to estimate economic benefits of wetland conservation in the Prairie Pothole Region. The model for estimating duck hatchlings (H) affected by the wetland restoration option ($WCMO$) is a function of the nesting pairs (NP), nest success (NS), renesting propensity (NI), and clutch size (CS) (Hansen et al. 2015):

$$H = NP \times NS \times NI \times CS. \qquad [3]$$

An additional factor, if one is focused on adult duck numbers, would be the one associated with survival from hatchlings to adult ducks (referred to as the reproductive success). It contains two aspects, the survival from hatching to fledging and the postfledging survival to recruitment, and is often measured by the number of offspring that enter the breeding population (Dzus and Clark 1998).

The use of existing nesting pair and nest success models, as well as field survey data (Reynolds et al. 2001, 2006; Mayfield 1975; Baldassarre 2014), allows us to generate estimates of these parameters for the five duck species (mallard, gadwall, blue-winged teal, northern pintail, and northern shoveler) in the Le Sueur River watershed (see Appendix section 0.3).

We should note that the model as outlined by Hansen et al. (2015) has the potential to be epistatic, as it takes, as its input, the grassland area surrounding a restored wetland (WCMO). To the extent that some other management option in our model may alter grassland area (e.g., WCMO, AFMO, BFMO), the grassland area becomes itself endogenous and induces epistasis in the model. However, the effect of surrounding grassland area is of secondary importance in the duck production model, and in this paper we abstract from this issue and use the model as nonepistatic and linear and separable in the discrete WCMO adoption decision variables.

4. Optimization and Seeding

Cost Assumptions

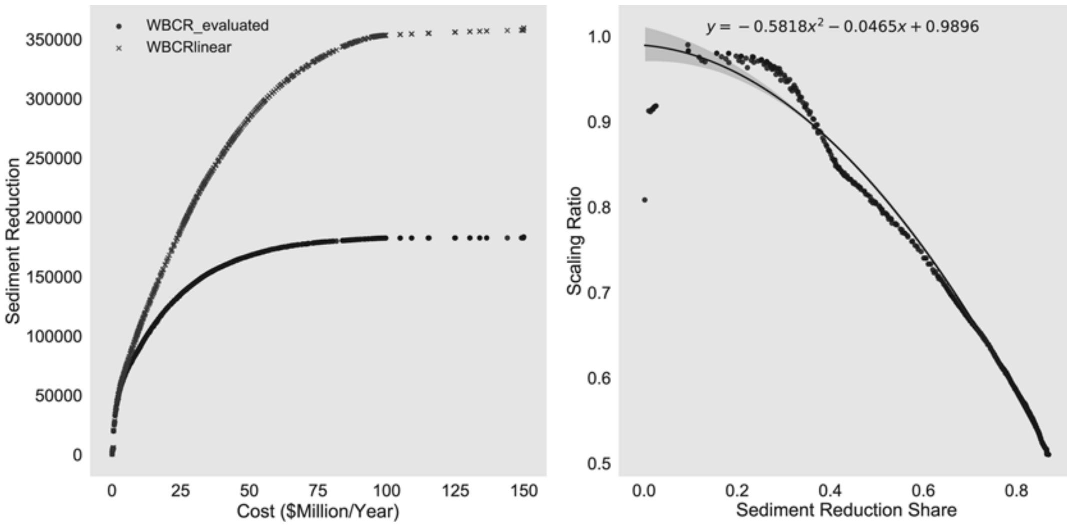
For the management options simulated, we largely maintain the cost assumptions developed by Cho et al. (2019), modifying those in two ways. First, based on Wade, Kurkalova, and Secchi's (2016) econometric estimates of costs of tillage adoptions, we use \$15/acre/year as the assumed cost of reduced tillage and \$30/acre/year as the assumed cost of conservation tillage management options. Those costs are used for the 4,626 TLMO candidate sites in the watershed. Second, for the cost of agricultural land conversion (relevant for AFMO, BFMO, and WCMO), we use area-specific real options estimates reported by Schroder, Lang, and Rabotyagov (2018) (Appendix Table A2). For the installation and management costs of the remaining management options, we use the estimates reported by Cho et al. (2019) (Appendix Table A3).

Creating Seeds

We estimate the incremental benefit from each of the modeled management options by running the simulation model one management option at a time (for each of 16,891 management options simulated) and computing the estimated sediment reduction benefit and the duck hatchling increase. Most of our management options are formulated as binary decisions, with the exception of tillage, where both reduced tillage and conservation tillage represent available conservation actions at cropland polygons in the watershed. For TLMO genes, the model was run on reduced tillage and conservation tillage, and those options were ranked using a benefit-to-cost ratio first. Uniformly, reduced tillage was a more efficient option, and a binary decision of continuing with baseline conventional tillage or adopting reduced tillage was left for the rank-

Figure 1

Overestimation of Sediment Reduction Benefit by the Linearized Sediment Reduction Function *(left);* Estimated Extent of the Scaling (Attenuation) Coefficient Needed to Adjust the Linearized Sediment Reduction Function Downward to Match Management Options Simulation Model Calculations *(right)*



ing procedure's consideration. For each gene and a weight on sediment reduction, λ, ranging from 0 to 1 in increments of 0.1, a weighted benefit-to-cost ratio was computed and scaled by multiplying it by 1,000 to avoid very small numbers. As a result, the ratio is expressed in kilograms per year of sediment reduction, and in 1 duck hatchling per dollar. The results were sorted for each λ in descending order. To create solutions based on wBCR, we selected top genes for each weight in increments of 100, assigning a "select" gene encoding to the top locations. The procedure resulted in 1,848 seeds being used.

EA Frontiers

Using the EA multiobjective optimization heuristic, we estimated three Pareto frontiers, running the algorithm to the consolidation ratio (share of solutions in the undominated archive looking 10 generations back present in the current generation) of 0.99 (Goel and Stander 2010). The first (F_0) started with a population of randomly generated solutions and did not incorporate any seeds that utilize domain-specific information or any sort of "intelligent paradigm." The second frontier (F_{unif}) included seeds that represented a zero cost baseline scenario, an "everything, everywhere" scenario, and solutions representing a uniform application of each of the MOSM options to the available candidate sites. The third frontier, $F_{\text{unif+wBCR}}$, used the 1,848 wBCR seeds in its initial population, as well as the seeds present in the F_{unif} frontier; 1,848 random seeds were inserted in the F_0 and F_{unif} initial populations to control for any effect of population size. All algorithms created a temporary population of 16 individuals per generation and used a single-point crossover with 1.0 probability, and a mutation rate of 0.003 was applied (with $16{,}891 \times 0.003 = 51$ expected random changes in every individual).

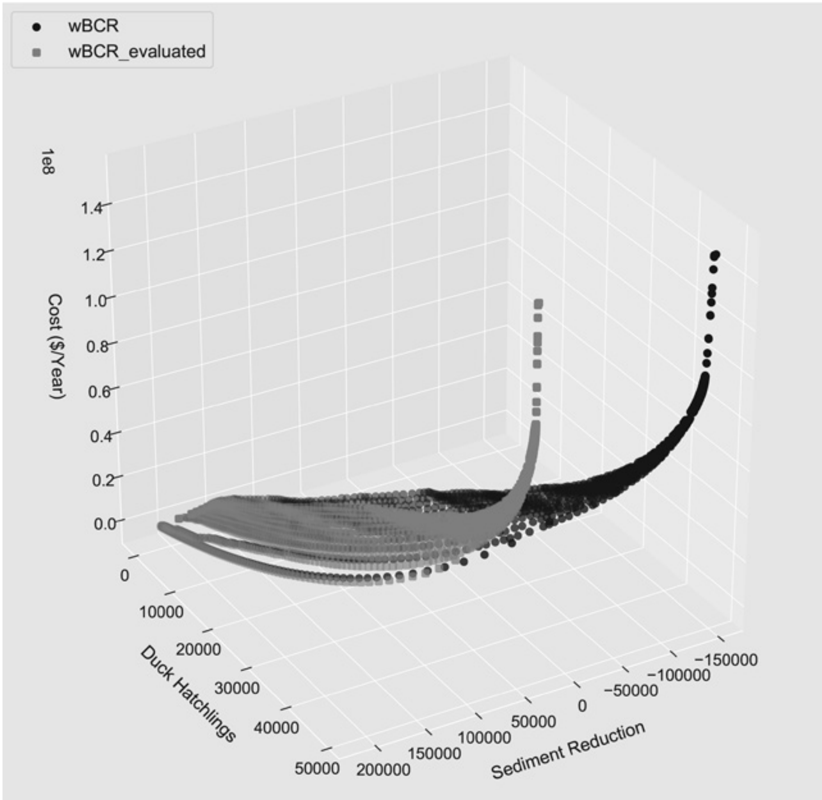
5. Results

Epistasis: Evaluation of wBCR Using the Simulation Model

The evaluation of wBCR demonstrates the effect of epistasis in the sediment model, in the sense that "the whole is not the sum of its parts" ($S(\mathbf{X}) \neq S_0 - \sum_{k=1}^{K} b_k x_k$). Simply add-

Figure 2

Pareto Front Estimated Using the wBCR Method, with Objectives Evaluated via Linear Approximation *(black)* versus Objectives Evaluated Using Simulation Models *(gray)*



ing the separate abatement benefits of each part generates the result that the total sediment reduction surpasses the sediment baseline. Figure 1 (left) shows all the nondominated solutions from scenario where $\lambda = 1$, that is, considering only the cost and sediment in the objective space, where the epistasis is depicted by the overestimation of sediment reduction by the linearized version of the model $(S(\mathbf{X}) > S_0 - \sum_{k=1}^{K} b_k x_k)$. Thus, there exists an attenuation of sediment reduction benefits as more effort is devoted to sediment reduction (a common finding in sediment reduction applications, as shown by Ran et al. [2013]).

Similarly, we compared the wBCR solutions based on linearization of sediment and duck benefits with the same wBCR-generated solutions evaluated via the MOSM and duck production models for the entire range of sediment objective weights ($\lambda = 0$ to $\lambda = 1$). Since the duck production model is not epistatic, the results are identical for the $\lambda = 0$ case. However, as the weight placed on sediment increases, the divergence between the two frontiers grows (Figure 2).[4] Since adding individual sediment reduction benefits overestimates the model-estimated benefit, at a certain point linearized benefit even surpasses the baseline, resulting in unreasonable (negative) values of outlet sediment (baseline less estimated sediment reduction).

One can further quantify the extent of epistasis present by finding, for a particular level

[4]Visualization available at https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/HIBNRC (3d-lambdaBCR.html).

of λ and cost, a scaling coefficient $\mu(C, \lambda)$, which would result in

$$S(\mathbf{X}) = S_0 - \mu(C, \lambda)\sum_{k=1}^{K} b_k x_k. \quad [4]$$

For example, for the case of $\lambda = 1$ we plot such scaling ratios as a function of desired sediment reductions (and the associated cost) in Figure 1 (right). The scaling ratio generally decreases with desired sediment abatement, although the empirical pattern is not monotone. Based on the differences between the two wBCR frontiers in our case, it is possible to "correct" for the epistasis in the linearized wBCR by scaling down the individual sediment reduction coefficients before doing the linear summation. We do point out that the epistasis adjustment depends on the specific level of desired sediment reduction, and a generally decreasing pattern in the adjustment factor is intuitive: at very low sediment reduction levels, efficient management options affecting water storage can be found in hydrologically independent locations and no adjustment is necessary; yet as desired sediment reductions grow, selecting more management options in connected flow paths becomes necessary, and accumulated redundancy in terms of water storage manifests itself in larger attenuation (smaller scaling coefficient). For example, for the 20% sediment reduction, the effects of epistasis seem trivial, so the adjustment will also be insignificant (scaling ratio ≈ 1). However, for the 50% sediment reduction, we should consider multiplying the sediment coefficients by a 0.8 scaling ratio to correct for the benefit overestimation caused by epistasis. In practice, one could develop approximate scaling ratios as functions of desired abatement levels and the appropriate weights given to different objectives (a sample quadratic epistasis adjustment function for $\lambda = 1$ is shown in Figure 4). Such adjustments can be used in the development of effective (although second-best) incentive policies such as taxes, subsidies, or trading schemes that would not overestimate an individual action's contribution to pollution reduction at the watershed outlet. Note that the scaling relationship is distinct from the often discussed "delivery ratio," as linearized incremental benefit estimates already implicitly incorporate such delivery ratios by evaluating sediment at the watershed outlet.

6. Estimated Frontiers

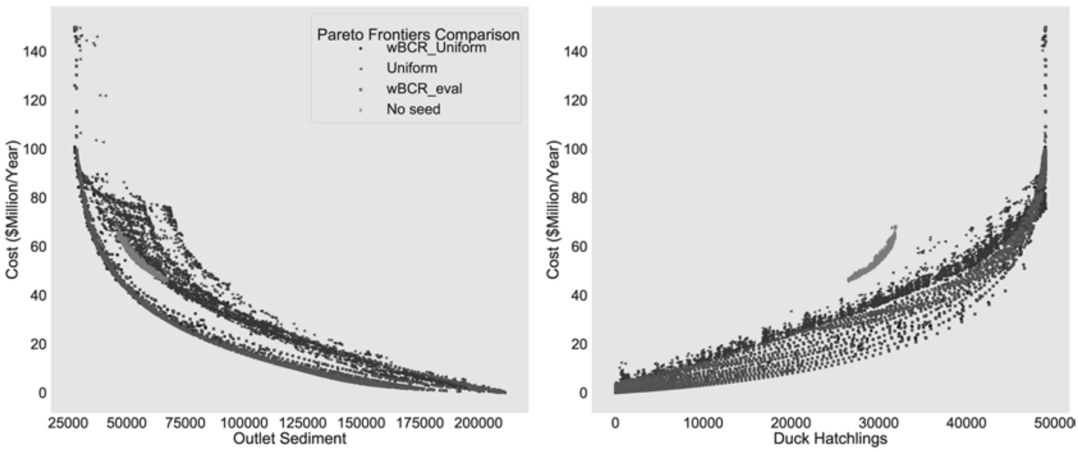
Poor Performance of Unseeded EA

Figure 3 presents the projections of the estimated Pareto fronts in sediment-cost and duck-increase-cost spaces. The first thing we note is that the estimated Pareto front discovered by the EA in a completely unguided fashion, F_0, is quite inefficient. Although it manages to converge, in part, to the F_{unif} front at its lower envelope in sediment-cost space (Figure 3, diamond marker front [or see the purple front in Appendix Figure A4] approaching the lower envelope of F_{unif} at around 50,000 tons of sediment level), it fails to do so in the duck-increase-cost space in a fairly dramatic fashion, where the projections of the two fronts do not even overlap. Furthermore, the unseeded approach fails to provide good coverage of the objective space. We can be fairly confident in not recommending running EA heuristics on a realistic problem without incorporating any domain-specific knowledge about the nature of trade-offs.

Although the presence of epistasis led the linearized wBCR to overestimate sediment reduction in the objective space, 90% of the wBCR solutions are still nondominated after the challenge by the EA. This means that in our example, the Pareto efficiency of wBCR approaches (in terms of its ability to find the solutions in the decision space) has largely been maintained in the presence of epistasis. Sediment abatement is concave in effort, suggesting that adoption of a management option attenuates the sediment reduction benefit at other management options as compared to the incremental benefit estimated in isolation. However, this attenuation does not appear to drive individual management options' sediment reduction to zero, as that could cause the EA to exploit such effects and eliminate wBCR-based solutions from the Pareto front. Thus, the wBCR approach, efficient under incorrect assumptions regarding the sediment objective function, is mostly efficient under the simulation approach as well.

Figure 3

Estimated Pareto Fronts (Seeding Benefits)



Benefits of Seeding

First, we see that the seeding approach we relied upon previously (e.g., Rabotyagov, Jha, and Campbell 2010) clearly outperforms the unseeded EA results, with F_{unif} clearly more efficient than F_0. However, given the very large search space in our applied problem, we can improve upon F_{unif} by incorporating solutions obtained using the wBCR approach. In fact, seeding the EA simulation model with wBCR-derived solutions does improve the performance of the EA in our application. Comparing $F_{\text{unif+wBCR}}$ with F_{unif}, $F_{\text{unif+wBCR}}$ generated solutions that dominate the ones from F_{unif}, supporting our hypothesis that adding our 1,848 wBCR seeds would significantly improve EA performance in both the sediment-cost and duck-cost dimensions. Efficiency gains are not trivial: for example, at the 100,000 tons/year sediment loading level (roughly a 53% reduction in sediment), $F_{\text{unif+wBCR}}$ contains solutions attaining that level at about the cost of $15 million annually, while the F_{unif} frontier dictates expenditures of upward of $27 million (a 45% inefficiency). Similarly, in the duck-cost space, obtaining 30,000 hatchlings is estimated to cost $16 million in the $F_{\text{unif+wBCR}}$ frontier, with roughly double that cost found in the F_{unif} front. Compared to a limited seeding approach, the magnitudes of efficiency gains from using wBCR-derived seeds are large. Not surprisingly, the gains are largest in the middle of the objective space, as F_{unif} "pins down" the endpoints of the Pareto front by using the zero cost baseline and the "everything, everywhere" scenario.

Even though the wBCR method does not necessarily result in Pareto-efficient solutions, we find that using the method to initialize the EA search improves EA performance substantially, and that the method produces solutions, 90% of which survive the EA challenge. The practitioners of EA-inspired simulation optimization may wish to generate scenarios based on wBCR or similar methods appropriate to their problem and test their efficiency in the EA framework. Running EAs already requires that the researchers do the (often substantial) work of being able to iteratively run the relevant simulation models, so the marginal cost of testing wBCR seeds (in addition to other scenarios that may be conjectured to perform well) is likely to be small. The benefits are twofold. If the problem is similar to the one we analyze here, large efficiency gains are possible compared to unseeded EA approaches. Even if wBCR solutions do not perform well, the researcher will have more confidence in interpreting and communicating EA results knowing that those results have been compared to the wBCR approach directly.

In fact, in our application, upon completion of the analysis, one can argue that the use of an EA for optimization is largely redundant, as a Pareto front of reasonable quality could be obtained by (1) running the model in a one-at-a time fashion to obtain incremental benefit estimates for each decision-making unit, (2) constructing the wBCR and sorting the decision-making units in a descending fashion, and (3) running the model for the solutions obtained via the sorting procedure to produce the trade-off frontier in objectives space. This finding is not expected to hold in general for all environmental (and water quality in particular) models. However, we believe that several features of the model employed in this application contribute to such finding. First, by design, the wildlife objective in the model is nonepistatic, and wBCR procedure can find efficient solutions along this dimension ($\lambda = 0$) exactly. Second, for sediment-reducing options that did not involve hydrologic routing, interaction (epistasis) effects were abstracted away at the stage of MOSM design. Finally, individual management options involving water storage (and thus expected to exhibit epistatic effects) are small compared to the overall scale of the watershed, and a selection of a single particular wetland, while decreasing the incremental effectiveness of other candidate wetlands, did not do so in a manner (1) strong enough to reduce the incremental effectiveness of another wetland to 0 and/or (2) disparately enough across candidate wetlands to be able to reverse the wBCR rank order. Thus, we conjecture that for models exhibiting similar characteristics, linearizing the model for purposes of optimization may be acceptable (although the performance of the solutions should still be simulated using the original process model), while applications involving decision-making units that are expected to be both interdependent and individually significant in terms of overall objectives may benefit from the wBCR procedure as a seeding paradigm, yet may require additional computational effort in exploiting epistatic effects in simulation optimization.

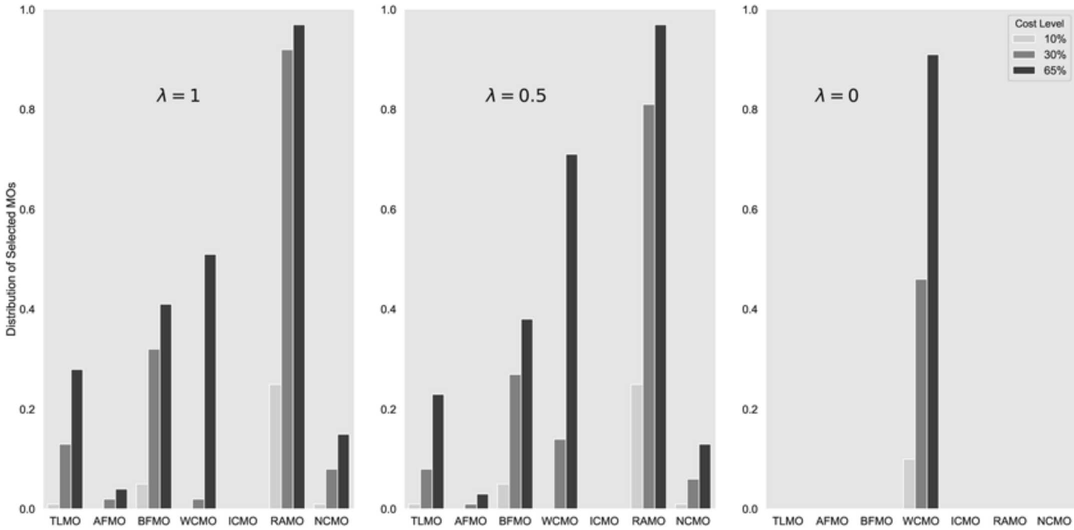
Selected Efficient Solutions

As we mention above, 90% of the wBCR solutions survived after the EA iterations and became members of the $F_{\text{unif+wBCR}}$ frontier. The weight λ represents the relative importance of duck hatchlings increase over sediment reductions in the wBCR method. Thus, a convenient consequence of most wBCR solutions surviving in the best estimated Pareto front is that solutions can be directly interpreted in light of the weight given to the environmental benefit objectives. When $\lambda = 1$, sediment reduction is the only priority, while $\lambda = 0$ means that we care only about increasing the duck population. At the same time, this means that at a roughly same level of cost, by choosing different values for λ, the solutions demonstrate the presence of trade-offs or synergies in the benefit dimension. For example, if we focus on the solutions at the level of the cost associated with a 30% sediment reduction at $\lambda = 1$, then such exclusive focus on sediment has a cobenefit of 587 ducks produced. However, at a similar cost level, the cobenefit of duck production goes up to 3,681 hatchlings for the solutions obtained using an equal weight on 1 ton of sediment decrease or a 1 duck hatchling increase ($\lambda = 0.5$). At the same time, one sacrifices only 1 percentage point in terms of sediment reduction (solution #1800050 obtaining a 29% sediment reduction versus solution #1100100 leading to a 30% sediment reduction). Focusing on ducks at the intermediate level ($4 million per year cost) can deliver less than a third of potential sediment reductions (9% sediment reduction). At the significantly higher cost level of over $26 million (associated with a Le Sueur Watershed Council goal of a 65% sediment reduction), the trade-offs are much less pronounced, as the intensity of management option adoption leads to a greater extent of cobenefits (synergies in environmental benefits).

These features of the solutions in the Pareto frontier emerge as a result of the structure of the management option evaluated. WCMO is the only management option that directly benefits duck production, so when $\lambda = 0$, the efficient solutions choose only WCMOs. Ten percent, 45%, and 90% of WCMOs are chosen, respectively, with a similar cost level for 10%, 30%, and 65% sediment reduction. The proportions of WCMOs are 0%, 2%, 50% for $\lambda = 1$ and 0%, 15%, 70% for $\lambda = 0.5$, which indicate that WCMOs become a less cost-efficient option as we put more weight

Figure 4

Distributions of Selected Management Options (MOs) for Different Weights on Sediment and Duck Objectives for the Solutions in Table 1



on sediment reduction. Instead, the ravine stabilization option (RAMO) has a 25%, 92%, 97% rate of selection at $\lambda = 1$ and 25%, 92%, 97% at $\lambda = 0.5$, which implies its relatively high cost-efficiency for sediment reduction. Meanwhile, the grass buffer option, BFMO, also plays a relatively important role in sediment reduction since it has 5%, 30%, 40% rates of selection for both $\lambda = 1$ and $\lambda = 0.5$.

Appendix Figure A6 shows the spatial pattern of management options selected for three different cost levels and weights placed on sediment and duck objectives. Figure 4 and Appendix Figure A6 taken together indicate several interesting features of management option selection in the study watershed. First, in-channel management (ICMO) is never efficient to select (due to its high estimated cost and limited effectiveness in storing water). Second, ravine stabilization (RAMO) is highly cost-effective for sediment control, and almost all candidate sites are selected even for moderate (30%) sediment reduction targets. At the same time, wetland restoration (WCMO) is not a cost-efficient option when the focus is exclusively on sediment, and moderate sediment reductions can be attained largely without any reliance on that option. Third, wetland restoration becomes necessary for the attainment of the stated watershed goal of 65% sediment reduction, with roughly half of the WCMO candidate locations restored, which leads to significant cobenefits in duck production (over 60% of maximum attainable hatchlings at that cost level). Yet, for the cost of attaining a 65% sediment reduction goal, virtually all restorable wetland sites could be converted, with large benefits for duck populations (yielding a concomitant 45% sediment reduction). Finally, the state of Minnesota recently adopted a regulatory policy of requiring riparian buffers (akin to the BFMO in our paper). We find that 100% adoption of BFMOs is not an efficient strategy, yet when sediment reduction is the goal, selecting a sizeable portion of candidate BFMO sites is cost-efficient.

Each individual map in Appendix Figure A6 can be viewed as showing the least-cost locations and combinations of conservation actions for a certain scenario in terms of sediment reduction and duck hatchling increment. The results show expected spatial patterns in terms of sediment-reducing actions concentrating near the watershed outlet and the river network, and the pattern is fairly robust with respect to relaxing the assumptions about individual benefit and cost estimates (Appendix section 0.7). We did not attempt to collapse

Table 1
Selected Solutions from the Estimated Pareto Frontiers

	Solution ID	Sediment Reduction (%)	Duck Increase	Cost ($/year)
At the Cost Level of 10% Sediment Reduction				
$\lambda = 1$	100100	10	0	573,057.62
$\lambda = 0.5$	100050	10	0	573,057.62
$\lambda = 0$	800000	1	2,322	549,465.35
At the Cost Level of 30% Sediment Reduction				
$\lambda = 1$	1100100	30	587	4,096,251.4
$\lambda = 0.5$	1800050	29	3,681	4,043,706.9
$\lambda = 0$	3600000	9	12,526	4,069,299.4
At the Cost Level of 65% Sediment Reduction				
$\lambda = 1$	5900100	66	23,386	26,598,914.96
$\lambda = 0.5$	7200050	65	29,110	26,831,805.06
$\lambda = 0$	7200000	45	37,999	26,452,110.12

the objective function into a single monetized metric, which would require models simulating the impact of a particular landscape configuration on all the relevant ecosystem services coupled with a model estimating the full economic value of the resultant pattern of ecosystem service provision. Still, a crude incorporation of existing value estimates for sediment reduction in the broader study region as well as the monetized value of ducks could be of interest. For example, Hansen et al. (2015) assess multiple studies of the economic value associated with duck hunting and use a value of $106 (in 2015 dollars) per bagged duck in their estimates of the monetary value of wetlands. To transfer the wetland's ecosystem service of duck hatchlings improvement to the economic values for duck hunting, they first applied a harvest rate of 5% (varying by duck species) to obtain the estimation of bagged ducks from hatchlings, and then multiplied it by the amenity value of $106 per bagged duck to estimate the total duck-hunting benefits. In our context, then, the expected value of an additional duck is approximately $5.00, or $2.50 (assuming a survival rate of 0.5) for each additional hatchling. So a total of 30,000 hatchlings, for instance, would result in around $0.75 million in hunting value benefits, reducing our minimum cost value of approximately 25 million by 3%. Similarly, for sediment reduction, Parveza et al. (2016) estimate the average monetary value of sediment reduction of $2.32 per ton, expressed in constant (year 2000) dollars. Applying a 5% inflation rate, the 2018 inflation-adjusted value would be around $5.56 per ton. As a consequence, a 50% sediment reduction can generate about $0.6 million in benefits, for a cumulative 5.5% cost reduction. Clearly, such a grossly simplified valuation approach misses many other ecosystem services being generated from identified landscape patterns (e.g., nitrogen or phosphorus reductions, flood control benefits), yet it highlights the need for both the incorporation of more comprehensive models of ecosystem services and valuation approaches in future work.

As in many similar studies (approximately) cost-efficient patterns of watershed conservation actions have been identified, including notional water quality objectives identified locally (a 65% sediment reduction in our application). At least three challenges loom in the policy realm: identifying or refining, in light of findings, the specific environmental targets desired by or acceptable to the local stakeholders and decision-makers; finding financial resources to support voluntary conservation actions among private landowners; and implementing a targeted policy capable of approximating efficient watershed solutions. At the very least, we find that by using a simple wBCR scheme, we can improve the circumstances surrounding those challenging decisions.

7. Conclusions and Future Directions

Simulation models are important in assessing the effectiveness and efficiency of landscape conservation actions and will likely grow in importance and relevance to environmental economics and the conservation community. Models shift the nonpoint-source pollution problem to a more manageable problem by helping to identify both the sources of pollution and the actions for pollution abatement. Despite the legitimate concerns associated with overparameterization and fundamental epistemic uncertainty in water quality and ecological models (see, e.g., Beven 2006), models are indispensable in nonpoint-source pollution research and policy proposals (see, e.g., Brown et al. [2015] in the context of water resources). In our application, we use a custom-built sediment model highly specific to the study watershed, but more generalizable modeling tools can provide the simulation component in simulation-optimization work and have been used elsewhere.

Once a simulation and scenario evaluation framework has been built, allowing assessment of scenarios of interest and setting the stage for optimization and trade-off analysis, care needs to be exercised in using EA heuristics. Many realistic applications ask for evaluation of problems with a very large search space. Adopting an EA heuristic can help in dealing with such issues, but similar to other research, we have shown that management option EAs can get bogged down and produce trade-off results that are not efficient. In our application, if we do not incorporate any domain-specific knowledge in terms of seeding, the algorithm produces results with a plausible shape for a Pareto frontier, yet those results are grossly inefficient. Incorporating more knowledge in the form of seeds brings successive improvements in performance. Some have referred to producing seeds as using an "intelligent paradigm" (Truemper 2016). We show that using more sophisticated versions of the intelligent paradigm (going from several seeds, which include likely end points of the Pareto front, to utilizing wBCR) produces marked improvements in efficiency.

In our context, the relatively familiar intelligent paradigm of using (weighted) benefit-to-cost ratios in large part produces solutions on the estimated Pareto frontier, with the EA using this information to fill out the Pareto frontier. Only 10% of wBCR solutions are subsequently dominated by the solutions found by EA. We cannot expect this to be a fully general phenomenon. That is, we expect that there will be instances where producing seeds based on a linearized approximation of the simulation model will prove to be fruitful in terms of improving efficiency, yet those solutions themselves may not survive to be members of the final estimated Pareto frontier. Even if the latter proves to be the case, results produced by EAs can sometimes be counterintuitive and difficult to interpret, both in terms of procedure used to generate the results and in terms of rationalizing the results in a manner consistent with researchers' and stakeholders' a priori expectations on what conservation actions should be chosen and where they should be implemented. At the same time, benefit-cost rules, often described in terms such as "benefit per dollar," "bang for the buck," or "return on conservation investment," are fairly well known even outside the research community and are regularly used in describing efficient allocation of limited conservation budgets to various stakeholders. Even taken in isolation of any optimization considerations, this suggests that it may be useful to generate solutions based on benefit-cost rules and to evaluate and challenge them in a simulation framework. In the current application, most of these "greedy" solutions survive the challenge, and solutions can be described directly in terms of the (weighted) benefit-to-cost ratio ranking procedure and the associated weights placed on different environmental objectives. In general, it may be the case that epistasis in the biophysical model is exploitable by the algorithm and greedy solutions get supplanted by solutions generated by an EA. Under those circumstances, the researchers and stakeholders can still be confident that a reasonable solution procedure has been tested and that EA solutions may inherit useful characteristics from the well-known ranking procedure.

In short, our findings suggest that an often useful precursor to undertaking an optimization heuristic such as an EA is to construct solutions that employ the (weighted) benefit-to-cost greedy ranking procedure. Then using these solutions one can (1) assess their performance using the simulation model employed, and (2) pass these solutions to the optimization heuristic as a way to both challenge the "conventional wisdom" embedded in benefit-to-cost ranking and provide the optimization heuristic with a set of intelligently selected starting points.

Environmental economists have long recognized that epistasis can be important, both on the environmental benefits side (e.g., Khanna et al. 2003; Parkhurst and Shogren 2007; Costello and Polasky 2004) and on the cost side, typically related to the actions of self-interested entities that can produce environmental benefits (e.g., firms or individual land owners). Schroder, Lang, and Rabotyagov (2018) deal with epistasis on the cost side in the context of watershed optimization induced by landowners owning multiple restorable wetland locations. Clearly, approaches utilizing game theory, where one agent's payoff is dependent on the actions of other agents, tackle epistasis directly (as presented by Fanokoa, Telahigue, and Zaccour 2011; Bulte and Horan 2003). At the same time, in the nonpoint-source water pollution context, complexities of ecohydrology appear to be sometimes used as a justification against implementing incentive-based policies. Kling (2011) calls for practical policies, which can be both defensible with respect to biophysical understanding of watersheds and transparently provide trading incentives to landowners, and Rabotyagov et al. (2014) explore this idea further and presented an empirical example (for a very skeptical look on perspectives of water quality trading, see Hoag et al. [2017]). Our current work recognizes complexities that are present on the biophysical side, yet we also find that, even when issues such as epistasis are present, reasonable simplifications can work well for a range of water quality improvement targets (and reasonable adjustments can be made to account for the main effects of epistasis). Simplifications, which linearize the problem and produce individual-level (as opposed to system-level) environmental benefits, can be useful for both optimization and trade-off analysis and continue to provide a basis and a rationale for a closer look at effective and approximately efficient incentive-based policies in nonpoint-source pollution problems.

Acknowledgments

This research was funded by the NSF grant EAR-1209402 and USDA-NIFA grant WNZ-A71219 under the Water Sustainability and Climate Program (WSC): REACH (REsilience under Accelerated CHange) and by the U.S. Forest Service Joint Venture Agreement 16-JV-11261975-057. We acknowledge helpful discussions with our REACH collaborators. All remaining errors are our own. The EA simulation results from different seeding paradigms are available at https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi%3A10.7910%2FDVN%2FLFSSOZ and https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/QPESTS for comparison. The MOSM documents can be found online at https://conservancy.umn.edu/statistics/stat.php?handle=11299/191082. The data and code for the duck production model estimation can be found at https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi%3A10.7910%2FDVN%2FJXSJ1G.

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