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Abstract. Climate change and urban growth impact habitats, species, and ecosystem services. To buffer against global change, an established adaptation strategy is designing protected areas to increase representation and complementarity of biodiversity features. Uncertainty regarding the scale and magnitude of landscape change complicates reserve planning and exposes decision makers to the risk of failing to meet conservation goals. Conservation planning tends to treat risk as an absolute measure, ignoring the context of the management problem and risk preferences of stakeholders. Application of risk management theory to conservation emphasizes the diversification of a portfolio of assets, with the goal of reducing the impact of system volatility on investment return. We use principles of Modern Portfolio Theory (MPT), which quantifies risk as the variance and correlation among assets, to formalize diversification as an explicit strategy for managing risk in climate-driven reserve design. We extend MPT to specify a framework that evaluates multiple conservation objectives, allows decision makers to balance management benefits and risk when preferences are contested or unknown, and includes additional decision options such as parcel divestment when evaluating candidate reserve designs. We apply an efficient search algorithm that optimizes portfolio design for large conservation problems and a game theoretic approach to evaluate portfolio trade-offs that satisfy decision makers with divergent benefit and risk tolerances, or when a single decision maker cannot resolve their own preferences. Evaluating several risk profiles for a case study in South Carolina, our results suggest that a reserve design may be somewhat robust to differences in risk attitude but that budgets will likely be important determinants of conservation planning strategies, particularly when divestment is considered a viable alternative. We identify a possible fiscal threshold where adequate resources allow protecting a sufficiently diverse portfolio of habitats such that the risk of failing to achieve conservation objectives is considerably lower. For a range of sea-level rise projections, conversion of habitat to open water (14–180%) and wetland loss (1–7%) are unable to be compensated under the current protected network. In contrast, optimal reserve design outcomes are predicted to ameliorate expected losses relative to current and future habitat protected under the existing conservation estate.

Key words: climate uncertainty; modern portfolio theory; multi-criteria decision analysis; reserve design; risk management; sea-level rise; spatial conservation planning; urbanization.

Introduction

Climate change is an undeniable threat to species, human infrastructure, and the continued production of ecosystem goods and services. Because of the large uncertainties associated with climate change, it also represents a significant risk-management problem (Intergovernmental Panel on Climate Change 2014). Conservation organizations have recognized the need to adapt management strategies to account for unknown and non-stationary system change, including increased uncertainty in climate drivers. Coastal systems are particularly vulnerable to large-scale change processes including rising sea levels, storms, erosion, ocean acidification, and strong human development pressures (Mcleod et al. 2010, Thorne et al. 2015). Given the high productivity of coastal systems, which support

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economically and ecologically important natural resources, impacts to coastal ecosystems are of considerable concern (Teal 1986, Mitsch et al. 2009). Developing long-term adaptation planning strategies to account for uncertain threats is critical to safeguard these resources and ensure their continued provision into the future.

Systematic conservation planning (SCP; Margules and Pressey 2000) has been promoted as an essential component of adaptation strategies designed to moderate impacts of climate change at a resolution that is well matched to the spatial scale of climate impacts (Groves et al. 2012). SCP, synonymous with spatial planning or reserve design, is defined as a set of tools and guidelines used to structure the management of conservation programs and answer questions of where best to place conservation actions and which actions to implement in these locations (Schwartz et al. 2017). SCP has been criticized for relying on prioritization algorithms that fail to account for spatial correlations among sites (Runting et al. 2018) and uncertainties associated with underlying biological processes (Moilanen et al. 2006*b*, Carvalho et al. 2011), or for expected outcomes following an action taken (Schwartz et al. 2017). Examples of systematic planning that consider uncertainty and risks to performance outcomes arising from model error or natural variation typically focus on seeking robust solutions (Moilanen et al. 2006*a*), avoiding worst-case outcomes or minimizing the difference from the best-case scenario (i.e., maximin or minimax regret solutions, respectively, Polasky et al. 2011), or even quantifying extreme risk (McNeil 1999). Such approaches, however, treat risk as an absolute by disregarding the specific decision context and tolerance levels for accepting the range of possible outcomes, some of which may be undesirable. The common practice of assuming that a decision maker is risk neutral when setting priorities and selecting conservation strategies precludes the opportunity for recognizing differences in risk attitudes and weighing trade-offs (Tulloch et al. 2015). A risk-averse attitude, in which a decision maker is willing to forego a higher expected value for lower but more guaranteed benefits, can lead decision makers to select precautionary conservation strategies. In contrast, a higher tolerance for risk may provide greater benefits but exposes stakeholders to more significant losses if an undesired future unfolds.

To support investment decisions that maximize future conservation returns while addressing important sources of uncertainty and the impacts of risk attitude, we borrow theory from the field of economics and approach climate change as analogous to an uncertain financial market. As economic theory suggests (von Neumann and Morgenstern 1947), expected return and risk (as measured by the variance-covariance of returns) are positively correlated and represent competing objectives, assuming that we desire high returns and low risk. We apply the principles of Modern Portfolio Theory (MPT), first introduced in economics by Markowitz (1952, 1959), to estimate the expected return on conservation design investments while accounting for risk. MPT postulates that an "asset" should not be evaluated for investment in isolation but, instead, that a portfolio of assets be considered based on its estimated composite benefits and by how each asset in the portfolio is expected to covary with all others as market conditions fluctuate. Such an approach recognizes the advantage of using information about the dependency structure of a portfolio over simple diversification strategies based on individual asset performance (Ando and Mallory 2012). MPT measures the benefits and risk of investing under market uncertainty in terms of expected return, variance, and covariance of a collection of assets. By quantifying how strongly assets are expected to move in synchrony when the system is subjected to shocks, investors can evaluate the trade-off between maximizing expected return for a given level of risk or minimizing risk for a given level of return. This characterization expands on a commonly held understanding of risk (i.e., the losses expected as a function of the probability of the occurrence of an undesired outcome) by representing risk as portfolio volatility (i.e., the variance and covariance among assets contributing to that return). The significance of this work was to shift focus from reliance on asset diversification as a proxy measure of risk management, to an explicit search for portfolios with minimal (or, preferably, negative) correlation of returns between assets. Viewing an investment portfolio as an inter-dependent collection of assets is an appropriate paradigm for many forms of systematic conservation planning, which aims at maximizing benefits by managing a diversity of resources over a spatial domain.

Conservation decisions must routinely consider trade-offs, which come in several forms including direct competition between resource objectives (e.g., habitat protection vs. recreational access), between overall expected benefits and risks, and between benefits and financial constraints (i.e., cost). Although SCP methods traditionally account for multiple objectives by embedding broad conservation goals and quantitative targets into value functions (Kukkala and Moilanen 2013), explicit consideration of trade-offs among objectives is more a recent feature (Watts et al. 2009). Applying an alternate approach to that of Runting et al. (2018), we expand the application of MPT for spatial planning by accounting for these broad categories of trade-offs in a hierarchical analysis using a combination of MPT and multi-criteria decision analysis (MCDA; Wallenius et al. 2008, Steele et al. 2009). Our framework simplifies complex problems by evaluating trade-offs first at the scale of the individual asset and then at the scale of the problem frame (i.e., the collection of assets). Multi-criteria decision analysis operates at the asset level (e.g., a parcel of land) to consider trade-offs among ecosystem outcomes, such as distinct landcover types that provision different ecosystem services, to produce a composite benefit reflecting stakeholder preferences. Differences in expected benefits are quantified over uncertainty by predicting changes to the asset as a function of climate or other drivers. Modern portfolio theory applies the asset-level analysis to a trade-off evaluation at the landscape level between expected return and risk among candidate portfolios (Fig. 1), and can include budget and other constraints. Thus, the framework enables a decision maker to evaluate trade-offs among resource objectives that are not valued equally by stakeholders (Garmendia and Gamboa 2012), and then assess the effects of uncertainty and risk on overall conservation performance. Integrating an

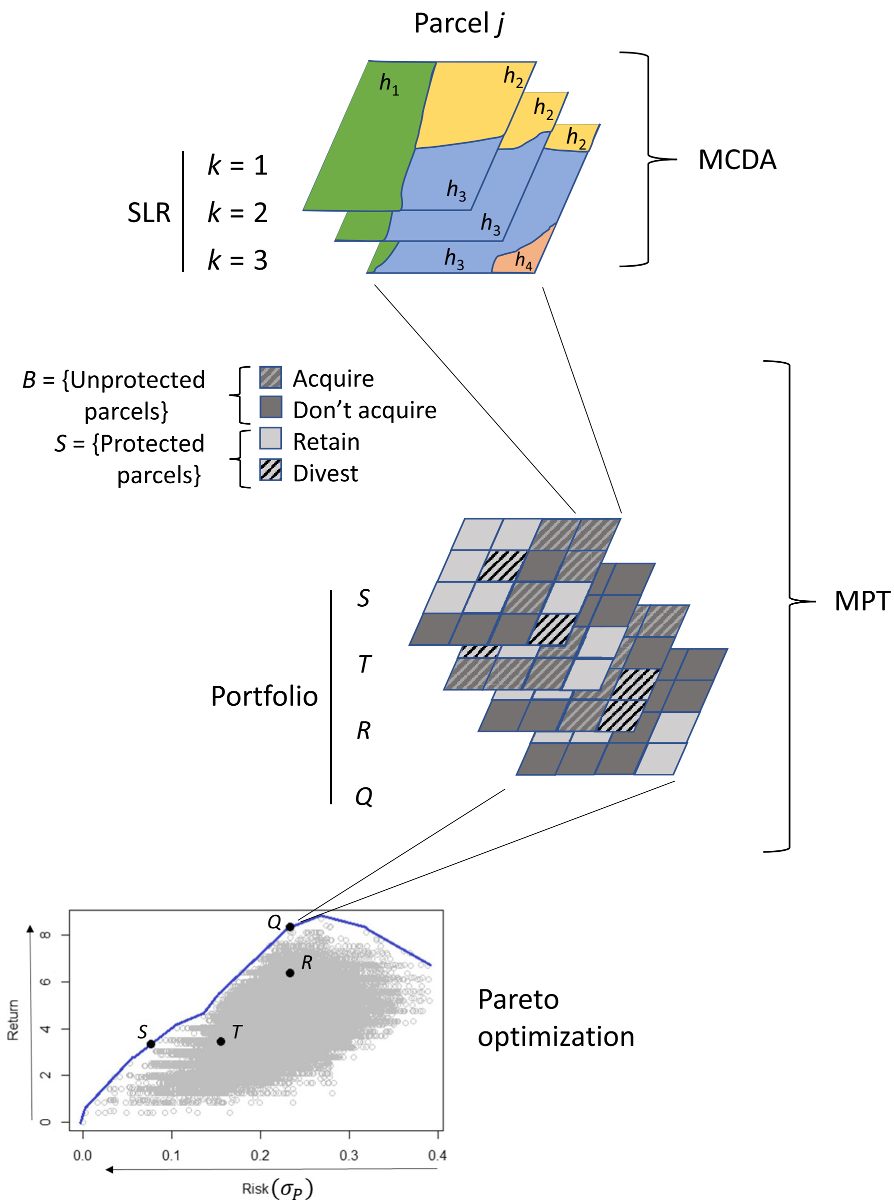

Fig. 1. Conceptual spatial planning model using multi-criteria decision analysis (MCDA) and modern portfolio theory (MPT). For each planning unit (parcel *j*), the MCDA evaluates the achievement of discrete habitat objectives, accounting for differences in expected habitat contributions under multiple sea-level rise (SLR) scenarios. Habitat cover types (h_1–h_4) are quantified by area under SLR scenario (k), weighted by relative stakeholder preference and normalized to produce a parcel value for each scenario. Parcels are identified as belonging to either set S (currently protected conservation estate) or to set B (currently unprotected lands). The MPT analysis quantifies the accumulated benefits and risks associated with SLR-induced variance and spatial correlation for candidate reserve design portfolios. A heuristic search algorithm identifies the Pareto frontier, defining the set of Pareto-optimal designs (blue line) and dominated alternatives (gray points). Hypothetical points R and T are dominated because points Q and S represent alternatives that improve on expected return or risk, respectively, without compromising the value of the other objective. On the Pareto frontier, point Q represents a portfolio with higher expected return relative to point S, but the increased benefit is achieved only at the cost of greater risk.

explicit evaluation of risk attitudes with a transparent assessment of competing objectives into a single spatial planning decision framework will expand the concept and applicability of robust climate adaptation strategies.

Here, we describe specification of the MCDA-MPT model as applied to coastal conservation planning efforts for transition and loss of valued habitats due to changing sea level and human development. Conservation decision makers anticipate the loss of important habitats as a function of sea-level rise (SLR) and rapidly expanding urban pressures. To adapt to anticipated changes, conservation practitioners seek to identify parcels that will preserve a representative collection of habitat types in sufficient quantity to provision future ecosystem services. Because habitats are not static, there is uncertainty about future landcover types and the benefits produced from any given reserve design. Recognizing recent efforts to address multi-objective spatial conservation planning problems for dynamic landscapes (e.g., Ando et al. 2018, Runting et al. 2018), we further extend the use of MPT by (1) structuring management objectives hierarchically to illustrate the scale of each analytic step, (2) considering the conservation benefits from divesting from protected lands to reallocate funds for protecting higher-valued parcels, and (3) applying axioms from game theory to a bargaining solution that identifies an optimal and equitable trade-off between portfolio benefits and risk.

We assume that decision makers would like to maximize benefits while minimizing risk when designing a network of protected parcels. We apply the principles of Pareto optimality to explore this bi-objective problem. A Pareto solution seeks to identify the frontier of non-dominated solutions, defined as those for which improvement on one objective can only occur with a loss in value for another (Kennedy et al. 2008), forming the basis for negotiating among a reduced number of equally optimal alternatives (Fig. 1). As proposed by our goals for the MPT analysis, the Pareto frontier describes the set of optimal reserve-design portfolios for a range of risk tolerance attitudes, representing trade-offs between minimized risk for a desired level of benefits and maximized returns for any stated level of risk.

We present an approach to address a common conservation challenge, applying a novel optimization algorithm to solve large combinatorial problems. We illustrate our reserve design framework by considering a large number of parcels (N = 1,244) for an ongoing conservation project on the coast of South Carolina, USA, which is threatened by sea-level rise and human development. We offer several approaches to generalize our findings. First, we integrate a multiple-objectives criteria analysis into the MPT framework. Second, we apply a game theory approach to compute a "fair point" trade-off among objectives of risk and reward along the Pareto-optimal frontier. Such bargaining solutions can address the distribution of benefits between cooperating decision makers or can identify the Pareto-optimal solution that balances trade-offs ("bargaining") among objectives. Third, we conduct a sensitivity analysis by contrasting the bargaining solution with the effects of variable risk attitudes on the spatial outcome of reserve design decisions. Fourth, we identify patterns of a "no regret" solution that is robust to risk. Finally, our quantitative reserve design framework considers divestment decisions, which, until recently, have rarely been discussed in the SCP literature.

Materials and Methods

Multi-criteria decision analysis and SLR uncertainty

To describe our model, we simplify the management problem by considering individual habitat types as proxy management objectives. We apply MCDA to calculate the expected benefits of each land parcel, based on predictions of future habitat composition. We consider SLR as a driver altering the relative quality, composition and value of habitat in coastal landscapes (Daniels et al. 1993, Craft et al. 2009). Expected value is quantified by normalizing habitat area across parcels to obtain relative values under each SLR scenario, then weighted according to stakeholder preferences, adjusted for urbanization probability, and scaled by cost (steps 1–5). Variance of this expectation over future sea level is measured as one component of risk assessment.

The basic unit of data for our analysis is d_{hjk}, representing the area (ha) of habitat type h in parcel j under SLR scenario k. These variables come from index sets: $h \in \mathrm{H}$, $j \in N$, and $k \in R$. Thus, the data required for each of N parcels are habitat extents as elements of an $H \times R$ matrix. For each $h \in H$, $j \in N$, and $k \in R$, we perform the MCDA using raw data d_{hjk}.

1) We normalize d_{hjk} across parcels to take values between 0 and 1, denoted by n_{hjk}

$$n_{hjk} = \frac{d_{hjk} - \min_{j \in N} d_{hjk}}{\max_{j \in N} d_{hjk} - \min_{j \in N} d_{hjk}}. \quad (1)$$

2) For each parcel j, we calculate the weighted sum of its constituent habitat types using habitat objective criteria weights w_h and denote expected parcel values for each SLR scenario by m_{jk}:

$$m_{jk} = \sum_{h \in H} w_h n_{hjk}. \quad (2)$$

3) We account for complex, spatial processes leading to land conversion using a dynamic urban growth model (Appendix S1: Section S1). Development probability u_j is incorporated as a modifier of parcel value to derive l_{jk}. In this formulation, parcel return increases proportionally with the probability of development. This strategy promotes anticipating

permanent loss by conserving parcels before they are developed and recognizes that the value of sites with lower development probabilities is more secure without explicit protection

$$l_{jk} = \frac{m_{jk}}{1 - u_j}. \tag{3}$$

4) We scale the value of a parcel by its cost to standardize benefits by cost, and represent this value by r_{jk}. We treat both Eqs. 3 and 4 as linear combinations of input variables because they make the least assumptions about risk and cost functions. Other formulations are possible.

$$r_{jk} = \frac{l_{jk}}{|c_j|}. \tag{4}$$

5) Future habitat conditions are described as a function of climate change and SLR projections. SLR probabilities (p_k) predict differences in the extent and configuration of coastal habitat cover types. We chose those associated with the 10th, 50th and 90th percentile of the local distribution estimated for 2050 (Appendix S1: Section S2; Horton et al. 2015) to represent three potential scenarios for SLR. For each, $j \in N$, the expected return is calculated as a weighted sum of r_{jk} values over SLR scenarios:

$$\mu_j = \sum_{k \in R} p_k r_{jk}. \tag{5}$$

MPT reserve design optimization

We extend the basic reserve design problem to consider a more complex set of decisions involving both acquisition and divestment decisions to design a future protected area. We evaluate Pareto optimality under both unconstrained and budget-constrained scenarios, the latter reflecting more realistic management limitations and where the benefits from divesting to acquire other parcels may be illuminating. Let us consider a set N of predefined parcels of land. For the basic reserve design problem, in which only parcel acquisition decisions are evaluated, the decision of whether to acquire is conditioned on the set of currently unprotected parcels. In our formulation, N will encompass the full study region and include both protected and unprotected parcels. Let S be the set of parcels that comprise the reserve (i.e., currently protected parcels) and let B represent the set of parcels being considered for addition into the reserve. For S, the decision is then whether to keep or divest from each member of the set. For $j \in S$, x_j takes a value of 1 if parcel j is sold and 0 if it is retained. Divesting results in a loss of all habitat benefit but its monetary value is added to the budget (less a 6% transaction cost; de Fontnouvelle and Lence 2002), allowing the acquisition of other parcels. Keeping a parcel incurs no additional cost (maintenance costs are not considered) and future habitat benefit is retained. Relative to a budget constraint, the cost of acquiring is negative while a positive income is realized by selling a parcel. Note, however, that in Eq. 4 we use the absolute value of c_j because we are interested in r_{jk} as a measure of per unit value of a parcel.

Similarly, let the complement to S be the set of parcels B that are currently unprotected and under consideration for addition into the reserve network. We assume that $S \cup B = N$ and $S \cap B = 0$. The decision is which set of parcels $j \in B$ to acquire. For $j \in B$, x_j takes a value of 1 if parcel j is acquired and 0 if it is not. Protecting a parcel (through purchase or easement) adds to the overall reserve benefit through its contribution of habitat while its cost reduces the available budget. Not acquiring a parcel incurs no cost but we consider that no conservation benefit is accrued because it remains unprotected.

The formulation of our MPT optimization begins with identifying the Pareto-optimal set of portfolios that maximize the expected return while minimizing the risk associated with a given combination of parcels, expressed as

$$\max \sum_{j \in B} x_j \mu_j + \sum_{j \in S} (1 - x_j) \mu_j \tag{6}$$

$$\begin{aligned} \min \sum_{j \in B} x_j \sigma_j^2 + \sum_{j \in B} \sum_{i \in B : i > j} 2 y_{ji} \sigma_j \sigma_i \rho_{ji} \\ + \sum_{j \in S} (1 - x_j) \sigma_j^2 + \sum_{j \in S} \sum_{i \in S : i > j} 2 y_{ji} \sigma_j \sigma_i \rho_{ji} \\ + \sum_{j \in B} \sum_{i \in S} 2 y_{ji} \sigma_j \sigma_i \rho_{ji} \end{aligned} \tag{7}$$

where μ_j is defined as in Eq. 5, x_j is a binary variable representing the decision to acquire ($x = 1$) or not acquire ($x = 0$) parcel j for $j \in B$, and to divest ($x = 1$) or retain ($x = 0$) for $j \in S$. Parcel variance σ_j^2 and correlation coefficient ρ_{ij} for each parcel pair are derived from Eq. 4 and probability p_k, using the *cov.wt* function in R (R Development Core Team 2016) to calculate a weighted variance-covariance matrix. Binary variable y_{ji} is used to linearize the formulation (where y_{ji} is defined as equivalent to $x_j x_i$) and is subject to the following constraints for all parcel pairs j and i (parameter and variable notation is summarized in Table 1):

$$x_j \geq y_{ji} \leq x_i \quad \forall\, i \in B, \forall\, j \in B, j > i$$

$$y_{ji} \geq x_j + x_i - 1 \quad \forall\, i \in B, \forall\, j \in B, j > i$$

$$1 - x_j \geq y_{ji} \leq 1 - x_i \quad \forall\, i \in S, \forall\, j \in S, j > i$$

$$y_{ji} \geq 1 - x_j - x_i \quad \forall\, i \in S, \forall\, j \in S, j > i$$

$$1 - x_i \geq y_{ij} \leq x_j \quad \forall\, i \in S, \forall\, j \in B$$

$$y_{ji} \geq x_j - x_i \quad \forall\, i \in S, \forall\, j \in B$$

$$x_j \in \{0, 1\} \quad \forall\, j \in N$$

$$y_{ji} \in \{0, 1\} \quad \forall\, i \in B, \forall\, j \in B, j > i$$

$$y_{ji} \in \{0, 1\} \quad \forall\, i \in S, \forall\, j \in S, j > i$$

$$y_{ji} \in \{0, 1\} \quad \forall\, i \in S, \forall\, j \in B.$$

We highlight that in our hierarchical formulation, portfolio value is a function of habitat composition, stakeholder preference, and risk of opportunity loss (development), while portfolio risk is driven by the uncertainty of future habitat composition under SLR.

Optimization algorithm for computing the Pareto-optimal frontier

Issues of dimensionality represent a major challenge for optimizing a large number of discrete decision variables (with N discrete assets to choose among, the number of portfolio combinations is equal to 2^N). To overcome this obstacle, we subset our data set to groups of ≤ 100 parcels each, still a large but more analytically tractable size. We combined parcels using qualitative criteria: general ecosystem type (e.g., coastal, upland, riverine), a sufficiently large extent to reduce positive correlation, and representation of hypothetical large-scale planning units for individual organizations (e.g., a National Wildlife Refuge, National Forest or municipality). For each parcel subset, we apply the Feasibility Pump Based Heuristic algorithm (Pal and Charkhgard 2017, 2019) to compute the Pareto-optimal frontier from Eqs. 6 and 7. Based on empirical testing of exact solutions and statistical measures used to evaluate the quality of an approximated solution, this heuristic approach finds good estimates of the true Pareto frontier in terms of the average distance between points on the approximate and true frontier (coverage), the spread of approximated points relative to the true range (uniformity), and identification of high benefit : risk ratios (density; Kohli et al. 2004, Pal and Charkhgard 2017). Solutions from each subset are combined to produce a single Pareto-optimal frontier for the full study area. Although it is possible that portfolio results at the subset or study-area scale may be affected by the designation of parcel subsets, it is beyond the scope of this paper to conduct a comprehensive sensitivity analysis of parcel groupings. Further details on the optimization approach are provided in Appendix S1: Section S3.

Table 1. Notation of parameters and variables used in the portfolio analysis and optimization.

Notation	Definition
Parameters	
N	index set of all parcels in study area
B	index set of parcels not currently part of the reserve but available for protection
S	index set of parcels already part of the reserve
H	index set of habitat types
R	index set of sea-level rise (SLR) scenarios
p_k	probability of SLR scenario $k \in R$
w_h	weight of habitat type $h \in H$
c_j	cost (+) to acquire parcel $j \in B$ or revenue generated (−) by divesting $j \in S$
u_j	probability of parcel $j \in N$ lost to development (i.e., urbanization)
μ_j	expected future return of parcel j calculated over SLR scenarios
d_{hjk}	hectares of habitat $h \in H$ in parcel $j \in N$ present under SLR scenario $k \in R$
ρ_{ji}	correlation coefficient for parcels $j,\ i \in N$
σ_j	standard deviation of parcel j calculated over SLR scenarios
Variables	
x_j	binary variable representing decision to buy (1) or not (0) for parcel $j \in B$, or decision to divest (1) or not (0) parcel $j \in S$
y_{ji}	binary decision variable used to linearize the optimization model; y_{ij}: $= x_j x_i$

Trading off among Pareto-optimal portfolios

All points on the Pareto frontier are acceptable solutions and represent a compromise between competing interests. In our case study, the trade-off is between maximizing the expected benefits of a future conservation area network and minimizing the risk of undesired outcomes under climate change. In reality, when designing a reserve this compromise likely will be negotiated among decision makers over time, which was impractical to consider for our analysis. Additionally, reliably assessing a decision maker's sensitivity to risk is notoriously complex (Howard 1988, Yechiam and Ert 2011) and often more difficult than eliciting relative preferences for discrete objectives. Instead, we take several approaches to generalize our findings in hopes of increasing decision makers' understanding of trade-off implications. First, we use the Nash bargaining solution (Nash 1950) to identify the point along the Pareto frontier that minimizes disparities in the achievement of one objective over the other. In essence, we search for a quantifiably "fair" point that satisfies a compromise between maximum return and minimal risk (Appendix S1: Section S4, Fig. S2; Santín et al. 2017). This approach links game theory with multi-objective decision analysis, by assuming an imaginary bargaining player is associated with each objective, to identify a Pareto-optimal that best satisfies all interests (Rao 1987). This approach could also be applied to assist multiple, cooperating decision makers design reserve networks when each collaborator may have a different levels of risk tolerance. Second, we conduct a sensitivity analysis of the effect of risk attitudes on the spatial outcome of reserve design decisions by comparing alternative risk tolerance levels to the Nash solution. Finally, we identify the pattern of a "no regret" solution that is robust to risk uncertainty (i.e., a portfolio that does not vary across risk-tolerance levels; Appendix S1: Section S4).

Budget-constrained optimization

To evaluate the sensitivity of reserve design outcomes to budget uncertainty we propose a series of four fiscal scenarios as a function of the proportion of total land area not currently in conservation status. This approach recognizes that not all unprotected parcels in the study area will be available for protection, and that sufficient funds are unlikely to be available to conserve all desired land even with multiple partners involved. Because effective land conservation strategies can take several forms (e.g., fee-simple purchase, fixed or rolling easements) and because few organizations can individually implement effective conservation at a large scale, we had no reasonable basis for estimating the costs of land protection or future budgets available to a new partnership. Instead, we simplify the problem by assuming the cost of protecting a parcel is equal to its area and set budget scenarios arbitrarily as a proportion of the approximately 60,000 ha of currently unprotected area in the study area (Appendix S1: Table S3). We evaluate fiscal uncertainty while holding risk uncertainty constant by using the Nash bargaining solution trade-offs (Appendix S1: Section S5).

Application and data

We apply our reserve design model to coastal South Carolina, USA, centered on Cape Romain National Wildlife Refuge (NWR; Appendix S1: Section S6). The NWR consists of approximately 27,000 ha of barrier islands, salt and freshwater marshes, sea turtle and bird nesting beaches, and threatened maritime forest (U.S. Fish and Wildlife Service 2010). Managers recognize that SLR and urban development are threatening the NWR mission for conserving critical wildlife habitat established under the existing extent of the refuge, and that acquiring or protecting new habitat to expand or relocate the existing refuge footprint is needed (Johnson et al. 2015). Acknowledging the legal and financial constraints limiting a major refuge expansion, Cape Romain NWR is engaging in efforts to establish diverse, local partnerships to develop collective understanding of threats and opportunities, and identify common objectives and potential solutions, including larger-scale conservation of key habitats (Johnson et al. 2015).

To translate global climate-change scenarios to parcel-specific habitat impacts within our study area, we commissioned a study of SLR projections that coupled ensemble models and multiple emission scenarios (representative concentration pathways) with local geophysical processes (Appendix S1: Section S2, Table S1; Lentz et al. 2015, Horton et al. 2015). From the distribution of these projections, we calculate discrete SLR scenarios and their associated probabilities of occurrence for the year 2050 (Appendix S1: Table S2, columns 1 and 2). We then match the predicted local vertical rises to the closest SLR estimates provided by the widely available Sea Level Affecting Marshes Model (SLAMM; Clough 2008). To develop the scenarios used in our study, we associate the SLR values documented in SLAMM with their appropriate emissions scenario and year combination (Appendix S1: Table S2, columns 3 and 4) to extract spatially resolved changes in habitat cover types over these uncertain futures. We overlay raster output of habitat projections with a spatial database of all protected and unprotected parcels in the study area and extract parcel-level habitat extent under each scenario using a custom Python script run in ArcGIS (v.10.4.1; ESRI, Redlands, California, USA; Data S1: Parcel_habitat_quantification).

We consider urban growth as a threat to habitat migration and the production of ecosystem services. To inform the reserve design model with additional information regarding parcel value we apply a simple cellular automata model that predicts several drivers of urban growth and estimates probabilities of land conversion (Jantz et al. 2010, Terando et al. 2014). To quantify the risk of habitat loss for parcels that were currently < 50% developed, we intersect parcel boundaries with the raster of urbanization probabilities and calculate a weighted pixel frequency to produce an area-weighted average probability of development for each parcel (Appendix S1: Sections S1; Data S1: Parcel_urban_prob). We apply these probabilities to Eq. 3 to adjust estimated parcel value.

Results

Predicting habitat outcomes under SLR and current reserve design

Model projections of future habitat extent for all 1,244 (protected and unprotected) parcels in our study region suggest substantial transitions of important cover types. Because wetlands are particularly susceptible to transition under SLR, we describe our results for these in greater detail than for other habitat types. Within the study area, current wetland habitat, aggregated across fresh- and saltwater types, represents 51% of the total study area, with 82% of this total under protection (Table 2, current extent). The projected loss of total wetland habitat ranges from < 1% under the low SLR scenario to nearly 7% under high SLR (Table 2, total future extent). The expected wetland loss, weighted by local SLR probability estimates, is 1.5% of total extant wetland area. Future conversion of any habitat type to open water is predicted to be greater, ranging from an increase of 14% to 180% from current open water extent. Ocean beach nesting habitat is expected to increase in area under moderate SLR (+10%) but decline by 13–14% under low and high SLR, respectively (Table 2). Tidal flats, in contrast, are expected to increase between 38% to 184% across SLR scenarios, and with a weighted mean of more than doubling in size.

Based on the current protected area (PA) network, we also evaluate the expected change in conserved habitats under the three SLR scenarios (Table 2, 2050 existing PA; Fig. 2 for wetland habitats). Expected outcomes differ as a function of SLR projection and habitat type, highlighting the need to consider spatial correlation. The extent of conserved intertidal scrub-shrub transition marsh and brackish marsh is predicted to increase under all SLR scenarios, while salt marsh and tidal swamp habitats decline proportionally with sea level in all cases. Other habitats, including swamp and freshwater marsh either increase or decrease in protected area depending on the scenario (Fig. 2). Changes in protected salt marsh and scrub-shrub transition marsh represent the most substantial impacts, with as much as 13,900 ha of saltmarsh lost and more than 9,000 hectares of transition marsh gained under a high SLR scenario. Combined, an overall loss of conserved marsh habitat is predicted regardless of future scenario, with totals ranging from an average of −0.3% under low SLR to more than −9.5% under high SLR (Fig. 2).

Pareto optimization

We approximated Pareto-optimal frontiers independently for each of 14 parcel subsets (Appendix S1: Fig. S1), first considering scenarios with no budget constraint. To evaluate the sensitivity of protected area design to variation in risk preference, we selected portfolio alternatives that represented the Nash bargaining solution along the frontier of each subset (Nash 1950, Santín et al. 2017) and two additional cases representing low- and high-risk trade-offs (Appendix S1: Section S4, Fig. S3). For each risk scenario, we display the spatial results of all 14 portfolios on a single map (Fig. 3) and depict outcomes and variability for wetland habitats under each optimal design relative to the expected amount of habitat protection under the current reserve network (Fig. 4).

The low-risk solution places greater emphasis on minimizing uncertainty and spatially correlated outcomes than on conservation returns, resulting in extensive divestments and moderate acquisition decisions (Fig. 3a). Given the risk of future inundation and conversion to open water, suggested divestment from low-lying habitats include most of the refuge and much of the Santee River delta. Such divestment is reflected in the loss of substantial wetland habitat, but with reduced risk of SLR uncertainty for those protected wetland types (Fig. 4; left panel). Decisions to acquire or keep parcels under a low-risk scenario range widely across habitat types and include lands just inland from the coast and upland from river basins (i.e., parcels with lower uncertainty and increased ability to support future wetlands). A high-risk scenario with no budget constraint seeks to maximize benefits through extensive parcel acquisition or retention, with minimal divestment (Fig. 3b). Risk of damages and loss from coastal or estuarine inundation is outweighed by the potential contribution of these habitats. In many cases, the expected habitat benefits under the worst-case scenario of the high-risk solution are higher than the best-case scenario of the low-risk solution (Fig. 4; right and left panels, respectively). Only small, interior parcels are suggested for divestment, possibly due to their limited contributions to portfolio benefits. These extremes, however unlikely, demonstrate the sensitivity of candidate solutions to risk attitude.

The Nash bargaining solution, representing a balance between trading off risk and benefits, offers more complex insights for spatial planning. In this case, the benefits of coastal and estuarine habitats exceed the risk of loss to SLR, similar to the patterns revealed under the high-risk solution (Fig. 4; middle and right panels, respectively). In addition, a strong pattern of parcel acquisition recommendations is seen along the development corridor inland from the NWR and adjacent to zone of urban expansion (Fig. 3c, southwest corner). Several large parcels near the refuge are identified for divestment. The largest of which (6,000 ha of National Forest) contains abundant freshwater swamp and upland habitat predicted to remain relatively static over time. Divestment from these parcels may reflect the expectation that swamp habitat will persist in abundance elsewhere in the study area, suggesting that higher habitat diversity is achieved by surrendering such parcels and acquiring other tracts anticipated to include future underrepresented or higher-value habitat.

Although we limited our analysis to only three risk scenarios, these were used to identify the set of robust parcel decisions that are unaffected by risk uncertainty (i.e., “no regret” solution). We found that a plurality of parcel decisions (70.6%) did not change as a function of risk attitude (Fig. 5). The pattern of these robust decisions offers insights regarding risk–reward trade-offs, with high-valued and unprotected parcels located just inland from the refuge, and along the lower or upper reaches of major river channels. Retention of currently protected parcels follows a similar pattern, with areas of the Santee Delta, some Refuge barrier islands, and parcels further inland expected to be high-value future habitats. Only 1.1% of the total parcel set identified as candidates for divestment are common across the three risk scenarios, none of which is located near the coast.

Table 2. Current and projected habitat distribution over three SLR scenarios (see Appendix S1: Table S1) and for current and optimal protected area (PA) designs.

Habitat	Current extent (ha)		2050, total future extent (ha)				2050 existing PA wt.avg (ha)	2050 optimal wt.avg (ha)	Optimum : current PA	Optimum : 2050 existing PA
	Total	Protected	Low	Med	High	wt.avg†				
Upland developed	518.2	243.9	566.1	566.1	566.1	566.2	261.8	520.3	2.13	1.99
Upland undeveloped	117,020.0	82,647.0	116,479.3	111,225.7	107,011.2	111,410.0	78,557.0	96,146.2	1.16	1.22
Estuarine beach	367.4	280.5	388.0	591.1	859.9	602.1	369.8	548.2	1.95	1.48
Tidal flat	829.1	817.8	1,146.9	1,824.2	2,352.8	1,799.6	1,756.3	1,683.4	2.06	0.96
Ocean beach	263.8	263.0	230.8	291.4	226.5	270.5	270.5	270.5	1.03	1.00
Ocean flat	36.5	36.5	27.8	10.0	-	11.3	11.3	11.3	0.31	1.00
Inland open water	3,299.0	3,001.2	3,297.4	2,909.5	2,523.1	2,910.1	2,626.5	2,525.8	0.84	0.96
Riverine tidal open water	398.2	257.9	454.7	232.7	115.1	250.1	152.2	199.0	0.77	1.31
Estuarine open water	4,861.5	4,574.5	6,087.2	9,842.7	19,946.3	10,901.9	10,200.9	10,360.6	2.26	1.02
Open ocean	850.6	830.3	862.2	1,461.5	3,722.1	1,738.6	1,714.1	1,691.6	2.04	0.99
Inland shore	28.6	24.0	28.6	28.6	24.6	27.9	23.2	27.5	1.14	1.19
Swamp	79,486.8	65,964.7	79,327.1	81,636.2	77,368.1	80,547.9	66,536.9	68,424.2	1.04	1.03
Brackish marsh	5,101.7	4,434.3	5,718.2	6,750.1	6,981.7	6,617.4	5,789.8	4,116.8	0.93	0.71
Cypress swamp	431.7	392.6	429.7	430.4	384.8	422.7	386.0	386.9	0.99	1.00
Inland fresh marsh	14,581.8	12,613.8	14,595.8	14,297.3	11,824.9	13,936.3	12,094.8	12,496.1	0.99	1.03
Tidal fresh marsh	2.2	2.2	2.1	1.6	0.6	1.5	1.5	1.5	0.71	1.00
Scrub/shrub trans marsh	1,647.4	1,432.5	2,207.9	4,819.7	14,079.0	5,928.3	4,705.1	5,001.3	3.49	1.06
Salt marsh	19,486.4	18,020.0	18,055.7	14,258.5	4,752.2	13,308.2	12,168.1	12,857.5	0.71	1.06
Tidal swamp	11,846.6	5,820.4	11,134.4	9,862.4	8,301.0	9,815.1	4,036.7	9,211.8	1.58	2.28
Total wetland	132,584.7	108,680.4	131,470.7	132,056.2	123,692.1	130,577.5	105,719.0	112,496.2	1.04	1.06

Note: Optimal reserve design is based on a Nash bargaining solution for portfolio return and risk tolerance levels. The final two columns compare the amount of protected habitat under an optimal future reserve design to the extent of currently protected habitat, and future protected habitat extent under an optimal design relative to the status quo protected area network, respectively.

† wt.avg refers to a weighted average expectation based on SLR probabilities estimated for 2050.

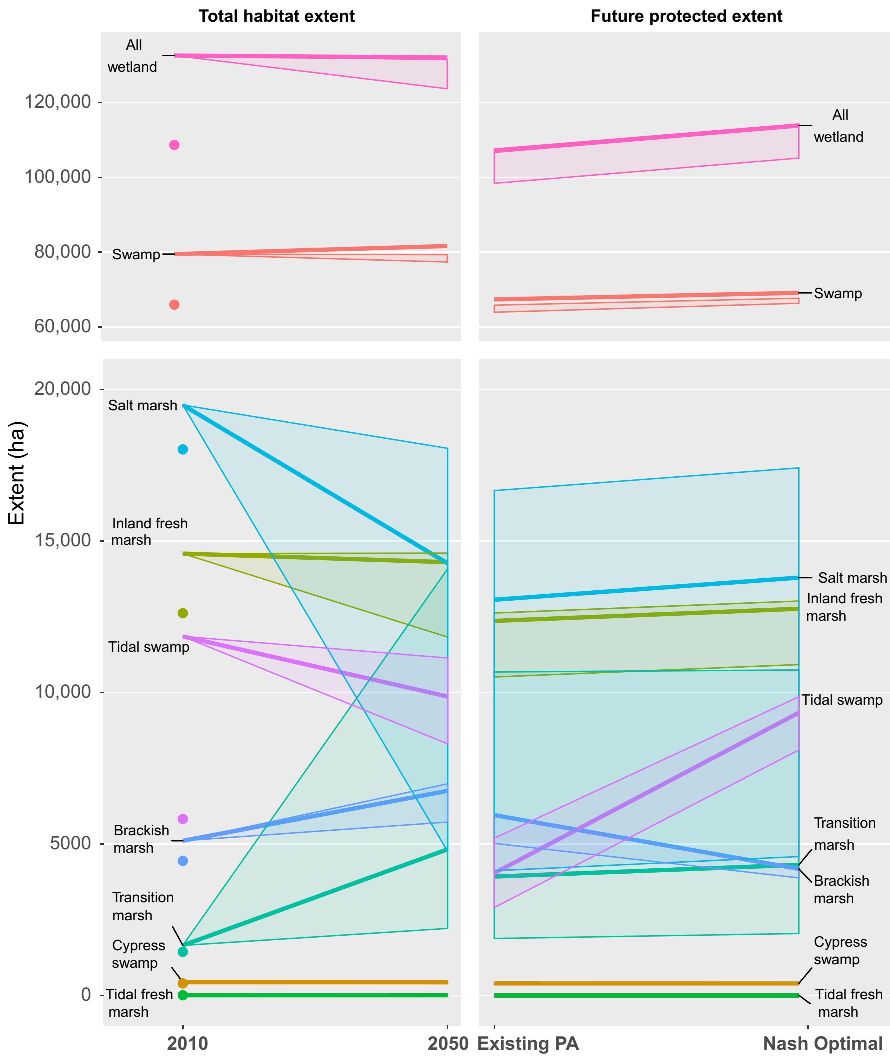

FIG. 2. Slope graphs (Tufte 1983) depicting predicted change in total available wetland habitat over the period 2010–2050 (left panels) and future extent of protected wetlands under existing and optimal reserve designs (right panels). Polygons represent future uncertainty regarding the degree of habitat transition or protection as a function of three sea-level rise (SLR) scenarios; heavy lines estimate trends under a medium SLR projection, thin lines represent high and low SLR projections. Some habitats (e.g., swamp) are predicted to increase in extent under medium SLR relative to high and low projections, hence the heavy line lying above the polygon. Colored points (left side of left panel) depict the extent of each habitat currently protected. The right panels describe the future protected extent of habitats under the existing protected-area network (left side; existing PA) and under a Nash-optimal reserve design (right side). Heavy and thin lines are as before, with the shaded areas representing scenario uncertainty. Note the change in scale (ha) on the *y*-axis for both upper panels (20,000 ha between tick marks compared to 5,000 ha in lower panels).

As a counterfactual analysis, we calculate differences in the amount of protected future habitat under a Nash-optimal design relative to the current reserve network, while accounting for uncertainty in SLR (Table 2, 2050 existing PA vs. 2050 Optimal). Gains in most wetland types under an optimal reserve design are substantial and, in many cases, confer an improvement relative to both current and future extent of habitat protected under the existing conservation estate (Fig. 2; right panel). For example, approximately one-half of the study area's tidal swamp is currently protected (5,800 of 11,800 ha). The future, weighted-average amount of tidal swamp conserved under the existing reserve network is only 41% of the total expected extent, whereas the Nash-optimal design protects an average of 94% this total available (Fig. 2, Table 2). Regardless of SLR projection, this solution conserves a greater amount of tidal swamp than is currently protected (with a mean increase of 58%), whereas the current design results in net habitat loss irrespective of future scenario. Conserved area of the three most extensive marsh habitat types in the study area (swamp, saltmarsh, and inland fresh marsh) increase by an average of 3–6% over the expected extent under the existing reserve design (Fig. 2, Table 2).

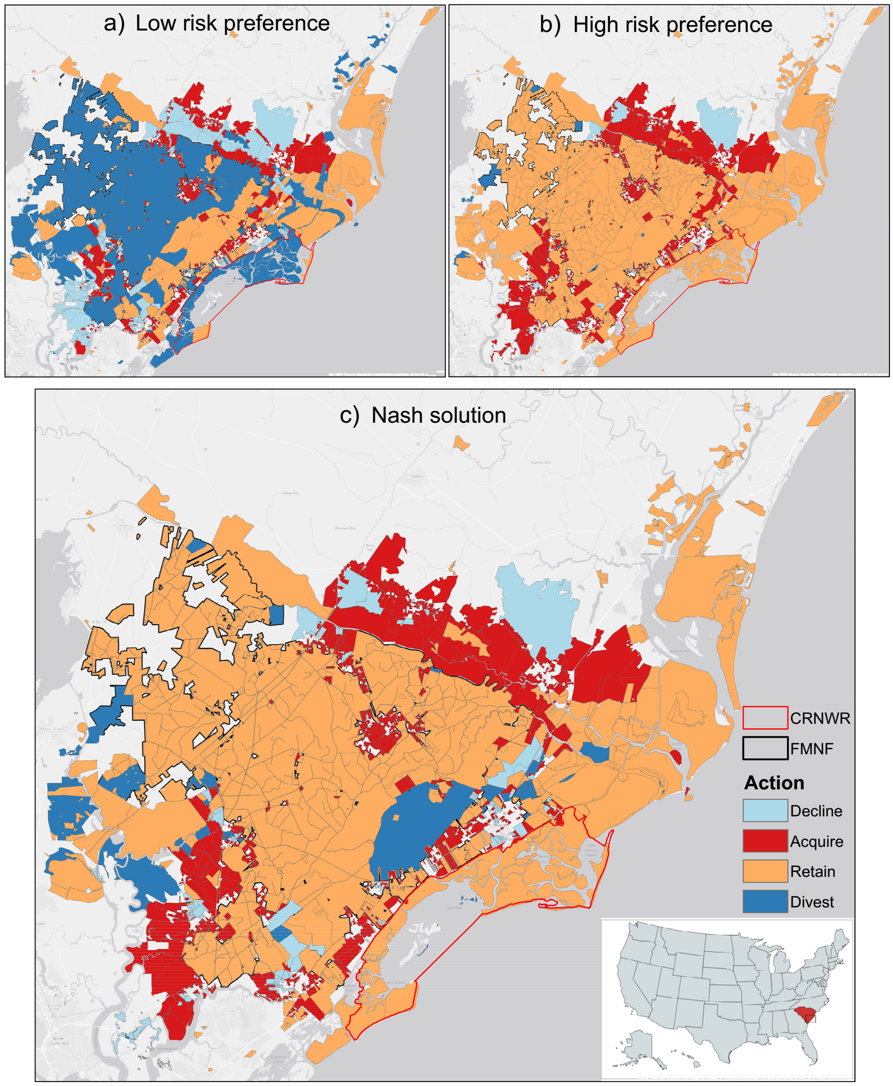

Fig. 3. Potential reserve designs optimized using MPT when a decision maker is (a) risk-averse and prioritizes how to minimize risk rather than achieve high returns (low risk preference), (b) is risk-seeking and considering a higher reward alternative (high risk preference), or (c) seeks a more balanced risk–reward outcome (Nash solution). Sea-level rise (SLR) uncertainty is included and is the same for all scenarios, thus emphasizing that differences in outcomes depicted here are driven entirely by decision-maker attitudes toward risk. Potential management actions for decision makers, including managers of Cape Romain National Wildlife Refuge (CRNWR) and Francis Marion National Forest (FMNF), include decline acquisition of an unprotected parcel, acquire an unprotected parcel, retain a currently protected parcel, or divest from a protected parcel. See inset map for location of study region.

Brackish marsh is the only wetland habitat expected to decline in area conserved relative to the existing reserve footprint (mean difference of −39%). Swamp, transition marsh, and tidal swamp increase in area protected, relative to the amount currently conserved, by 4%, 249%, and 58%, respectively. Overall, expected wetland protection increases by an average of 6% under an optimal reserve design relative to the existing footprint, and an average of +4% relative to the amount of wetland currently conserved. Counterfactual results are provided in Table 2 (final column) for all 19 habitat types as the ratio of optimal : current design. Notable results include a nearly 50% increase in protection of estuarine beach, a 19% increase in inland shore habitat, and a 22% increase in protection of upland undeveloped lands. Counterfactual comparisons for wetland outcomes across the three risk tolerance alternatives demonstrate the trade-offs between expected benefits and variance (Fig. 4).

Budget-constrained optimization

We constrained the model to four hypothetical budget limitations (as percentages of the area of unprotected land; Appendix S1: Section S5, Table S3) for exploring

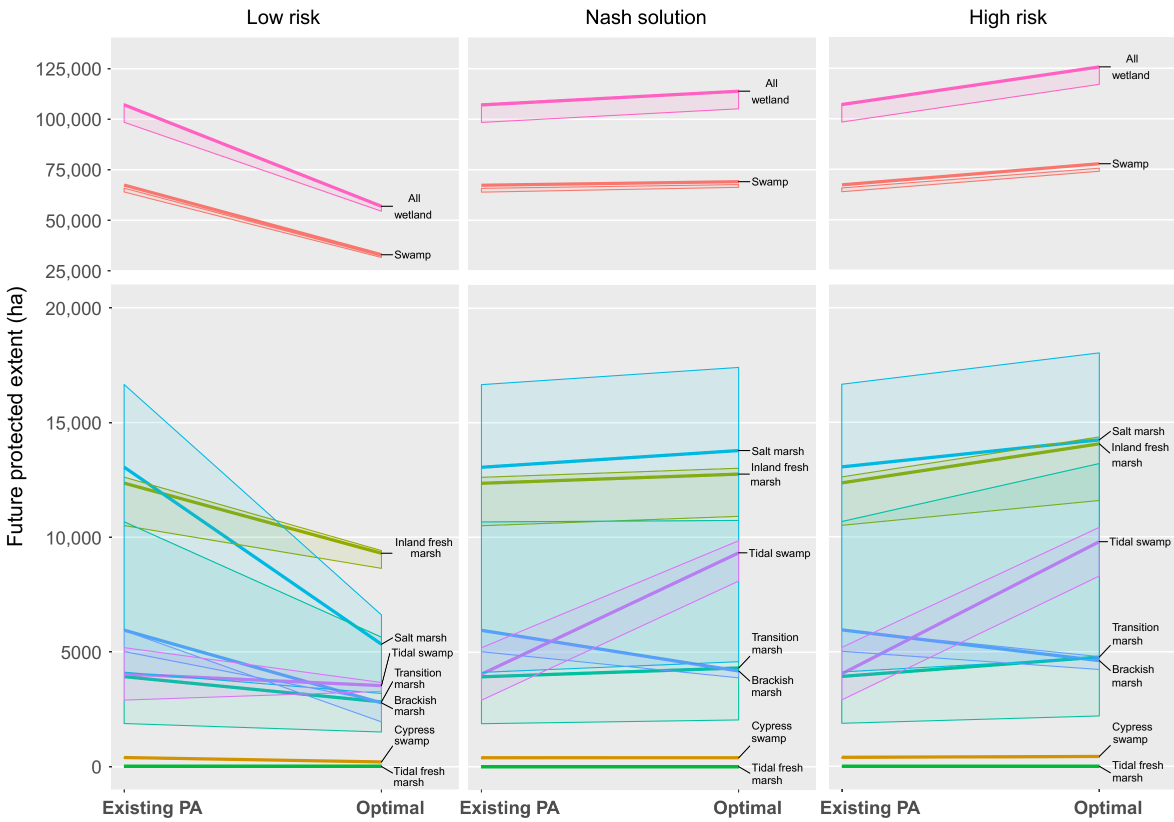

FIG. 4. Slope graphs depicting counterfactual comparisons between future protected wetland habitat under the existing protected area network (left side of each panel) and three Pareto-optimal reserve designs (right side of each panel). Polygons represent future uncertainty regarding the degree of habitat protection as a function of three sea-level rise (SLR) scenarios; heavy lines estimate trends under a medium SLR projection, thin lines represent high and low SLR projections. Some habitats (e.g., swamp) are predicted to increase in extent under medium SLR relative to high and low projections, hence the heavy line lying above the polygon. Under a low-risk preference (left panels), optimal future protection is lower for all wetland habitats relative to the existing reserve footprint, although uncertainty is considerably reduced. Under the Nash bargaining and high-risk preference solutions (middle and right panels, respectively), all habitat types except scrub-shrub transition marsh increase in protected extent relative to the current protected-area design. Expected benefits and variance over SLR scenarios for the high-risk solution are not substantially greater than under the Nash solution, but increased variance is observed for several habitat types (e.g., tidal swamp, inland fresh marsh). Not depicted in the figure is the projected *total* amount of each wetland habitat available for protection (this quantity can be found on the right side of the left panels in Fig. 2). Note the change in scale (ha) on the *y*-axis for both upper panels (25,000 ha between tick marks compared to 5,000 ha in lower panels).

the effects of various levels of financial resources on trade-offs between expected habitat benefits and risk. A constrained optimization is more likely to provide insights into decisions to divest from currently conserved areas to fund acquisition of parcels that better meet future habitat needs. For these scenarios, we do not analyze the sensitivity or counterfactuals as above, but instead focus on inference gained through adding fiscal constraints to the reserve design optimization, which directly impact the equilibrium of investment decisions.

Based on allocations of total available budget under each fiscal scenario, we approximate Pareto-optimal frontiers for the 14 parcel subsets. We compute a Nash bargaining solution for each subset, then combine these for each scenario and graphically portray the global portfolios (Fig. 6). As expected, the number of divestment decisions declines as the total budget increases. With increasing budgets, the switch from “divest” to “retain” currently protected parcels is most pronounced nearer (≤20 km) the coastline and along rivers. As budgets increase, land acquisition decisions also appear to be focused in proximity to river channels as well as near-shore parcels inland between the refuge and the National Forest. Both regions are likely candidates for future wetland habitat that may replace those lost to SLR. Additional details on budget scenario outcomes are provided in Appendix S1: Section S5, Table S4.

Viewing budget scenario outcomes of the benefits, associated risks and costs associated with a reserve design strategy allows us to directly evaluate trade-offs

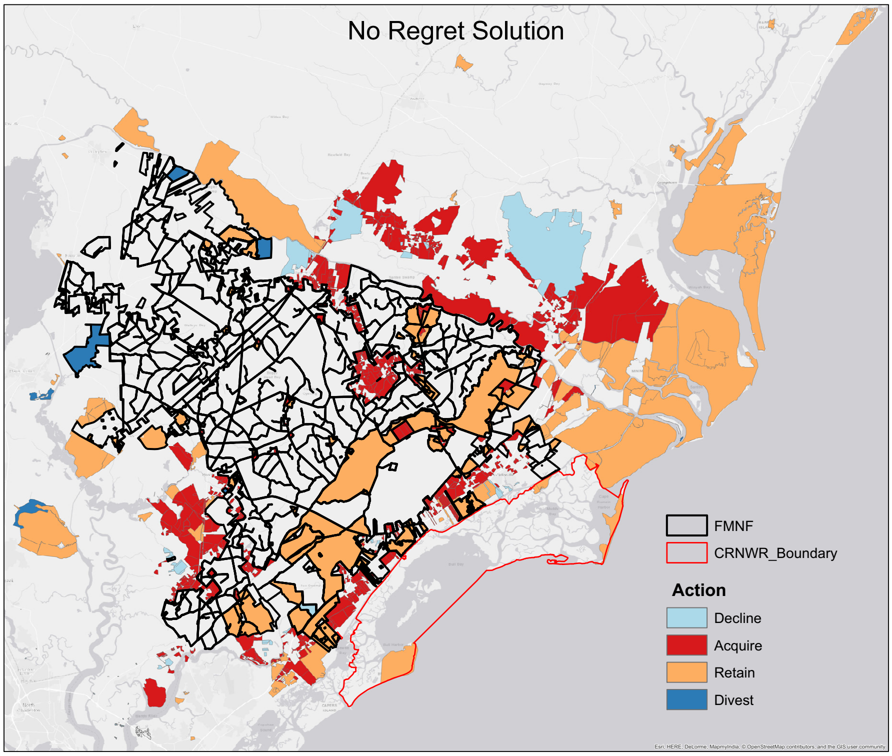

FIG. 5. Reserve design solutions that are robust to uncertainty related to a decision maker's risk preference attitude as depicted in Fig. 3. This robust solution represents a "no regret" set of candidate decisions across this spectrum of subjective risk tolerance levels.

between these broad objectives (based on Nash bargaining solutions and scaled for comparison; Fig. 7). As expected, the costs of implementing a reserve design increase linearly with available budget. Habitat benefits increase to a threshold budget of 35% of available land, after which they appear to level off. Perhaps surprisingly, our risk metric declines dramatically with an increase in budget from 10% to 20% and then appears to stabilize. This may suggest the existence of a budget threshold where sufficient financial flexibility allows acquiring a diverse enough portfolio to ameliorate correlated risk. Assessing the relative trade-offs among these three parameters, in conjunction with spatial depictions of alternative solutions, can aid a decision maker in deciding on a land acquisition strategy that best meets their agency's mission (Appendix S1: Section S5).

DISCUSSION

The stability, resilience, and adaptability of a system, whether a community, an ecosystem, or a financial system, has been linked to diversification (Markowitz 1952, Holling 1973, Figge 2004). Indeed, resilience theory posits that maintenance of diversity (of assets, processes, or governance structures) is an essential component for ensuring the transformability and potential of complex adaptive systems (Holling 2001, Folke 2006, Folke et al. 2010). Presaging the concerns of later resilience thinking regarding the potential dangers of reducing system heterogeneity through an "aggressive pursuit of efficiency" (Johnson et al. 2013), Markowitz (1952) rejected the hypothesis that an investor should seek to maximize a discounted return because optimizing for an expected value will fundamentally fail to recognize diversification as preferred strategy. MPT provides a means for optimizing allocation decisions by accounting for both expected returns and the risks associated with uncertain outcomes. This approach treats risk more comprehensively than traditional diversification approaches by considering the synchrony of future outcomes between all assets (Ando and Mallory 2012). Thus, more explicit portfolio risk management is achieved than by considering simpler proxy representations of diversity. In our case study, we demonstrated that although a risk-averse solution achieves reductions in variance, it can also produce management outcomes that are substantially lower than even the worst-case scenario under higher risk preferences. Because resource managers have been characterized as often acting in ways consistent with risk aversion (Howitt et al. 2005), the ability to quantify the effects of risk preference will be invaluable to natural resource management.

Integrating MCDA with mean-variance portfolio optimization offers a powerful analytical framework for making efficient allocation decisions with limited budgets when accounting for multiple conservation targets

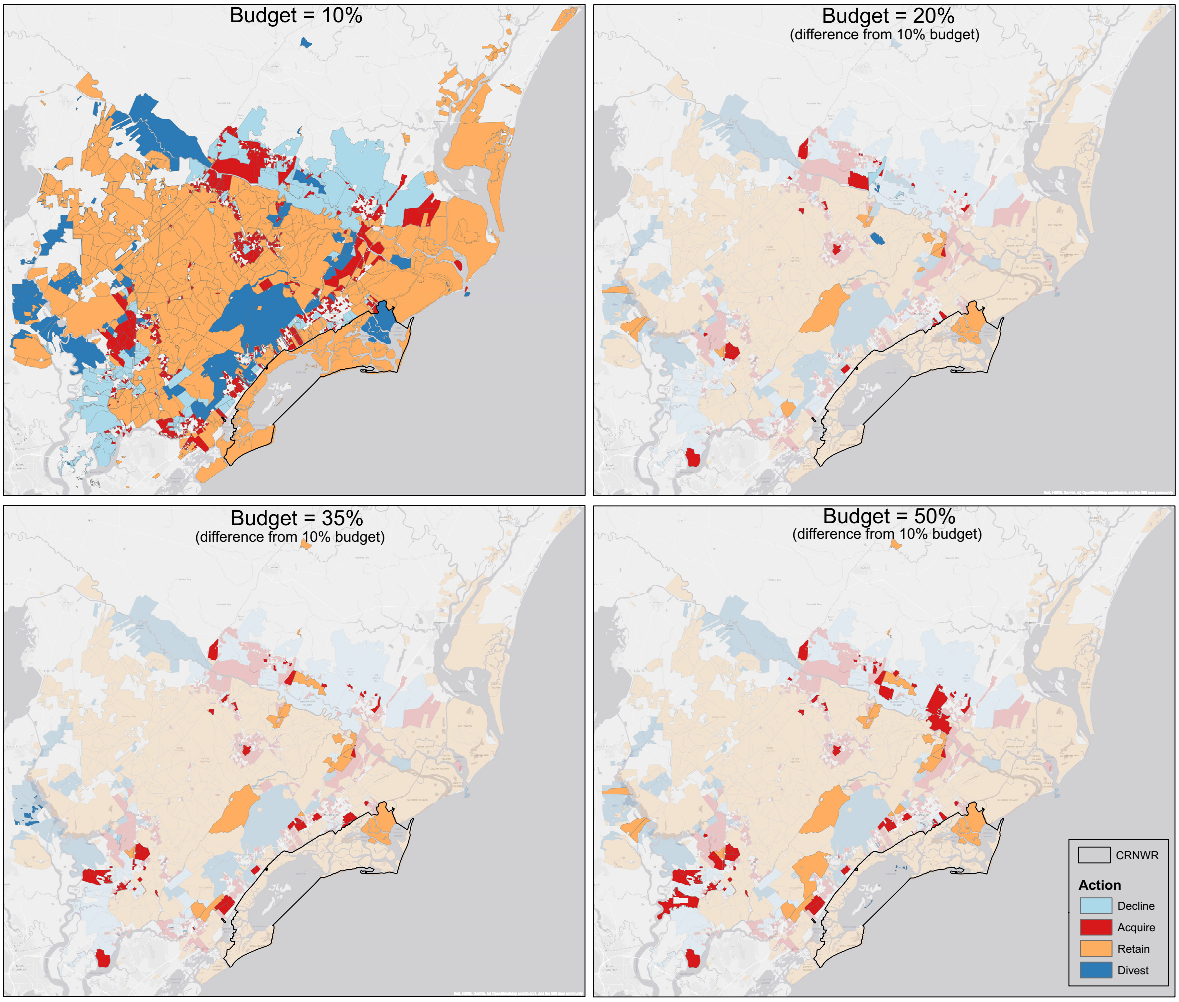

Fig. 6. Effect of budget constraints on optimal MPT reserve design portfolios. Budget constraints are represented as the proportion of total area of land in unprotected status (i.e., ostensibly available for acquisition). Budgets are allocated to 14 sub-groupings of parcels based on the relative proportion of land acquisition decisions recommended for an unconstrained analysis. The Nash solution was selected for each sub-group (see Appendix S1: Fig. S1) to formulate the global reserve design. Highlighted parcels for 20%, 35%, and 50% available land scenarios depict changes in the optimal decision relative to that under a budget of 10%.

and the risks of an uncertain future. The ability to identify a relatively small subset of Pareto-optimal portfolios from the near infinite number of possible alternatives represents a significant benefit to decision makers who can become overwhelmed by the complexity of the portfolio decision. An additional advantage of this approach is the flexibility of a hierarchical objectives framework to make explicit trade-offs among competing management criteria at the parcel level and between return and risk for the portfolio. The latter trade-offs, along the efficient frontier, will be based on risk preferences, beliefs about the likelihood of future climate conditions or the desired level of resource performance, with the knowledge that all identified options are Pareto optimal.

Although developed for financial applications, the MPT framework has seen a growing number of applications for natural resource management (Koellner and Schmitz 2006, Moore et al. 2010, Schindler et al. 2010, Ando and Mallory 2012, Convertino and Valverde 2013, Mallory and Ando 2014, Anderson et al. 2015), several of which contribute important advances in spatial planning for climate change adaptation, including novel methodological approaches for addressing multiple objective problems (Ando et al. 2018, Runting et al. 2018). Many of these studies, however, do not take full advantage of MPT's analytical power. For example, some case studies demonstrate negligible correlation among assets (Convertino and Valverde 2013) while others include sites that are entirely synchronous across scenarios (Marinoni et al. 2011); both of these cases are uninformative from a risk perspective. Other applications have reduced problem dimensionality by formulating the decision variable as continuous (e.g., representing the proportions of a budget to allocate to

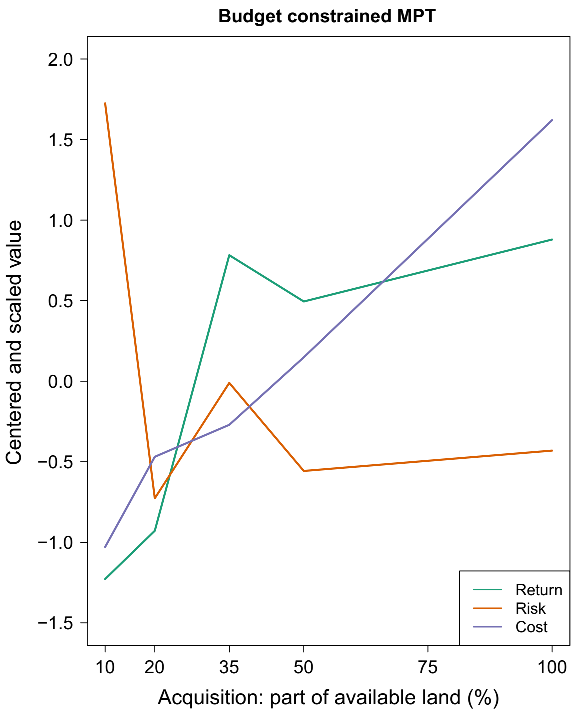

Fig. 7. Trade-off comparisons, based on Nash bargaining solutions, among the primary metrics of the MPT analysis: portfolio reward, risk, and cost. To compare across independently derived metrics, we centered each variable on zero and scaled by one standard deviation.

broad subregions or planning units; Marinoni et al. 2011, Ando and Mallory 2012), rather than a discrete variable representing decisions pertaining to each asset (Runting et al. 2018). We have specified an analytical approach to be more explicit in supporting decision-making by addressing a large set of relevant considerations of coastal zone managers, including competing objectives among multiple decision makers, an appropriately scaled decision variable (e.g., the parcel-unit), an analytical method for seeking a balance between risk and benefits, and a means to evaluate divestment decisions for more efficient, long-term planning.

Here, we apply MCDA-MPT to a case study using simplified resource objectives and a small number of climate-change scenarios to demonstrate an approach that we believe will be useful in supporting coordination of conservation planning at the scale of actual decisions made by state, federal, and non-governmental land managers. The uncertainty of climate change impacts to natural resources and ecosystem goods and services, and variation in stakeholder willingness to accept the inherent risk of any management decision, suggest this as an appropriate approach for evaluating adaptation actions such as designing new protected area networks. The results from our study indicate that changes in important habitat types could be substantial in coastal South Carolina, and that losses of protected wetlands under the current conservation network will be highly variable as a function of SLR, possibly exceeding 9% of current extent. The expected improvements to future habitat preservation under an optimal portfolio design are able to counteract many of these losses. Importantly, in some cases the MPT solution produced a net gain of conserved habitat relative to the amount currently under protection, regardless of SLR scenario, whereas the current reserve footprint resulted in an overall loss of this habitat. Our analysis reveals that parcel-level decisions may be somewhat robust to differences in risk attitudes, with nearly three-quarters of parcel decisions remaining unchanged across a moderate range of risk tolerances. Evaluating the dynamics of portfolio cost, risk and return over several hypothetical budget scenarios provides additional insights into the trade-offs and interactions among management objectives when constraints were imposed. The dynamics of investment and divestment decisions are strongly governed by both fiscal resources and risk attitude. Identifying changes in the rate of marginal return, either along the Pareto frontier or as a function of changes in constraints (e.g., investment levels), is an additional strength of portfolio analysis (Polasky et al. 2008). For our case study, identifying the investment threshold resulting in substantial increases in return with a marginally smaller increase in risk represents such an inflection point. Considering the Pareto frontier, representing direct trade-offs between management return and risk, the Nash bargaining solution provides an analytical means to locate the point of diminishing marginal returns (Appendix S1: Fig. S3) on either objective, which can be a useful place to begin negotiations. To our knowledge this is the first application of such an approach to SCP.

There are several considerations that should be addressed prior to implementing decisions based on this portfolio optimization framework. Importantly, the basis by which we evaluated reserve portfolios was a function of SLR and subsequent habitat transition projections, which originated from simple SLAMM model output. Although widely used, this model has been criticized for limitations in how input data (e.g., DEMs) are used, its lack of predictive hydrodynamics, simplistic assumptions regarding erosion, storm impacts, accretion and sedimentation processes, and for ignoring feedback mechanisms between SLR and system responses (Craft et al. 2009, Donoghue et al. 2013). We acknowledge numerous recent advances in SLR modeling, particularly efforts to understand marsh migration dynamics that account for finer scale details of local conditions, including feedback between geomorphology and marsh evolution, sediment transport, and colonization by wetland flora, to provide more accurate predictions of habitat changes (Brand et al. 2012, Fagherazzi et al. 2012, Thorne et al. 2015). However, we chose to use the SLAMM model because it is freely available and easily interpreted, making it a sensible choice to demonstrate principles and gain inferences using the MPT analysis. Understanding the uncertainties around prediction of changes in individual habitat types, one approach to reduce such error was to group all wetland types together, possibly at the expense of lower precision.

An additional limitation of constrained portfolio optimization is computational complexity; the general problem has been long recognized by computer scientists as NP hard (Sarkar et al. 2006). Even with an efficient search algorithm (Pal and Charkhgard 2019), this complexity resulted in the need to subset available parcels to allow for tractability and reasonable computational time, acknowledging that such groupings required some arbitrary assumptions. Although we stratified these groups by similar ecological characteristics and into potential planning units, our evaluation did not account for trade-offs among subgroups nor did we conduct sensitivity analyses to quantify the effect of subsetting on optimal results.

Such limitations also precluded consideration of parcel connectivity as an optimization criterion for evaluating portfolio benefits. Connectivity is a well-recognized design criteria in spatial planning (Sarkar et al. 2006, Pressey et al. 2007), from the context of maintaining species richness (e.g., island biogeography theory), maintaining species dynamics (e.g., metapopulation theory) or, in the context of SLR, supporting landward migration of coastal habitat. One practical solution to improve connectivity is to use postprocessing algorithms to generate more compact reserve alternatives to compare with Pareto alternatives (Udell et al. 2018). It is important, however, to consider whether contiguous parcels are positively correlated in expected future value and how such dynamics would impact portfolio risk. An evaluation of the trade-offs between connectivity and risk criteria may be a useful topic for future research.

Important considerations specific to our model formulation include the treatment of urbanization probability estimates and the significance of divestment decisions for currently protected lands. In spatial conservation planning, urbanization is viewed as a threat leading to permanent loss of a parcel for protection. One approach to address this issue is by framing the problem as a sequential reserve design whereby a site-ordering algorithm is used to identify the sequence in which parcels might be acquired to maximize portfolio return while accounting for the dynamic risk of parcel loss (Sarkar et al. 2006, Moilanen and Cabeza 2007). Because of the large number of parcels, we simplified our problem to a single-stage optimization in which higher risk of urbanization raises a parcel's values above that of its habitat benefits alone to modify the likelihood that the parcel will be selected for conservation. In this sense, we implicitly accounted for temporal dynamics of parcel utility by a measure that represents spatiotemporal patterns of land conversion. Valuing parcels as a linear function of urbanization risk may be reasonable in some circumstances, but other approaches exist for addressing development risk (Costello and Polasky 2004).

Divestment from public or privately held conservation lands may be seen as undesirable (but see Alagador et al. 2014). However, recognizing that dynamic habitats can limit expected gains in efficiency under assumptions of static reserve boundaries, researchers have explored relaxing of restrictions on irreversible reserve design decisions (Strange et al. 2006). Although relinquishing an entire protected area may be unprecedented, agencies are authorized to modify their holdings or exchange small parcels for others of equal value (Thompson 2004). Precedent also exists for transferring public lands to resolve conflicts or address greater societal needs, such as a Congressional Act that transferred nearly 800 acres (1 acre = 0.40 ha) from Olympic National Park to assist the Quileute Tribe to relocate from rising seas, erosion, and tsunami threat (U.S. Congress 2012). In our case study, only strong risk aversion led to recommendations for divesting from nearly all coastal refuge holdings. The ability to reinvest funds generated from divestments may also be desirable when budget constraints limit the ability to appropriately diversify assets. A more feasible alternative may be for public land managers to engage in flexible conservation contracts with private landowners. Term-limited conservation easements, with contract negotiations based on the expected longevity of benefits, would allow limited financial resources to be used for conserving future high-value areas rather than being tied up in managing parcels in perpetuity. There are risks to fixed-term contracts, however, including added transaction costs, increased instability in land-use planning, and possible disincentives for landowners wishing to provide a long-term conservation legacy (Thompson 2004).

Conclusions

Expanding or altering existing protected area networks is a necessary adaptation strategy to sustain conservation objectives and mitigate the effects of climate change and land conversion. Securing diversified assets in a conservation portfolio is an accepted strategy for increasing system resilience to offset unknown future conditions. We have expanded the use of MPT for spatial conservation planning to account explicitly for the rationale underlying diversification, which is to maximize future complementarity of a collection of protected lands by minimizing potentially correlated outcomes. This reserve design framework offers several benefits relevant for supporting conservation problems beyond our application to coastal South Carolina. Our model approach includes an optimization algorithm that accommodates large, multi-objective decision problems, an axiomatic selection method (the Nash bargaining solution) to equitably balance trade-offs when negotiating among different risk attitudes is not practical, and consideration of the potential benefits of both investment and divestment of assets. Identifying Pareto-optimal solutions over climate and budget uncertainties, and across a spectrum of stakeholder preferences, provides critical insights on the sensitivity of conservation strategies to risk and risk attitudes. The influence of differing levels of risk tolerance in driving management policy is rarely considered in environmental decision-making (Greiner et al. 2009). Our approach is not limited to spatial conservation planning but could be applied to a wide range of resource allocation or investment decisions for which unresolvable uncertainty requires strategic risk management. Examples include allocating research or monitoring funding to maximize learning to directly inform management decisions, evaluating the risks of introducing disease or unwanted species in translocation or restoration programs, spatial management of invasive species or communities of conservation concern, and assessing the success and risks of alternative urban planning policies in response to uncertain threats.

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Supporting Information

Additional supporting information may be found online at: http://onlinelibrary.wiley.com/doi/10.1002/eap.1962/full

Data Availability

Data associated with this study are available from the USGS ScienceBase Catalog: https://doi.org/10.5066/p91xu2on