Resilient Provision of Ecosystem Services from Agricultural Landscapes: Trade-offs Involving Means and Variances of Water Quality Improvements

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We assess the trade-offs and synergies involved in reducing agriculture-generated nutrient loads with different levels of resilience. We optimize the selection of least-cost patterns of agricultural conservation practices for both the expected performance of the conservation actions and its variance. Securing nutrient loads with a higher level of resilience is costly, with marginal costs of resilience generally declining with lower loads. We find that the main trade-off dimension is between cost of conservation investments and ecosystem service objectives, as opposed to pronounced mean-variance or between-nutrient objectives trade-offs. We find relative synergies in agricultural conservation investments aimed at nutrient reductions.

Key words: Agricultural conservation practices, agricultural nonpoint-source pollution, ecosystem services trade-offs, multiobjective optimization, evolutionary algorithms, safety first, resilience.

JEL codes: Q25, C63.

In recent years, the concept of ecosystem services and natural capital has garnered significant attention from the research, policy, and conservation community (see, for example, Heal and Small 2002; Boyd and Banzhaf 2007; Zhang et al. 2007; Polasky and Segerson 2009; Barbier 2015; and a special feature in the *Proceedings of National Academy of Sciences* in 2015 devoted to the topic). For intensively managed agriculturally dominated landscapes, there can be both complementarities and competition between ecosystem services, including the provisioning services of food, feed, fuel, and clean water, the regulating service of waste processing (provided by streams), and the cultural ecosystem services tied to the presence of wildlife for hunting or recreation. Given the signals provided by agricultural markets, it is not surprising that the agricultural system heavily favors production of private ecosystem services (food, feed, and fuel) (Lichtenberg 2002, 1254). The Midwestern United States, for example, has the highest rates of crop growth in the world, to the point that agriculture affects regional climate (Mueller et al. 2016). At the same time, heavy reliance on fertilizer use has caused some scientists to suggest that humanity has exceeded its "safe operating space" with respect to nutrient loads (Steffen et al. 2015).

The recognition of these issues has led to extensive agri-environmental policy efforts in the United States and elsewhere, as well as

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literature identifying approaches for incorporating ecological objectives in policy (Lichtenberg 2002; Lankoski and Ollikainen 2003; Bateman et al. 2013). While these efforts have found some success, most scientific assessments of environmental impacts of U.S. agriculture indicate many remaining concerns. Some of these concerns include fish and wildlife habitat (U.S. Department of Agriculture–Conservation Effects Assessment Project, Wildlife National Assessment 2015), air pollution (Mueller, Mendelsohn, and Nordhaus 2011), and nutrient pollution (U.S. Environmental Protection Agency [EPA] 2015).

Understanding trade-offs or potential synergies (e.g., Karp et al. 2015) requires two things.[1] First, it is necessary to understand the underlying ecosystem service production process and the economic inputs that go into their production.[2] However, the ecological production functions themselves are often poorly understood and may exhibit complex nonlinear dynamics with thresholds (e.g., Carpenter et al. 2015; Barbier et al. 2008). Even in the best case of relatively small scientific uncertainty, they may be represented by computer simulation programs that do not correspond to traditional economic understanding of a production function (e.g., Heal and Small 2002).

A second component of a meaningful evaluation of trade-offs is an understanding of how nonmarket ecosystem services can be improved at the lowest sacrifice to marketed goods (i.e., the trade-offs given by a relevant Pareto-efficient frontier). One dimension of the trade-offs between different classes of ecosystem services is uncertainty in the provision of a particular joint product from an ecosystem. In addition to having different opportunity costs, alternative ecosystem service bundles can differ in terms of the risk associated with their provision. That is, some conservation investments may consistently yield a given bundle of ecosystem services while others may on average yield a higher level of services, but with a wider variability of provision over time. Thus, the mean-variance trade-off for a particular cost of conservation investment may be relevant in policy (e.g., Ando and Mallory 2012).

Consideration of trade-offs between means and variances of ecosystem services is closely related to the notion of resilience in ecosystem service provision. The notion of resilience is nuanced and complex, but for the sake of concreteness we adopt a definition similar to one used in Gren (2010)—namely, the reliability of ecosystem service provisions under exogenous shocks, specifically weather risk.[3] In this article, we explore trade-offs for the expected provision level and for different levels of resilience (specified as simulated probability of attaining the desired provision level) for the case of a single nonmarket ecosystem service and then expand the notion of trade-offs to multiple dimensions of aquatic ecosystem services where we focus on the joint probability of meeting desired ecological targets.[4] To do so, we adopt a multi-objective optimization approach with the objectives specified as means and standard deviations of desired ecosystem outputs. For this application, we focus on a heavy agricultural watershed in Iowa and use nutrient loads as proxies for aquatic ecosystem services. This approach is relevant to situations where the connection between human actions on the landscape and ecosystem services is characterized by a complex relationship involving nonlinearities, nonconvexities, and nonseparabilities (for example, conservation network design as in Parkhurst and Shogren 2007).

Resilience in the Provision of Ecosystem Services

The concept of resilience has been used extensively by many disciplines, each approaching the concept from somewhat different perspectives and providing different definitions. We refer the reader to Longstaff, Koslowski, and Geoghegan's (2013) typology and translation

[1] Heal et al. (2001) called the presence of synergies a "conservation umbrella."

[2] See Heal and Small (2002) for an interesting distinction between economic and noneconomic inputs into the ecosystem services production function. Economic inputs have opportunity costs, while others, like sunlight needed for agricultural production, although essential, are noneconomic. In our application, economic inputs include foregoing crop production entirely and planting perennial grass or bringing machinery, expertise, and labor inputs for the adoption of "working land" conservation practices.

[3] Social preference for reliability of goal attainment is reflected in the required "margin of safety" in the Total Maximum Daily Load regulations, requiring either to explicitly reduce allowable pollutant loads in a watershed based on modeled uncertainty or to employ conservative modeling assumptions (http://water.epa.gov/lawsregs/lawsguidance/cwa/tmdl/TMDL-ch3.cfm).

[4] However, as Heal and Small (2002) point out, "We are powerfully ignorant about the technology that produces ecosystem services." While true, ignorance should not be a reason not to explore the implications of existing levels of understanding of some dimensions of ecosystem services production process embodied, in our case, in the ecohydrologic model. See Kling (2011) for a call to action while acknowledging the deep uncertainties involved and importance of learning and adaptive management.

of the concept among different disciplines. Intuitively, the notion of resilience deals with the ability of a system to perform desired functions under external shocks. Within the above-mentioned typology, we adopt the definition referred to as Type I resilience: the capacity of a system "to rebound and recover." Simply put, we spatially optimize the selection of agricultural conservation practices that optimize both the expected performance of the conservation actions and their variance in providing ecosystem services (Shortle and Horan 2013 suggest a similar approach).

Conceptual Model and Background

Next, we sketch a simple model to aid in the conceptual framing of our work that links the concept of resilience as defined above to a metric of joint ecological-economic outputs. We define a joint ecological-economic production function as $S(\boldsymbol{x}; \varepsilon) : \mathbb{R}^{\boldsymbol{m}} \rightarrow \mathbb{R}^{\boldsymbol{k}}$, where $\boldsymbol{x}$ is an $m \times 1$ vector of controllable economic inputs into the production of ecosystem services (e.g., land, machinery, labor, fertilizer input, conservation practices) over the relevant spatial and temporal scale, which produces a $k \times 1$ vector of monetized benefits/costs and nonmonetized ecosystem services, and ε represents exogenous factors (e.g., rainfall, solar radiation, commodity prices or government policy), which are treated as random. One of the components of the output vector serves to monetize the choices made with respect to human actions, $\boldsymbol{x}$. Depending on the availability of data and models, the monetizing component can range from a full accounting of net social benefits measuring welfare impacts of marketed ecosystem services and nonmarket values of some nonmarket ecosystem services, to simply measuring estimated engineering costs associated with $\boldsymbol{x}$. Within this joint ecological-economic metric, decision makers specify a set of desirable performance targets, $\bar{S}$. Appropriately signing outputs so that they are all desirable, the problem of resilience can be written as $\max_x P\big(S(\boldsymbol{x}; \varepsilon) \geq \bar{S}\big)$; that is, resilient actions are those that maximize the probability of meeting a desired level of monetized and nonmonetized ecosystem services.

This approach is a version of Roy's (1952) safety-first criterion.[5] Safety-first approaches have found numerous applications in agricultural and environmental economics.[6] As highlighted by Shortle and Horan (2013), Total Maximum Daily Load incorporates a safety-first approach through the requirement of a "margin of safety" constraint on the allowable watershed pollution loads. Another example is that the government of Canada considered a climate mitigation policy requiring 95% certainty in agricultural carbon sequestration credits (Rabotyagov 2010). These examples emphasize the direct policy relevance of the resilience framework and the findings from this work.

In many applications, the trade-offs associated with resilience can be appropriately formulated by minimizing the (nonstochastic) cost of achieving a single stochastic ecosystem service objective with a given probability. The resilience objective for a single ecosystem service, S_i, is typically written as a constraint, $P\big(S_i(\boldsymbol{x}; \varepsilon) \geq \bar{S}_i\big) \geq \alpha$, where α is the level of resilience (or reliability) of the system and $\bar{S}_i$ is the objective target set for the ecosystem service. Rewriting the probabilistic constraint in a deterministic form can be accomplished when the distribution of the random term is known. In this case, a deterministic constraint involving the controlled mean and variance of ecosystem service provision can be written as $E_\varepsilon(S_i(\boldsymbol{x}))+ F_z^{-1}(1-\alpha)Var(S_i(\boldsymbol{x}))^{0.5} \geq \bar{S}_i$, where $F_z^{-1}(1-\alpha)$ defines the critical value of the standardized distribution of S_i. For high desired levels of confidence α (so that $F_z^{-1}(1-\alpha) < 0$), the term $(F_z^{-1}(1-\alpha)Var(S_i(\boldsymbol{x}))^{0.5})$ has the standard interpretation of a "margin of safety" or of an "uncertainty discount." Trade-offs between costs and the resilience of providing nonmonetized ecosystem services can be quantified by the higher cost of resilience. Previous work has found resilience to be costly, with the exact level depending on the particular situation, varying from single-digit percentage uncertainty discounts for soil carbon sequestration (Rabotyagov 2010) to almost doubling the costs of pollution reduction when resilience increases from 50% to 95% (Bÿstrom, Andersson, and Gren 2000; Elofsson 2003), to a seven-fold

[5] More broadly, this kind of formulation can be described as a P-model of Chance-Constrained Programming (CCP) of Charnes and Cooper (1959), and CCP can be described as a class of anticipative (nonadaptive) stochastic programming approaches (Poojari and Varghese 2008).

[6] Of many past efforts, examples include Paris (1979), Beavis and Walker (1983), Lichtenberg and Zilberman (1988), McSweeny and Shortle (1990), Bigman (1996), Willis and Whittlesey (1998), Horan and Shortle (2011), Elofsson (2003), Gren (2008), Kampas and White (2003), and Rabotyagov (2010).

increase in costs of controlling N runoff (McSweeny and Shortle 1990).[7]

The case of no uncertainty in the opportunity costs of ecosystem services provision allows for a particularly convenient inversion of the probability statement to describe resilient levels of provision. If $\boldsymbol{x}$ is costly, the constraint will be binding and $E_\varepsilon(S_i(\boldsymbol{x}^*)) + F_z^{-1}(1-\alpha)Var(S_i(\boldsymbol{x}^*))^{0.5} = \bar{S}_i$ represents the α-quantile of the controlled provision distribution (also sometimes referred to as a claimable amount, as in Kurkalova 2005) and $\boldsymbol{x}^*$ denotes choices leading to resilient provision. When multiple objectives are brought under the joint probabilistic constraint $(P(S_i(\boldsymbol{x};\varepsilon) \geq \bar{S}_i\ ,\ S_k(\boldsymbol{x};\varepsilon) \geq \bar{S}_k) \geq \alpha^n)$, such an inversion from joint probabilities to unique quantiles is no longer possible, except for the case of statistically independent objectives, where the jointly α^n-resilient set is constructed of individual (marginal) α-resilient provision levels. Instead, combinations of individual provision levels that jointly produce the desired α-level resilience will be required.[8] In short, a simple interpretation of results as producing uniquely resilient levels for each ecosystem service target no longer applies.

Fortunately, if we ask "what is the joint resilience associated with a particular solution $\boldsymbol{x}$ and specified objectives $\bar{S}$?," the answer, expressed as a joint probability, is easy to understand. Namely, the probability is $P(\boldsymbol{x}) = \int I\left[S(\boldsymbol{x};\varepsilon) \geq \bar{S}\right]dF(\varepsilon)$. In some cases, when a single stochastic objective is encountered and a particular distribution for the random factor (e.g., normal) is assumed, the probability can be retrieved from existing tables. In cases where the ecological production process is linear and separable $(S(\boldsymbol{x};\varepsilon) \equiv \boldsymbol{s}(\varepsilon)'\boldsymbol{x})$, analytical expressions can be constructed (e.g., Kampas and White 2003). However, even for a single dimension of ecosystem service output, where the production process takes place over K locations and where multiple actions (J) are available in $\boldsymbol{x}$, construction of (conditional on $\boldsymbol{x}$) variance to arrive at the standardized ecosystem output involves estimating $\frac{KJ(KJ-1)}{2}$ terms of the variance-covariance matrix, which would account for all the spatial and action-related covariances. This is a common problem that arises in risk management, and analytical techniques, such as copula estimation, exist to aid researchers and decision makers (Cherubini, Luciano, and Vecchiato 2004).

Gren (2010) considered several abatement actions and the implied abatement correlations across actions in estimating the resilience value of wetlands for nutrient reduction; however, her analysis did not incorporate spatial correlations, and Kampas and White (2003) have shown that ignoring correlations introduces larger bias in probabilistic constraints than incorrect distribution specification. Rabotyagov (2010) considered two agricultural conservation actions as well as spatial correlation for soil carbon sequestration. However, the introduction of multiple dimensions, as well as the distributional assumptions needed to make probability statements, further complicates the issue. For instance, Kampas and Adamidis (2005) pointed out that under the log-normality assumption of pollution reduction from a single action, the sum of reductions does not follow the log-normal distribution as Gren, Destouni, and Tempone (2002) assumed.

Natural science knowledge suggests that important dimensions of $S(\boldsymbol{x};\varepsilon)$ are nonlinear and nonseparable (examples provided in Carpenter et al. 2015), and thus obtaining analytical expressions for the overall resilience value is more difficult. One issue that arises in this context is computational cost associated with evaluating $S(\boldsymbol{x};\varepsilon)$ many times. For example, we could build the objective of resilience directly into the multi-objective trade-off analysis (see Rabotyagov, Jha, and Campbell 2010), but instead we formulate the objectives in terms of means and standard deviations.

Trade-off Development

We develop Pareto frontiers for cost, mean of ecosystem services, and resilience objectives. When the economic-ecological production function can be explicitly written, exact multi-objective optimization can generate the trade-off frontier (see Polasky et al. 2008; Toth and McDill 2009). When the $S(\boldsymbol{x};\varepsilon)$

[7] An obvious source of affecting costs of resilience lies with the choice of the critical value $F_z^{-1}(1-\alpha)$. Under uncertainty about the form of the controlled distribution, one can purchase resilience with respect to distributional uncertainty by relying on the Chebyschev Inequality (e.g., Gren 2010). This, however, appears unnecessarily conservative for most practical applications.

[8] This is akin to confidence ellipses encountered in joint significance testing of regression parameters. For the introduction to the issues encountered in joint chance constraints, see Bawa (1973), Prekopa (1970), and Willis and Whittlesey (1998) for an applied agricultural economics example or Hong, Yang, and Zhang (2011) for the modern operations research perspective.

function cannot be written in a compact mathematical form but is represented by a computer simulation program, simulation-optimization methods can be used. We follow the latter approach here. Multi-objective evolutionary algorithms are powerful optimization heuristics capable of dealing with potential nonconvexities in optimization and iteratively using simulation model output to (approximately) develop multiple-objective Pareto-efficient sets in a single optimization run.[9]

We use a model of joint economic-ecological production process, where the human actions considered are "working land" agricultural conservation practices largely consistent with the prevailing crop system and "land retirement" by establishing perennial grass cover on cropland. These actions represent economic inputs into the production of (proxies for) freshwater and coastal aquatic ecosystem services associated with reducing ambient nitrogen (N) and phosphorus (P) loads.

Scientific consensus exists on the fact that human activity has altered both the nitrogen and phosphorus cycles (Millenium Ecosystem Assessment 2005, ch. 12), with some beneficial (increased crop production) and some deleterious (eutrophication) effects on ecosystem services. The exact targets for nutrient loads and concentrations are an active area of research and policymaking (Evans-White 2013; Heiskary and Bouchard 2015; U.S. EPA 2015), but it is well understood that excess nutrient loads negatively impact many ecosystem services from freshwater and coastal systems. We take as a starting point that it is desirable to reduce N and P and elucidate the trade-offs involved in controlling the mean and standard deviation of nutrient pollution.

Model Application

There are K decision-making units ("fields") in the watershed, each field being characterized by a unique combination of physical characteristics (soil, slope) and location in the watershed. The ambient water quality is monitored both in-stream and at the outlet of the watershed. Let $r_i = r_i(\mathbf{x_i},\ \xi)\ \forall\ i = 1,\ldots,K$ be the i^{th} field emissions given the actions taken at field level, where $\mathbf{x}_i$ represents the $J \times 1$ vector of actions implemented at each field and ξ represents the stochastic weather factor. The set of actions consists of baseline activity, a set of working land conservation practices, and land retirement.

Our ecological production function is a water quality production function, $\mathrm{W}(\mathbf{r}(\mathbf{x},\boldsymbol{\xi}))$, that is the result of the complex spatial interactions between the edge-of-field emissions leaving the fields, which are represented by an ecohydrologic simulation model.[10] Given the stochastic nature of weather, we are interested in finding the least-cost spatial combinations, $\mathbf{x}$, that reduce expected values of nutrient pollution as well as their standard deviations. Using optimization results, we construct a measure of resilience, defined as the probability of achieving a particular target, and analyze the trade-off between costs and different levels of resilience. We start by considering the case of a single nutrient pollutant (a proxy for diminished aquatic ecosystem services upstream and downstream) and then move to the case of two pollutants.

Single Pollutant Case

We begin by solving the multi-objective problem that simultaneously minimizes

$$(1)\quad Min_{\mathbf{x}}\ \left[C(\mathbf{x}),\ \ E_T[N(\mathbf{x})],\ \ Var_T[N(\mathbf{x})]^{0.5}\right]$$

where $\mathbf{x}$ represents a $KJ \times 1$ vector representing a particular placement of conservation practices, $\mathrm{W}(\mathbf{r}(\mathbf{x},\boldsymbol{\xi})) \equiv\ N(\mathbf{x})$ represents the simulated, over period of length T,

[9] Deb (2001) is the classic introduction to evolutionary algorithms. Nicklow et al. (2009) and Maier et al. (2014) discussed some recent applications focused on water resources, and Kennedy et al. (2008) and Porto, Correia, and Beja (2014) provided terrestrial ecosystem management examples. Herman et al. (2014) explored trade-off generation under deep uncertainty. Recent examples for trade-off development using multi-objective evolutionary algorithms in agriculturally dominated ecosystems include Gramig et al. (2013), Bostian et al. (2015), Ahmadi et al. (2013), Rabotyagov et al. (2014), and Chichakly, Bowden, and Eppstein (2013), who incorporated measures of resilience to anticipated climate change.

[10] As Lichtenberg (2002) explains, "There is not a simple monotonic relationship between emissions at the level of an individual field and impacts on environmental quality at the ambient scale with which policy is actually concerned. Fate and transport are typically non-linear and depend on space and time in complex ways, making extrapolation of field-level emissions to ambient pollutant concentrations quite complex." We refer the reader to Lichtenberg (2002) and Shortle and Horan (2013) for reviews of these and other issues associated with nonpoint source pollution from agriculture, as well as to Rabotyagov et al. (2014) for an attempt to simplify the "ecological production" process. Uncertainty in the model structure itself is not considered in this article, although we recognize this as likely important for both better science and policy relevance (see Herman et al. 2014).

vector of annual nitrogen loads, $E_T[N(\mathbf{x})]$ is the mean nitrogen load over the historical simulation period, $Var_T[N(\mathbf{x})]^{0.5}$ is the standard deviation, and $C(\mathbf{x})$ is the estimated cost of that particular combination of conservation investments in the watershed.

The solution vector $\mathbf{x}^*$ defines the Pareto-efficient set (P_f), where each element is represented by a unique combination of cost, expected nutrient load, and the standard deviation of loads:

$$(2) \quad P_f(\mathbf{x}^*) = \{C(\mathbf{x}^*),\ E_T[N|(\mathbf{x}^*)], \\ Var[N(\mathbf{x}^*)]^{0.5} \nexists\ \mathbf{x} \neq \mathbf{x}^*, \\ P_f(\mathbf{x}) \succ P_f(\mathbf{x}^*)\}.$$

That is, a pattern of conservation investments defines the Pareto-efficient frontier if there is no other conservation action pattern that is a Pareto improvement ($\succ$) in the cost-mean-standard deviation space. The Pareto-efficient frontier defines the set of optimal trade-offs; for example, the lower envelope of the set with respect to mean N and conservation action costs gives the equivalent of the total abatement cost curve for expected nutrient pollution. It also offers valuable information on the possible mean-variance trade-offs, where, for a given cost, a trade-off between expected ecosystem service performance and its standard deviation could be seen. For the single stochastic objective, it is straightforward to "collapse" the three-dimensional Pareto frontier into a set of "resilient trade-offs" between cost and resilient provision of an ecosystem service. Specifically, finding resilient solutions involves solving a chance-constrained optimization problem:

$$(3) \quad Min_{\mathbf{x}}\ C(\mathbf{x})\ s.t.\ \Pr\left\{\mathrm{N_t}(\mathbf{x}) \leq \bar{N}\right\} \\ \geq \alpha\ \forall t = 1, \ldots, T$$

where $\bar{N}$ is the target level of N loads, and α the desired level of resilience measured as the probability of achieving the target.

We use the Pareto frontier $P_f(\mathbf{x}^*)$ and employ two approaches to approximate solutions to equation (3), approaches that we label as "normal" and "nonparametric." Under both approaches, we transform equation (3) using its deterministic counterpart as:

$$(4) \quad Min_{\mathbf{x}}\ C(\mathbf{x})\ s.t.\ E_T\ \{\mathrm{N}(\mathbf{x})\} \\ +\phi^\alpha Var_T(N(\mathbf{x}))^{0.5} \leq\ \bar{N}$$

where ϕ^α is the critical value of the standardized distribution of $N(\mathbf{x})$.

The solution to the chance-constrained problem (3) must be a member of the Pareto frontier in the cost-mean-standard deviation space: $\hat{\mathbf{x}} \subset \mathbf{x}^*$. The converse is not true: a particular solution from a multi-objective optimization program need not be optimal for a chance-constraint program. The supplementary online appendix provides the demonstration of this point.

Under the normal approach, we assume the standardized distribution of the pollution load follows a normal distribution and use $\phi^\alpha = \Phi^{-1}(\alpha)$, the standard normal critical value that depends on α (1.64 for $\alpha = 0.95$). Under the normality assumption, we consider $\alpha -$ *resilient* pollution loads to be $E_T\left\{\mathrm{N}(\hat{\mathbf{x}})\right\} + \Phi^{-1}(\alpha) Var_T(N(\hat{\mathbf{x}}))^{0.5}$ and can focus on the results in terms of trade-offs between cost and resilient nitrogen loads.

Note the direct policy relevance of this approach. A watershed manager who wishes to ensure that the target is met 75% of the time rather than just 50% of the time can be informed of the additional cost associated with this higher level of resilience.

Nonparametric Approach

An alternative approach is to employ nonparametric bootstrap methods (Efron 1979) and define the resilience levels based on bootstrapped quantiles. Since our data (nitrogen loads simulated over a period of time) is serially dependent, we employ the block stationary bootstrap method (Politis and Romano 1992, 1994). Observations are resampled in blocks of random length, with the length of the block being determined by a geometric distribution. The block resampling preserves the lag dependence in the original data. The bootstrapped data is stationary if the block length is determined using a geometric distribution. Additionally, the block bootstrap works well under very weak conditions on the dependency structure of the original data.

For any efficient combination of conservation practices ($\mathbf{x}^*$) that is part of the Pareto frontier $P_f(\mathbf{x}^*)$, we take the model-simulated $T \times 1$ vector of nitrogen values $N(\mathbf{x}^*)$ to construct a nonparametric distribution via a stationary bootstrapping approach using blocks of unequal length. To obtain trade-offs involving $\alpha - resilient$ nitrogen loads, for each bootstrap replicate series, we compute the sample α-quantile and average the results over many replications. The interpretation of the bootstrapped $\alpha - resilient$ Pareto frontier is similar to the previous one, each solution representing a nondominated combination of cost and $\alpha - resilient$ nitrogen loads that corresponds to a given level of resilience, α. The magnitude of the differences between the normal and nonparametric approaches is an empirical question.

Multiple Pollutants: A Case of Nitrogen and Phosphorus

We also develop trade-offs that involve the means and the variances of multiple ecological objectives. In this case, we modify the multi-objective minimization problem to include the means and standard deviations of N and P:[11]

$$(5)\quad Min_{\mathbf{x}}\ [\ C(\mathbf{x}),\ \ E_T[N(\mathbf{x})],\ Var_T[N(\mathbf{x})]^{0.5}, E_T[P(\mathbf{x})],\ \ Var_T[P(\mathbf{x})]^{0.5}]$$

where $\mathbf{x}$ represents a particular placement of conservation practices, $N(\mathbf{x})$ and $P(\mathbf{x})$ are the vectors of nitrogen and phosphorus loads of length T, $E[.]$ is the expected water quality outcome measured as a (historical) sample mean of nitrogen and phosphorus, $Var_T[N(\mathbf{x})]^{0.5}$ and $Var_T[P(\mathbf{x})]^{0.5}$ are respective standard deviations, and $C(\mathbf{x})$is the annual cost of the particular combination of conservation investments in the watershed.

Similarly to the univariate case, the solution is represented by a Pareto set, P_f^{NP}, where each element represents a nondominant combination of cost, mean, and standard deviation values for nitrogen and phosphorus emissions associated with a spatial combination of conservation practices. As discussed above, it is more intuitive to consider actual trade-offs between mean and variance control or to characterize a particular solution in terms of the probability (resilience value) of meeting a specified target.

In order to characterize joint resilience implied by the solutions in the Pareto-frontier, we rely on the nonparametric bootstrap, now using two dimensions. Resilience is defined as the joint simulated probability of achieving both N and P targets. Similarly to the univariate stationary bootstrapping, we use the vectors of simulated nitrogen and phosphorus loads to generate bootstrap replicates using blocks of unequal length. The stationary bootstrapping procedure involves the simultaneous use of both vectors, thus preserving the correlation between controlled loads of N and P. That is, given a particular joint target $(\bar{N},\ \bar{P})$, we can construct characterization of the trade-off frontier in terms of cost, mean nitrogen, mean phosphorus, and simulated joint resilience of achieving the specified target. The resilience level is estimated as the simulated probability, $p(\mathbf{x}_i)$:

$$(6)\, p(\mathbf{x}_i) = \sum_{r=1}^{M} \left\{ \sum\nolimits_{t=1}^{T} I\Big(N(\mathbf{x})_{rt} \le \bar{N},\ P(\mathbf{x})_{rt} \le \bar{P}\Big)/T \right\} /M$$

where T is the length of the model simulation, $\mathbf{x}_i$ is the particular pattern of conservation investments evaluated, and M is the number of bootstrap replications.

To approximate the solution sets for the multi-objective problems (1) and (5), we use a simulation-optimization framework using the Soil and Water Assessment Tool (SWAT) as the ecohydrological simulation model and a modification of the Strength Pareto Evolutionary Algorithm 2 (SPEA2; Zitzler, Laumans, and Thiele 2002) as the multi-objective optimization heuristic, as described by Rabotyagov, Jha, and Campbell (2010). The simulation-optimization framework simultaneously minimizes the cost, the twenty-year means ($T = 20$), and standard deviations of annual N for the single pollutant case and for both N and P loads for the two-pollutant case.[12] The solutions are sets of Pareto-nondominated watershed configurations P_f and P_f^{NP}. To assess convergence, we use a consolidation ratio proposed

[11] If the objective were to be specified as minimizing the variance—for example, the sum, or a linear index of two nutrients—the covariance term would enter into problem specification. Alternatively, the resilience objective specified as a joint probability could be simulated within the optimization loop (as in Poojari and Varghese 2008). We leave those extensions to future work.

[12] The resulting relatively small sample size used to construct the model-simulated mean and the standard deviation is one of the limitations of the study and can introduce imprecision in resilience estimates. To the extent that mean and standard deviation estimates are not biased, we try to improve precision by bootstrapping optimized series.

by Goel and Stander (2010) and used by Rabotyagov et al. (2014).

SWAT is designed to run watershed simulations based on a wide range of inputs: weather data, soil characteristics, plant growth and crop rotations, nutrient management, nutrient transport and transformation, and land use and management practices. This process model can be used to estimate the changes in nutrient emission in response to changes associated with alternative conservation practices, crop choices, and rotation alternatives. The model is maintained by the U.S. Department of Agriculture and has been used in a wide range of applications (Arnold et al. 1998; Arnold and Fohrer 2005; Gassman et al. 2007).

Study Area: Boone River Watershed

The Boone River watershed is a typical agricultural watershed in central Iowa with more than 90% of its area dedicated to corn and soybean production. The watershed's tributaries offer critical habitat to the Topeka shiner (*Notropis topeka*), a federally listed endangered species, and to other fish and mussel species. Additionally, the watershed tributaries feed the Des Moines River, a major water source for the biggest metropolitan area in Iowa. The lower part of the watershed is used for recreation activities.

Given the extent of the agricultural activities, high levels of agriculture-contributed nitrogen, phosphorus, and sediment loads contribute to the water quality impairments. A successful calibration for the current Boone River watershed SWAT baseline was obtained by using monthly streamflow and nutrient data and incorporating earlier calibration efforts (Gassman 2008).[13] The set of conservation practices selected for achieving the nutrient reduction includes working land practices: cover crop, no-till, the combination of cover crops and no-till, and land retirement. Typically, cover crops are grown during late fall and early spring. In the Midwest, where there are no markets for cover crops, cover crops are promoted for their direct environmental benefits (recycling nutrients and preventing nutrient leaching) and indirect economic benefits (improving soil health by preventing soil erosion). Cover crops are effective in reducing both nitrogen and phosphorus losses. No-till is a type of tillage where no more than 30% of the crop residue is removed. No-till is effective in reducing erosion and phosphorus runoff. Land retirement involves taking land out of production and the establishment of perennial grasses.

The cost estimates for conservation practices used in this study are drawn from several sources: no-till at $6 per acre (Iowa State Extension budgets), cover crops at $35 per acre (Iowa Nutrient Reduction Strategy), $41 per acre for the combination of no-till and cover crops, and $254 per acre for the average cash rental rate for the watershed (Iowa State Extension cash rental rates estimates) as the cost of land retirement. The cost of conservation practices is additional to the cost of baseline activities, considered to be zero in this application. One expects the actual farmers' willingness to accept such conservation practices to vary throughout the watershed (e.g., Lynne, Shonkwiler, and Rola 1988). Data and space limitations lead us to leave the important issue of cost heterogeneity to future research (although, see Latacz-Lohmann and Schilizzi 2005 and Rabotyagov et al. 2014b for relevant ideas related to implementing efficient conservation efforts).

Results and Discussion

The simulation model allows us to evaluate counterfactual watershed scenarios in terms of estimated costs of conservation practices and their implications for mean and variance of corresponding annual nutrient loads from 1993 to 2013. We estimate the Pareto-efficient frontiers for a single pollutant (N) and multiple pollutants (N and P). In the first part of our analysis, we focus on the total level of emissions (loads) by offering a short analysis of the mean-variance trade-offs and how these trade-offs relate to the choice of the conservation actions. Next, we analyze the trade-offs between achieving a pollution target with a given resilience level and the estimated cost of conservation actions. The set of resilience values (α) ranges from 50% to 95% in 5% increments, as well as 99%. Nutrient pollution targets are chosen as a

[13] The present SWAT simulations are being performed with an updated SWAT version 2012 code (SWAT2012, Release 6150, which contains corrected algorithms that more correctly simulate movement of nitrate through subsurface tile lines, as well as numerous other enhancements that were not present in the SWAT2005 code).

range of percent reductions from the historical baseline loads.

Single Pollutant Case: Nitrogen, Mean-variance Trade-offs

The results of the multi-objective optimization defined by equation (1) can be visually depicted by a three-dimensional scatter plot (P_f), where each point on the frontier represents the least-cost watershed configuration that achieves a given expected value of N loads and has the lowest standard deviation (see figure A.2 in the supplementary online appendix). Figure 1 depicts the extent of the mean-variance trade-offs from the frontier. Specifically, figure 1(a) shows a fairly linear positive relationship between the mean and the standard deviation of N loads, as standard deviation increases with the mean. Additionally, the analysis of the mean-coefficient of variation (ratio of standard deviation to the mean) plot (see figure 1[b]) shows three patterns: a steep increasing trend for the low range of N loads (below 3,000 tons) where the standard deviation increases at a faster rate than the mean, followed by a smoother declining pattern where the standard deviation increases at a slower rate than the mean. For larger loads (above 4,500 tons), the ratio of standard deviation to mean settles around 0.5. These patterns can be explained by the distribution of the conservation practices selected by the algorithm (see the supplementary online appendix, figure A.3).

Next, we quantify the cost to achieve a particular level of nitrogen loads under different levels of resilience. More explicitly, for any level of resilience, α, we construct resilient Pareto frontiers, where each Pareto frontier can be viewed as the total cost curve for which the corresponding N loads are achieved with probability α. As previously described, we use two approaches (normal and nonparametric) to construct the resilient Pareto frontiers that correspond to different resilience levels. The normal approach assumes that the standard normal critical values are used to weigh the standard deviations while the nonparametric approach uses stationary bootstrap to simulate the quantiles. Simulated nutrient load series pass stationarity tests, and we use 10,000 bootstrap replications with a mean block length of 5. The new Pareto frontiers transform the mean N values of the original Pareto frontier into α-resilient levels while keeping the costs and the watershed configurations unchanged.

Figure 2 depicts the α-resilient Pareto frontiers for four levels of resilience: median (50), 75, 90, and 99, given the two approaches, as well as the mean-cost trade-off. The horizontal axis depicts the resilient loads, and the vertical axis shows the total annual costs. Notice that under the normal approach (left panel), the corresponding levels of resilience for mean and median are identical, while under the nonparametric approach the two trade-off frontiers are different, with the bootstrapped mean trade-off frontier being entirely above the median (right panel). Under both approaches, the α-resilient Pareto frontiers move further away from the left corner as resilience levels increase. For any cost level (consider a horizontal line), the resilient level of N loads increases as we move from one frontier to another. This shows us how much resilience can be achieved under a given budget. Likewise, for any level of resilient N loads, the cost increases as we move from one frontier to another. The vertical distance between frontiers represents how much it would cost to make the same level of N load more resilient.

Next, we analyze the trade-off in achieving different pollution targets at different resilience levels. One way to analyze these trade-offs is, for any given target, to construct cost-resilient curves corresponding to an α-resilient N target expressed as a percentage reduction from the baseline. As expected, more stringent targets (higher percentage reductions, lower loads) cost more, and the costs of achieving a given target increases with the resilience level. For less stringent targets, the costs-resilience curves are convex, with nonconvexity patterns for more stringent targets. For example, when the target is set to a 70% reduction, the cost is flat once a high level of resilience (80) is achieved. More details, including a visual depiction of these curves, can be found in the supplementary online appendix (figure A.5).

Resilience: Marginal Cost Curves

Another way to analyze the resilience-cost trade-off is to answer the question of how much it would cost to achieve an additional level of resilience. We focus our analysis on three levels of reductions: low (20%), average (45%), and high (70%). For each of the three targets, figure 3 summarizes the cost curves

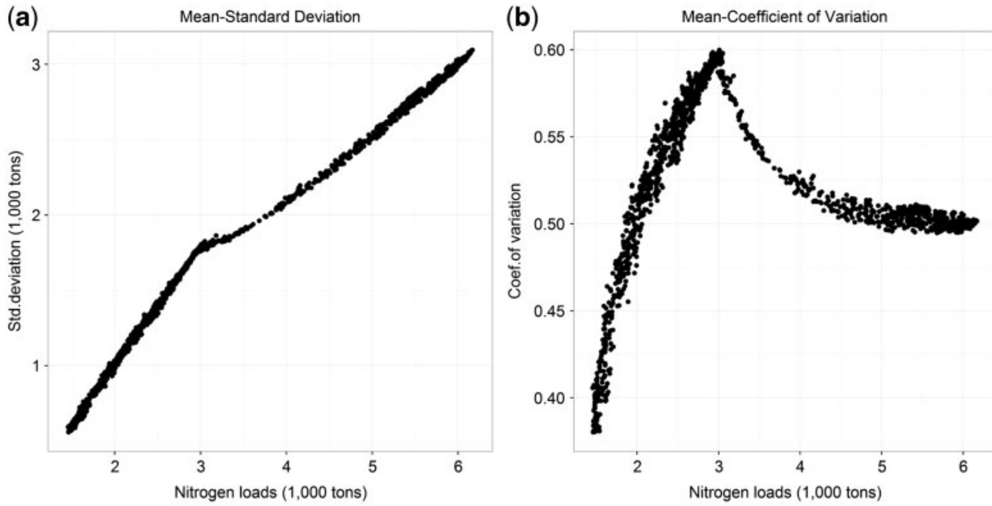

Figure 1. (a) Mean-variance trade-offs; (b) mean-coefficient of variation

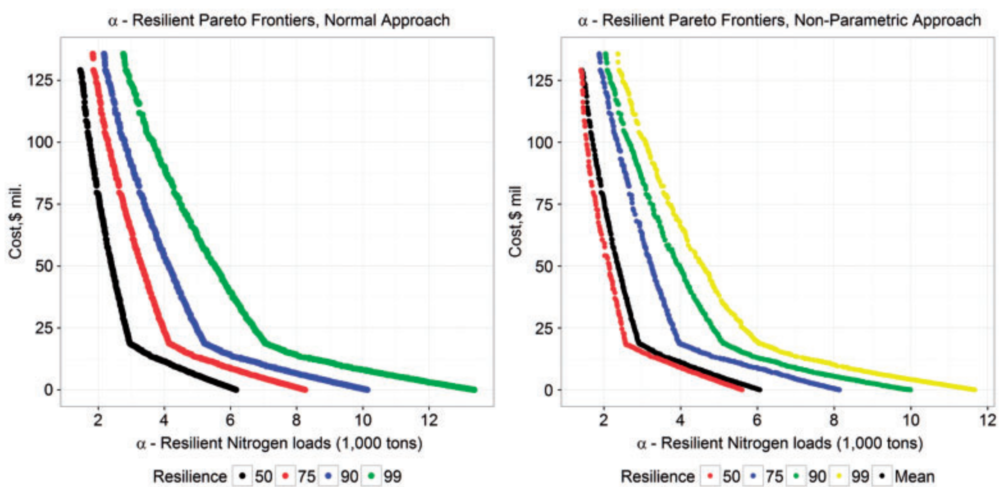

Figure 2. α Resilient Pareto frontiers (left: normal approach, right: nonparametric approach)

for securing the targets at an additional resilience level under the two approaches. These curves can be interpreted as the marginal cost of resilience. Although the marginal cost curves have a similar shape, their magnitudes differ across the two approaches. The marginal cost curve when the target is low (20% reduction) is almost flat for resilience levels lower than 80. However, for higher resilience, the marginal costs display a sharp increase, with the increase being sharper under normal approach. The marginal cost curve for the intermediate target displays more than one pattern. Under the normal approach (figure 3, left panel), marginal costs are increasing for lower resilience, flat for moderate resilience, and increasing for higher resilience levels. However, the patterns are different under the nonparametric approach (see figure 3, right panel): relatively flat for lower levels, increasing for moderate levels, and decreasing and flat for higher levels of resilience. The marginal costs for the most stringent target are increasing for lower levels, decreasing for moderate levels, and flat for higher resilience levels under both distributional approaches. The diversity of patterns across targets and resilience levels can be explained by the distribution of the conservation practices (these are provided in table A.1 of the supplementary on

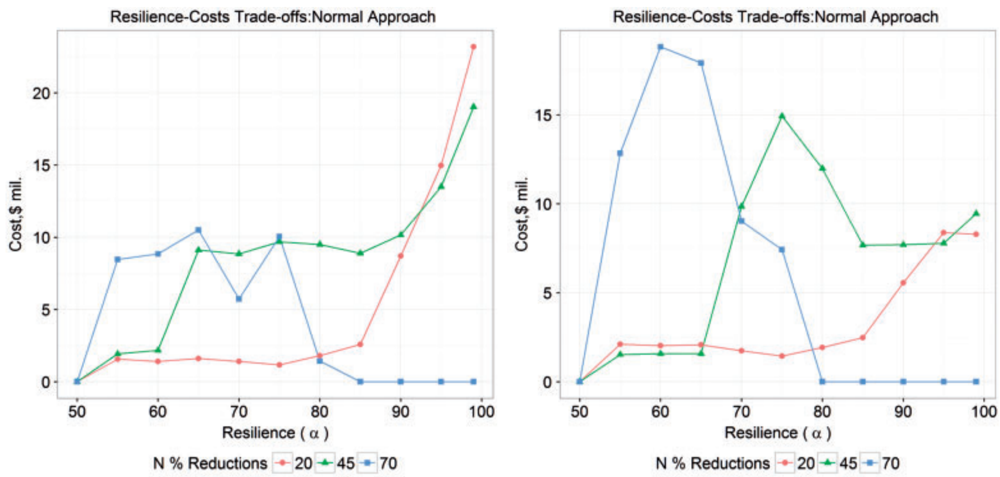

Figure 3. Marginal costs of additional resilience for different resilient N targets

line appendix). The costs of achieving resilient loads corresponding to 45% reductions range from 13 million to 87 million over the considered resilience levels. Similar to McSweeny and Shortle (1990), we find that to control a single-year N load with 99% resilience is almost seven times costlier than controlling N with median resilience.

Resilient N Loads for Different Cost (Budget) Levels

The α-resilient Pareto frontiers can also provide insight into the different load levels that can be secured under different levels of resilience when we impose a limit on total costs (iso-cost curves). Figure 4 can be used to see how much resilience can be obtained under a given budget. Next, we present the results for four cost (budget) levels: 10 million, 20 million, 50 million, and 100 million. For each budget level, we construct iso-cost curves showing the trade-offs between resilience and different levels of attainable loads.

Figure 4 shows that the iso-cost curves are increasing (with curves developed under the normal approach being convex), showing that when keeping the cost (budget) constant, higher levels of required resilience translate to higher levels of loads, or, alternatively, lower load levels have lower resilience levels. The empirical findings also show that the size of these trade-offs decreases as the total costs (budget levels) increase as the iso-cost curves corresponding to lower budgets tend to have steeper slopes (more evident in the nonparametric approach). For any of the chosen budget and any resilience levels, smaller loads (more reductions) can be claimed under the nonparametric approach (see figure 4, right vs. left panel), suggesting that the normal approach is more conservative in this case.

Multiple Targets: Nitrogen And Phosphorus

Next, we present the simulation results for the case when two pollutants (N and P) are jointly targeted. We approximate the Pareto frontier for five objectives: cost and means and standard deviations of N and P. The Pareto frontier we obtain is valuable in that it can show the nature of trade-offs along different values of N and P, as well as corresponding variability and cost.

Visualizing across five dimensions is challenging but can be aided by radar (spider) plots. Specific solutions of interest (a few at a time) can be analyzed as well. The top row of figure 5 plots a few solutions to demonstrate relevant trade-offs and synergies of particular interest (e.g., mean–standard deviation comparisons in the left column of figure 5 and mean N and mean P comparisons in the right column). The plots show fairly strong negative correlation (trade-offs) between values of cost and means and standard deviations of nutrient loads, with generally positive correlations among nutrient means and standard deviations. When we plot all efficient solutions (bottom row of figure 5), we lose the ability to distinguish individual solutions but gain some visual insight into the nature of the overall pattern of trade-offs and synergies.

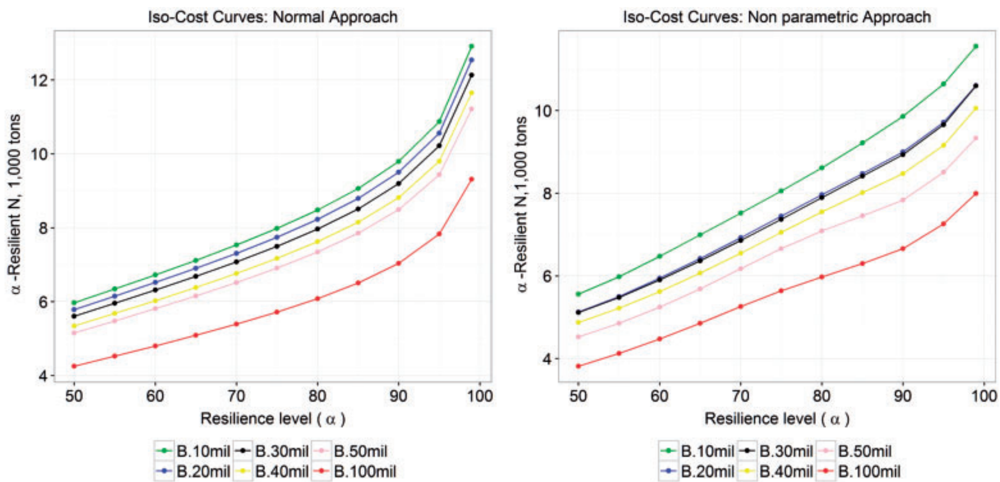

Figure 4. Resilience: iso-cost curves (left: normal approach, right: nonparametric approach)

Consider the bottom-left panel of figure 5, and the mean N, mean P, and cost axes. The nonconvex shape of the plot between those axes says that there are no solutions in the Pareto frontier that simultaneously have high cost and high mean N and P loads (compensating for those with smaller values on other axes). This suggests a strong trade-off existing between mean nutrient loads and cost. A convex shape with respect to other axes does not mean that trade-offs do not exist among the remaining pairs of objectives but that there exist efficient solutions that exhibit synergies (comovement) along those dimensions. For example (figure 6), trade-offs between N and P control exist, but synergies are also present (pairwise comparison of mean N and P on the bottom-right panel of figure 5). A presence of at least some synergies is also apparent by considering pairwise trade-offs between means and standard deviations (consistent with the limited nature of mean-variance trade-off for N explored in figure 1[a]), whereas, as can be seen from the nature of the trade-offs between costs and standard deviations (shown on the right panel of figure 5 for the case of standard deviation of P; N results are similar), there are no synergies between cost and risk and we see strong trade-offs consistent with the notion that resilience is always costly (the lower the standard deviations, the higher the costs). However, we do not see strong trade-offs between means or standard deviations of nutrient reduction objectives.

Next, we make the connection to resilience. Since we are interested in the joint constraint $\Pr\{N_t(\mathbf{x}) \le \bar{N},\ P_t(\mathbf{x}) \le \bar{P}\} \ge \alpha\ \forall t = 1, \dots, T$, we cannot be assured of joint resilience optimality of solutions obtained by the multi-objective program as the algorithm does not directly simulate the joint probability. However, we can still provide an *ex post* assessment of the solutions in terms of joint resilience. To do so, we again rely on the (now joint) nonparametric bootstrap approach, using 10,000 replicates and computing the simulated resilience using equation (6).

A three-dimensional illustration of these trade-offs when the targets are set equal to 45% reductions for both N and P (equation 9) is presented in the supplementary material (figure A.6). Each element on this frontier (a three-dimensional projection of the five-dimensional Pareto frontier) is assessed for a resilience (probability) level of achieving this joint target. Figure 6 shows the results of the frontier assessment for joint resilience. Consistent with our expectation, not all members of the Pareto frontier are efficient with respect to cost and resilience when a specific nutrient objective is specified. But, as the lower envelope of data in figure 6 shows, the estimated frontier does show that higher resilience generally comes at a higher cost. Figure 7 depicts the marginal costs of achieving additional levels of resilience for the three specified targets, while table A.2 (see the supplementary online appendix) describes in detail the total and marginal costs, as well as the distribution of conservation practices. The overall pattern of joint resilience assessment of the five-dimensional frontier for a range of targets may suggest that, for the

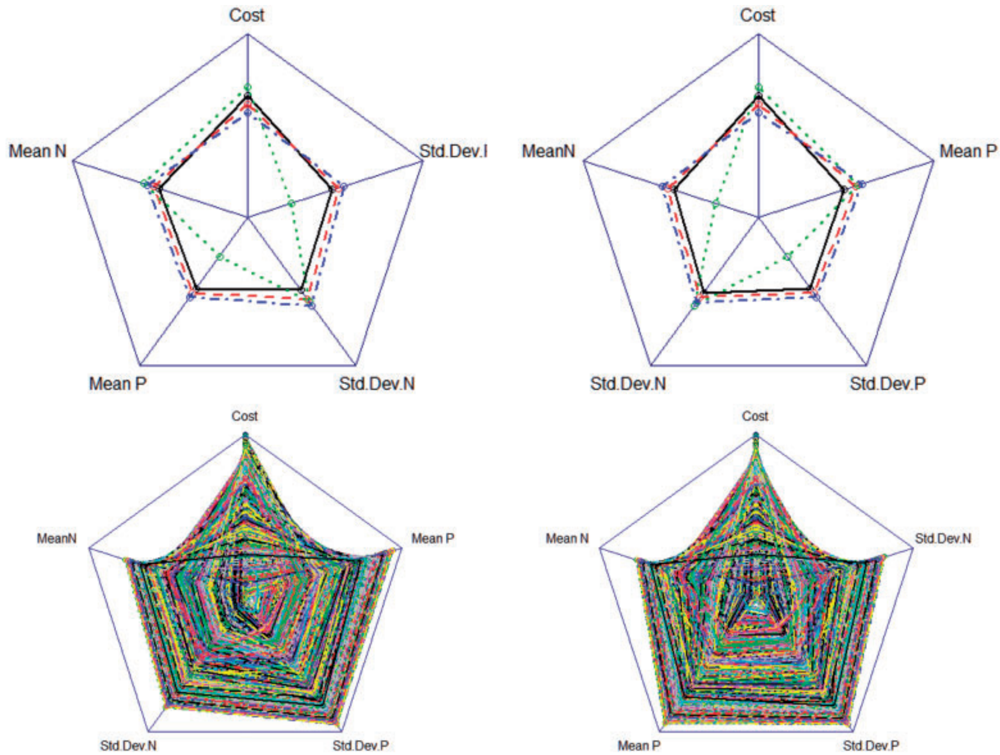

Figure 5. Pareto-optimal frontier: cost, means (N, P), and standard deviation (N and P)

Note: The values of the axes increase from inwards to outwards.

system under study and given the conservation options, attaining joint resilience of 80% presents a particularly costly hurdle. Also, we see, for example, that the solution estimated to have 70% resilience has a higher cost than a solution estimated to have 75% resilience (see figure 6). The negative marginal costs are not economically sensible, and they likely occur due to some optimization inefficiencies (note that the estimated five-dimensional frontier aims at assessing trade-offs across a wide range of nutrient reductions, not just the 45% selected for analysis here).

Overall, the costs of achieving the joint target are higher than in the case of a single pollutant and range from 22 million to 107 million. This is to be expected as a joint probability is going to be smaller than a marginal one. The distribution of the conservation practices also changes, with more land retirement being used more extensively at any given resilience level. The spatial placement of the conservation practices associated with these solutions is provided in the supplementary online appendix.

Conclusions and Caveats

Many ecosystem services are rivals, and important trade-offs exist in their production processes. Understanding the nature of these trade-offs requires: (*a*) defining a quantifiable measure of the underlying ecosystem production process and of the economic inputs that go into these productions functions; and (*b*) exploring alternative resource allocation decisions to identify, at least approximately, Pareto-efficient ways of producing different ecosystem services. Uncertainty in the provision of a particular ecosystem service adds another dimension to the nature of these trade-offs, where different ecosystem services differ both in terms of the expected outcomes and in terms of risks. In this work, we draw on the literature in resilience to monetize the size of these trade-offs.

We study the trade-offs for aquatic ecosystem services in a landscape dominated by agricultural activity. Particularly, we focus on controlling the loads of agricultural nutrients (N and P) as a means to improve the

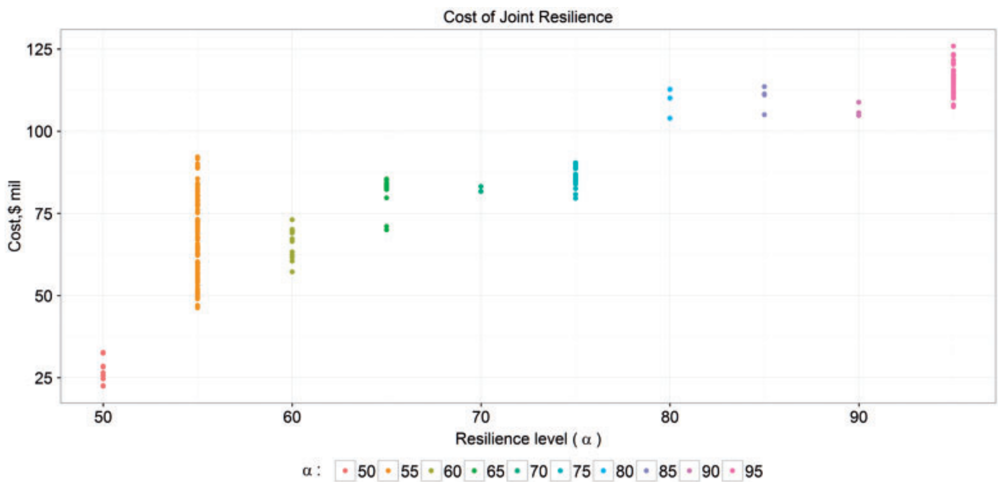

Figure 6. Joint resilience assessment of the solutions in the Pareto frontier (given a 45% reduction target in N and P)

upstream and downstream water quality. Economic inputs into water quality production are a set of conservation practices that can be implemented on agricultural landscapes for controlling the loads of nutrients, while the ecological production function is an ecohydrologic simulation model relating human actions to changes in nutrient loads. By integrating a heuristic global optimization with an ecohydrologic model, we meet the conditions of having a science-based representation of the water quality production function ($W_t(\mathbf{r}(\mathbf{x}, \xi_t))$) and its dependence on the exogenous stochastic weather factors, and we have the ability to produce an approximate Pareto frontier that accounts for multiple trade-off dimensions.

We quantify the trade-offs involved in achieving different levels of nutrient loads with different levels of resilience, where resilience is defined as the probability of attaining the desired level of nutrient loads. We spatially optimize the selection of least-cost patterns of agricultural conservation practices, or both the expected performance of the conservation actions and its variance. We analyze the trade-offs for a single nutrient (ecosystem service) and then expand our analysis to include multiple nutrients (multiple ecosystem services).

We apply our modeling framework to the Boone River watershed in Iowa. The empirical results are consistent with previous studies: securing nutrient loads with higher levels of resilience is costly. However, the marginal cost of resilience exhibits fairly complex behavior, varying with both the desired levels of nutrient control and the level of resilience required. For the case of N, we found that focusing on larger nutrient reductions allows the achievement of resilience at a smaller additional cost than when seeking only modest nutrient reductions. In our application, this is due to the ability of perennial grassland to buffer against exogenous shocks and to drastically reduce variability in nutrient loads (as shown before, for example, in Rabotyagov, Jha, and Campbell 2010). Furthermore, the main trade-off dimension is between cost of conservation investments and ecosystem service objectives, as opposed to pronounced mean-variance trade-offs or strong trade-offs between the two nutrient objectives. While some meaningful trade-offs exist between nutrient objectives, our findings highlight the presence of relative synergies in agricultural conservation investments aimed at nutrient reductions. We offer a visual depiction of trade-offs and synergies in multiple policy objectives. However, while relative synergies exist, controlling risk of nutrient loads has high opportunity costs and resilience comes at a significant premium.[14]

[14] We note recent research by Carpenter et al. (2015), who provided examples showing that, in nonlinear systems, reducing high-frequency variance can lead to an increase in low-frequency variance, thereby undermining the resilience objective. We constructed spectrum plots of controlled variance of nutrients, and we see a decrease in variance at all spectra, as the conservation investment cost increases.

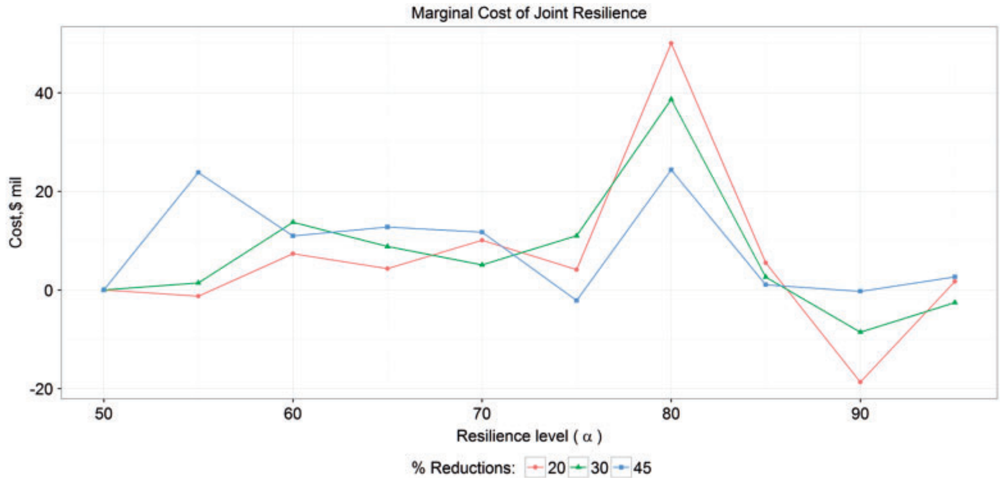

Figure 7. Marginal costs of joint resilience

The policy relevance of these findings is direct. If the goal of policymakers is to meet an ecosystem objective 50% of the time, this can generally be achieved at a much lower cost than if the goal is to meet that same objective 80% or 90% of the time. Importantly, the methods implemented here can quantify both the magnitude of these additional costs and the set of conservation practices needed to achieve increased resilience at the least cost. By constructing the entire marginal cost curve of resilience for a single or multiple objectives, policymakers can see how much it will cost to achieve different levels of resilience and take this directly into account when setting targets. While few disagree that additional resilience in a system is desirable, the costs of achieving higher levels of resilience are relevant to the discussion. The methods employed here were applied to a water quality case, but they have broad relevance to single- or multi-objective ecosystem policies, including habitat preservation, design of conservation corridors, flood protection, and a range of biodiversity concerns.

In considering particularly the findings for the Boone River watershed, it is important to acknowledge that our optimization algorithm was not exactly tailored to the optimal joint resilience question, but instead focused on providing an overall picture of feasible tradeoffs. Limitations associated with uncertainty in model structure, the simplicity of economic cost representation, and the level of spatial resolution of the ecohydrologic model present ample opportunities for future research. However, these results demonstrate the utility of an approach that integrates scientific understanding of complex systems with the practical need to see how production of nonmarket ecosystem services can be accomplished at the lowest possible sacrifice of economic inputs.

Supplementary Material

Supplementary material is available at http://oxfordjournals.org/our_journals/ajae/online.

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