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Accounting for Upper Limit in Return from Conservation Investments in Risk Diversification Strategies

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Applications for risk diversification strategies in addressing conservation problems commonly ignore upper limits in returns, which may not reflect that these economic returns are often beyond the scope of what conservation assets can produce given constraints on species, sites, or activities. The objective of this research is to identify the consequences of failing to account for upper limits on returns from conservation in a modern portfolio theory (MPT) framework. We find that the amount of risk reduction conservation organizations can achieve with the same level of compromise in the expected return on investment is higher when returns are constrained.

Key words: biodiversity, climate and market uncertainty, conservation assets, constrained returns, modern portfolio theory

Introduction

With persistent uncertainty related to the effectiveness of conservation investments, the design and planning of such investments based purely on historical data may yield misleading results (Cho et al., 2018; Newbold, 2018; Snäll et al., 2021). Modern Portfolio Theory (MPT), a quantified version of "Do not put all your eggs in one basket", developed by Markowitz (1952) and published in the financial literature, has been applied in recent years to help diversify risk in conservation investments (Shipway, 2009). This tool accounts for heterogeneities in climate and market uncertainty to minimize risk associated with investment portfolios that focus on conservation-related assets such as species, sites, and activities (Ando and Mallory, 2012; Eaton et al., 2019).

Despite the merits of MPT, applications to conservation investment have not accounted for upper limits in returns that arise from physical limitations. In a species conservation context, return on conservation investment is clearly bounded by the total amount of species habitat

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available (e.g., the forested area that can be protected for a given site). A conservation organization will also face an upper limit in return to conservation if individual values for species conservation do not scale with the number of species protected. For example, surrogate bidding in nonmarket valuation studies may indicate that the willingness to pay to protect 100 animals is no different than the willingness to pay to protect 1,000 animals (Kahneman and Knetsch 1992). Economic returns generated from ignoring such upper limits are not reflective of what the conservation assets can actually produce given constraints on species, sites, or activities and can lead conservation organizations to inefficiently focus investment toward certain high-return assets. In other words, conservation organizations may not be able to "put all their eggs in one basket" if the basket is not large enough to hold every egg.

This limitation of MPT comes from its original application to financial investments, where the asset market is perfectly competitive and no single investor is capable of influencing the returns of an asset, and thus does not face an upper limit constraint. Early applications of MPT to conservation problems did not consider potential constraints to each asset, and most subsequent studies continue to overlook this issue (e.g., Figge, 2004; Ando and Mallory, 2012). For example, none of the 26 species-habitat MPT case studies summarized by Ando et al. (2018) considered an upper limit constraint in returns.

A limited number of recent studies have sought to improve conservation related MPT applications by indirectly limiting returns due to physical constraints (Jin et al., 2016; Runting et al., 2018). For example, Jin et al. (2016) applied MPT to the implementation of an ecosystem-based fishery management approach in different geographic regions. The authors considered the limited stock of each fish species available to harvest in their MPT application by constraining the maximum weight applied to each species' harvest. Similarly, Runting et al. (2018) reformulated an integer quadratic programming MPT approach with a binary decision variable representing whether each site is selected for wetland protection. By using a binary decision variable, the authors indirectly accounted for limited returns based on each site's limited availability, along with other physical considerations such as connectivity necessary for the landward migration of wetlands. However, it remains unclear how the benefits of risk diversification are impacted by physical constraints.

The objective of this research is to identify the impacts of failing to account for upper limits on returns from conservation investment in an MPT framework and to understand the implications of accounting for these limits. To achieve the objective, we develop a MPT framework with and without upper limit constraints (referred to as 'constrained MPT' and 'naive MPT', respectively) using county-level return on investments (ROIs) for conservation of forest biodiversity in the central and southern Appalachian region of the United States (see Figure 1). Then, we conceptually illustrate the impacts of upper limits on MPT outcomes using two hypothetical counties with different expected ROI and associated risk levels. Next, We compare MPT outcomes between the two approaches using two metrics measuring the effectiveness of risk diversification: the slope of the efficient frontier representing risk-reward trade-offs and the vertical distance between the simple diversification point and the efficient frontier representing the difference in potential expected ROI gained by the different MPT frameworks, given the same risk level.

We choose to frame the models at the county level since counties (1) provide a relevant spatial grain when deciding how to allocate conservation budgets, (2) are a relevant administrative and political unit for regional and local land-use planning in the United States, and (3) are the level of units our socio-economic variables are available (Le Bouille, Fargione, and Armsworth, 2023).

Because of the covariance in returns between counties, reducing risk implies forgoing expected return (i.e., spreading ones bets on conservation). The extent of risk reduction conservation organizations can attain with the same level of compromise in expected return is hypothesized to be different for the two MPT approaches. Restrictions on portfolio weights with constrained MPT impose a degree of "bet spreading" while naïve MPT does not. Therefore, the constrained MPT is useful for conservation investment when a regulatory cap on budget allocation

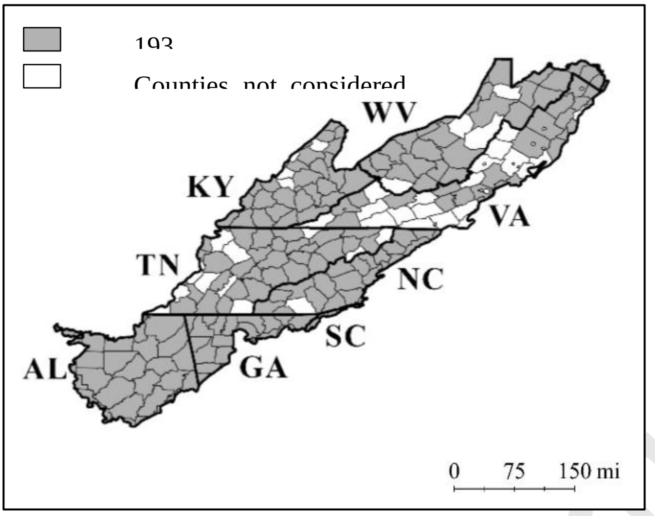


Figure 1. Map of 193 counties used for naïve MPT and constrained MPT
Notes: 53 counties are not considered for analysis since they are consolidated city-counties or counties with negative relative opportunity costs that do not face urban development concern

for each site is present. Many conservation partnership programs are limited by regulatory constraints imposed by partnership funds. These kind of regulatory constraints would imply that upper limits on returns would diminish the value added from using MPT. However, if the constraints force conservation organizations to bet spread anyway, then it is wise to use MPT to allocate the bet spread in the best way possible. Our constrained MPT approach is designed to serve this very purpose.

Methods

Naïve MPT framework

Suppose a conservation organization wishes to allocate optimal portfolio weights across the counties. By modifying the framework developed by Runting et al. (2018) where risk minimization and expected return maximization are combined in a single framework, we develop a naïve MPT approach formatted as a quadratic programming problem without upper limit constraints as:

(1) $$Min_W \ \lambda \boldsymbol{W^T \Sigma W} - \boldsymbol{W^T}\mathbf{M}$$

subject to

(2) $$\mathbf{0} \leq \boldsymbol{W} \leq \boldsymbol{I}$$

(3) $$\boldsymbol{W^T I} = 1$$

where λ is a weight for risk minimization which represents relative emphasis on risk mitigation from zero to infinity, $\boldsymbol{W^T \Sigma W}$ is the weighted sum of the variance of counties representing the portfolio's variance (or risk) where $\boldsymbol{W^T}$ is a vector transpose of $\boldsymbol{W}$, a $n \times 1$ vector of efficient portfolio weights across n counties as the decision variable, and $\boldsymbol{\Sigma}$ is an $n \times n$ variance-covariance matrix of ROIs across n counties. The variance-covariance matrix between county i and county j is calculated as $E[(ROI_i - E[ROI_i])(ROI_j - E(ROI_j))]$, where ROI_i (or ROI_j) is the ROI for county i (or j) under s uncertainty scenarios. $\mathbf{M}$ is an $n \times 1$ vector of expected ROIs, which are calculated as expected values of ROIs for n counties: $E[ROI_i] = \sum_s p \times ROI_{is}$ where p is the probability of uncertainty scenario s occurring, which is equal to $\frac{1}{s}$ by assuming a uniform probability distribution among s scenarios, and ROI_{is} is the ROI for county i under specific uncertainty scenario s. $\boldsymbol{W^T}\mathbf{M}$ is the expected ROI of the portfolio calculated by the weighted average of $\mathbf{M}$ with efficient portfolio weight $\boldsymbol{W}$.

The objective function in equation (1) maximizes expected ROI (i.e., $\boldsymbol{W^T}\mathbf{M}$) or minimizes the portfolio's variance (i.e., $\boldsymbol{W^T\Sigma W}$) at a certain weight for risk minimization (λ). Equation (2) represents the minimum and maximum constraint on portfolio weights, and $\mathbf{0}$ and $\boldsymbol{I}$ are $n \times 1$ vectors whose elements are equal to 0 and 1, respectively. The sum of all portfolio weights is always equal to 1 for any given risk level.

Constrained MPT framework

For constrained MPT, we consider two layers of constraints—physical limitations and total budget constraints under the assumption that a conservation organization wishes to allocate optimal portfolio weights across the counties. To account for both constraints, we replace the decision variable of efficient portfolio weights shown in equation (1) with a decision variable for efficient budget allocation across counties X shown in equation (4) below:

(4) $$Min_X \;\; \lambda \boldsymbol{X^T \Sigma X} - \boldsymbol{X^T}$$

subject to

(5) $$\mathbf{0} \leq \boldsymbol{X} \leq \boldsymbol{C}$$

(6) $$\boldsymbol{X^T I} = \mathrm{B}$$

where $\boldsymbol{X^T}$ is a vector transpose of $\boldsymbol{X}$, a $n \times 1$ vector of efficient budget allocation in dollars across n counties as the decision variable, $\boldsymbol{C}$ is an $n \times 1$ vector of county-level physical constraints, whose elements are specified as the product of the size of eligible forestland (i.e., unprotected private forestland) as a physical constraint and unit opportunity cost for conservation as a cost constraint across n counties, and B is a hypothetical total budget amount for the entire region.

The precise knowledge of $\boldsymbol{C}$ in the future by the conservation organization is not possible as the size of eligible forestland and unit opportunity cost vary under s uncertainty scenarios. Given the unknown probability distribution of uncertainty scenarios, we use its average value across the scenarios for each county for the model. By doing so, we implicitly assume that $\boldsymbol{C}$ is normally distributed, and thus its mean value is a meaningful representation of $\boldsymbol{C}$. For the sensitivity analysis, we estimate the model using the upper limits on both (high and low) ends of 95% confidence interval of their probability density distributions since upper limits at the mean may not encompass the entire spectrum of potential outcomes of constrained MPT. By performing the sensitivity analysis, we partially encompass infrequent occurrences that can exert significant influence on the size of eligible forestland and unit opportunity cost.

The objective function in equation (4) maximizes the weighted sum of expected ROIs ($\boldsymbol{X^T}\mathbf{M}$) and minimizes the portfolio's variance (i.e., $\boldsymbol{X^T\Sigma X}$). Equation (5) specifies the county's physical constraint $\mathbf{C}$ across n counties, and equation (6) constrains the hypothetical total budget B. The physical constraints are fixed for counties by uncertainty scenario, while hypothetical total budget constraints may change depending on the budget available for the entire region. The physical and budget constraints are specified by equations (5) and (6), respectively, as the total budget is spread from one county to another after meeting each county's physical constraint $\mathbf{C}$ as each county's expected ROI goes to 0 (represented as a step function) until exhausting total budget B.

We calculate efficient portfolio weight $\boldsymbol{W}$ for constrained MPT by dividing efficient budget allocation $\boldsymbol{X}$ by total budget B to derive the efficient portfolio's expected ROI and corresponding variance as the weighted sum of expected ROIs ($\boldsymbol{W^T}\mathbf{M}$) and the variance of counties ($\boldsymbol{W^T\Sigma W}$) for the risk measure. In doing so, we derive efficient frontiers for naïve and constrained MPT under various levels of risk minimization weight λ by connecting points of expected ROIs and corresponding standard deviations for both MPT approaches. Because ideal funding amount for the forest conservation for biodiversity of the study area is unknown, we compare outcomes of the hypothesis found in the conceptual framework related to the impact of hypothetical total budget amounts on degree of deviation between naïve and constrained MPT. Specifically, we compare outcomes based on the two approaches under three hypothetical total budget constraints: low, moderate, and high total budget (i.e., \$3 million, \$50 million, and \$1 billion).

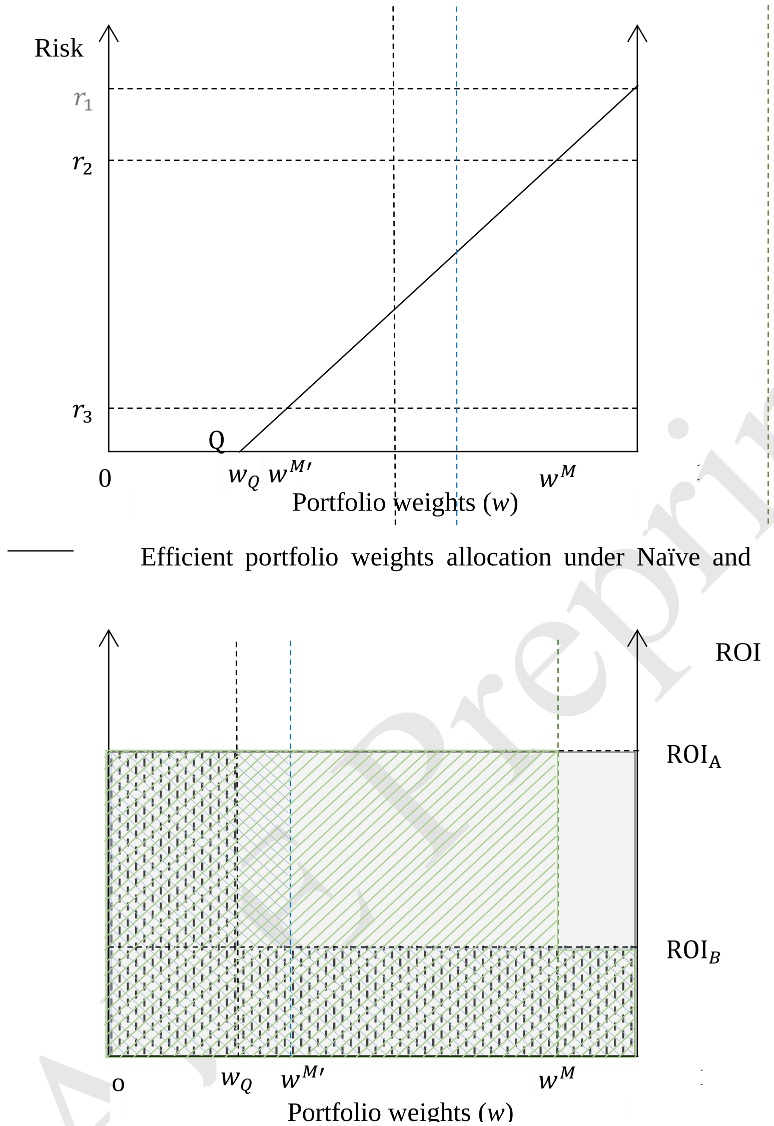
Given the various ranges of expected ROI and standard deviation for each approach that are reflected in various lengths of the frontiers, we normalize risk level as the percent above minimum risk (referred to as 'risk tolerance level') to compare outcomes based on naïve and constrained MPT at the same degree of risk that conservation organizations can tolerate. If the feasible risk levels were different between the approaches, our comparisons would be limited. For example, if minimum risk levels were 0 and 3 for naive and constrained MPT, respectively, we could not compare the efficient portfolios at a risk level of 3, which is not the minimum risk level associated with naïve MPT. By drawing the efficient frontiers where the x-axis represents risk tolerance level normalized as stated above, efficient frontiers are comparable at every risk tolerance level and show expected ROIs attainable at any risk tolerance level across different MPT specifications.

Conceptual illustration

Suppose a conservation organization wishes to allocate optimal portfolio weights between counties A and B based on naïve and constrained MPT. County A has a higher expected ROI with higher risk than county B ($ROI_A > ROI_B$). The positively sloping diagonal line in the upper graph of Figure 2 shows the allocation of efficient portfolio weights between the two counties at different risk levels based on naïve and constrained MPT. The lines indicated by w^M and $1-w^M$ represent the upper limits on weights assigned to counties A and B as the total weight between the two cannot exceed the full capacity of available resources. The lower graph of the figure illustrates different areas portrayed by changes in expected ROI, $wROI_A + (1-w)ROI_B$, corresponding to portfolio weights between the two counties based on naïve and constrained MPT shown in the upper graph.

Based on the naïve MPT outcome, a conservation organization with maximum risk level r_1 protects all conservation assets in county A (w = 1 in the upper graph of Figure 2), with the corresponding expected ROI being area *afho* in the lower graph. By comparison, consider the case where the constraint is binding in county A. Constrained MPT allocates weight w^M to county A with the remaining weight, $1-w^M$, distributed to county B at the maximum risk level of r_2, corresponding to $w = w^M$. The resulting expected ROI is shown by area *af'h'o* for county A and area *g'ghh'* for county B. These results suggest that constrained MPT mitigates maximum risk relative to naïve MPT by $r_1 - r_2$ but corrects expected ROI by area *f'fgg'* compared to naïve MPT.

Conservation investment would be divided between the two counties at lower risk than risk level r_1 based on naïve MPT. With weight assignments of w_Q and $1-w_Q$ for counties A and B, respectively, the minimum risk level of 0 is reached. As a result, expected ROI at the minimum risk level for naïve MPT is shown as the sum of area *aceo* for county A and area *dghe* for county B. By comparison, consider the case where the constraint is binding in county B, where $w^{M'}$ *and* $1-w^{M'}$ represent upper limits on weights assigned to counties A and B. Constrained MPT would allocate weight, $1-w^{M'}$, to county B and the remaining weight, $w^{M'}$, would be distributed to county A at the minimum risk level of r_3. Expected ROIs are shown by area *ac'e'o* for county A and area *d'ghe'* for county B. These results suggest that constrained MPT sacrifices the minimum risk level by r_3 but increases expected ROI by area *cc'd'd* relative to naïve MPT because of the added weight to the higher ROI county (i.e., county A) based on constrained MPT. Other cases could include a situation where county B provides both lower expected ROI and



Area *afho* representing the expected ROI based on naïve MPT at

Area *af'g'gho* representing the expected ROI based on constrained MPT at

Area *acdgho* representing the expected ROI based on naïve MPT at minimum risk

Area *ac'd'gho* representing the expected ROI based on constrained MPT at minimum

Figure 2. Consequences of failing to account for an upper limit constraint in MPT.

Notes: The upper graph of the figure shows allocations of efficient portfolio weights between two counties (w^M and $1 - w^{M\prime}$ represent upper limits on weights for counties A and B, and w_Q and $1 - w_Q$ represent weights at the minimum risk level for counties A and B) at different risk levels (0 and r_1 for minimum and maximum risk level based on naïve MPT and r_2 and r_3 for minimum and maximum risk levels based on constrained MPT) based on \ MPTs. The lower graph of the figure illustrates changes in expected ROI ($\mathrm{ROI_A}$ as expected ROI for county A and ROI_B as expected ROI for county B) corresponding to efficient portfolio weights between the two counties ($w^{M\prime}$ and $1 - w^{M\prime}$ represent weights assigned to counties A and B for the case where the constraint is binding in county B at minimum risk level, and w^M and $1 - w^M$ represent weights for counties A and B where the constraint is binding in county A at maximum risk.) based on naïve and constrained MPT shown in the upper graph.

higher risk. In this case, budget constraints on county A could both lower the expected ROI and increase the risk of investing.

At the maximum risk level, naïve MPT maximizes risk and expected ROI by allocating a weight above the feasibility of county A (w=1 in the upper graph) while at the minimum risk level, naïve MPT minimizes risk by allocating a weight above the feasibility of county B ($w=w_Q$ in the upper graph). However, constrained MPT prevents the over-allocation of weights to counties A and B, respectively, at maximum and minimum risk levels. By doing so, the optimal portfolio based on constrained MPT suggests high risk but high expected ROI at the minimum risk level, whereas it compromises expected ROI at the low risk level in comparison with the optimal portfolio generated based on naïve MPT.

Other cases are also possible. For example, in a situation where county B provides both lower expected ROI and higher risk, any upper limit constraint on the weight that can be assigned to county A will both lower the expected ROI and increase the associated risk. More generally, we can then see that adding upper limit constraints on how much investment can be directed to each asset is ambiguous in terms of whether it will increase or decrease expected ROI and associated risk.

The overall budget to be invested in conservation also matters. If the overall budget is small relative to the level of investment each asset can receive, accounting for upper limits on how much investment is possible for each asset is irrelevant. In contrast, when the overall program budget is large enough that the constraints may be binding, accounting for this in the optimization approach becomes more important. Risk and expected ROI corrections made by constrained MPT, relative to naïve MPT, intensify with a greater hypothetical total budget because the share of the budget assigned to each county, constrained by its upper limit, decreases with a higher hypothetical total budget. Thus, we hypothesize that the total budget available to a conservation organization influences the degree of deviation of risk level and corresponding expected ROI between the two approaches.

Before developing a fuller empirical application, we first consider a simple two-county case as an example to illustrate the effects of risk level and expected ROI on naïve and constrained MPT. While these comparisons are sufficient to build intuition for changes in return and risk, the notion of upper limits on return is grounded in the assumption of a linear relationship between risk and return, implying a clear and consistent trade-off between the two. However, real-world dynamics render the risk-return relationship more intricate, subject to fluctuations over time and diverse scenarios. Notably, factors like the physical constraints for conservation could also be influenced by climate and market uncertainties. Besides, we do not consider richer patterns of covariance. Accounting for covariance structure differences is where the strength of MPT reveals itself, and we next examine this with our empirical application. Furthermore, we assume the two counties are not perfectly correlated with each other, and thus the risk diversification strategy used has a feasible solution for both MPT approaches.

Illustrative example: Forest conservation in Central and Southern Appalachia

To illustrate our framework, we apply MPT to forest conservation in a biodiversity hotspot – central and southern Appalachia. We select the central and southern Appalachian region as the study area because it provides critical habitat and a corridor for biodiversity (Zhu et al., 2021), and the region is expected to experience further climate change impacts and urban development pressure (Rogers et al., 2016). For both MPT approaches, we use expected ROIs for biodiversity conservation in 2050, which is far enough into the future to observe the impact of climate and market uncertainty on benefits and costs. The benefit component for expected ROI is calculated by estimating future species ranges using species distribution models. The conservation cost component for expected ROI is proxied as urban return minus forestland return (referred to as "relative opportunity cost") under the assumption that urban development is the dominant competing land use for forestland. This assumption is based on evidence that urbanization is the main driver of forest loss in the study region (Wear and Greis, 2013; Keyser et al., 2014).

Estimating scenario specific ROI

Scenario-specific expected ROIs are structured by combining predicted future benefit scenarios and relative opportunity cost scenarios at the county level for 193 of 246 total counties in our study area. Fifty-three counties are not considered in our analysis since they are either consolidated city-counties or counties where urbanization is not a primary concern (see Figure 1). Scenarios for predicting future biodiversity benefits are only related to climate change, and multiple climate scenarios are considered. In comparison, relative opportunity costs are projected under various climate and market scenarios associated with different climate, land use, and market conditions.

Multiple sources of uncertainty associated with benefits and costs derived from climate and market scenarios may have (i) different forms of variability and covariance structures (ii) different patterns of covariance structure across county within each type of uncertainty, and (iii) different patterns of covariance structure between each type of benefit and cost uncertainty. Due to these covariance structure differences, efforts to diversify market-induced risk may undermine or complement efforts to diversify climate-induced risk.

The benefit component for biodiversity ROI was taken from Zhu et al. (2021) which estimated species distributions for 258 forest-dependent vertebrates of policy concern as determined by US Fish and Wildlife Service (2020) and Landscape Conservation Cooperative Network (2020). Future species distributions in 2050 were specified as the benefit component for biodiversity since they are direct representations of areas where species can be found and protected (Fuentes-Castillo et al., 2019). The species distribution model (SDM) Maxent was used to forecast future species distributions under future climate scenarios for two representative concentration pathways (RCPs; RCP4.5 and RCP 8.5) and six General Circulation Models (GCMs; ACCESS1-0, CanESM2, CCSM4, CNRM-CM5, CSIRO-Mk3, and INM-CM4) (Phillips, 1956; Flato et al., 2014) using the ClimateNA database (Wang et al., 2016).

Maxent was used to estimate probabilities of climatic suitability for species at the 1-km^2 pixel level under 12 future climate scenarios (i.e., 6 GCMs, each associated with RCP 4.5 and 8.5). Then, probabilities were converted into binary variables using a 10% training presence threshold, which allows the top 90% of predicted probabilities to be considered as suitable habitat and the remaining 10% as unsuitable habitat (Peterson et al., 2011). Next, pixel areas from the suitability binary variables are aggregated for all 258 species at the county level, and these estimates were specified as the benefit component of species distributions for all species under 12 future climate scenarios. See Zhu et al. (2021) for more details related to the methodology used to project future species distribution.

For future urban return needed to estimate relative opportunity cost, annualized median assessed land value was determined by broadly emulating Lubowski et al. (2006) using the following procedure. First, land value ratios per hectare were estimated by dividing assessed land value per hectare by total assessed value at the parcel level for sample counties where data were available. Second, land value ratios at the parcel level were converted to the census block group (CBG) level by regressing land value ratio per hectare against socioeconomic and location variables at the CBG level (see Liu et al., 2019 for more details). Third, median housing price in 2050 under three real estate market conditions (upturn, moderate, downturn) was projected based on recent real estate growth cycles to account for the effect of real estate market uncertainty on urban return. Finally, median assessed land value per hectare was estimated by multiplying median housing price under the three real estate market conditions by land value ratio per hectare, which was then annualized (see Mingie and Cho, 2020 for details).

The effect of climate and market uncertainty on forestland return was considered by projecting future harvest volume and timber price to estimate future annualized forest return using

Soil Expectation Value (SEV). County-level harvest volume projections were created for three Special Report on Emission Scenarios (SRES; A1B, A2, and B2). State-level timber prices were estimated based on a stochastic modeling approach using regional stumpage price datasets from Timber Mart-South (2015) and other timber price reports. Three timber price scenarios were estimated: high (2050 mean plus standard deviation), moderate (2050 mean), and low (2050 mean minus standard deviation).

Scenarios have been represented slightly differently across climate change assessment reports and our study draws on products that span different reports. The A1B and A2 scenarios in the SRES correspond better with the RCP8.5 scenario. Meanwhile, the B2 scenario in the SRES corresponds better with RCP4.5. The full set of scenarios we consider in our analyses are generated by cross-factoring an emissions scenario with a GCM for making climate predictions and an assumption about timber volume, timber price and the real estate market. Under the more intensive emissions situation (RCP 8.5), we include 324 possible futures were developed (2 SRES * 6 GCMs * 3 timber volume scenarios * 3 timber price scenarios * 3 real estate market scenarios). In addition, under an assumption of more moderate future emissions (RCP4.5), we include a further 162 possible futures (1 SRES * 6 GCMs * 3 timber volume projections * 3 timber price scenarios * 3 real estate market scenarios).

A shared-based land use model was applied at the county level using historical land use data from the National Land Cover Database (NLCD, 2016) and the historical relative opportunity cost data. We forecasted forestland area in each county under diverse scenarios in 2050 using the parameters from the land use model and the forecasts of the relative opportunity costs under different scenarios. While the land use change model predicts the forest area that will remain in the county in 2050 with or without investment, it does not forecast where exactly this forest area will be located within the county. The improvements in the persistence probabilities for species resulting from protecting forestland in different counties do not consider the proximity of counties to one another.

We also needed to make an additional assumption to convert changes in forest within climatically suitable areas for a species into a statement about region-wide species persistence in 2050. Following Armsworth et al. (2020), the probability of persistence function was assumed as a linear, piecewise continuous, hockey-stick function, which allowed the persistence probability to equal zero when no forest remained but increase linearly when forest area in the county increased until a saturation threshold at 1 was reached. We also considered the difference of ecological quality between protected forest and private forest, treated as intermediate usable habitat, and differentiated the land use types by assigning two weights (i.e., 1 or 0.25) to protected forest and private forest, respectively (see Armsworth et al., 2020 for more details).

Based on the probability of persistence function and average opportunity cost, the marginal benefit to cost ratio in each county was estimated, which was optimized by both naïve and constrained MPT. Finally, expected marginal ROI under each scenario was defined as the change in species richness (i.e., number of species) by aggregating relevant probabilities for 258 species, which was optimized by both naive and constrained MPTs (Kang, Sims, and Cho, 2022).

Empirical Results

Figure 3 shows four efficient frontiers indicating the expected ROI-risk tolerance relationship for portfolios generated from naïve MPT and constrained MPT with three hypothetical total budget constraints with upper limits at the mean. The four efficient frontiers are upward sloping implying higher return (i.e., expected ROI) with higher risk. The four frontiers are also concave-shaped implying that risk diversification becomes more costly (i.e., more return is sacrificed) as portfolio risk is reduced.

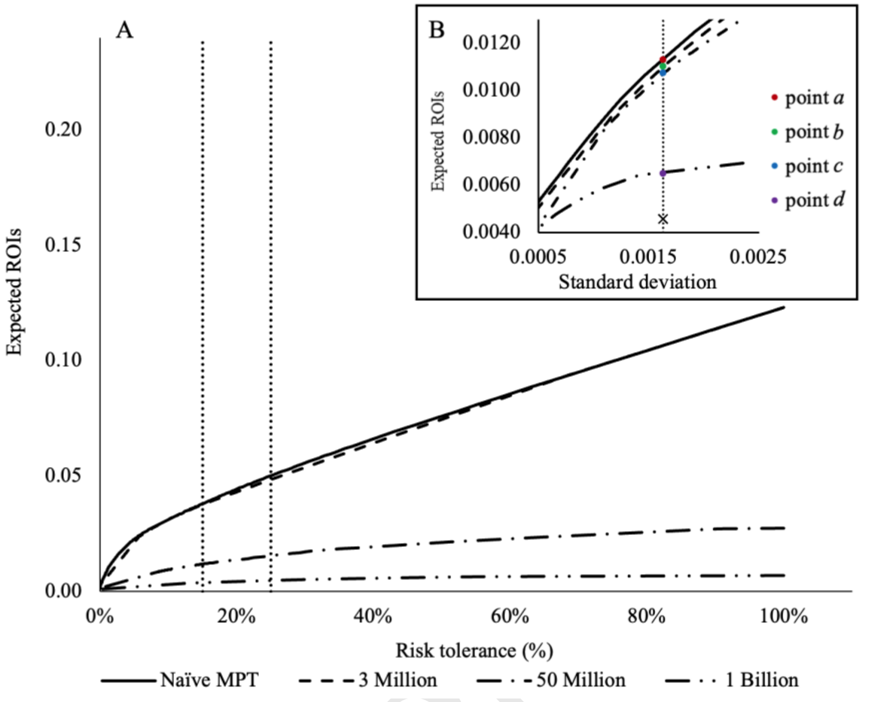


Figure 3. Four efficient frontiers of the expected ROI-risk tolerance relationship for portfolios from naïve MPT and constrained MPT with three budgets ($3 million, $50 million, and $1 billion) with upper limits at the mean. (A) Constraints on asset returns lower the slope of the frontier at many reasonable risk tolerance levels implying less expected ROI must be forfeited to reduce risk. (B) Constraints on asset returns also reduce the increase in expected ROI that can be achieved through risk diversification.
Notes: Points *a*, *b*, *c*, and *d* are the points on the efficient frontiers for naïve MPT, and constrained MPT with $3 million, $50 million, and $1 billion, respectively, with the same standard deviation as point X.

Figure 3 illustrates how constraints on returns impact the effectiveness of risk mitigation in two ways. First, the constraints reduce how much expected ROI must be foregone to achieve the same level of risk reduction (see Figure 3A). The slope of the frontier is smaller under constrained MPT than under naïve MPT especially at higher budget amounts where constraints are binding for more counties. These findings imply that when a conservation organization will have to spread more investment around due to a larger total budget, it can reduce risk with less loss in expected return with constrained MPT than with naïve MPT.

Figure 3B also shows how constraints on returns could force land managers in the Appalachian region to spread their bets by spreading the budget to a greater number of counties. This bet spreading behavior yields an expected ROI closer to what would be achieved if the budget was to be divided evenly among all counties (i.e., simple diversification; point marked as an X in Figure 3B). Specifically, the difference in expected ROI at the same risk level between the constrained efficient frontiers and the simple diversification point decreases as the budget increases.[1] Points *a*, *b*, *c*, and *d* are points on the efficient frontier for naïve MPT and constrained MPT with $3 million, $50 million, and $1 billion budgets, respectively, at the same standard

[1] We make comparisons using the expected ROI-standard deviation frontiers, instead of the expected ROI-risk tolerance frontiers because the simple diversification portfolio cannot be normalized.

Table 1. Portfolio expected ROI for biodiversity conservation, portfolio risk reflected in its standard deviation, number of counties selected, number of counties bound by upper limit constraints, and average costs of selected counties from naïve MPT and constrained MPT with three total budgets under four risk levels with upper limits at the mean

			Constrained MPTs		
		Naïve MPT	**$3 million**	**$50 million**	**$1 billion**
Minimum risk level	Portfolio's expected ROI	0.00173	0.00119	0.00104	0.00091
	Portfolio's standard deviation	0.00005	0.00004	0.00004	0.00004
	# of counties selected	12	12	12	16
	# of counties bound by its upper limit constraint	-	0	1	9
	Average cost of selected counties	$90,762,849	$90,762,849	$90,762,849	$92,585,968
15% risk level	Portfolio's expected ROI	0.03792	0.03760	0.01174	0.00372
	Portfolio's standard deviation	0.01607	0.01617	0.00185	0.00040
	# of counties selected	3	4	8	35
	# of counties bound by its upper limit constraint	-	1	4	27
	Average cost of selected counties	$8,386,061	$7,200,854	$17,481,817	$32,823,862
25% risk level	Portfolio's expected ROI	0.04996	0.04902	0.01534	0.00474
	Portfolio's standard deviation	0.02667	0.02735	0.00307	0.00065
	# of counties selected	3	4	9	43
	# of counties bound by its upper limit constraint	-	1	3	38
	Average cost of selected counties	$3,253,555	$7,200,854	$10,461,209	$24,450,516
Maximum risk level	Portfolio's expected ROI	0.12324	0.12324	0.02744	0.00691
	Portfolio's standard deviation	0.10734	0.10734	0.01234	0.00228
	# of counties selected	1	1	9	59
	# of counties bound by its upper limit constraint	-	0	8	58
	Average cost of selected counties	$3,645,232 …	$3,645,232 …	$5,588,646 …	$17,942,059 .

deviation as point X. The vertical distances from simple diversification portfolio X to *a*, *b*, *c* and *d* represent differences in potential expected ROI gained by the different MPT frameworks, given the same risk level. The longer vertical distance from X to *a* compared to distances from X to *b*, *c*, and *d* reinforces the notion that MPT is less efficient with constrained MPT since constraints direct more investment to counties with a smaller ROI.

Table 1 shows optimal portfolio expected ROI for biodiversity conservation and risk, reflected in its standard deviation, at four risk levels from naïve MPT and constrained MPT with three hypothetical total budget scenarios with upper limits at the mean. At the maximum risk level, the results show that constrained MPT compromised expected ROI while improving risk mitigation to a greater extent compared to naïve MPT. At the minimum risk level, constrained MPT gained higher expected ROI by reducing risk mitigation more than naïve MPT. These findings imply that constrained MPT corrects misallocated portfolio weights, and based on this correction, the tradeoff between risk and expected ROI at maximum and minimum risk levels, respectively.

Deviations in risk level and expected ROI between naïve and constrained MPT depend on how efficiently county portfolio weights are bound by upper limits. For example, portfolio weights for constrained MPT with a $3 million total budget did not deviate much from those from naïve MPT since counties with optimal budgets above county-level physical constraints (e.g., 1 of 16 counties selected at four risk tolerance levels) were rare. No correction of risk and expected ROI is made by constrained MPT with a $3 million budget at the maximum risk level since the efficient portfolios between the two models are the same: all investment is allocated to a single county, Coosa County (AL). The upper limit constraint of Coosa County (AL) is less than the total budget of $3 million. Thus, the efficient portfolio weight of the county is not bound by its upper limit. Similarly, efficient portfolio weights between the approaches are the same at the minimum risk level (see Table S1 for details on portfolio weight allocations) since all efficient portfolio weights do not reach their upper limits. As a result, the efficient portfolio is the same regardless of whether the upper limit is considered or not. In contrast, deviation was much more apparent if the total budget for constrained MPT increased to $1 billion since counties with optimal budgets above county-level budget constraints (e.g., 81 of 85 counties selected at four risk tolerance levels) were much more numerous (see Table 1). These findings show that the degree of correction in risk and expected ROI made by constrained MPT is greater with higher total budgets, and greater diversification of counties is achieved regardless of risk mitigation especially when higher total budgets are considered.

Table 2 illustrates heterogeneity in different aspects of sixteen selected counties, among which three counties are chosen twice in different risk levels, from naïve MPT. Ten of the sixteen counties are categorized as rural counties. The sizes of the counties display considerable disparities. For example, Randolph, WV, the largest county among the sixteen counties (402,033 hectares), is almost five times in size relative to Jefferson, WV, the smallest county among the sixteen counties (82,416 hectares). Forestland area generally reflects the size of the county, and the ratio of public to private forestland on average over the 486 uncertainty scenarios ranges between 0 and 16 across the sixteen counties. The average species ranges for 258 species vary from 10.5 million to 55.4 million hectares across the counties over the uncertainty scenarios. The scale and variation of the urban return is greater than the forest return. As a result, the discrepancy of relative opportunity costs is determined more by the urban return than the forest return. A noticeable disparity is found in the ROIs across the counties. In particular, a $1 million investment would allow persistence of 0.1232 additional species in Coosa, AL, which is more than three hundred times greater than the expected ROI in Buncombe County, NC (0.0004) in average over the uncertainty scenarios.

Table 2. Summary of the sixteen selected counties from naïve MPT under four risk levels.

		County	**Type**	**Size (hectare)**	**Size of forestland (hectare)**	**Private forestland (hectare)**	**Public forestland (hectare)**	**Species ranges of 258 species (hectare)**	**Forest return ($/hectare)**	**Urban return ($/hectare)**	**Relative opportunity cost ($/hectare)**
Minimum risk level	Buncombe, NC	Urban	244,890	162,436	128,962	33,474	33,554,911	87	1,959	1,872	0.0004
	Haywood, NC	Rural	205,647	163,698	55,369	108,329	29,633,914	76	1,057	981	0.0011
	Henderson, NC	Urban	138,699	86,721	70,874	15,847	19,234,632	65	1,824	1,758	0.0006
	Jackson, NC	Rural	182,754	154,343	8,906	145,437	26,604,084	104	901	797	0.0008
	Transylvania, NC	Rural	140,519	119,281	34,785	84,496	19,626,066	91	952	862	0.0010
	Greenville, SC	Urban	292,390	151,886	151,886	-	38,557,472	55	1,731	1,676	0.0009
	Sevier, TN	Rural	222,275	161,512	88,767	72,745	29,947,641	65	1,015	950	0.0005
	Roanoke, VA	Urban	95,201	66,524	61,410	5,115	12,886,994	130	1,438	1,308	0.0005
	Fayette, WV	Rural	255,761	219,338	200,872	18,467	36,137,436	60	390	330	0.0023
	Jefferson, WV	Urban	82,416	23,413	23,167	246	10,526,362	62	1,544	1,482	0.0008
	Nicholas, WV	Rural	251,337	203,827	175,096	28,730	35,744,704	20	226	206	0.0049
	Randolph, WV	Rural	402,033	353,349	156,814	196,535	55,448,499	68	552	484	0.0035
15% risk level	Clay, AL	Rural	218,645	157,964	124,256	33,708	27,414,832	45	85	40	0.0415
	Wolfe, KY	Rural	84,926	67,963	53,030	14,933	11,480,003	47	69	22	0.0463
	Preston, WV	Rural	254,289	193,619	186,693	6,925	36,454,081	17	119	102	0.0185
25% risk level	Clay, AL	Rural	218,645	157,964	124,256	33,708	27,414,832	45	85	40	0.0415
	Coosa, AL	Rural	239,645	171,112	171,112	-	30,449,521	46	68	21	0.1232
	Wolfe, KY	Rural	84,926	67,963	53,030	14,933	11,480,003	47	69	22	0.0463
Maximum risk level	Coosa, AL	Rural	239,645	171,112	171,112	-	30,449,521	6	8	1	0.1232

Notes: Species ranges are average values of 258 species over 486 uncertainty scenarios, and private forestland, forest return, urban return, relatively opportunity cost, and ROI are average values over 486 uncertainty scenarios.

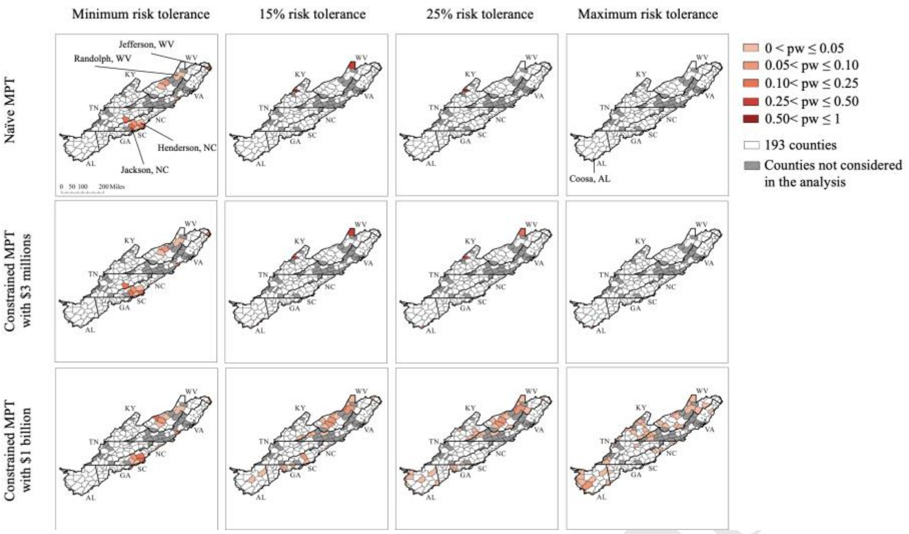


Figure 4. Spatial distributions of portfolio weight allocations from naïve MPT and constrained MPT with \$3 million and \$1 billion total budgets at four risk tolerance levels (i.e., minimum, 15%, 25%, and maximum risk tolerance levels) with upper limits at the mean

Figure 4 shows the spatial distributions of portfolio weight allocations from naïve MPT and constrained MPT with \$3 million and \$1 billion total budgets at four risk tolerance levels (i.e., minimum, 15%, 25%, and maximum risk tolerance) with upper limits at the mean. At minimum risk tolerance, we observe that a portfolio weight of 0.12 is assigned to Henderson County (NC) based on constrained MPT with a \$1 billion total budget, whereas the same county's portfolio weight is 0.24 for naïve MPT. The portfolio weight of 0.24 without an upper limit constraint does not exceed the county-level budget constraint of \$120 million if the total budget constraint was \$3 million. Consequently, the portfolio weight of 0.24 remains the same between naïve MPT and constrained MPT at minimum risk tolerance when a \$3 million total budget is considered. (See S1 and Table S1 in the Supplementary Material for discussion on portfolio weights between the two MPT approaches with three hypothetical total budgets and four risk levels.) These findings suggest that correction of misleading portfolio weights by constrained MPT occurs only if the optimal budget assigned to a county without a total budget constraint is above the county's budget constraint.

Figures S1 and S2 and Tables S2 and S3 in the Supplementary Material, respectively, show 1) the expected ROI-standard deviation frontiers and 2) optimal portfolio expected ROI for biodiversity conservation and risk under four risk levels between naïve MPT and constrained MPT with three hypothetical total budget scenarios using upper limits on both ends of 95% confidence interval of their probability density distributions. These consistent findings with different size of upper bound constraints reaffirm the robustness of characteristics discussed on 1) and 2) regardless of the size of upper limit constraints used in the constrained MPT.

Discussion

The comparison of MPT outputs with and without upper limit constraints shows that the change in portfolio risk that conservation organizations can achieve with the same level of compromise in expected ROI is higher with constrained MPT than with naïve MPT. This finding has implications for conservation strategies with different objectives. Constrained MPT is useful when seeking to protect species that are habitat specialists, such as several highly endemic salamanders in our case study region. It is also useful when prioritizing land that is only available for conservation acquisition occasionally because there may only be a few properties available in a desirable location during a period when the conservation program must allocate its budget.

Other possible circumstances that fit well for constrained MPT is when additional capacity constraints might be limiting (e.g., if the conservation program relies on partners for long-term management of the site). For example, the Critical Ecosystem Partnership Fund (CEPF, 2022) supports protecting natural areas essential to biodiversity with designated budget amounts. There are state programs also that cap how much any one state can receive. For example, the Cooperative Endangered Species Conservation Fund supports section 6 of the ESA (Pittman-Robertson Wildlife Restoration Act, 1937; US Fish and Wildlife Services, 2021) and provides grants to States and Territories for species and habitat conservation actions on non-federal land. State allocations from this fund are derived from an established formula and specific constraints. The funding proportion given to each state does not change from year to year since these appropriations are based on the program's formula.

Despite our study's contribution, conservation organizations should be mindful of the limitations associated with solely relying on upper limits on returns from conservation using a constrained MPT. The precise projections of the upper limits are not possible given the unknown probability distribution of uncertainty scenarios. Instead, we use average values of upper limits on returns across the scenarios for the main finding and vary their values as a sensitivity analysis. This type of approach offers layers of optimal solutions and allows a comparison of their implications for conservation decisions. Yet, conservation organizations need to go beyond comparing outcomes using multiple upper limits as they have little reference for which upper limits are most relevant to their conservation decision making. Furthermore, the unexpected economic, political, and technological shifts may result in the upper limits beyond what are covered by the scenario-specific projections. The potential occurrence of such extreme conditions hinders the application of the constrained MPT.

Another aspect of limitation lies on the influences of behavioral and social factors on conservation decisions. Conservation decision-making and behavior can deviate from rational expectations as they can be linked to social, psychological and behavioral factors. For example, emotion, habit, culture and involvement are found to have significantly and positively associated with conservation behavior (Singha et al., 2022), resulting in overreactions or underreactions to conservation commitment. As a result of these influences, conservation organizations may deviate from the optimal risk-diversification strategies with their decision-making processes. Consequently, their portfolios of conservation practices might exceed the projected upper limits on return, which in turn can shape dynamics of conservation behaviors. Likewise, we modeled a range of future scenarios, but obviously our models would not perform well if future black swan like events fall well outside the range that we consider.

It is also worth mentioning caveats for identifying future research needs. Our constrained MPT models focus on upper limits in returns that arise from physical limitations of conservation investments, while a conservation organization also faces upper limits due to diminishing returns. For example, a conservation organization attempting to protect species habitat for a specific target site faces diminishing returns at each target site since the number of species preserved per unit area will monotonically decrease as each additional unit area is protected if the response of each species to protection is not convex (Popov et al., 2022). In a way, our constrained MPT takes account of marginal returns with a step function where ROI goes to 0 when the weight crosses a threshold of the physical constraint in equations (5) and (6). The use of a step function reflects the fact that practitioners may only be able to coarsely estimate diminishing returns since data on the marginal effect of conservation investment is limited. Thus, future research could explore developing another modified constrained MPT framework accounting for upper limits in returns that arise from both physical limitations and diminishing returns when data on the marginal effect of conservation investment is viable.

We recognize there are other limitations to existing applications of MPT (both naïve and constrained MPT) in conservation. As with any approach, assumptions must be made. For example, applications of MPT in conservation typically assume static, one-off decisions which are relevant to some conservation programs (e.g., those needing to allocate funds during fixed windows of time), but not others (e.g., those planning acquisition strategies that are to be implemented gradually over a couple of decades). In reality, conservation agencies typically face scenarios in which building conservation programs at different sites takes time. In the interim, they accumulate new information relevant for final decision making (Pressey et al. 2013). To address this challenge, future research will have to develop a dynamic counterpart to the MPT approach to conservation planning and use it to determine a time series of portfolios of target sites for conservation that accommodates future spatial and temporal uncertainties.

Also, applications of MPT (both naïve and constrained MPT) are limited in the number of assets they can consider, which can result in a reliance on relatively coarse units such as counties in our empirical analysis. Specifically, the MPT cannot determine optimal solutions when the number of scenarios available is equal to or smaller than the number of assets considered because in such case the information needed to calculate the variance-covariance matrix for the solution of portfolio weights would not be sufficient (Mallory and Ando 2014). We have not yet compared the relative importance of accounting for upper limit constraints on how much investment can be directed to different assets to the relative importance of accounting for other refinements of MPT. We chose to focus here on the role of upper limit constraints on potential targets for investment because these constraints have the potential to induce some degree of risk spreading, which has been touted as a prevailing benefit of MPT. In our empirical application, we find that including these constraints enhanced the benefits of applying MPT. In essence, if a conservation organization must spread investment around anyway, it would be wise to use MPT to maximize the benefits of doing so.

Conclusion

The constrained MPT model is structured to correct potentially misleading portfolio weights from naïve MPT that does not account for upper limits in returns from conservation investments. We find that the amount of reduction in risk conservation organizations can achieve with the same level of compromise in expected ROI is higher with constrained MPT than with naïve MPT. However, our findings also suggest that improvement can be made only if the total budget assigned to a conservation organization is large enough so that portfolio weights from naïve MPT allocate beyond physical limitations determined by upper limits of potential target sites or regions that trigger misallocation of portfolio weights for target sites. For this reason, divergences between each approach's outcomes becomes more evident if the total budget for constrained MPT is higher, and the degree of divergence depends on how physical limitations bind and correct for misleading portfolio weights.

Constrained MPT can help conservation organizations by providing risk-mitigating portfolios of conservation targets that consider each target site's upper limit constraint. Comparing naïve and constrained MPT outcomes under various total budget constraint levels illustrate the vulnerability of naïve MPT and can help conservation organizations evaluate risk-diversifying strategies that are specific to different available total budget levels. Constrained MPT for a given risk tolerance level and specific total budget can identify a risk- and budget-specific portfolio of target sites for biodiversity conservation. This implication suggests that the portfolio weights associated with the risk-mitigating allocation of conservation investment can be adjusted by a conservation organization's risk tolerance and the total budget it manages.

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