

# When portfolio theory can help environmental investment planning to reduce climate risk to future environmental outcomes—and when it cannot

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## Abstract

Variability among climate change scenarios produces great uncertainty in what is the best allocation of resources among investments to protect environmental goods in the future. Previous research shows Modern Portfolio Theory (MPT) can help optimize environmental investment targeting to reduce outcome uncertainty with minimal loss of expected level of environmental benefits, but no work has yet identified the types of cases for which MPT is most useful. This article assembles data on 26 different conservation cases in three distinct ecological settings and develops new metrics to evaluate how well MPT can reduce uncertainty in future outcomes of a set of environmental investments. We find MPT is broadly but not universally useful and works best when multiple investments have negatively correlated outcomes across climate scenarios; a second-best investment has expected value almost as good as the value in the best investment; or multiple investments have little uncertainty in ecological outcomes.

## KEYWORDS

climate change, conservation, diversification, environmental investments, finance, MPT, portfolio, risk, uncertainty

## 1 | INTRODUCTION

Climate change threatens many species and ecosystem services (Thomas et al., 2004). Uncertainty associated with future climate projections complicates decision making associated with the future management of natural resources (Ahmadalipour, Moradkhani, & Rana, 2018; Thorne et al., 2017), and quantifying that uncertainty is a growing area of research (e.g., Allen, Stott, Mitchell, Schnur, & Delworth, 2000; Frigg, Thompson, & Werndl, 2015; Shiogama et al.,

2015). The Intergovernmental Panel on Climate Change recognizes uncertainty in both future emissions and climate models (Stocker et al., 2013) by using a multi model ensemble of General Circulation Models (GCMs) and a range of Representative Concentration Pathways (RCPs). For instance, Collins et al. (2013) report a range of global mean surface temperature in 2100 using an ensemble of GCM's from 2.6 to 4.8 °C using RCP 8.5 and 1.1 to 2.6 °C using RCP 4.5. Regional climate models provide climate scenarios at smaller scales than the global circulation models, but downscaling approaches inherit

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the uncertainty and errors of the global circulation models chosen to drive them (Pourmohhtarian, Driscoll, Campbell, Hayhoe, & Stoner, 2016).

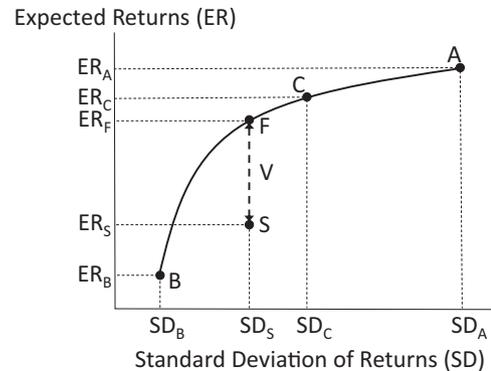
Uncertainty in climate projections suggests that natural resource managers need ways to spatially stratify management investment across the extent of a natural resource (Thorne et al., 2017). Risk-averse decision makers benefit from planning tools that find investment strategies with less uncertainty in their future total values. One tool adapted from finance, Modern Portfolio Theory (MPT), diversifies investments between multiple assets (things in which one could invest) to reduce uncertainty in total future returns with minimized loss in the expected value of those returns (Ando & Mallory, 2012). This tool has been adapted to many kinds of environmental investment problems including fishery management (Anderson, Moore, McClure, Dulvy, & Cooper, 2015; Sanchirico, Smith, & Lipton, 2008), biodiversity conservation (Figue, 2004; Koellner & Schmitz, 2006), and control of pests and invasive species (Aker, Kompas, & Ward, 2015; Yemshanov et al., 2014). Additionally, researchers are working to couple complex reserve site selection (RSS) tools like Marxan (e.g., Ball, Possingham, & Watts, 2009) with MPT to reduce conservation outcome uncertainty (Liang et al., 2018).

Previous research shows cases for which MPT can reduce risk at low cost but has not shown if there are environmental investment cases for which MPT is not useful. Extensive data are needed to carry out an efficient portfolio analysis; one would only want to prepare those data if the method were likely to reduce outcome uncertainty with little sacrifice of expected return and if MPT would perform better than simple diversification that just divides an investment evenly among assets (Pyke & Fischer, 2005). This article applies a consistent stylized form of MPT to 26 heterogeneous conservation investment decision cases and identifies correlations between features of those cases and the success of MPT in mitigating future outcome uncertainty.

## 2 | METHODS

### 2.1 | Overview of MPT

A portfolio is a set of investments in multiple things or places called assets; in our examples, conservation investments are allocated among spatial subregions of a planning area. The fraction of total portfolio investment in a particular subregion is that subregion's weight. MPT solves for the portfolio weights that minimize the variance of the total ecological value of the chosen investments for a given expected value of the portfolio. This optimization problem is solved for multiple levels of expected ecological value (or return) to find a set of efficient portfolios. Plotting the expected return versus the

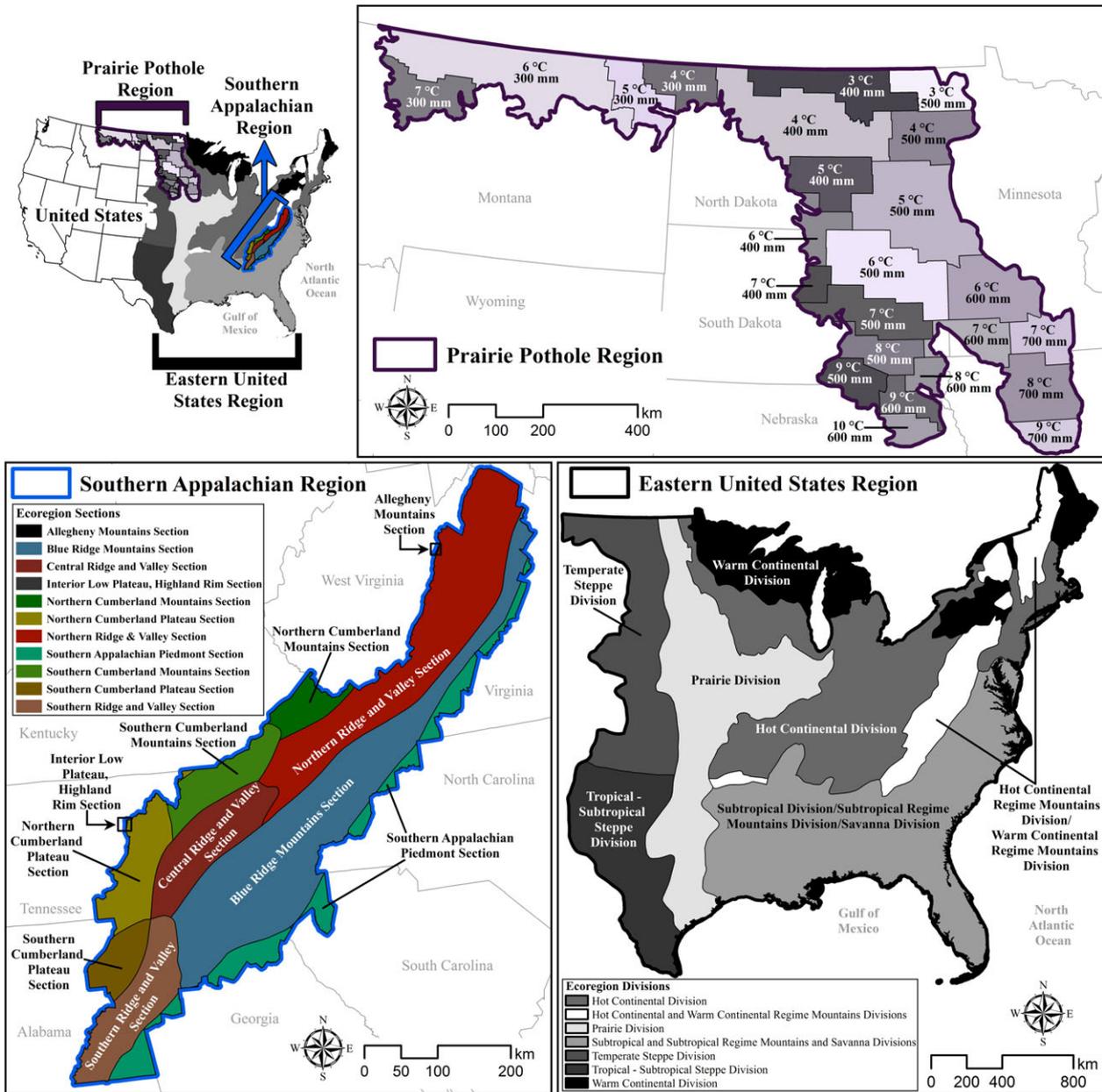


**FIGURE 1** Stylized efficient frontier: The curve is a stylized representation of portfolios on an efficient frontier. Point A has the highest standard deviation of outcomes, point B has the lowest, and point C has the median. Point S represents the outcomes for a simply diversified portfolio constructed by dividing investment evenly between all subregions. Point F is the point on the efficient frontier with the same standard deviation as point S; the vertical distance between them is  $V = ER_F - ER_S$  and  $D = \frac{100 \times V}{ER_F}$ . If  $SD_S > SD_A$  or  $SD_S < SD_B$ , then  $V$  and  $D$  are not defined

standard deviation of returns of the efficient portfolios yields an efficient frontier (Figure 1); the exact shape varies across cases. Portfolios with high risk and low return exist below the frontier but would never be chosen. Portfolios above the frontier with low risk and high return do not exist. The highest level of expected return on the frontier, Point A, also has the highest standard deviation of return because the portfolio represented by that point has all investment in the subregion with the highest expected return and is risky because it is not diversified. Moving from right to left on the efficient frontier, one can shift some investment out of the best subregion into others; this diversification reduces the expected return of the portfolio but also reduces uncertainty in portfolio returns.

### 2.2 | MPT data construction and analysis

This article studies investment allocation cases in three different settings (Figure 2) with outcome forecasts from different climate change scenarios and models; see Supporting Information. First, we study habitat conservation in the Prairie Pothole Region (PPR), a region of the Northern American Central Plains grasslands that is a highly productive area for wetland-associated birds (Batt, Anderson, Anderson, & Caswell, 1989; Johnson et al., 2005; Naugle, Johnson, Estey, & Higgins, 2001). We explore changes in habitat suitability for waterfowl and amphibians across 24 climatic subregions derived from geographic patterns of mean annual precipitation (mm) and temperature ( $^{\circ}\text{C}$ ) isoclines from a 30-year climate normal (1961–1990) (Millett, Johnson, & Guntenspergen, 2009; Winter, 2000). Second, we prioritize conservation among 11 section-level ecoregions in southern Appalachia to preserve future suitable habitat for 34 plethodontid salamander species grouped by global and regional conservation status



**FIGURE 2** Study areas of analyses: Subregions used for MPT analyses. The U.S. portion of the Prairie Pothole Region has 24 climatic subunits derived from geographic patterns of mean annual precipitation (mm) and temperature (°C) isoclines from a 30-year climate normal (1961–1990) (Millett et al., 2009). The Southern Appalachian Region has 11 section-level ecoregions (Bailey & Cushwa, 1981) used for the salamander analysis. The Eastern United States region has 7 subregions, merged from 10 division-level ecoregions (Bailey & Cushwa, 1981), for the bird analysis

(Davic & Hartwell, 2004; Milanovich, Peterman, Nibbelink, & Maerz, 2010). Third, we explore bird habitat conservation across 7 division-level ecoregions of the Eastern United States (Askins, 1993; Robbins, Sauer, Greenberg, & Droege, 1989) for a group of all species, a group of 7 species of IUCN concern, and 11 individual species that are either an IUCN species of concern or have a NatureServe National Conservation Status Rank of “vulnerable” or “apparently secure” (Matthews, Iverson, Prasad, & Peters, 2007).

We construct and analyze data sets as follows (details are in Supporting Information). First, we define the universe of

subregions by the context of the case. The PPR is recognized by a combination of physical and biotic factors; that defines the spatial extent of our MPT targeting (Omernik, 1987). Southern Appalachian salamanders have limited ranges and abilities to migrate in response to climate change pressure; this defines the spatial extent of MPT targeting for salamander habitat. Birds can migrate with ease compared to salamanders; thus, we conduct MPT targeting for birds over most of the Eastern United States.

Second, each broad region is divided into subregions selected so that future ecological benefits exhibit variation

across climate scenarios. We split the PPR into subregions that encompass regional gradients in precipitation and temperature. We use ecoregions in the analyses of bird and salamander conservation targeting because they capture variation in the factors that govern the structure and function of ecosystems (Bailey, 2009).

Third, we define the return on investment to be optimized as a measure of benefit per unit of cost (Ando, Camm, Polasky, & Solow, 1998). We use land values as a measure of cost and use ecological outcome measures common to each case to measure benefit. For the PPR, we use three benefit indices: the cover cycle index (CCI), a measure of wetland quality that has been used to study waterfowl habitat; hydroperiod, or time of inundation; and spring inundation, which is even more closely tied to wetland biota and diversity (particularly of amphibians) than hydroperiod (Fay, Guntenspergen, Olker, & Johnson, 2016; Johnson et al., 2005; Johnson et al., 2010; Werner, Johnson, & Guntenspergen, 2013). For salamanders and birds, we use the probability that a subregion is climatically suitable for the species. For a benefit metric for a group of species, we sum the probabilities in the subregion for all the species in the group and divide by the area of the subregion. Figure 3 uses some of those benefit data to illustrate how the subregion that seems the best place for conservation investment depends on which climate scenario one looks at.

Fourth, we construct the probability distribution of returns in the future from a probability distribution of climate change scenarios over each subregion and the ecological returns for each subregion in each climate scenario from step three. We perform the MPT analysis following Ando and Mallory (2012) in step five.

### 2.3 | Metrics of MPT effectiveness

New measures capture three kinds of MPT effectiveness for each MPT analysis that are unit free and thus comparable across cases with different units of measurement (Figure 1). Two elasticities of return quantify what percentage of expected returns must be sacrificed to reduce standard deviation by 1%. First, we quantify this tradeoff for an incremental change from the riskiest point, A (edge elasticity,  $\eta_E$ ):

$$\eta_E = \left( \frac{\partial ER}{\partial SD} \right) \Big|_A \left( \frac{SD_A}{ER_A} \right). \quad (1)$$

Second, we calculate elasticity of return for a discrete change from the riskiest point to a point with the median risk (arc elasticity,  $\eta_A$ ) by dividing the percentage change in expected return from point A to point C (the middle of the efficient frontier) by the corresponding percentage change in standard deviation:

$$\eta_A = \left( \frac{ER_A - ER_C}{SD_A - SD_C} \right) \left( \frac{(SD_A + SD_C) / 2}{(ER_A + ER_C) / 2} \right). \quad (2)$$

Each of these elasticities is smaller when the efficient frontier is flatter. That means you can reduce risk without much cost in lost expected return, so a small elasticity indicates that MPT is more effective.

The third efficacy metric,  $D$ , equals the percentage difference in expected returns between a point  $F$  on the efficient frontier and the outcome of simple diversification (a portfolio  $S$  with investment divided equally among all subregions to the efficient frontier). The shortest vertical distance from simple portfolio  $S$  to the efficient frontier is  $V = ER_F - ER_S$ , and

$$D = \frac{100 \times (ER_F - ER_S)}{ER_F}. \quad (3)$$

The expected return on the simple portfolio is  $D$  percent lower than the efficient frontier. When  $D$  is larger, it is more useful to use MPT instead of simple diversification. Note that an alternative metric of the inefficiency of simple diversification is presented in Supporting Information.

### 2.4 | Metrics of case characteristics

We develop new metrics of three kinds of characteristics of conservation cases that may be associated with MPT efficacy. First, we create two measures of exceptionalism;  $\Delta E_1$  captures how much higher the expected return is for the best subregion than for the second best, and  $\overline{\Delta E}$  gives an overall measure of how much expected returns decline down the ranks from one subregion to that with the next best expected return. We rank the  $M$  subregions in descending order of expected returns:  $ER_1, ER_2, \dots, ER_M$ . The percentage difference in expected return from the best subregion to the next best,  $\Delta E_1$ , is

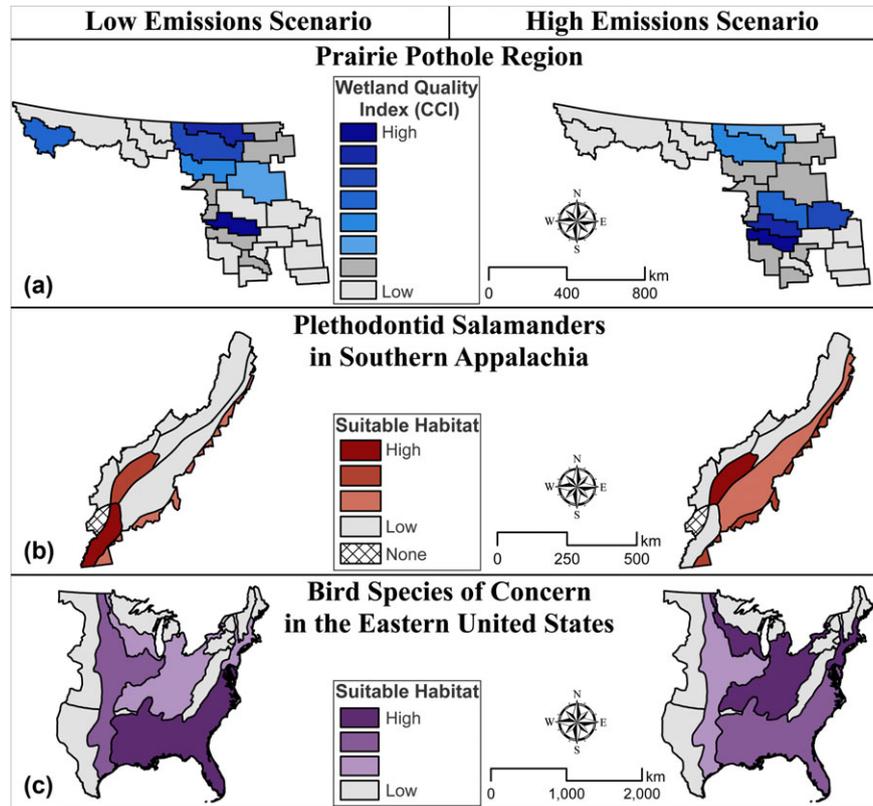
$$\Delta E_1 = \frac{100 \times (ER_1 - ER_2)}{ER_1}. \quad (4)$$

The average percentage difference in expected returns from each subregion to the subregion ranked below it,  $\overline{\Delta E}$ , is

$$\overline{\Delta E} = \left( \sum_{i=1}^{M-1} \frac{(ER_i - ER_{i+1})}{ER_i} \right) \frac{100}{M-1}. \quad (5)$$

Diversification reduces the standard deviation of total returns by shifting some investment out of the subregion with the highest expected return. If that subregion is exceptional, diversification will be costly. We hypothesize that  $\Delta E_1$  and  $\overline{\Delta E}$  will be positively correlated with the elasticities  $\eta_E$  and  $\eta_A$ .

Second, we create measures of the presence of negative correlations among subregions of a case. There are  $M-1$  covariances with the subregion that has the highest expected value; the metric  $\sigma_{1j}[-]$  equals the percent of those that are negative.



**FIGURE 3** Uncertainty in climate change from low and high carbon emissions scenarios causes uncertainty in how to allocate conservation investments among assets. (a) Asset prioritization for the prairie pothole region is based on average wetland quality index (CCI) with the top six assets shown in blue (predictions based on 100-year sequences from community climate system model). (b) Asset prioritization for southern Appalachia is based on average suitable habitat for all species of plethodontid salamanders with the top three assets shown in red (predictions based on year 2050 from the Hadley Centre coupled model). (c) Asset prioritization for the Eastern United States is based on the average suitable habitat of bird species with a concerned status (i.e., IUCN Red List near threatened, vulnerable, or endangered) with the top three assets shown in purple (predictions based on year 2100 from average of three climate models)

The metric  $\sigma_{ij}[-]$  equals the percent of all covariances in the matrix that are negative. When negative correlations are present, if one subregion performs poorly at least the other will do well and MPT analysis can be useful. We hypothesize that  $\sigma_{1j}[-]$  and  $\sigma_{ij}[-]$  will be negatively correlated with  $\eta_E$  and  $\eta_A$ .

Third, we create measures of the presence of low-risk options. The coefficient of variation  $CV_i = SD_i/E[R]_i$  measures riskiness of a subregion as the ratio of its standard deviation to its expected return. The lowest  $CV$  and the mean  $CV$  in the set of  $CV$  measures for all  $M$  subregions are

$$CV_{\min} = \min \{ CV_i \}, \text{ and } \overline{CV} = \frac{\sum_{i=1}^M CV_i}{M}. \quad (6)$$

Diversification could work by putting investment in a low-risk subregion. We hypothesize that  $CV_{\min}$  and  $\overline{CV}$  will be positively correlated with the elasticities of return  $\eta_E$  and  $\eta_A$ .

### 3 | RESULTS

Table 1 reports the features of the portfolio selection cases we analyze. In some cases, the second-best portfolio is almost exactly as good as the first whereas in others one loses almost 80% of expected return by shifting investment from the best to the second-best portfolio. Means of  $\Delta E_1$  and  $\overline{\Delta E}$  are 33 and 29. Cases also vary widely in how much negative covariance there is across returns on different subregions. Some cases have no negative correlations. In others, 80% of the subregions are negatively correlated with the subregion that has the best expected return, and in a few cases over half of all the covariances between subregions are negative. The metrics  $\sigma_{1j}[-]$  and  $\sigma_{ij}[-]$  have means of 29 and 22. Some of the conservation cases have subregions that are relatively low-risk options, but not all.  $CV_{\min}$  ranges from 0.00 to 1.6 with a mean of 0.24, and  $\overline{CV}$  ranges from 0.02 to 2.5 with a mean of 0.62.

Both the edge and the arc elasticities in Table 1 and panel (A) of Figure 4 are less than one in magnitude for all cases

**TABLE 1** Metrics<sup>a</sup> for all conservation cases

	$\Delta E_1$	$\overline{\Delta E}$	$\sigma_{1j}[-]$	$\sigma_{ij}[-]$	$\overline{CV}$	$CV_{\min}$	$\eta_E$	$\eta_A$	$D$
Birds in Matthews et al. (2007)									
All 146 bird species	3.74	16.5	33.3	47.6	0.021	0.004	0.072	0.074	21.4
Seven species of IUCN concern	14.5	12.3	16.7	9.52	0.068	0.005	0.196	1.641	NA <sup>b</sup>
Common loon	79.6	73.3	50.0	31.0	1.014	0.294	0.879	0.850	15.5
American bittern	39.9	28.5	0.00	19.0	0.319	0.111	0.459	0.641	30.4
Northern bobwhite	13.3	12.0	0.00	28.6	0.107	0.008	0.213	0.158	NA <sup>b</sup>
Red-headed woodpecker	17.6	26.8	66.7	57.1	0.136	0.012	0.215	0.150	15.7
Chimney swift	0.07	15.0	0.00	0.00	0.069	0.033	0.249	0.336	18.1
Clay-colored sparrow	17.0	47.1	16.7	23.8	0.968	0.339	0.144	0.785	0.05
Bachman's sparrow	72.0	41.1	0.00	0.00	0.582	0.098	1.071	3.003	0.04
Painted bunting	21.7	31.5	16.7	28.6	0.494	0.031	0.196	0.134	28.1
Loggerhead shrike	31.3	21.0	16.7	19.0	0.254	0.018	0.359	0.295	NA <sup>b</sup>
Yellow-throated vireo	6.37	25.1	33.3	47.6	0.202	0.040	0.341	0.459	22.5
Black-and-white warbler	44.7	41.9	83.3	52.4	0.164	0.032	0.333	0.279	0.01
Golden-winged warbler	13.5	47.4	33.3	28.6	0.248	0.039	0.023	0.505	69.7
Cerulean warbler	38.5	49.5	33.3	19.0	0.433	0.140	0.341	0.608	43.2
Sedge wren	38.2	37.8	66.7	19.0	0.713	0.168	0.353	0.815	85.9
Prairie Pothole Region (Fay et al., 2016)									
Cover Cycle Index (CCI)	16.2	11.2	82.6	47.1	0.818	0.566	0.401	0.366	21.8
Spring inundation	22.8	19.7	0.00	0.00	0.788	0.193	0.821	0.833	26.3
Hydroperiod	42.0	12.8	0.00	0.00	0.392	0.265	0.897	0.709	52.7
Salamanders in Milanovich et al. (2010)									
NatureServe categories									
Critically imperiled (S1)	7.07	19.4	11.1	11.1	0.937	0.391	0.083	0.214	35.8
Imperiled (S2)	41.7	25.2	11.1	8.89	1.611	0.983	0.526	0.477	38.2
Vulnerable (S3)	66.5	23.9	11.1	20.0	0.885	0.332	0.698	0.625	30.1
Apparently secure (S4)	69.9	24.4	11.1	25.6	0.814	0.189	0.761	0.715	20.2
Secure (S5)	44.1	25.1	66.7	13.3	0.827	0.256	0.492	0.401	37.3
IUCN Red List categories									
Concerned (NT, VU, EN)	44.8	44.7	11.1	6.67	2.481	1.585	0.694	0.626	36.6
Least concerned	57.6	24.8	88.9	17.8	0.814	0.171	0.638	0.559	28.8
Average	33.3	29.2	29.2	22.4	0.622	0.242	0.441	0.625	29.5
Minimum	0.07	12.0	0.00	0.00	0.021	0.004	0.072	0.074	0.01
Maximum	79.6	73.3	88.9	57.1	2.481	1.585	1.071	3.003	85.9

<sup>a</sup> $\Delta E_1 \equiv$  % difference in expected return from best subregion to next best;  $\overline{\Delta E} \equiv$  average % difference in expected return from one subregion to that with next best expected return;  $\sigma_{1j}[-] \equiv$  % of subregions with which best subregion is negatively correlated;  $\sigma_{ij}[-] \equiv$  % of covariances among all subregions that are negative;  $CV_{\min} \equiv$  smallest coefficient of variation of a subregion;  $\overline{CV} \equiv$  average coefficient of variation;  $\eta_E \equiv$  edge elasticity;  $\eta_A \equiv$  arc elasticity;  $D \equiv$  % vertical distance from simple portfolio  $S$  to frontier.

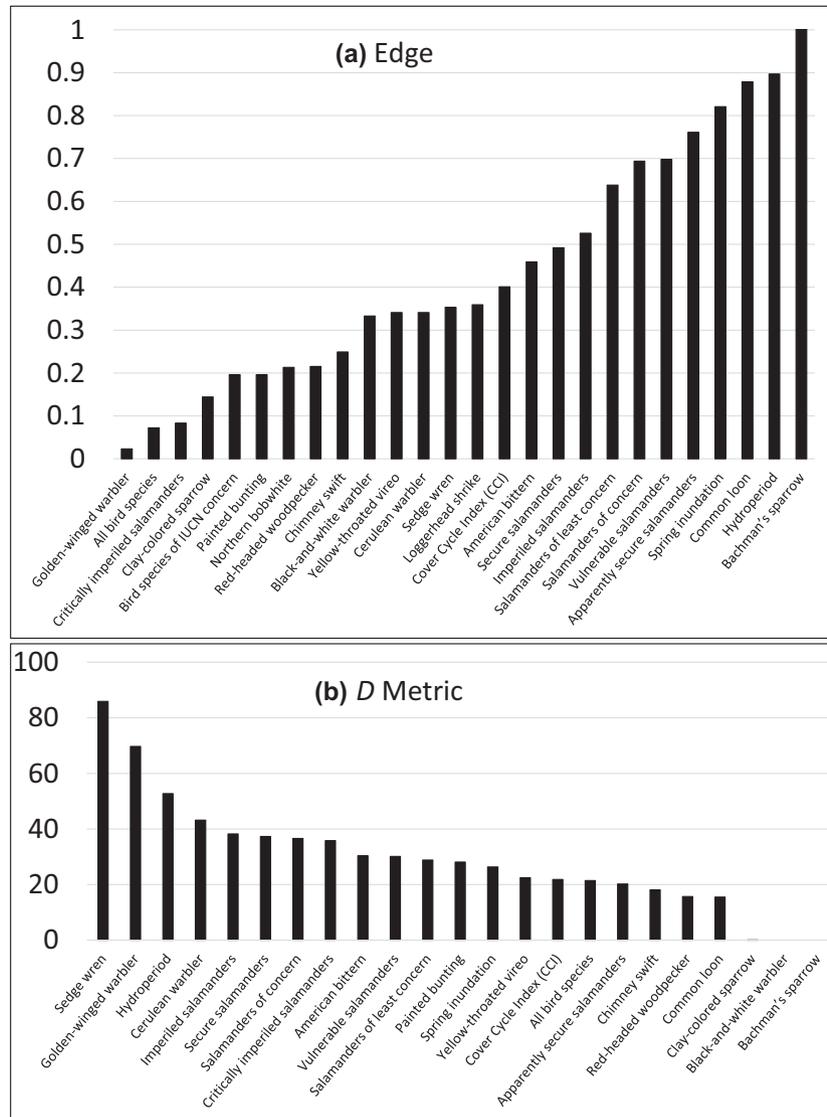
<sup>b</sup>If  $S$  lies to the left or right of the efficient frontier,  $D$  is not defined (see Figure 1).

except two, with means of 0.44 and 0.62. In general, MPT could reduce outcome uncertainty by  $X\%$  with a less than  $X\%$  loss of expected return. However, MPT is not universally effective; both elasticities are greater than one for the Bachman's sparrow, and the arc elasticity for the set of bird species of IUCN concern is very high (1.6).

On average, the simply diversified portfolio for a conservation case has an expected return that is 30% lower than the effi-

cient portfolio with the same risk;  $D$  varies from almost 0 to 86. Panel (B) of Figure 4 shows that  $D$  is greater than or equal to 20 for three-quarters of the cases; expected conservation outcomes from simply dividing investment evenly across the landscape are more than 20% lower than the efficient frontier.

Our ability to identify separate effects of case features on metrics of MPT success in a regression analysis is limited by the number of cases. We discuss such regressions in



**FIGURE 4** MPT effectiveness results. (a) Edge elasticity metrics listed in the seventh column of Table 1. (b) *D* metric listed in the last column of Table 1

Table S3 of the Supporting Information, but focus here on pairwise correlations between metrics in Table 2.

Edge elasticity is lower when the subregion with the best return is not much better than the others (the correlation coefficient with  $\Delta E_1$  is 0.802 with  $p$  value of 0.000) as, for example, in allocating conservation for all Eastern bird species or for all critically imperiled salamander species in southern Appalachia. Conversely, MPT may not be helpful if only one subregion provides plausible habitat for the conservation target, as with the Bachman's sparrow. The correlation of  $\eta_E$  with  $\Delta E$  is positive but not significant; the measure of how quickly expected returns fall as you move down the rankings is not strongly associated with the cost of reducing risk.

The edge elasticity is lower when there are negative covariances widespread throughout the matrix as measured by

$\sigma_{ij}[-]$ ; the correlation coefficient between  $\sigma_{ij}[-]$  and  $\eta_E$  is  $-0.437$  with a  $p$  value of 0.025. For example, the CCI has more negative correlations among subregions than do the hydroperiod and the spring inundation metrics, and the edge and arc elasticities of the efficient frontier are smaller for the CCI than for the other two metrics.

The edge elasticity is lower when the landscape has good low-risk options; the correlation coefficients between  $\eta_E$  and  $\overline{CV}$  and  $CV_{\min}$  are 0.415 and 0.291, respectively, and the former is significant with a  $p$  value of 0.035. For example, there are many places in the range of the northern bobwhite where outcomes for that species do not vary much with climate scenarios (Hernández, Brennan, DeMaso, Sands, & Wester, 2013) so it is easy to find a low-risk option. In contrast, outcomes for the common loon vary

**TABLE 2** Correlations<sup>a</sup> between measures of MPT efficacy and characteristics of cases

	Correlation coefficient <sup>a</sup>	<i>p</i> Value <sup>b</sup>
Correlation <sup>c</sup> with $\eta_E$		
$\Delta E_1$	0.802	0.000 <sup>b</sup>
$\overline{\Delta E}$	0.178	0.385
$\sigma_{1j}[-]$	-0.149	0.466
$\sigma_{ij}[-]$	-0.437	0.025 <sup>b</sup>
$\overline{CV}$	0.415	0.035 <sup>b</sup>
$CV_{\min}$	0.291	0.149
Correlation <sup>c</sup> with $\eta_A$		
$\Delta E_1$	0.439	0.024 <sup>b</sup>
$\overline{\Delta E}$	0.220	0.279
$\sigma_{1j}[-]$	-0.028	0.218
$\sigma_{ij}[-]$	-0.458	0.018 <sup>b</sup>
$\overline{CV}$	0.072	0.728
$CV_{\min}$	-0.023	0.911
Correlation <sup>d</sup> with <i>D</i>		
$\Delta E_1$	-0.090	0.685
$\overline{\Delta E}$	-0.036	0.871
$\sigma_{1j}[-]$	0.032	0.884
$\sigma_{ij}[-]$	-0.256	0.239
$\overline{CV}$	0.096	0.664
$CV_{\min}$	0.111	0.613

<sup>a</sup>Each correlation coefficient is calculated over the values of the two statistics for the conservation cases listed in Table 1.

<sup>b</sup>Significance levels denoted as \*\*\* $p \leq 0.01$ ; \*\* $0.01 < p \leq 0.05$ ; \* $0.05 < p \leq 0.10$ .

<sup>c</sup> $N = 26$ .

<sup>d</sup> $N = 23$ .

greatly across climate scenarios so there are no good low-risk options to use in constructing a low-variance portfolio of reserves.

The correlation coefficients between the arc elasticity  $\eta_A$  and characteristics of conservation cases in Table 2 have similar patterns as for the edge elasticity, but the correlations are smaller and only the metrics  $\Delta E_1$  and  $\sigma_{ij}[-]$  have *p* values below 0.05. To accomplish a large reduction in uncertainty, the portfolios often contain investments in more than just a few subregions and the cost of risk reduction is hard to predict.

The measure of how much higher expected returns can be if one uses MPT rather than simple diversification, *D*, is only weakly correlated with features of conservation cases (Table 2). The one correlation of note is that of -0.256 with  $\sigma_{ij}[-]$ ; *D* may be smaller when there are many negative covariances in the matrix that could fortuitously improve the performance of simple diversification. That correlation is not statistically significant, with a *p* value of 0.239; however,  $\sigma_{ij}[-]$  is statistically significant in a regression in Table S3 of the Supporting Information.

## 4 | DISCUSSION

Our simplified methodology (see discussion of limitations in Supporting Information) allows many cases to be analyzed in the same way to identify patterns between case characteristics and MPT performance. We find that MPT can be used to help design many different kinds of sets of environmental investments that are buffered against outcome uncertainty. For the 26 diverse conservation cases we analyze, MPT can often find portfolios that reduce outcome uncertainty for a cost of lost expected return that is proportionately smaller than the reduction in risk. Furthermore, MPT performs better than simply dividing total investment equally among assets (in our applications, subregions), with average gains in expected returns of 20%, and some cases with even 80% higher returns from MPT than simple diversification.

However, we also find that MPT is not universally successful. We identify three features of cases that are good candidates for using MPT: many negative correlations among the ecological returns in different assets; a second-best asset that has expected ecological returns almost as good as the returns in the best asset; and many assets that have little uncertainty in their ecological outcomes across climate scenarios. Those three characteristics are intuitive, so resource-investment planners can anticipate whether a case is likely to have any of those features and thus whether MPT is likely to provide low-cost environmental risk reduction.

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## REFERENCES

- Allen, M. R., Stott, P. A., Mitchell, J. F. B., Schnur, R., & Delworth, T. L. (2000). Quantifying the uncertainty in forecasts of anthropogenic climate change. *Nature*, *407*, 617–620.
- Ahmadalipour, A., Moradkhani, H., & Rana, A. (2018). Accounting for downscaling and model uncertainty in fine-resolution seasonal climate projections over the Columbia River Basin. *Climate Dynamics*, *50*, 717–733.
- Akter, S., Kompas, T., & Ward, M. (2015). Application of portfolio theory to asset-based biosecurity decision analysis. *Ecological Economics*, *117*, 73–85.

- Anderson, S., Moore, J., McClure, M., Dulvy, N., & Cooper, A. (2015). Portfolio conservation of metapopulations under climate change. *Ecological Applications*, 25(2), 559–572.
- Ando, A., Camm, J., Polasky, S., & Solow, A. (1998). Species distributions, land values, and efficient conservation. *Science*, 279, 2126–2128.
- Ando, A., & Mallory, M. (2012). Optimal portfolio design to reduce climate related conservation uncertainty in the Prairie Pothole Region. *Proceedings of the National Academy of Sciences of the United States of America*, 109(17), 6484–6489.
- Askins, R. (1993). Population trends in grassland, shrubland, and forest birds in eastern North America. *Current Ornithology*, 1, 1–34.
- Bailey, R. (2009). *Ecosystem geography: From ecoregions to sites* (2nd ed.). New York: Springer.
- Bailey, R., & Cushwa, C. (1981). Ecoregions of North America (map). FWS/OBS-81/29. Washington, DC: U.S. Fish and Wildlife Service.
- Ball, I. R., Possingham, H. P., & Watts, M. (2009). Marxan and relatives: Software for spatial conservation prioritisation. In A. van der Valk (Ed.), *Spatial conservation prioritisation: Quantitative methods and computational tools* (pp. 185–195). Oxford: Oxford University Press.
- Batt, B., Anderson, M., Anderson, C., & Caswell, F. (1989). The use of prairie potholes by North American ducks. In A. van der Valk (Ed.), *Northern prairie wetlands* (pp. 204–227), Ames, IA: Iowa State University Press.
- Collins, M., Knutti, R., Arblaster, J., Dufresne, J. -L., Fichefet, T., Friedlingstein, P., ... Wehner, M. (2013). Long-term climate change: Projections, commitments and irreversibility. In T. F. Stocker, D. Qin, G. -K. Plattner, M. Tignor, S. K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex, and P. M. Midgley (Eds.), *Climate change 2013: The physical science basis. Contribution of working group I to the fifth assessment report of the intergovernmental panel on climate change*. Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press.
- Davic, R., & Hartwell, H. Jr (2004). On the ecological roles of salamanders. *Annual Review of Ecology, Evolution, and Systematics*, 35, 405–434.
- Fay, P., Guntenspergen, G., Olker, J., & Johnson, W. (2016). Climate change impacts on freshwater wetland hydrology and vegetation cover cycling along a regional aridity gradient. *Ecosphere*, 7(10), e01504.
- Figge, F. (2004). Bio-folio: Applying portfolio theory to biodiversity. *Biodiversity and Conservation*, 13, 827–849.
- Frigg, R., Thompson, E., & Werndl, C. (2015). Philosophy of climate science part II: Modeling climate change. *Philosophy Compass*, 10, 965–977.
- Hernández, F., Brennan, L., DeMaso, S., Sands, J., & Wester, D. (2013). On reversing the northern bobwhite population decline: 20 years later. *Wildlife Society Bulletin*, 37, 177–188.
- Liang, J., Gao, X., Zeng, G., Hua, S., Zhong, M., Li, X., & Li, X. (2018). Coupling Modern Portfolio Theory and Marxan enhances the efficiency of lesser white-fronted Goose's (*Anser erythropus*) habitat conservation. *Scientific Reports*, 8(1), 214.
- Johnson, W., Millett, B., Gilmanov, T., Voldseth, R., Guntenspergen, G., & Naugle, D. (2005). Vulnerability of Northern Prairie wetlands to climate change. *BioScience*, 55, 863–872.
- Johnson, C., Werner, B., Guntenspergen, G. R., Voldseth, R. A., Millett, V., Naugle, D. E., ... Olawsky, C. (2010). Prairie wetland complexes as landscape functional units in a changing climate. *BioScience*, 60, 128–140.
- Koellner, T., & Schmitz, O. (2006). Biodiversity, ecosystem function, and investment risk. *BioScience*, 56, 977–985.
- Matthews, S., Iverson, L., Prasad, A., & Peters, M. (2007). *A climate change atlas for 147 bird species of the Eastern United States* [database]. Retrieved from <https://www.nrs.fs.fed.us/atlas/bird>, Northern Research Station, Delaware, Ohio: USDA Forest Service.
- Milanovich, J., Peterman, W., Nibbelink, N., & Maerz, J. (2010). Projected loss of a salamander diversity hotspot as a consequence of projected global climate change. *PLoS One*, 5(8), e12189.
- Millett, B., Johnson, W., & Guntenspergen, G. (2009). Climate trends of the North American prairie pothole region 1906–2000. *Climatic Change*, 93(1), 243–267.
- Naugle, D., Johnson, R., Estey, M., & Higgins, K. (2001). A landscape approach to conserving wetland bird habitat in the Prairie Pothole Region of East South Dakota. *Wetlands*, 21(1), 1–17.
- Omernik, J. (1987). Ecoregions of the conterminous United States. *Annals of the American Association of Geographers*, 77(1), 118–125.
- Pourmokhtarian, A., Driscoll, C. T., Campbell, J. L., Hayhoe, K., & Stoner, A. M. (2016). The effects of climate downscaling technique and observational data set on modeled ecological responses. *Ecological Applications*, 26(5), 1321–1337.
- Pyke, C., & Fischer, D. (2005). Selection of bioclimatically representative biological reserve systems under climate change. *Biological Conservation*, 121, 429–441.
- Robbins, C., Sauer, J., Greenberg, R., & Droege, S. (1989). Population declines in North American birds that migrate to the neotropics. *Proceedings of the National Academy of Sciences of the United States of America*, 86, 7658–7662.
- Sanchirico, J. N., Smith, M. D., & Lipton, D. W. (2008). An empirical approach to ecosystem-based fishery management. *Ecological Economics*, 64, 586–596.
- Shiogama, H., Stone, D., Emori, S., Takahashi, K., Mori, S., Maeda, A., ... Allen, M. R. (2015). Predicting future uncertainty constraints on global warming projections. *Scientific Reports*, 6, <https://doi.org/10.1038/srep18903>.
- Stocker, T. F., Qin, D., Plattner, G. -K., Tignor, M., Allen, S. K., Boschung, J., ... Midgley, P. M. (Eds.) (2013). *Climate Change 2013: The physical science basis. Contribution of working group I to the fifth assessment report of the intergovernmental panel on climate change*. Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press.
- Thomas, C., Cameron, A., Green, R., Bakkenes, M., Beaumont, L., & Collingham, Y. (2004). Extinction risk from climate change. *Nature*, 427(6970), 145–148.
- Thorne, J. H., Choe, H., Boynton, R. M., Bjorkman, J., Albright, W., Nydick, K., ... Schwartz, M. W. (2017). The impact of climate change uncertainty on California's vegetation and adaptation management. *Ecosphere*, 8(12), e02021 <https://doi.org/10.1002/ecs2.2021>

- Werner, B., Johnson, W., & Guntenspergen, G. (2013). Evidence for 20th century climate warming and wetland drying in the North American Prairie Pothole Region. *Ecology and Evolution*, 3(10), 3471–3482.
- Winter, T. (2000). The vulnerability of wetlands to climate change: A hydrologic landscape perspective. *Journal of the American Water Resources Association*, 36(2), 305–311.
- Yemshanov, D., Koch, F., Lu, B., Lyons, D., Prestemon, J., Scarr, T., & Koehler, K. (2014). There is no silver bullet: The value of diversification in planning invasive species surveillance. *Ecological Economics*, 104, 61–72.

## SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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