Accounting for upper limits on returns from conservation investments in risk diversification strategies

Nawon Kang[1], Charles A. Sims[2], Paul R. Armsworth[3], James C. Mingie[4], Gengping Zhu[5], Seong-Hoon Cho[6]*

* Corresponding author

Selected Paper prepared for presentation at the 2023 Agricultural & Applied Economics Association Annual Meeting, Washington, DC; July 23-25, 2023

[1] Department of Agricultural Economics, Texas A&M University, nawonkang@tamu.edu
[2] Department of Economics, The University of Tennessee, cbsims3@utk.edu
[3] Department of Ecology and Evolutionary Biology, The University of Tennessee, p.armsworth@utk.edu
[4] Department of Agricultural and Resource Economics, The University of Tennessee, jmingie@vols.utk.edu
[5] Department of Entomology, Washington State University, gengping.zhu@wsu.edu
[6] Department of Agricultural and Resource Economics, The University of Tennessee, scho9@utk.edu

Accounting for upper limits on returns from conservation investments in risk diversification strategies

Abstract

Applications of risk diversification strategies to conservation problems assume returns do not diminish with greater investment. Not accounting for diminishing returns may cause the allocation of investment to a single or limited target site, which may not reflect the fact that additional conservation return will likely decline as more area is protected. 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 expected return on investment is higher with constrained MPT than with naïve MPT. 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 that trigger the misallocation of portfolio weights for target sites. For this reason, the divergence between the two models' outcomes becomes more evident if the total budget for constrained MPT is higher, and the degree of the divergence depends on how physical limitations bind and correct for misleading portfolio weights.

Keywords: Biodiversity conservation investment, Risk-diversification strategy, Modern Portfolio Theory, Diminishing return, Climate and market uncertainties

Accounting for upper limits on returns from conservation investments in risk diversification strategies

1. Introduction

Conservation investments tend to be controversial due to high levels of uncertainty caused by climate and market changes (Cho et al. 2018, Newbold 2018). Due to these uncertainties, planning conservation investments based purely on historical data may yield misleading results (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 to help diversify risk in conservation investments (Shipway, 2009). This tool accounts for heterogeneities in climate and market uncertainties to minimize risk associated with investment portfolios targeting various types of assets such as species, sites, and activities (Ando and Mallory 2012, Eaton et al. 2019).

Despite its merits, applications of MPT to conservation investments to date have not accounted for upper bounds on returns that arise from physical limitations and diminishing returns of the asset. For example, a conservation organization attempting to protect species habitat for a specific target site faces diminishing returns at each target site because the number of species preserved per unit area will monotonically decrease as each additional unit area is protected as long as the species’ responses to protection are not convex (Withey et al. 2012, Popov et al. 2021). Regardless of potential diminishing returns, return on conservation investment is clearly bounded by the total amount of species habitat available (e.g., forested area that can protected for a given site is limited). A conservation organization will also face an upper bound due to diminishing returns if habitat protection increases the cost of acquiring additional unprotected habitat. For example, protecting large acreages may raise the price of neighboring parcels due to increased scarcity of land available for industrial or commercial uses or due to people valuing living near protected areas. Ignoring these upper bounds imply that the economic returns are beyond the scope of what the conservation assets can produce given constraints on species, sites, or activities and lead conservation organizations to inefficiently focus investments on 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 so that one investor is incapable of influencing returns from the asset, and thus does not face diminishing returns. Early applications of MPT to conservation problems did not consider the availability of each asset, and most subsequent studies continue to overlook this issue (e.g., Figge 2004, Ando and Mallory 2012, Liang et al. 2018). For example, none of the twenty-six case studies summarized by Ando et al. (2018) that use MPT for allocating investments for species-habitat conservation considered an upper bound on returns.

Limited recent studies have sought to improve the application of MPT by indirectly limiting returns due to physical constraints (Jin et al. 2016, Runting et al. 2018). For example, Jin et al. (2016) applied portfolio theory to help implement ecosystem-based fishery management in different geographic regions. The authors considered the limited stock of each fish species to harvest in their MPT application by constraining the maximum weight applied to the harvest of each species. Similarly, Runting et al. (2018) reformulated an integer quadratic programming MPT problem with a binary decision variable representing whether each site is selected or not for a reserve site selection problem involving the landward migration of wetlands. By using the binary decision variable, the authors indirectly accounted for limited returns based on the sites' limited availability, along with other considerations such as connectivity for the landward migration of wetlands. However, it remains unclear how the benefits of risk diversification are impacted by these physical constraints and, more generally, diminishing returns of conservation investments that depend on an asset's relative cost and benefit.

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

The physical constraint is characterized by the amount of budget needed to protect all available species habitat (i.e., all unprotected private forestland) in a given county, where ROI goes to 0 when the weight crosses a threshold of the physical constraint. This step function reflects the fact that practitioners may only be able to coarsely estimate diminishing returns since data on the marginal effect of conservation investments is limited. The amount of risk reduction conservation organizations can achieve with the same level of compromise in expected ROIs is hypothesized to be dissimilar with the constrained MPT than with the naïve MPT. Restrictions on portfolio weights with the constrained MPT impose a degree of bet spreading while the naïve MPT does not. This would imply that constraints on returns would diminish the value added from an MPT approach. However, if the constraints make conservation organizations spread bets anyway, then it is wise to use MPT to allocate the bet spread in the best way possible. Our constrained MPT is designed to serve this very purpose.

2. **Method**

2.1. Conceptual illustration

Suppose a conservation organization wishes to allocate optimal portfolio weights between counties A and B based on the naïve and constrained MPTs. County A has larger expected ROI than county B ($ROI_A > ROI_B$). The positively sloping diagonal line in the upper graph of Figure 1 shows the allocations of the efficient portfolio weights between the two counties (w and $1 - w$ for counties A and B, respectively) at different risk levels based on the naïve and constrained MPTs. The $w^M$and $1 - w^M$ represent the upper bounds on the weights assigned to counties A and B. The lower graph of the figure illustrates the changes in expected ROI, $wROI_A + (1 - w)ROI_B$, corresponding to the portfolio weights between the two counties based on the naïve and constrained MPTs 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 1), with the corresponding expected ROI being the area □ *afho* in the lower graph. By comparison, consider the case where the constraint is binding in county A. The 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 the constrained MPT mitigates the maximum risk level relative to the naïve MPT by $r_1 - r_2$ but corrects expected ROI by the area □ *f'fgg'* compared to the naïve MPT.

The conservation investment would be divided between the two counties with lower risk than the risk level r_1 based on the 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 for the minimum risk level for the naïve MPT is shown as the sum of the area □ *aceo* for county A and the area □ *dghe* for county B. By comparison, consider the case where the constraint is binding in county B, where $w^{M\prime}$ and $1 - w^{M\prime}$ represent the upper bounds on the weights assigned to counties A and B. The constrained MPT would allocate weight, $1 - w^{M\prime}$, to county B and the remaining weight, $w^{M\prime}$, would be distributed to county A at the minimum risk level of r_3. The expected ROIs are shown by the area □ *ac'e'o* for county A and the area □ *d'ghe'* for county B. These results suggest that the constrained MPT sacrifices the minimum risk level by r_3 but increases expected ROI by the area of □ *cc'd'd* relative to the naïve MPT because of the added weight to the high ROI county (i.e., county A) based on the constrained MPT. Other cases would include a situation where county B provides both a lower expected ROI and a higher risk. In this case, budget constraints on county A could both lower the expected ROI of investment and increase the risk of investing.

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

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

The overall budget to be invested in conservation also matters. If the overall budget is small relative to the levels of investment each asset can receive, then accounting for upper bounds on how much investment is possible in each asset is irrelevant. In contrast, it is when the overall program budget is large that these constraints may bind, meaning accounting for them in the optimization becomes more important. The risk and expected ROI corrections made by the constrained MPT, relative to the naïve MPT, intensify with the increased hypothetical total budget because the share of the budget assigned to each county, constrained by its upper bound, decreases with the higher hypothetical total budget. Thus, we hypothesize that the total budget assigned to a conservation organization influences the degree of deviation of the risk level and corresponding expected ROI between the two models.

We consider these two counties as an example to illustrate the effects of risk levels and expected ROIs on naïve and constrained MPTs. While these comparisons are sufficient to build intuition for changes of return and risk, we do not consider richer patterns of covariance, which is where the strength of MPT reveals itself and which we later examine through an 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 MPTs.

2.2. Naïve MPT framework

By modifying the framework developed by Runting et al. (2018) where risk minimization and expected return maximization is combined in a single framework, we develop a naïve MPT framework formatted as a quadratic programming problem without upper bound constraints as:

$$Min_W \ \lambda W^T \Sigma W - W^T \mathrm{M} \tag{1}$$

subject to

$$0 \leq W \leq I \tag{2}$$

$$W^T I = 1 \tag{3}$$

where λ is a weight for risk minimization which represents the relative emphasis on risk mitigation from zero to infinity, $W^T \Sigma W$ is the weighted sum of the variance of counties representing the portfolio's variance (or risk) where W^T is a vector transpose of W, which is an $n \times 1$ vector of efficient portfolio weights across n counties as the decision variable, and Σ is an $n \times n$ variance-covariance matrix of the 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 different s uncertainty scenarios. M is an $n \times 1$ vector of expected ROIs, which are calculated by the expected values of the 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. $W^T \mathrm{M}$ is the expected ROI of the portfolio calculated by the weighted average of M with the efficient portfolio weight W.

The objective function in equation (1) maximizes the expected ROI (i.e., $W^T \mathrm{M}$) or minimizes the portfolio's variance (i.e., $W^T \Sigma W$) at a certain weight for risk minimization (λ). Equation (2) represents the minimum and maximum constraint on portfolio weights, and 0 and 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.

2.3. Constrained MPT framework

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

$$Min_X \, \lambda X^T \Sigma X - X^T \mathrm{M} \quad (4)$$

subject to

$$0 \leq X \leq C \quad (5)$$

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

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

The objective function in equation (4) maximizes the weighted sum of expected ROIs (X^TM) and minimizes the portfolio's variance (i.e., $X^T \Sigma X$). Equation (5) specifies the county's physical constraint C across n counties, and equation (6) constrains the hypothetical total budget B. The physical constraints are fixed for counties under uncertainty scenarios, while the hypothetical total budget constraints may change depending on the available budget for the entire region. The physical and budget constraints are considered and specified by equations (5) and (6), respectively, as total budget is spread from one county to another after meeting each county's physical constraint 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 W for constrained MPT by dividing efficient budget allocation X by total budget B to derive the efficient portfolio's expected ROI and corresponding variance as the weighted sum of expected ROIs (W^TM) and the variance of counties ($W^T \Sigma W$) for the risk measure. In doing so, we derive efficient frontiers for naïve and constrained MPT under various levels of weight for risk minimization λ by connecting points of expected ROIs and corresponding standard deviations for both MPT approaches. To test the hypothesis found in the conceptual framework related to the impact of the hypothetical total budget amount on the degree of deviation between naïve and constrained MPT, we compare outcomes based on the two models under three hypothetical total budget constraints: low, moderate, and high total budget (i.e., \$3 million, \$50 million, and \$1 billion).

Then, we normalize the risk level as the % above the minimum risk level (referred to as 'risk tolerance level') to compare outcomes based on the naïve and constrained MPTs at the same degree of risk that conservation organizations can endure. If the feasible risk levels were different between the models, our comparisons would be limited. For example, if the minimum risk levels were 0 and 3 for the 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 for the naïve MPT. By drawing the efficient frontiers where the x-axis is the risk tolerance level normalized as stated above, the efficient frontiers are comparable for every risk tolerance level and show the expected ROIs attainable for any risk tolerance level across four different MPT specifications.

3. Illustrative example: Forest conservation in Central and Southern Appalachia

To illustrate our framework, we apply our model 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 a critical habitat and corridor for biodiversity (Levine et al. 2021), and the region is anticipated to suffer from climate change and urban development (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 reflect the impact of climate and market uncertainties on benefits and costs. The benefits for expected ROI are calculated by estimating future species distributions using species distribution models. The conservation cost for expected ROI is proxied by 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 losses in the study region (Wear and Greis 2013, Keyser et al. 2014). We aggregate expected ROIs for 258 forest-dependent vertebrate species that are of policy concern (Zhu et al. 2021) as expected ROI for biodiversity conservation 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 2).

The MPT scenario-specific expected ROIs are structured by combining predicted future benefit scenarios and relative opportunity cost scenarios (see 3.1 Estimating scenario specific ROI for details of how scenario specific ROI are estimated). Scenarios for predicting future biodiversity benefits are only related to climate change, and thus we consider multiple climate scenarios. In comparison, relative opportunity costs are forecasted under scenarios associated with climate, land use, and market conditions (see S1. Uncertainty Scenarios in Supplementary Material for details of how uncertainty scenarios were constructed).

3.1 Estimating scenario specific ROI

The benefit measure for biodiversity ROI in the central and southern Appalachian region was taken from Zhu et al. (2021) which specified the species distributions of 258 forest-dependent vertebrates of policy concern for the US Fish and Wildlife Service (2020), and Landscape Conservation Cooperative Network (2020). Zhu et al. (2021) chose future species distributions in 2050 as the benefit measure for biodiversity since they are direct functions of the areas where species can be found and protected (Fuentes-Castillo et al. 2019). The authors used Maxent as the species distribution model (SDM) to forecast future species distributions under future climate scenarios for two representative concentration pathways (RCPs; RCP4.5 and RCP 8.5) with 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 given various climate scenarios. Then, the 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, the pixel areas of the suitable binary variables are aggregated for all 258 species at the county level and these estimates were specified as the benefit measure of species distributions for all species. See Zhu et al. (2021) for details of the methodology used to project future species distribution for 258 forest-dependent vertebrates.

For future urban return to estimate relative opportunity cost, annualized median assessed land value was determined by generally following Lubowski et al. (2006) using the following procedure. First, we estimated land value ratios per hectare by dividing assessed land value per hectare by total assessed value at the parcel level for sample counties where data were available. Second, we converted land value ratios at the parcel level 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). We estimated median assessed land value per hectare for three market conditions (upturn, moderate, downturn) by multiplying land value ratio per hectare by median housing price for each market condition. Finally, median assessed land value per hectare, as urban return, was estimated by multiplying median housing price by land value ratio per hectare, averaged at the county level and annualized (see Cho et al. 2018 for more details).

For forestland return to estimate relative opportunity cost, we estimated future annualized forest return using Soil Expectation Value (SEV) based on projected timber prices and per hectare timber harvest volumes under an infinite series of identical harvest rotations of 50-75 years and a discount rate of 5% with identical timber management practices. For each state, we specified high (mean price plus one standard deviation), moderate (mean price), and low (mean price minus one standard deviation) timber price scenarios in 2050 using a Brownian motion process estimated from state-level timber price data. Stumpage price data for the projection of timber prices was collected from Timber Mart-South (Timber Mart-South 2015) and division of forestry offices from 8 states: AL, GA, KY, NC, SC, TN, VA, WV. Historical timber volume data was collected from the Forest Inventory and Analysis (FIA) Database (USDA Forest Service 2018) (see Cho et al. 2018 for more details). Then, we filtered out consolidated city-counties and counties with negative relative opportunity costs that do not face urban development concern.

Specifying the benefit measure of biodiversity as species distributions and relative opportunity cost as the cost measure described above, we took the outcome from Armsworth et al. (2020), who developed a modeling framework to estimate ROIs for biodiversity conservation. The authors applied a shared-based land use model at the county level to consider the marginal change in hectares of private forest resulting from conservation investment. Armsworth et al. (2020) assumed that as suitable species habitat or forest area in a county increased, the forest within the suitable habitat area increased because location data for the land use model was absent. Additionally, the probability of persistence for each species was independent and was proportional to the total amount of forest area within future suitable habitat. The probability of persistence function was assumed as a linear, piecewise continuous, hockey-stick function, which allowed the persistence probability to go to zero when no forest remained but increase linearly when forest area in the county increased until a saturation threshold at 1. The authors also considered the difference of ecological quality between protected forest and private forest as intermediate usable habitat and differentiated them by assigning two different weights (i.e., 1 or 0.25) to protected forest and private forest, respectively (see Armswroth et al. 2020 for more details). Based on the probability of persistence function and the average opportunity cost, the marginal benefit to cost ratio in each county was estimated, which was optimized by both naïve and constrained MPTs. Finally, expected ROI under uncertainty scenarios 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 et al. 2022).

3.2 Empirical Results

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

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

However, Figure 3B also shows how constraints on returns forces the Appalachian land manager to spread her bets by forcing her to spread the budget to a larger number of counties. This bet spreading behavior yields an expected ROI closer to what she would achieve if she were to divide the budget evenly among all counties (simple diversification; 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 portfolio decreases as the budget increases.[7] Points *a, b, c,* and *d* are the points on the efficient frontiers for the naïve MPT, and the constrained MPT with $3 million, $50 million, and $1 billion, respectively, with the same standard deviation as point X. The vertical distances from simple diversification portfolio X to *a*, *b*, *c* and *d* represent the difference in potential expected ROI gained by different MPT frameworks, given the same risk level. The longer vertical distance from X to *a* over the distances from X to *b, c,* and *d* reinforces the notion that MPT must be less efficient for constrained MPT since the constraints force the land manager to put all her eggs in more baskets.

Table 1 shows the portfolio's expected ROI for biodiversity conservation and risk, reflected in its standard deviation, at maximum and minimum risk levels from the naïve and

[7] Note that 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.

constrained MPTs with three hypothetical total budget scenarios. The results show that, at the maximum risk level, the constrained MPT compromised expected ROI while improving risk mitigation to a greater extent compared to the naïve MPT. At the minimum risk level, the constrained MPT gained higher expected ROI by reducing risk mitigation more than the naïve MPT. These findings imply that constrained MPT corrects misallocated portfolio weights, and based on this correction, the tradeoff between risk level and expected ROI at maximum and minimum risk levels, respectively.

The deviations in risk level and expected ROI between the naïve and constrained MPTs depend on how efficiently the portfolio weights of the counties are bound by their upper limits. For example, portfolio weights for the constrained MPT with a $3 million total budget did not deviate much from those from the naïve MPT since counties with optimal budgets above county-level physical constraints (i.e., 1 of 16 counties selected for four risk tolerance levels) were rare. In particular, no correction of risk and expected ROI is made by the constrained MPT with a $3 million budget at the maximum risk level, as the efficient portfolios between the two models are exactly the same: all investment allocated to a single county, Coosa County (AL). The upper bound 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. Likewise, the efficient portfolio weights between the models are exactly the same at the minimum risk level (see Table S1 for details on portfolio weight allocations) because all efficient portfolio weights do not reach their upper bounds. As a result, the efficient portfolio is the same regardless of whether the upper limit is considered or not. In contrast, the deviation was much more evident if the total budget for constrained MPT increased to $1 billion since counties with optimal budgets above county-level budget constraints (i.e., 81 of 85 counties selected for four risk tolerance levels) were much more numerous (see Table 1). These findings show that the amount of correction in risk and expected ROI made by the constrained MPT is greater with higher total budgets, and greater diversification among counties regardless of risk mitigation is generated especially with higher total budgets compared to lower total budgets.

Figure 4 shows the spatial distributions of portfolio weight allocations from the naïve MPT and the constrained MPT with \$3 million and \$1 billion total budgets at four different risk tolerance levels (i.e., minimum, 15%, 25%, and maximum risk tolerance levels). At the minimum risk tolerance level, we observe that the portfolio weight of 0.12 is assigned to Henderson County (NC) based on the constrained MPT with a \$1 billion total budget, whereas the same county's portfolio weight is 0.24 for the naïve MPT at the minimum risk tolerance. The portfolio weight of 0.24 without an upper bound constraint would 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 would remain the same between the naïve MPT and constraint MPT with a \$3 million total budget at minimum risk tolerance. (See Tables S1 and S2 in the Supplementary Material for details of portfolio weights between the two models with three hypothetical total budgets at four different risk levels and highlights of the analysis.) These findings suggest that correction of misleading portfolio weights by the constrained MPT occurs only if the optimal budget assigned to a county without a total budget constraint is above the county's budget constraint.

4. Discussion

We identified the consequences of failing to account for upper bound constraints that are attributable to both physical limitations and diminishing returns of target sites in a MPT framework using a case study involving the conservation of biodiversity at the county level in the central and southern Appalachian region. The comparison of MPT outputs with and without upper bound constraints shows that the change in portfolio risk that conservation organizations can achieve with the same level of compromise in expected ROIs is higher with the constrained MPT than with the naïve MPT, and this finding has implications for conservation strategies with different targets. The 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 properties that are only available for conservation acquisition occasionally because there may only be a few properties available in locations a conservation program would like to prioritize during the period when a conservation program must allocate its budget. Other possible circumstances that fit well for the constrained MPT is when other capacity constraints might be limiting, e.g., if the conservation program relies on partners for long-term management of the site.

Likewise, the constrained MPT is also useful for conservation investment with a regulatory cap on budget allocation for each site. Many conservation partnership programs are limited by regulatory constraints imposed by partnership funds. For example, the Critical Ecosystem Partnership Fund (CEPF 2022), which supports protecting natural areas essential to biodiversity, provides small grants of up to $20,000 for each eligible site and large grants of up to $150,000. There are state programs as well that cap how much any one state can receive. For example, the Cooperative Endangered Species Conservation Fund supports under 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 lands. State allocations from this fund are derived from an established formula: one-third of the allocation is based on the land area of the state and two-thirds is based on its human population size. Bounds are also placed on the formula such that no state may receive less than 1 percent of the total available for apportionment or more than 5 percent. The funding proportion given to each state does not change from year to year since these appropriations are based on the formula.

Despite our study's contribution, it is worth mentioning a caveat for identifying future research needs. Our constrained MPT models are framed to account for the upper bounds of returns from conservation investments in target counties. However, in some circumstances, including lower bounds is also necessary. For example, if the application of MPT for biodiversity conservation involves creating portfolios of species, instead of creating portfolios of sites such as our case study, the possibility of zero or extremely small portfolio weights is concerning. The reason for this concern is that such possible outcome implies that species are completely fungible, which would lead to poor ecological outcomes if an entire species was lost following such suggestions. Thus, future research could explore developing a modified constrained MPT framework consisting of both upper and lower bound constraints.

5. Conclusion

The constrained MPT model is structured to correct potentially misleading portfolio weights from the naïve MPT that does not account for upper bounds of 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 ROIs is higher with the constrained MPT than with the 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 the naïve MPT allocate beyond physical limitations and diminishing returns determined by the upper bounds of potential target sites or regions that trigger misallocation of portfolio weights for target sites. For this reason, the divergence between the two models' outcomes becomes more evident if the total budget for constrained MPT is higher, and the degree of the divergence depends on how physical limitations and diminishing returns bind and correct for misleading portfolio weights.

The constrained MPT can help conservation organizations by offering risk-mitigating portfolios of conservation targets that consider each target site's upper bound constraint. Comparing the naïve and the constrained MPT outcomes under various total budget constraint levels illustrates the vulnerability of the naïve MPT and helps conservation organizations evaluate risk-diversifying strategies that are specific to different available total budget levels. The 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 means the portfolio weights associated with the risk-mitigating allocation of conservation investment can be adjusted by the conservation organization's risk tolerance and the total budget it manages.

We recognize there are other limitations to existing applications of 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). Also, applications of MPT are limited in how many assets they can consider, which can result in a reliance on relatively coarse units (see Mallory and Ando 2014 for more discussion). We have not yet compared the relative importance of accounting for upper bound constraints on how much can be invested in different assets to the relative importance of accounting for other potential refinements of MPT. We chose to focus here on the role of upper bound 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 made the case for using MPT stronger. In essence, if a conservation organization is going to have to spread investments around anyway, it would be wise to use MPT to maximize the potential benefits available from doing so.

Reference

Ando, A.W., Fraterrigo, J., Guntenspergen, G., Howlader, A., Mallory, M., Olker, J.H., Stickley, S., 2018. When portfolio theory can help environmental investment planning to reduce climate risk to future environmental outcomes—and when it cannot. Conservation Letters 11, e12596. https://doi.org/10.1111/conl.12596

Ando, A.W., Mallory, M.L., 2012. Optimal portfolio design to reduce climate-related conservation uncertainty in the Prairie Pothole Region. Proceedings of the National Academy of Sciences 109, 6484–6489. https://doi.org/10.1073/pnas.1114653109

Cho, S., Lee, J., Roberts, R., Yu, E.T., Armsworth, P.R., 2018. Impact of market conditions on the effectiveness of payments for forest-based carbon sequestration. Forest Policy and Economics 92, 33–42. https://doi.org/10.1016/j.forpol.2018.03.009

Critical Ecosystem Partnership Fund (CEPF). 2022. URL https://www.cepf.net/

Eaton, M.J., Yurek, S., Haider, Z., Martin, J., Johnson, F.A., Udell, B.J., Charkhgard, H., Kwon, C., 2019. Spatial conservation planning under uncertainty: adapting to climate change risks using modern portfolio theory. Ecological Applications 29, e01962. https://doi.org/10.1002/eap.1962

Figge, F., 2004. Bio-folio: applying portfolio theory to biodiversity. Biodiversity and Conservation 13, 827–849. https://doi.org/10.1023/B:BIOC.0000011729.93889.34

Fuentes-Castillo, T., Scherson, R.A., Marquet, P.A., Fajardo, J., Corcoran, D., Román, M.J., Pliscoff, P., 2019. Modelling the current and future biodiversity distribution in the Chilean Mediterranean hotspot. The role of protected areas network in a warmer future. Diversity and Distributions 25, 1897–1909. https://doi.org/10.1111/ddi.12988

Jin, D., DePiper, G., Hoagland, P., 2016. Applying Portfolio Management to Implement Ecosystem-Based Fishery Management (EBFM). North American Journal of Fisheries Management 36, 652–669. https://doi.org/10.1080/02755947.2016.1146180 [dataset] Kang, N., Sims, C., Armsworth, P., Zhu, G., Mingie, J., and Cho, S.-H., 2022. Risk diversification strategies for biodiversity conservation investment", Mendeley Data, V1, https://doi.org/10.17632/6kmckbx4zz.1

Keyser, T., Malone, J., Cotton, C., Lewis, J., 2014. Outlook for Appalachian-Cumberland forests: a subregional report from the Southern Forest Futures Project. General Technical Report - Southern Research Station, USDA Forest Service.

Landscape Conservation Cooperative Network. 2020. Appalachian. URL https://lccnetwork.org/lcc/appalachian

Levine J, Bryant D, Watland A, and Medlock K. 2021. Appalachian Annual Report: A year in review. The Nature Conservancy.

Liang, J., Gao, X., Zeng, G., Hua, S., Zhong, M., Li, Xiaodong, Li, Xin, 2018. Coupling Modern Portfolio Theory and Marxan enhances the efficiency of Lesser White-fronted Goose's (Anser erythropus) habitat conservation. Sci Rep 8, 214. https://doi.org/10.1038/s41598-017-18594-2

Liu, X., Cho, S.-H., Hayes, D.J., Armsworth, P.R., 2019. Potential efficiency gains in payment programs from resolving spatial and temporal heterogeneity in the cost of supplying forest carbon. Journal of Environmental Management 250, 109421. https://doi.org/10.1016/j.jenvman.2019.109421

Lubowski, R.N., Plantinga, A.J., Stavins, R.N., 2006. Land-use change and carbon sinks: Econometric estimation of the carbon sequestration supply function. Journal of Environmental Economics and Management 51, 135–152. https://doi.org/10.1016/j.jeem.2005.08.001

Mallory, M.L., Ando, A.W., 2014. Implementing efficient conservation portfolio design. Resource and Energy Economics 38, 1–18. https://doi.org/10.1016/j.reseneeco.2014.05.001

Markowitz. H. 1952. “Portfolio selection.” J. Financ. 7(1): 77–91.

Newbold, T., n.d. Future effects of climate and land-use change on terrestrial vertebrate community diversity under different scenarios. Proceedings of the Royal Society B: Biological Sciences 285, 20180792. https://doi.org/10.1098/rspb.2018.0792

Peterson, A. T., Soberón, J., Pearson, R. G., Anderson, R. P., Martínez-Meyer, E., Nakamura, M., and Araújo, M. B. 2011. Ecological niches and geographic distributions (MPB-49). Princeton University Press.

Phillips, N.A., 1956. The general circulation of the atmosphere: A numerical experiment. Quarterly Journal of the Royal Meteorological Society 82, 123–164. https://doi.org/10.1002/qj.49708235202

Pittman-Robertson Wildlife Restoration Act, 16 U.S.C § 669c. 1937. URL https://www.govinfo.gov/app/details/USCODE-2011-title16/USCODE-2011-title16-chap5B-sec669c

Popov, V., Shah, P., Runting, R.K., Rhodes, J.R., 2022. Managing risk and uncertainty in systematic conservation planning with insufficient information. Methods in Ecology and Evolution 13, 230–242. https://doi.org/10.1111/2041-210X.13725

Rogers, B.M., Jantz, P., Goetz, S.J. and Theobald, D.M., 2016. Vulnerability of tree species to climate change in the Appalachian Landscape Conservation Cooperative. In Climate change in wildlands (pp. 212-233). Island Press, Washington, DC.

Runting, R.K., Beyer, H.L., Dujardin, Y., Lovelock, C.E., Bryan, B.A., Rhodes, J.R., 2018. Reducing risk in reserve selection using Modern Portfolio Theory: Coastal planning under sea-level rise. Journal of Applied Ecology 55, 2193–2203. https://doi.org/10.1111/1365-2664.13190

Shipway, I., 2009. Modern Portfolio Theory. Trusts & Trustees 15, 66–71. https://doi.org/10.1093/tandt/ttn129

Snäll, T., Triviño, M., Mair, L., Bengtsson, J., Moen, J., 2021. High rates of short-term dynamics of forest ecosystem services. Nat Sustain 4, 951–957. https://doi.org/10.1038/s41893-021-00764-w

Timber Mart-South (TMS). 2015. Product and services. URL http://www.timbermart-south.com

U.S. Department of Agriculture, Forest Service. 2018. FIA data and tools. URL https://www.fia.fs.fed.us/tools-data/index.php

U.S. Fish and Wildlife Service. 2020. Endangered Species Act. URL https://www.fws.gov/endangered/laws-policies

U.S. Fish and Wildlife Services. 2021. Cooperative Endangered Species Conservation Fund Grants: Section 6 of the Endangered Species Act. URL https://www.fws.gov/media/cooperative-endangered-species-conservation-fund-grants-section-6-endangered-species-act

Wang, T., Hamann, A., Spittlehouse, D., Carroll, C., 2016. Locally Downscaled and Spatially Customizable Climate Data for Historical and Future Periods for North America. PLOS ONE 11, e0156720. https://doi.org/10.1371/journal.pone.0156720

Wear, D.N., Greis, J.G., 2013. The Southern Forest Futures Project: technical report. Gen. Tech. Rep. SRS-GTR-178. Asheville, NC: USDA-Forest Service, Southern Research Station. 542 p. 178, 1–542. https://doi.org/10.2737/SRS-GTR-178

Withey, J.C., Lawler, J.J., Polasky, S., Plantinga, A.J., Nelson, E.J., Kareiva, P., Wilsey, C.B., Schloss, C.A., Nogeire, T.M., Ruesch, A., Ramos Jr, J., Reid, W., 2012. Maximising return on conservation investment in the conterminous USA. Ecology Letters 15, 1249–1256. https://doi.org/10.1111/j.1461-0248.2012.01847.x

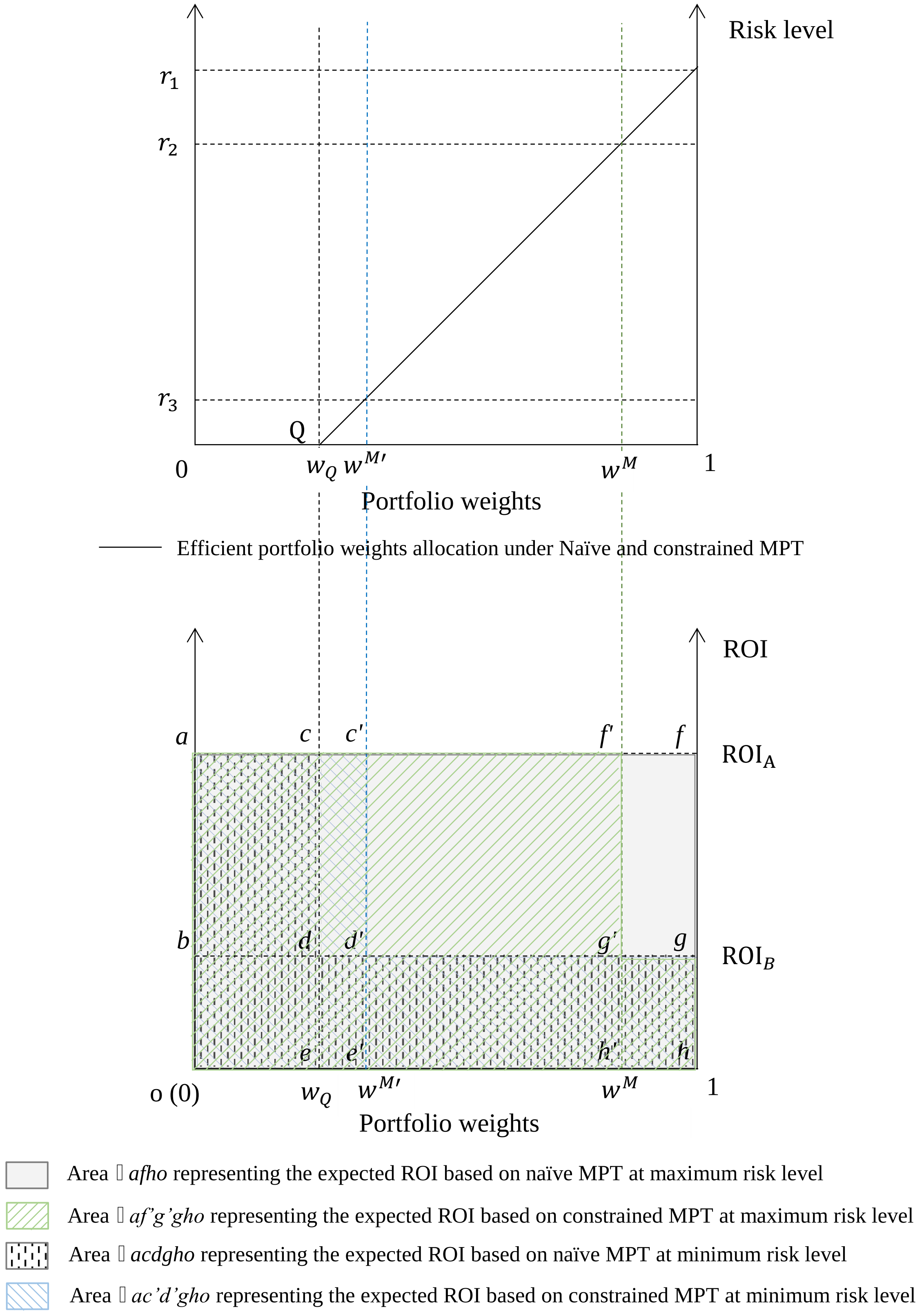
Zhu, G., Papeş, M., Giam, X., Cho, S.-H., Armsworth, P.R., 2021. Are protected areas well-sited to support species in the future in a major climate refuge and corridor in the United

States? Biological Conservation 255, 108982.
https://doi.org/10.1016/j.biocon.2021.108982

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 bound constraints, and average costs of selected counties from naïve MPT and constrained MPT with three total budgets under minimum and maximum risk levels

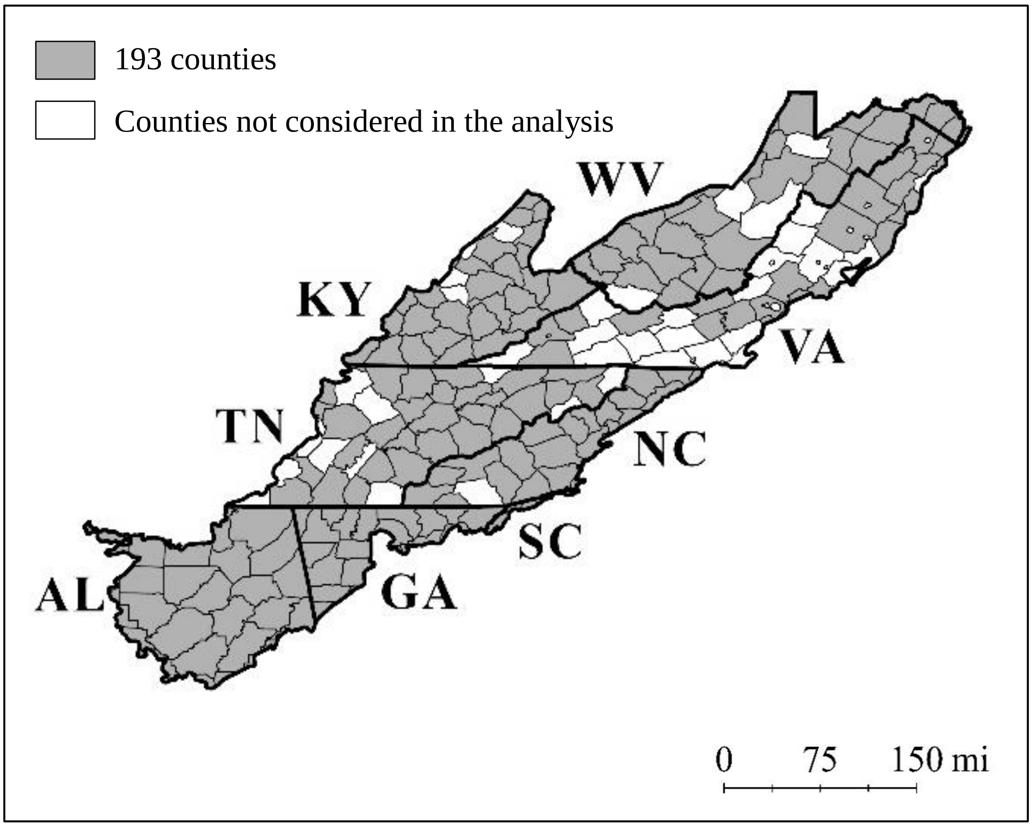
		Naïve MPT	Constrained MPTs		
			$3 million	$50 million	$1 billion
Minimum risk level	Portfolio's expected ROI	0.00173	0.00119	0.00104	0.00091
	Portfolio's standard deviation	0.00005	0.00004	0.00004	0.00004
	# of counties selected	12	12	12	16
	# of counties bound by its upper bound constraint	-	0	1	9
	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 bound 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 bound 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 bound constraint	-	0	8	58
	Average cost of selected counties	$3,645,232	$3,645,232	$5,588,646	$17,942,059

Figure 1. Consequence of failing to account for the upper bound constraint in MPT.



The upper graph of the figure shows the allocations of the efficient portfolio weights between the two counties (w and $1 - w$ for counties A and B, respectively) at different risk levels based on the naïve and constrained MPTs. The lower graph of the figure illustrates the changes in expected ROI corresponding to the efficient portfolio weights between the two counties based on the naïve and constrained MPTs shown in the upper graph.

Figure. 2. Map of 193 counties used for naïve MPT and constrained MPT



Note: 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

Figure 3. Four efficient frontiers of the expected ROI-risk tolerance relationship for portfolios from the naïve MPT and the constrained MPTs with three budgets ($3 million, $50 million, and $1 billion). (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.

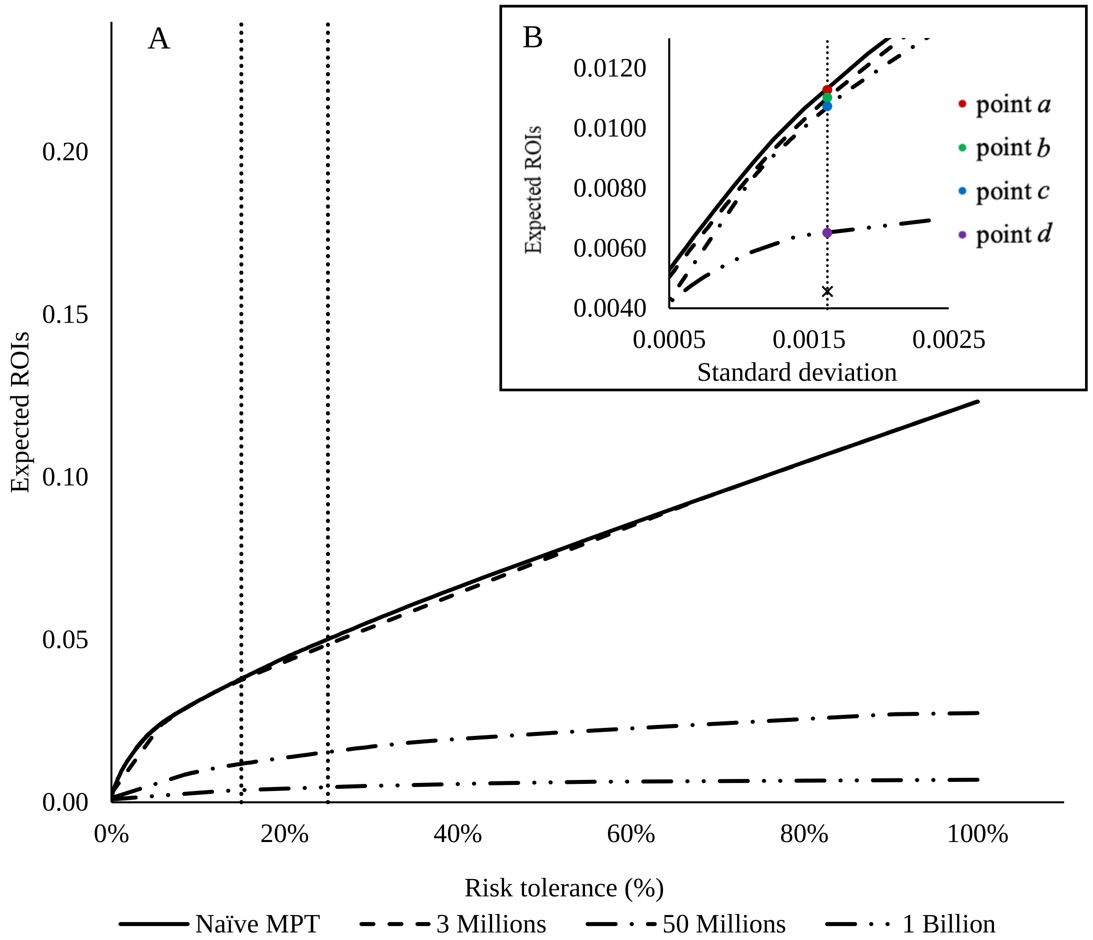
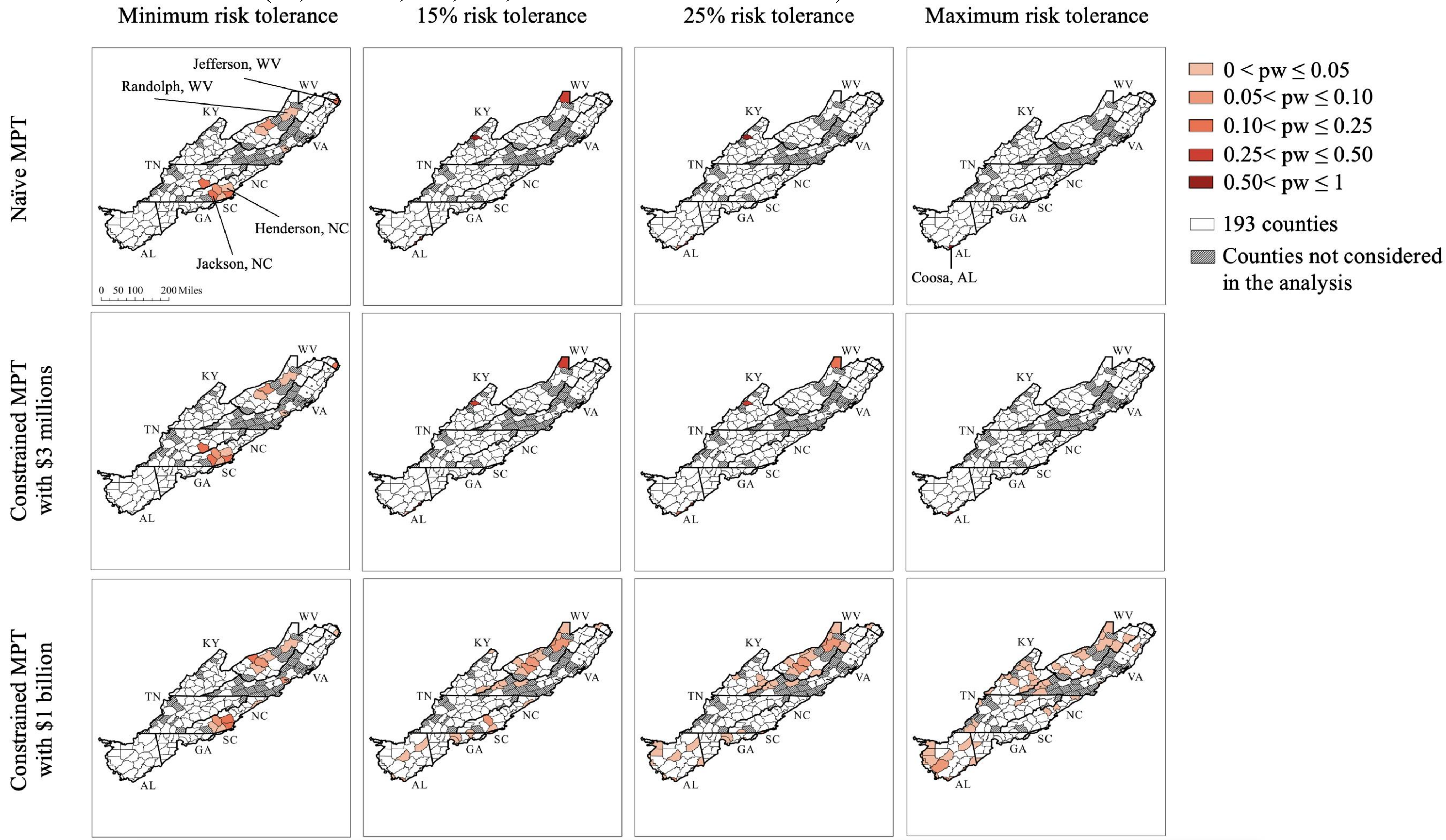


Figure 4. Spatial distributions of portfolio weight allocations from the naïve MPT and the constrained MPT with $3 million and $1 billion total budgets at four different risk tolerance levels (i.e., minimum, 15%, 25%, and maximum risk tolerance levels)



Supplementary material

S1. Uncertainty scenarios

This subsection describes future uncertainty scenarios used for each estimation of future species distribution, urban return, and forest return. Future species distribution, the measure of benefit for conservation investment, was only affected by climate changes, and, therefore, 12 climate scenarios were used: 6 GCMs with RCP 4.5 showing a stabilization of CO_2 emissions with climate policy scenarios, and 6 GCMs with RCP8.5 showing high CO_2 emissions and representing business as usual scenarios. For future urban return, three economic growth scenarios were considered (USDA Forest Services 2012), whereas for future forest return, 81 climate and market uncertainty scenarios were used. Specifically, three GCMs with three Special Report on Emission Scenarios (SRES, Nakicenovic et al. 2000) were used for estimating timber volume to reflect climate uncertainty in forest return and three timber prices and three economic growth scenarios were applied to timber prices to reflect market uncertainty. In conclusion, 162 scenarios for each SRES were created from 6 GCMs with one RCP, 3 GCMs corresponding to each SRES volume scenario, three timber prices, and three economic growth scenarios. This leads to a total of 486 scenarios for estimating scenario specific ROIs.

S2. The pattern of portfolio weight distribution

Figure 4 also shows that portfolio weights from naïve MPT spread out among counties at minimum risk tolerance level and gradually concentrate to fewer counties as risk tolerance level increases. For example, portfolio weights from naïve MPT are assigned to 10 counties at minimum risk tolerance level, while the entire portfolio weight is concentrated in a single county at maximum tolerance (see Table S1 in Supplementary material for the entire list of portfolio weights across different risk tolerance levels). A similar pattern of more diverse target counties with lower risk tolerance levels or vice versa is found for constrained MPT with a $3 million total budget (see Table 1 for details).

In contrast to naïve MPT and constrained MPT with a $3 million total budget, Table 1 shows that the number of counties with positive portfolio weights from constrained MPT with a $1 billion increases with increasing risk tolerance level. For example, portfolio weights are assigned to 14, 35, 41, and 58 counties, respectively, at minimum, 15%, 25%, and maximum risk tolerance levels for constrained MPT with a $1 billion total budget. This pattern of results is interesting in a sense that it contradicts the conventional wisdom of greater diversification for lower risk tolerance levels and vice versa which coincide with outputs of naïve MPT and constrained MPT with a $3 million total budget as well. While deviating from conventional wisdom, expected ROIs and their standard deviations for the portfolio of counties for constrained MPT with a $1 billion total budget still fulfill the condition of higher return with higher risk or lower risk with lower return. For example, the expected ROI of portfolios from constrained MPT with a $1 billion total budget are 0.1221, 0.5263, 0.6981, and 1.5315, and their corresponding standard deviations are 0.0092, 0.0653, 0.1044 and 0.3904 respectively, at minimum, 15%, 25%, and maximum risk tolerance levels.

We examine the underlying reason for greater diversification at greater risk tolerance level for constrained MPT with a $1 billion total budget by comparing the mechanisms of constrained MPT and naïve MPT. Naïve MPT selects a portfolio of minimum standard deviations and covariances across expected ROIs under different climate and market scenarios with diverse counties at minimum risk tolerance level, while it selects a portfolio of maximum expected ROIs by focusing on a single county with the highest expected ROI at maximum risk tolerance level, both regardless of total budget constraints. As a result, a greater number of counties are selected at lower risk tolerance levels or vice versa using native MPT. In contrast, the portfolio of maximum expected ROIs for constrained MPT exhausts the total budget by selecting a greater number of counties because of their lower average cost than the counties selected for a portfolio of minimum standard deviations and covariances with lower expected ROI and higher average cost. This pattern of greater number of counties for the portfolio of maximum expected ROI compared to the portfolio of minimum standard deviations and covariances from constrained MPT becomes more evident with a higher total budget constraint.

Table S1. Portfolio weights from naïve MPT and constrained MPTs with \$3 million, \$50 million, and \$1 billion budgets at minimum, 15%, 25%, and maximum risk tolerance levels.

	Minimum risk				15%				25%				Maximum risk			
Counties	Naïve MPT	3 millions	50 millions	1 billion	Naïve MPT	3 millions	50 millions	1 billion	Naïve MPT	3 millions	50 millions	1 billion	Naïve MPT	3 millions	50 millions	1 billion
Bibb, AL							0.1167	0.0366			0.1256	0.0366				0.0366
Blount, AL								0.0278				0.0088				0.0349
Chilton, AL							0.1058	0.0518				0.0518				0.0518
Clay, AL					0.2108	0.2852	0.0029		0.1408	0.2889	0.0360				0.0994	0.0050
Cleburne, AL							0.1446		0.0000	0.0000	0.1263	0.0078			0.1570	0.0078
Coosa, AL						0.0183			0.0567	0.1265			1.0000	1.0000	0.0729	0.0036
DeKalb, AL								0.0038				0.0237				0.0237
Fayette, AL												0.0133				0.0181
Jackson, AL																0.0576
Lawrence, AL												0.0075				0.0075
Marion, AL																0.0304
Walker, AL																0.0387
Winston, AL												0.0104				0.0104
Chattooga, GA																0.0111
Fannin, GA								0.0107				0.0107				
Gilmer, GA								0.0151				0.0151				
Habersham, GA								0.0279				0.0388				
Haralson, GA								0.0000								0.0233
Rabun, GA								0.0003				0.0003				
Towns, GA												0.0008				
White, GA								0.0212				0.0212				
Clay, KY																0.0008
Clinton, KY																0.0063
Estill, KY																0.0075
Greenup, KY								0.0347								
Harlan, KY								0.0069				0.0183				0.0183
Jackson, KY							0.0467				0.0467				0.0467	0.0023
Knott, KY												0.0109				0.0109
Letcher, KY												0.0095				0.0095
McCreary, KY				0.0001												0.0001
Magoffin, KY																0.0119
Martin, KY																0.0096
Morgan, KY																0.0148
Rockcastle, KY															0.0699	0.0038
Wayne, KY																0.0321
Wolfe, KY					0.5244	0.3825			0.8025	0.3825	0.0225				0.0229	0.0011
Alleghany, NC																0.0132
Avery, NC																0.0065
Buncombe, NC	0.0490	0.0490	0.0419	0.2414												
Clay, NC								0.0035				0.0035				
Haywood, NC	0.0541	0.0541	0.0550	0.0543				0.0543								
Henderson, NC	0.2448	0.2448	0.2522	0.1246												
Jackson, NC	0.1521	0.1521	0.1419	0.0071				0.0027								
Rutherford, NC								0.0363				0.0363				0.0363
Transylvania, NC	0.0240	0.0240	0.0229	0.0256				0.0300				0.0300				
Wilkes, NC				0.0368				0.0436								
Yancey, NC																0.0153
Greenville, SC	0.0250	0.0250	0.0254	0.1087												
Pickens, SC								0.0946				0.0946				
Grainger, TN				0.0050												0.0138
Lincoln, TN																0.0221
Marion, TN																0.0126
Overton, TN																0.0125
Pickett, TN				0.0039												0.0039
Sequatchie, TN																0.0099
Sevier, TN	0.1574	0.1574	0.1668													
Dickenson, VA								0.0125				0.0125				0.0125
Franklin, VA																0.0796
Page, VA																0.0135
Roanoke, VA	0.0468	0.0468	0.0474	0.0803												
Scott, VA															0.1502	0.0075
Tazewell, VA								0.0370				0.0370				
Wise, VA								0.0057				0.0104				0.0104
Barbour, WV							0.2903	0.0145			0.1881	0.0145				0.0145
Boone, WV								0.0344				0.0344				
Braxton, WV								0.0217				0.0217				0.0217
Clay, WV							0.1542	0.0077			0.1542	0.0077				0.0077
Fayette, WV	0.0309	0.0309	0.0319	0.0663				0.0663				0.0663				
Hardy, WV																0.0221
Jefferson, WV	0.1281	0.1281	0.1296	0.0343												
Kanawha, WV				0.1910												
Lincoln, WV												0.0122				0.0122
Logan, WV																0.0235
Monroe, WV												0.0095				0.0095
Morgan, WV								0.0294				0.0294				
Nicholas, WV	0.0615	0.0615	0.0603	0.0195				0.0360				0.0360				0.0360
Pendleton, WV												0.0038				0.0102
Preston, WV					0.2648	0.3141	0.1385	0.0190		0.2021	0.3004	0.0190			0.3809	0.0190
Raleigh, WV				0.0093				0.0692				0.0692				
Randolph, WV	0.0263	0.0263	0.0248	0.0008				0.0759				0.0759				0.0173
Summers, WV																0.0166
Taylor, WV								0.0097				0.0097				0.0097
Upshur, WV								0.0582				0.0582				
Wyoming, WV												0.0208				0.0208

Reference

Nakicenovic N, Alcamo J, Davis G, Vries BD, Fenhann J, Gaffin S, et al. 2000. Special report on emissions scenarios.

U.S. Department of Agriculture, Forest Service. 2012. Future of America's forest and rangelands: Forest Service 2010 Resources Planning Act Assessment. USDA Forest Service, Washington, D.C., Gen. Tech. Rep. WO-87. URL https://www.fs.usda.gov/treesearch/pubs/41976