Essays on Conservation Investment for Biodiversity under Future Uncertainties

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ABSTRACT

This thesis is built with two essays on conservation investment for biodiversity under future uncertainties by using a risk-diversification strategy based on modern portfolio theory (MPT). The first essay is about broad application of MPT in conservation investment allocation, next, the second essay advances the MPT with consideration of the availability of each asset. The purpose of the first essay is to identify optimal conservation investment allocations for target regions and species under uncertain conditions. We develop a two-step approach using MPT to estimate an investment portfolio represented by percentages of conservation investment allocated to counties and taxonomic groups (referred to as 'portfolio weights') under climate and market uncertainties. The outcome from each step has a vital implication in its own right. For example, conservation decisions that allow for selecting sites for risk diversification fit the purpose of the first step of our MPT approach. Likewise, conservation investments that benefit biodiversity for particular species for a selected site are made based on the relative importance among species in diversifying risk in that site, fitting the purpose of our MPT second step. The two-step MPT approach as a whole allows the greatest flexibility on where and what to protect for conservation investment under uncertainty, and thus would be applicable for the distribution of general conservation funds without prior motivation to protect either specific sites or species.

The second essay is for identifying the consequence of failing to account for the upper bound constraint in MPT framework and to understand the implications of correcting the failure. By comparing MPT outputs with and without upper bound constraints, we infer how the application of MPT without constraints generates misleading recommendations to conservation organizations and identify what may be the implications of correcting them. Consequently, we

show that evaluating the impacts of ignoring upper bound constraints is an important task for conservation portfolio development in determining a conservation organization's ability to safeguard against the risks of climate and market uncertainties. The MPT models in two essays are applied in the central and southern Appalachian region of the United States.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 2: Spatial and taxonomic diversification for conservation investment under uncertainty

Chapter 3: Accounting for limitations on availability of different assets in risk diversification strategies for biodiversity conservation

Appendix: Supplemental Material

LIST OF ATTACHMENT

CHAPTER 1: INTRODUCTION

Introduction

Biodiversity is under threat because of the loss, modification, and fragmentation of habitats caused by land development and climate change (Northrup et al. 2019, Power & Jetz 2019). Land development for human use has induced high rates of extinction and decreased biodiversity as native vegetation that serves as habitat is often removed during urbanization, which is one of the main reasons for land development (Chemini & Rizzoli 2014). The expansion of land development causes changes in habitat configuration and connectivity and thus has serious ramifications for biodiversity (Bai et al. 2019). Anthropogenic climate change is another major threat to biodiversity. Many species have shifted their geographic ranges toward higher latitudes and elevations in the northern hemisphere as a result of global warming (Chen et al. 2010, Moritz & Agudo 2013).

In response to the threats that land development and climate change pose to biodiversity, Modern portfolio theory (MPT) has received much attention as a risk-diversification strategy for constructing efficient portfolios of species (Koellner & Schmitz 2006, Sanchirico et al. 2008, Moore et al. 2010, Schindler et al. 2010, Anderson et al. 2014) or of sites (Ando & Mallory 2012, Mallory & Ando 2014, Shah et al. 2017, Beyer et al. 2018, Eaton et al. 2019, Vinent et al. 2019). The tool is commonly used to integrate market fluctuations related to conservation costs, climate uncertainties related to conservation benefits, or both (Ando et al. 2018). For example, Koellner & Schmitz (2006) illustrate how to handle biodiversity portfolios in ways that manage performance risk by highlighting how the diversity of temperate grassland species has a substantial positive impact on another important ecosystem service, the risk-adjusted yield of biomass. Beyer et al. (2018) apply MPT to identify a global portfolio of habitats for guiding conservation action and strategic investment for coral reefs under rapid climate change. Sharma & Cho (2020) adopt MPT to identify a cost-efficient budget distribution for forest protection focused on carbon storage in eight states in the central and southern Appalachian region.

On the other hand, the early applications of MPT to conservation problems does not consider the availability of each asset, and most of the subsequent literature has continued to overlook this issue (e.g., Figge 2004, Crowe and Parker 2008, Ando and Mallory 2012, Shah et al. 2017, Liang et al. 2018). For example, Figge (2004) suggests employing the portfolio theory in environmental problem, by highlighting the importance of diversifying the gene species and to mitigate the risk from intensive investment in individual gene and species. However, the author does not account for the limited availability of each gene and species to invest. More recently, twenty-six case studies summarized by Ando et al. (2018) use MPT for risk diversifying allocation of investment for species habitat conservation under climate uncertainty without considering an upper bound constraint in MPT framework. Ignoring the upper bound constraint in these studies might have estimated expected return and its standard deviation (risk), factors that determine the portfolio, inaccurately since the conservation outcome for species habitat would have a clear constraint on its available size at the target site or region.

The separate branches of literature on efficient portfolio analysis for conservation are helpful for developing conservation investment programs that focus on protecting either species or sites under uncertainty. Also, limited studies that account for the upper bound constraint of conservation investment to the application of MPT generate portfolios that help conservation organizations develop more realistic risk-mitigation strategies than those produced from MPT without accounting for the constraint. Despite the merits of MPT, its applications to conservation investment decisions to date have two major downsides: (1) they have only dealt with a single-dimension optimal solution, either seeking to protect species or protect sites but not both, and (2) they did not pinpoint the specific downside of not accounting for the upper bound constraint in MPT.

In response to the first downside of MPT, the first essay focuses on identifying optimal conservation investment allocations for target regions and species within those regions under uncertain conditions. We develop a two-step approach using MPT to estimate an investment portfolio represented by percentages of conservation investment allocated to counties and taxonomic groups (referred to as 'portfolio weights') in the central and southern Appalachian region under climate and market uncertainties. In the first step, optimal target counties are identified and corresponding portfolio weights for biodiversity protection are estimated at four portfolio risk-tolerance levels represented by the standard deviation of expected return on investment (ROI). The four sets of portfolio weights indicate optimal percentages of budget allocation at the county level for the protection of overall biodiversity at four different risk-tolerance levels. In the second step, taxonomic group portfolio weights are estimated for each individual target county chosen at each risk-tolerance level in the first step. The taxonomic group portfolio weights indicate optimal percentages of budget allocation that benefit the biodiversity of four particular taxonomic groups for each individual target county. The two-step MPT approach as a whole is critical because spatial diversification in the first step does not isolate specific amounts of conservation investment tailored to specific taxonomic groups, while the second step lacks the spatial diversification component.

Then, to address the second downside of MPT application, the objective of the second essay is to identify the consequences of failing to include upper bound constraints in the MPT framework and to understand the implications of correcting the failure. To achieve the objective, we first conceptually illustrate the consequences of failing to account for the upper bound constraint by comparing the MPT outcomes with and without the upper bound constraint for two hypothetical counties. Then, we illustrate the effects of constraints on species habitat for biodiversity protection by developing a quadratic programming model for a given risk level with and without the constraints. The two types of MPT models are applied at the county level in the central and southern Appalachian region under climate and market uncertainties. We hypothesize that efficient portfolio weights for conservation targets using MPT without upper bound constraints on available conservation return at each county (referred to as 'naïve MPT') diverge from MPT with the upper bound constraints (referred to as 'constrained MPT'). By comparing MPT outputs with and without upper bound constraints, we infer how application of the naïve MPT generates misleading recommendations to conservation organizations and identify what may be the implications of correcting them. Our findings will contribute to the conservation literature by offering conceptual and empirical evidence of correcting the failure to account for upper bound constraints in the MPT framework. Understanding the impacts of upper bound constraints in the MPT framework is an important task for conservation portfolio development in determining a conservation organization's ability to safeguard against the risks of climate and market uncertainties.

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CHAPTER 2:
SPATIAL AND TAXONOMIC DIVERSIFICATION FOR CONSERVATION INVESTMENT UNDER UNCERTAINTY

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Abstract

Conservation organizations often need to develop risk-diversification strategies that identify not just what species to protect but also where to protect them. The objective of this research is to identify optimal conservation investment allocations for both target sites and species under conditions of uncertainty. We develop a two-step approach using modern portfolio theory (MPT) to estimate percentages of conservation investment (referred to as 'portfolio weights') for counties and taxonomic groups in the central and southern Appalachian region under climate and market uncertainties. The portfolio weights across the counties and taxonomic groups from the two steps entail both spatial and taxonomic diversification strategies. Conservation decisions that allow for selecting sites for risk diversification fit the purpose of the first step. Likewise, conservation investments that benefit biodiversity of particular taxonomic groups for the selected sites are made based on the relative importance in diversifying risk among species in a given area, fitting the purpose of the second-step. The two-step MPT approach as a whole allows the greatest flexibility on where and what to protect for conservation investment under uncertainty, and thus would be applicable for the distribution of general conservation funds without predisposition toward protecting either specific sites or species.

1. Introduction

Biodiversity is under threat because of the loss, modification, and fragmentation of habitats caused by land development and climate change (Northrup et al. 2019, Power & Jetz 2019). Land development for human use has induced high rates of extinction and decreased biodiversity as native vegetation that serves as habitat is often removed during urbanization, which is one of the main reasons for land development (Chemini & Rizzoli 2014). For example, the diversity of native bird species in urban areas is largely dependent on the amount of native vegetation present (Dale 2018). The expansion of land development causes changes in habitat configuration and connectivity and thus has serious ramifications for biodiversity (Bai et al. 2019). Anthropogenic climate change is another major threat to biodiversity. Many species have shifted their geographic ranges toward higher latitudes and elevations in the northern hemisphere as a result of global warming (Chen et al. 2010). The geographic ranges of species of conservation concern are projected to be further affected by climate change in the future (Moritz & Agudo 2013). A meta-analysis of 133 studies covering 120 threatened terrestrial mammal species and 569 threatened bird species across four continents concluded that 47% of the mammals and 23% of the birds had been negatively affected by climate change in at least part of their distribution (Pacifici et al. 2017).

In response to the threats that land development and climate change pose to biodiversity, considerable interest has focused on allocating conservation investments towards habitat protection to mitigate the loss of biodiversity (Scroggie et al. 2019). For example, payments for ecosystem services to private landowners as compensation for supporting biodiversity conservation have gained popularity (Salzman et al. 2018). Conservation investment in habitat protection to promote biodiversity typically focuses on identifying either species or sites to protect (Cuesta et al. 2017, Boland & Burwell 2020). Regardless of its aim, habitat protection tends to be controversial, mainly because of uncertainties about the costs and benefits associated with it. Land development is a critical source of uncertainty, as it depends on real estate market fluctuations that influence the costs of conservation investment (Cho et al. 2018). Climate uncertainty is also important for conservation investment decisions, as climate change poses an increasingly imminent threat to biodiversity benefits at multiple scales (Urban 2015).

Modern portfolio theory (MPT) has received much attention as a risk-diversification strategy for constructing efficient portfolios of species (Koellner & Schmitz 2006, Sanchirico et al. 2008, Moore et al. 2010, Schindler et al. 2010, Anderson et al. 2014) or of sites (Ando & Mallory 2012, Mallory & Ando 2014, Shah et al. 2017, Beyer et al. 2018, Eaton et al. 2019, Vinent et al. 2019). The tool is commonly used to integrate market fluctuations related to conservation costs, climate uncertainties related to conservation benefits, or both (Ando et al. 2018). For example, Koellner & Schmitz (2006) illustrate how to handle biodiversity portfolios in ways that manage performance risk by highlighting how the diversity of temperate grassland species has a substantial positive impact on another important ecosystem service, the risk-adjusted yield of biomass. Beyer et al. (2018) apply MPT to identify a global portfolio of habitats for guiding conservation action and strategic investment for coral reefs under rapid climate change. Sharma & Cho (2020) adopt MPT to identify a cost-efficient budget distribution for forest protection focused on carbon storage in eight states in the central and southern Appalachian region.

The separate branches of literature on efficient portfolio analysis for species or sites are helpful for developing conservation investment programs that focus on protecting either species or sites under uncertainty. Despite the merits of MPT, its applications to conservation investment decisions to date have a major downside: they have only dealt with a single-dimension optimal solution, either seeking to protect species or protect sites but not both. However, conservation organizations often want to identify not just what species to protect but also where to protect them as a risk-diversification strategy. For example, conservation organizations often evaluate which species are most in need of conservation as well as which sites can be protected most effectively. Even given these practical needs, studies that deal with both dimensions of conservation decision-making under uncertainty are absent from the literature.

The objective of this research is to identify optimal conservation investment allocations for target regions and species within those regions under uncertain conditions. We develop a two-step approach using MPT to estimate an investment portfolio represented by percentages of conservation investment allocated to counties and taxonomic groups (referred to as 'portfolio weights') in the central and southern Appalachian region (see Figure S.1. in Supplementary Material) under climate and market uncertainties. In the first step, optimal target counties are identified and corresponding portfolio weights for biodiversity protection are estimated at four portfolio risk-tolerance levels represented by the standard deviation of expected return on investment (ROI). The four sets of portfolio weights indicate optimal percentages of budget allocation at the county level for the protection of overall biodiversity at four different risk-tolerance levels. In the second step, taxonomic group portfolio weights are estimated for each individual target county chosen at each risk-tolerance level in the first step. The taxonomic group portfolio weights indicate optimal percentages of budget allocation that benefit the biodiversity of four particular taxonomic groups for each individual target county.

The sequence of the two steps is determined based on the assumption that the first step finds the risk diversification strategy that focuses on spatial targeting (referred to as ‘spatial diversification’) for overall biodiversity protection and the second step determines the risk diversification strategy (referred to as ‘taxonomic diversification’) that optimally distributes county-level investment shares from the first step among specific taxonomic groups. The two-step MPT approach as a whole is critical because spatial diversification in the first step does not isolate specific amounts of conservation investment tailored to specific taxonomic groups, while the second step lacks the spatial diversification component.

2. Method

In the first-step of the MPT approach, we used the expected county-level returns on investment (ROIs) of biodiversity conservation for protecting 258 forest-dependent vertebrates that are of policy concern at the county level. In the second-step, we used the expected ROIs of four taxonomic groups (i.e., amphibians, birds, mammals, and reptiles) in each of the first step’s optimally selected counties. We chose 2050 as a future timeframe for the modeling because it is far enough in the future to allow climate and market uncertainties to influence benefits and costs. The species benefits for the expected ROIs of biodiversity and of taxonomic groups were calculated by estimating future species distributions using species distribution models (SDMs) (see S.1. in Supplementary Material for details of how future species distributions were predicted).

The conservation costs for the expected ROIs were specified 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. The relative opportunity cost considers the cost of avoiding the conversion of unprotected forestland to urban land. The assumption is made based on evidence that urbanization and land fragmentation predominantly change the spatial structure of forest landscapes in the study region (Wear & Greis 2013, Keyser et al. 2014). For example, urbanization-driven forest loss centers around the Cumberland Plateau region (Keyser et al. 2014). To predict the forest landowners’ relative opportunity costs, we needed forecasts of annualized forest and urban returns (see S.2. in Supplementary Material for details of how relative opportunity costs were predicted).

Our cost estimate represented by relative opportunity cost reflects the cost of avoiding forestland conversion and does not consider the costs of ongoing management associated with maintaining conservation benefits. Consequently, we do not differentiate among the costs of protecting different taxonomic groups, which could vary among the groups, and thus the costs are different across counties, but within a county they are the same for the four groups. Nevertheless, Gordon et al. (2020) found no statistically significant differences in total (or mean) species recovery costs among vertebrate taxonomic groups. Thus, these costs are likely to have small differences among vertebrate taxonomic groups, leading us to focus on the costs of avoiding conversion, which also is the most straightforward to generalize to a taxonomic group.

We estimated the expected ROIs for individual species for each county in 2050 by using their future benefit measures and relative opportunity costs (see S.3. in Supplementary Material for details of how expected ROIs were estimated). We aggregated the expected ROIs of 258 forest-dependent vertebrates into one expected ROI for overall biodiversity conservation at the county level for 193 of 246 total counties in the study region. The 193 counties remained after filtering out consolidated city-counties and counties that do not face urban development pressures (see Figure S.1. in Supplementary Material). Then, we specified the 193 counties as potential conservation targets in the first step, where portfolio weights were determined representing optimal percentages of conservation investment for overall biodiversity across counties at four risk-tolerance levels. In the second step, we selected counties with positive portfolio weights assigned in the first step at four risk-tolerance levels and determined portfolio weights for the protection of four taxonomic groups for each individual county selected. By focusing on counties with positive portfolio weights in the first step to determine portfolio weights for taxonomic groups in the second step, we implicitly assume that counties with non-positive weights in the first step are excluded from spatial and taxonomic diversification strategies because they are of no consequence for those.

Below, is a description of how we used the scenario-specific expected ROIs (see S.4. in Supplementary Material for details of scenario design) to derive efficient portfolios for each step of our MPT approach (see Figure S.2. for schematic diagram of the empirical framework and their related scenarios).

2.1. Modern Portfolio Theory (MPT) framework

For simplicity, we offer a single MPT framework below, because the same MPT framework was applied in both steps of the two-step approach. Under climate and market uncertainties, the MPT framework determines the optimal portfolio weight w_i for an asset i by minimizing the portfolio's variance σ_P^2 for a particular portfolio P of assets, conditional on the weights that achieve a target level of the portfolio's expected ROI, $\bar{\mu}_P$ as follows:

$$Min_w: \sigma_p^2 = w^T \Omega w \tag{1}$$

subject to

$$w^T \mu = \bar{\mu}_P \tag{2}$$

$$w^T 1 = 1 \tag{3}$$

where w is an n $\times$ 1 vector of optimal portfolio weights w_i, w^T is a 1 $\times$ n vector transpose of w, Ω is an n $\times$ n variance-covariance matrix, and σ_P^2 is the portfolio's variance, which is the variance of the weighted sum of the expected ROIs of assets (i.e., counties in the first step and taxonomic groups in the second step). The variance of an asset i is calculated as $\sigma_i^2 = \sum_{s\in S}(r_{is} - \mu_i)^2 p_s \; \forall i \in n$, in which μ_i is the expected ROI of asset i under all climate and market scenarios and is equal to $\sum_{s\in S} r_{is} p_s \; \forall i \in n$, r_{is} is the ROI of asset i in scenario s, and p_s is the probability of scenario s occurring.

The optimal solutions from the second step of the two-step approach may yield zero or extremely small portfolio weights for any of the four taxonomic groups within a selected county indicating zero or an extremely small percentage of the budget being allocated to the target taxonomic group. This possibility is concerning since it implies that taxonomic groups are completely fungible, which would inevitably lead to poor ecological outcomes if an entire taxonomic group of a selected county were lost following such recommendations. Thus, we ran an alternative second step that constrains portfolio weights required for each taxonomic group within each selected county to a minimum of 10%. Although we mainly discuss the portfolio weights of the second step without the 10% constraint in the results and discussion sections, we briefly comment on the alternative outcome as a sensitivity analysis in Supplementary Material. We note that changes in the portfolio weights triggered by the constraint can be mostly explained by covariance structure among taxonomic groups (see S.6. and Table S.2. for detailed outcomes).

Consistent with a uniform prior on climate and market uncertainty, we assumed an equal probability of each scenario by setting p_s to be the inverse of the number of the scenarios. Optimal portfolio weights w were obtained by solving minimization problems for both steps. We derived an efficient portfolio frontier by connecting the coordinates between aggregated expected ROIs and their standard deviations at 100 different points. While an infinite number of points could be chosen, the 100 points were arbitrarily selected for a given portfolio frontier with the equal intervals between the points (i.e., a single portfolio frontier for targeting overall biodiversity and different numbers of portfolio frontiers for targeting specific taxonomic groups for the selected counties at the different risk levels). The optimal portfolio frontiers were converted to maps and pie charts that illustrate how conservation organizations with various risk-tolerances can optimally distribute the portfolio weights of each target county for overall biodiversity and the portfolio weights for each taxonomic group given the optimally selected counties.

For illustrative purposes, we assumed risk-tolerances of conservation organizations represented by four standard deviations: 5% points above the minimum standard deviation (referred to as '5% risk-tolerance'), 15% points above the minimum standard deviation (referred to as '15% risk-tolerance'), 25% points above the minimum standard deviation (referred to as '25% risk-tolerance'), and maximum standard deviation (referred to as 'maximum risk-tolerance'). We focused on the portfolios with various risk options as MPT is commonly used to identify diverse portfolios that reduce risk by different amounts (Schuster et al. 2020). We assumed that risk-tolerances of conservation organizations are consistent across both steps. For example, a conservation organization evaluating spatial diversification in the first step at maximum risk-tolerance would use the same risk-tolerance in evaluating taxonomic diversification in the second step.

The product of the portfolio weights from the two steps offers the optimal portfolio weight of a taxonomic group in a selected county for a given risk-tolerance. Using these weights and a hypothetical total budget of US$1 million, we calculated how much of the investment budget to optimally distribute to each county for the biodiversity of the particular taxonomic group for each risk-tolerance.

3. Results

Figure 2.1. and Figure 2.2. (respectively show the mean-standard deviation relationships for the portfolio frontier from the first step (spatial diversification of biodiversity) and 12 portfolio frontiers (i.e., five counties at 5% risk-tolerance, three counties at 15% risk-tolerance, three counties at 25% risk-tolerance, and one county at maximum risk-tolerance) from the second step (taxonomic diversification), given the selected counties from the first step at these risk-tolerances. As Clay County (AL), Wolfe County (AL), Preston County (WV) and Coosa County (AL) were selected at more than a single risk-tolerance in the first step, 8 of 12 portfolio frontiers in the second step are unique. All portfolio frontiers consistently show a concave relationship between the expected ROI and its standard deviation (risk), reflecting an increase in the risk-return tradeoff (i.e., the potential sacrifice in the expected ROI for a given decrease in its standard deviation towards the origin) effected by the covariance structure across counties and

taxonomic groups. The relevant meanings and implications of the rates of changes in the slopes of the efficient frontiers are provided in S.5. (Supplementary Material).

Table 2.1. and Figure 2.3. A-D show the optimal portfolio weights under the four risk-tolerances for the portfolio frontier from the first step shown in Figure 2.1. The portfolio weights generally indicate that the lower the risk-tolerance, the greater the number of counties assigned portfolio weights, which is consistent with a risk diversification pattern. The findings suggest that the target counties are conditional on risk-tolerance. For example, the counties with the two highest portfolio weights are (1) Preston County (WV) and Leslie County (KY) at 5% risk-tolerance, (2) Wolfe County (KY) and Preston County (WV) at 15% risk-tolerance, and (3) Wolfe County (KY) and Clay County (AL) at 25% risk-tolerance. The county with the highest portfolio weight is Coosa County (AL) at maximum risk-tolerance. The portfolio weights at lower risk-tolerances versus higher risk-tolerances are dictated by the differences in expected ROIs among selected counties, their standard deviations, and the covariances across the ROIs under different future climate and market scenarios.

Specifically, the expected ROIs and their standard deviations for the counties selected in the first step were consistently lower at lower risk-tolerances. For example, the five counties selected at 5% risk-tolerance had a 76% lower average expected ROI and a 87% lower average standard deviation than the single county selected at maximum risk-tolerance. (see Table 2.2. for the averages and standard deviations for target counties under different risk-tolerances.) In addition, selected counties for portfolios at lower risk-tolerances tend to have lower covariances across the ROIs under different climate and market scenarios. For example, the average pairwise covariance among the selected counties for the portfolio at 5% risk-tolerance (i.e., Clay County, Jackson County (KY), Leslie County (KY), Wolfe County (KY), and Preston County (WV)) was 0.000078, while the average covariance among the selected counties for the portfolio at 25% risk-tolerance (i.e., Clay County (AL), Coosa County (AL), and Wolfe County (KY)) was 0.0015561, which was 181% greater than the value for 5% risk-tolerance.

The optimal portfolio weights for the four taxonomic groups from the second step, given a specific risk-tolerance and the selected counties from the first step (Table 2.1., Figure 2.4. A-D) indicate that the target taxonomic groups are conditional on the selected counties as well as the risk-tolerance. The portfolio weights for the four taxonomic groups varied considerably across the counties for the same risk-tolerance. For example, at 5% risk-tolerance, more than 40% of portfolio weights were assigned to the mammal group in Leslie County (KY), and Wolfe County (KY), whereas only 15% of portfolio weights were assigned to the mammal group in Preston County (WV). (see Figure 2.4. A for the maps and pie charts of the portfolio weights and the locations of the counties.) The difference is triggered by differences in the expected ROIs and standard deviations for the same taxonomic group across the counties. For example, at 5% risk-tolerance, the mammal group had the lowest expected ROIs and standard deviations in Leslie County (KY), and Wolfe County (KY), while the same mammal group had the highest expected ROI and standard deviation in Preston County (WV). These findings suggest that conservation organizations may take different conservation strategies for taxonomic diversification in different counties even for a given decrease in risk-tolerance, depending on the counties' expected ROIs and standard deviations.

Likewise, the portfolio weights for the four taxonomic groups varied considerably across risk-tolerances for a given county. For example, at 5% risk-tolerance in Clay County (AL), portfolio weights of 4%, 12%, 76%, and 8% were assigned to amphibian, bird, mammal, and reptile groups, respectively, while at 25% risk-tolerance, portfolio weights of 7%, 54%, 0%, and 38% were assigned to those taxonomic groups, respectively (Figure 2.4. B-D for the maps and pie charts of the portfolio weights and the locations of the counties). These findings suggest that conservation organizations can adjust conservation investments that benefit the biodiversity of the four taxonomic groups in a particular county to accommodate the level of risk they can endure based on the taxonomic groups' expected ROIs and standard deviations in that county. For example, since the mammal group had the lowest expected ROI and standard deviation in Clay County (AL) at 5% risk-tolerance most portfolio weight was assigned to the mammal group in that county, while at 25% risk-tolerance, most portfolio weight was assigned to the taxonomic groups with the second-lowest and third-lowest expected ROIs: bird and reptile groups (see Table 2.2. for the expected ROIs and standard deviations for the four taxonomic groups in selected counties under the four risk-tolerances). Moreover, the overall allocation of the conservation budget among the taxonomic groups varied across risk-tolerances. For example, at 5% risk-tolerance, portfolio weights of 27%, 19%, 33%, and 21% were assigned to amphibian, bird, mammal, and reptile groups, respectively, while at maximum risk-tolerance, portfolio weights of 100%, 0%, 0%, and 0% were assigned to the respective taxonomic groups (See Figure 2.4. A and D for the bar graph for the overall portfolio weights for each taxonomic group). These findings suggest that conservation organizations' investments for each taxonomic group can be modified to fit their risk-tolerances.

Table 2.1. also summarizes the amounts of the total budget optimally distributed to the counties for conservation investments that benefit biodiversity of particular taxonomic groups

using the product of the portfolio weights from the two steps and a hypothetical total budget of US$1 million. At 5% risk-tolerance in Preston County (WV), the largest percentage of the budget (49% of the total budget allocated to that county) targeted US$144,630 to benefit biodiversity of the bird group, whereas at 25% risk-tolerance in Wolfe County (KY), the largest percentage of the budget (44%) targeted US$361,582 to benefit biodiversity of the reptile group. These findings and overall numbers suggest that increases in risk-tolerance expand the optimal budget for conservation investment to protect a particular taxonomic group in a selected county or vice versa.

Allocating funds to a particular taxonomic group in a given county would increase the expected number of species in the county. We report the subsequent increases in expected numbers of species in Table 2.3 corresponding with the optimal budget distribution in Table 2.1. The values are estimated by multiplying the average ROI for each taxonomic group reported in Table 2.3. with the budget allocated to the corresponding taxonomic group reported in Table 2.1. The values in the table show the average increases in the numbers of species when the optimal budget amount is invested in a specified county. These average benefit estimates reflect an overall baseline assumption where each scenario associated with climate, market, and economic growth rate are given uniform (or equal) probability. Therefore, this finding implies that the projected value is not directly linked to any specific scenario or any specialized conservation action or any ongoing management associated with maintaining conservation benefits. Instead, it is simply the average of the change in the number of species conserved as the consequence of reversing urban growth resulting from land protection investments based on the future species' distributions and future conservation costs. Hence, the budget allocations from the second step are assumed as the amounts of the total budget optimally distributed to the counties for conservation investments benefiting biodiversity of particular taxonomic groups for each county.

Because of the considerable differences in the expected ROIs across species and counties (Table 2.2.), the amount of optimal budget allocated to a county does not linearly increase the expected number of species (see Table 2.3 for increases in expected numbers of species by county). For example, the 65% of total budget for the reptile taxonomic group (i.e., US$134,492 out of US$207,212) optimally allocated to Preston County (WV) at 5% risk-tolerance yields 37% of the total increase in expected number of species for the reptile taxonomic group. In contrast, only 5% of total budget for the reptile taxonomic group (i.e., US$10,696 out of US$207,212) optimally allocated to Wolfe County (KY) at 5% risk-tolerance yields 17% of the total increase in expected number of species for the reptile taxonomic group. This comparison suggests that the conservation investment for the reptile group is more cost efficient in Wolfe County (KY), than in Preston County (WV). These findings imply that conservation organizations may target Wolfe County (KY) over Preston County (WV) if they want to focus on improving biodiversity of the reptile group.

4. Discussion

We developed a two-step approach using MPT that estimates portfolio weights for counties and taxonomic groups based on the central and southern Appalachian region under climate and market uncertainties. The portfolio weights across the counties and taxonomic groups from the two steps entail a combined spatial and taxonomic diversification strategies.

Our three main results of spatial, taxonomic, and combined spatial and taxonomic diversification strategies each have their own unique implications for conservation organizations with differing goals and conditions. For example, a species-threat abatement and restoration (STAR) metric developed by the International Union for Conservation of Nature (IUCN) Species Survival Commission quantifies the contributions of specific conservation and restoration actions in specific locations for terrestrial amphibians, birds, and mammals (IUCN 2021a). The STAR metric supports conservation organizations and agencies in identifying geographic targets for the protection of overall biodiversity by adding STAR metrics among taxonomic groups. By applying the STAR metric instead of the expected ROI to the first step, portfolios of target sites for biodiversity can be created to help spatial diversification.

Conservation organizations also often develop lists of species in different threat categories for protective measures in a priority site. For example, the IUCN (2021b) reports the Mediterranean Red List of Species that informs the threat status of species in the Mediterranean Basin, which is the second largest biodiversity hotspot globally. The probability of extinction is one of the main attributes that determines to which of the nine different threat categories a species is assigned (IUCN 2012). Accounting for the impact of climate change on population decline by developing models of bioclimatic habitat or population dynamics is encouraged in assessing species for the IUCN Red Lists (IUCN 2019). While the effects of climate change on the species are analyzed using various model outputs under different future climate scenarios, the scenario-specific models cannot help to identify portfolios of threatened species that can diversify climate and other types of risk. Thus, the application of our second step to the Mediterranean Red List to develop diversified conservation investments that benefit biodiversity of particular taxonomic groups is critically needed.

Because of this flexibility, the GCF is a suitable candidate for the application of the two-step MPT approach, which can suggest the spatial portfolios that are also tailored for diversifying conservation investments that benefit biodiversity of particular species or taxonomic groups.

Despite our study's contribution, we offer several caveats. Our empirical model is framed at the county level and taxonomic group levels, whereas conservation decision-making is often made at finer individual parcel and species levels. We are capable of creating binary suitability layers for individual species at the 1-km^2 pixel level, however, establishing cost data at this scale for a large study area is challenging because of the difficulty of obtaining consistent cost data that are composed of returns from both urban and forestland at that fine scale. With those data available, future research could explore the two-step MPT approach at the individual parcel or site level and/or the individual species level to provide more refined policy implications. This kind of framework would require switching from optimally solving for continuous portfolio weights for budget allocations across counties and taxonomic groups to binary decisions for specific parcel sites for conservation investment for individual species' biodiversity. In addition, such a revised framework would need to include considerations relevant at the parcel or site scale, for example species connectivity and adjacency to other protected sites.

The use of county-level relative opportunity cost to proxy conservation costs for the four taxonomic groups within a county in the second-step of the MPT approach is another limitation of our study if such cost is similar across counties. The reason is that it does not incorporate differences in cost associated with conservation actions or any ongoing management associated with maintaining conservation benefits for each taxonomic group. Such differences in cost are important to consider in a taxonomic diversification strategy for the case where the relative opportunity cost is similar across counties because some taxonomic groups are more expensive to conserve, especially if they require intensive actions. For example, nest boxes may be needed to conserve some bird groups, while predator exclusion fencing may be necessary for the effective protection of some mammal groups, and such costs are drastically different and become a significantly different component of total cost if the relative opportunity cost is similar. In short, an analysis that considers costs of ongoing management associated with maintaining conservation benefits or of conservation activities would likely need to be done on a species-by-species or taxonomic group-by-taxonomic group basis for the case where the relative opportunity cost is similar across counties.

5. Conclusion

The optimal portfolio weights for the counties and taxonomic groups from our two-step approach offer risk-diversification information to help conservation organizations determine which taxonomic groups to protect in which counties and the shares of the total investment budget to allocate for given market and climate risk levels. Further, our two-step MPT approach can identify different optimal target counties and taxonomic groups along a continuum of assumed risk levels. These optimal risk diversification strategies can be presented to conservation organizations, who can then choose a strategy that matches their risk-tolerances. The outcome from each step has a vital implication in its own right. For example, conservation decisions that allow for selecting sites for risk diversification fit the purpose of the first step of our MPT approach. Likewise, conservation investments that benefit biodiversity for particular species for a selected site are made based on the relative importance among species in diversifying risk in that site, fitting the purpose of our MPT second step. The two-step MPT approach as a whole allows the greatest flexibility on where and what to protect for conservation investment under uncertainty, and thus would be applicable for the distribution of general conservation funds without prior motivation to protect either specific sites or species.

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Appendix.

Table 2.1. Portfolio weights for the counties selected in the first step (referred to as 'Portfolio weights 1'), portfolio weights for the four taxonomic groups in the second step (referred to as 'Portfolio weights 2'), and the portion of total budget optimally distributed to the counties for the conservation investments that benefit biodiversity of particular taxonomic groups under four risk-tolerances using a hypothetical total budget of US$1 million (referred to as 'Optimal budget distribution of US$1 million').

Four risk-tolerances	Counties	Portfolio weight 1	Portfolio weight 2				Optimal budget distribution of US$1 million			
			Amphibian	Bird	Mammal	Reptile	Amphibian	Bird	Mammal	Reptile
5%	Clay (AL)	5%	4%	12%	76%	8%	$2,140	$6,019	$37,048	$3,780
	Jackson (KY)	18%	30%	6%	44%	19%	$53,156	$11,376	$77,932	$33,837
	Leslie (KY)	25%	29%	12%	49%	10%	$72,422	$29,292	$123,107	$24,407
	Wolfe (KY)	3%	10%	10%	49%	32%	$3,214	$3,303	$16,537	$10,696
	Preston (WV)	49%	28%	29%	15%	27%	$137,863	$144,630	$74,747	$134,492
15%	Clay (AL)	21%	7%	46%	29%	18%	$14,759	$96,803	$61,695	$38,967
	Wolfe (KY)	53%	12%	20%	28%	39%	$65,594	$108,451	$149,292	$206,784
	Preston (WV)	26%	33%	36%	22%	10%	$85,192	$91,780	$55,800	$24,882
25%	Clay (AL)	13%	7%	54%	0%	38%	$9,514	$70,612	$0	$50,073
	Coosa (AL)	6%	5%	43%	38%	14%	$3,284	$26,510	$23,742	$8,837
	Wolfe (KY)	81%	15%	29%	12%	45%	$118,073	$233,199	$94,574	$361,582
maximum	Coosa (AL)	100%	100%	0%	0%	0%	$1,000,000	$0	$0	$0

Table 2.2. Expected ROIs and their standard deviations (SD) for the counties selected in the first step under different risk-tolerances (i.e., 5%, 15%, 25%, maximum) represented by the four dashed vertical lines in Figure 2.4., and for taxonomic groups in selected counties in the second step.

Risk-tolerances	Counties	Step 1 Expected ROIs (SD)	Step 1 Average	Step 2 Expected ROIs (SD) Amphibian	Bird	Mammal	Reptile
5%	Clay (AL)	0.0415 (0.0254)	0.0300 (0.0140)	0.01513 (0.01262)	0.00833 (0.00536)	0.00463 (0.00377)	0.01342 (0.00766)
	Jackson (KY)	0.0200 (0.0066)		0.00703 (0.00285)	0.00537 (0.00233)	0.00293 (0.00149)	0.00461 (0.00189)
	Leslie (KY)	0.0235 (0.0076)		0.00861 (0.00312)	0.00600 (0.00259)	0.00365 (0.00169)	0.00519 (0.00220)
	Wolfe (KY)	0.0463 (0.0238)		0.01572 (0.01096)	0.01346 (0.00777)	0.00539 (0.00416)	0.01170 (0.00617)
	Preston (WV)	0.0185 (0.0067)		0.00594 (0.00257)	0.00472 (0.00217)	0.00591 (0.00284)	0.00196 (0.00165)
15%	Clay (AL)	0.0415 (0.0254)	0.0354 (0.0186)	0.01513 (0.01262)	0.00833 (0.00536)	0.00463 (0.00377)	0.01342 (0.00766)
	Wolfe (KY)	0.0463 (0.0238)		0.01572 (0.01096)	0.01346 (0.00777)	0.00539 (0.00416)	0.01170 (0.00617)
	Preston (WV)	0.0185 (0.0067)		0.00594 (0.00257)	0.00472 (0.00217)	0.00591 (0.00284)	0.00196 (0.00165)
25%	Clay (AL)	0.0415 (0.0254)	0.0703 (0.0521)	0.01513 (0.01262)	0.00833 (0.00536)	0.00463 (0.00377)	0.01342 (0.00766)
	Coosa (AL)	0.1230 (0.1070)		0.03979 (0.04145)	0.03237 (0.02714)	0.01376 (0.01303)	0.03733 (0.03493)
	Wolfe (KY)	0.0463 (0.0238)		0.01572 (0.01096)	0.01346 (0.00777)	0.00539 (0.00416)	0.01170 (0.00617)
maximum	Coosa (AL)	0.1230 (0.1070)	0.1230 (0.1070)	0.03979 (0.04145)	0.03237 (0.02714)	0.01376 (0.01303)	0.03733 (0.03493)

Table 2.3. Subsequent increases in expected numbers of species corresponding with the optimal budget distribution in Table 2.1.

Four risk-tolerances	Counties	Amphibian	Bird	Mammal	Reptile
5%	Clay (AL)	0.0000	0.0001	0.0002	0.0001
	Jackson (KY)	0.0004	0.0001	0.0002	0.0002
	Leslie (KY)	0.0006	0.0002	0.0004	0.0001
	Wolfe (KY)	0.0001	0.0000	0.0001	0.0001
	Preston (WV)	0.0008	0.0007	0.0004	0.0003
15%	Clay (AL)	0.0002	0.0008	0.0003	0.0005
	Wolfe (KY)	0.0010	0.0015	0.0008	0.0024
	Preston (WV)	0.0005	0.0004	0.0003	0.0000
25%	Clay (AL)	0.0001	0.0006	-	0.0007
	Coosa (AL)	0.0001	0.0009	0.0003	0.0003
	Wolfe (KY)	0.0019	0.0031	0.0005	0.0042
maximum	Coosa (AL)	0.0398	-	-	-

The values in the table show the average increase in the number of species persisting when the optimal budget amount is invested in a specified county.

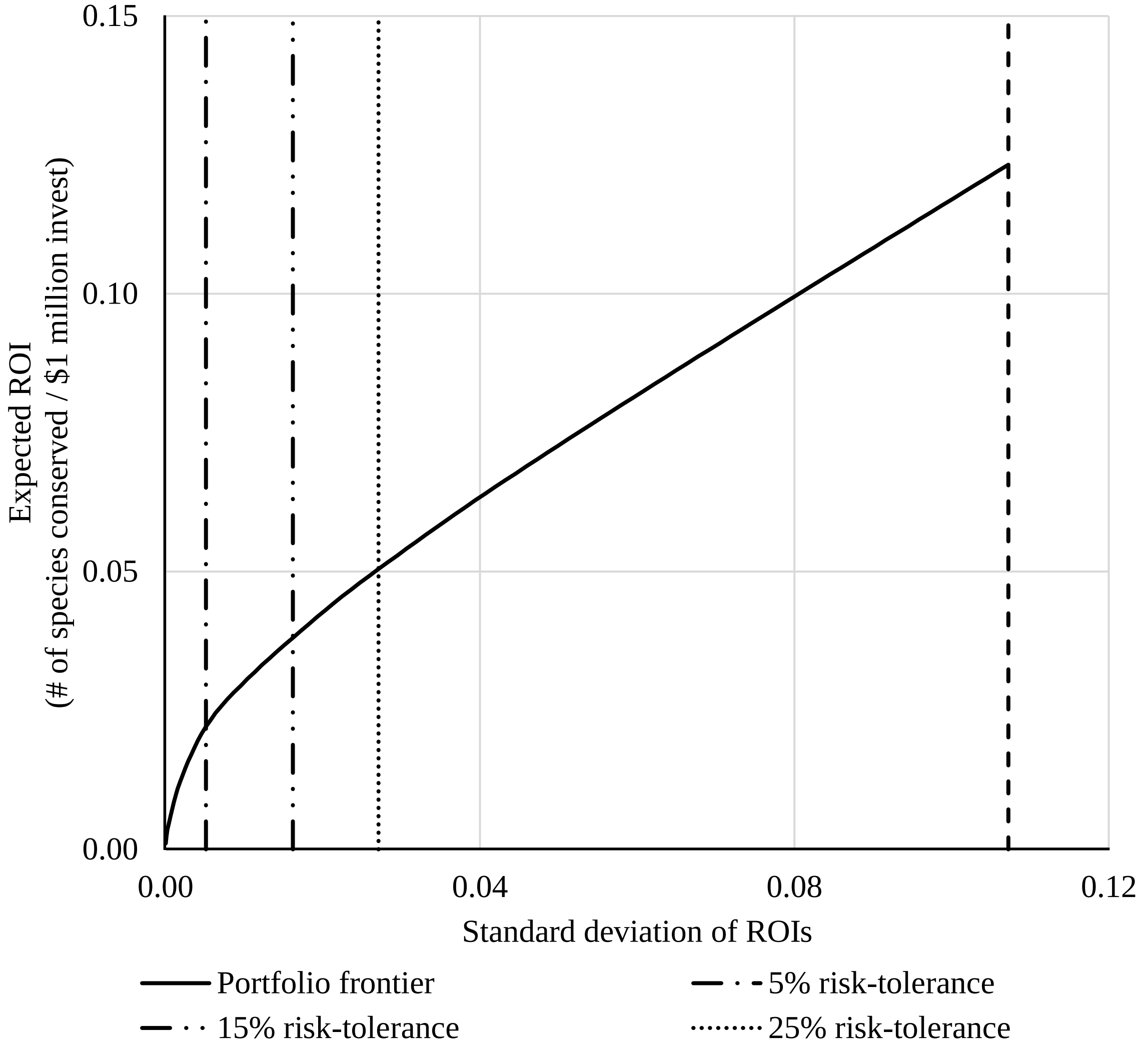
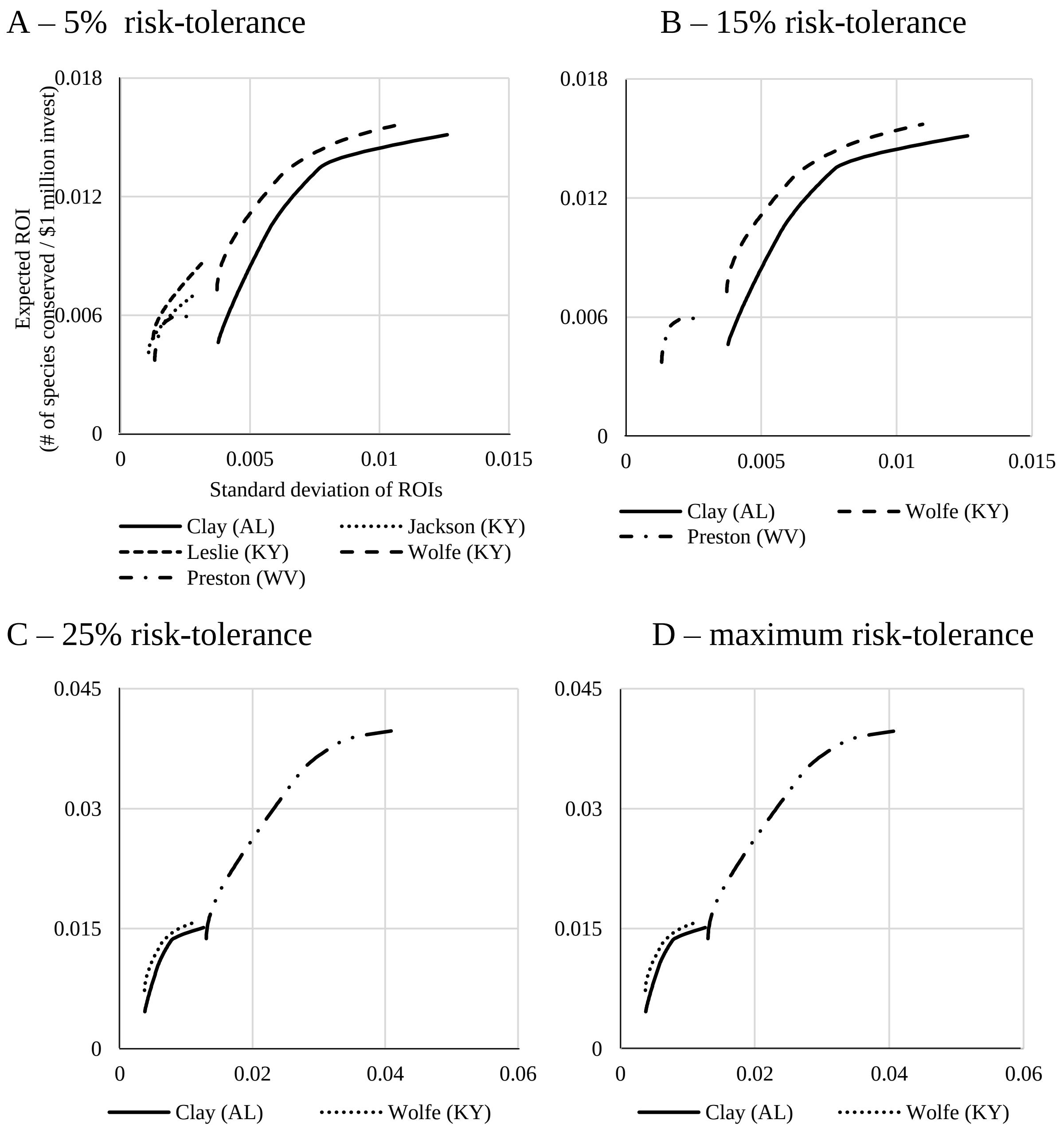


Figure 2.1. Mean-standard deviation relationships for the portfolio frontier from the first step (spatial diversification of overall biodiversity)



Note: The risk-tolerance in each graph title is the same as for spatial diversification in the first step.

Figure 2.2. Mean-standard deviation relationships for 12 portfolio frontiers (i.e., 5 counties at 5% risk-tolerance, 3 counties at 15% risk-tolerance, 3 counties at 25% risk-tolerance, and 1 county at maximum risk-tolerance) from the second step for taxonomic diversification, given the counties selected in the first step at the four risk-tolerances represented by the four dashed vertical lines in Figure 2.1.

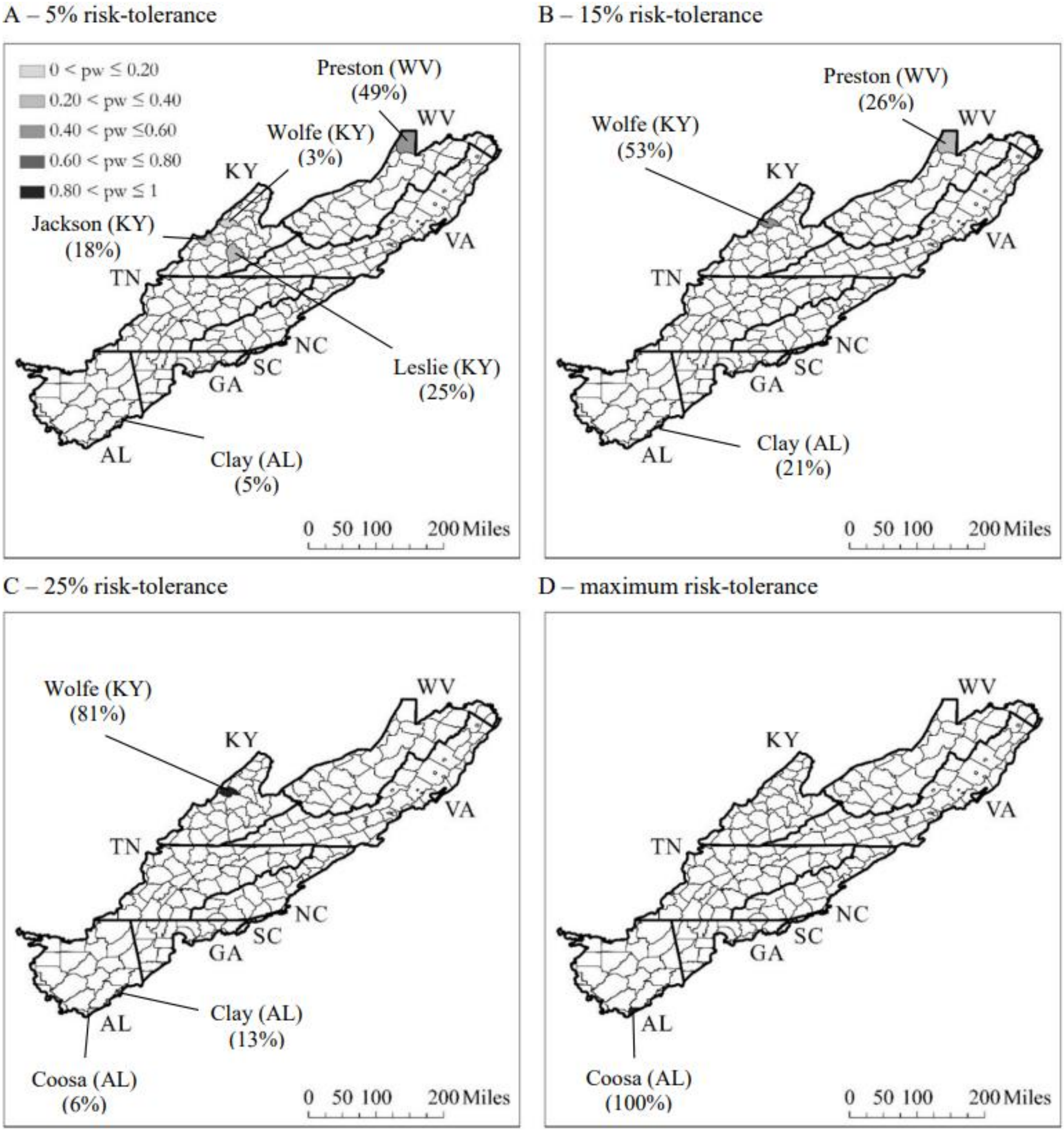


Figure 2.3. The optimal portfolio weights for the counties selected in the first step at 5%, 15%, 25%, and maximum risk-tolerances represented by the four vertical lines in Figure 2.1.

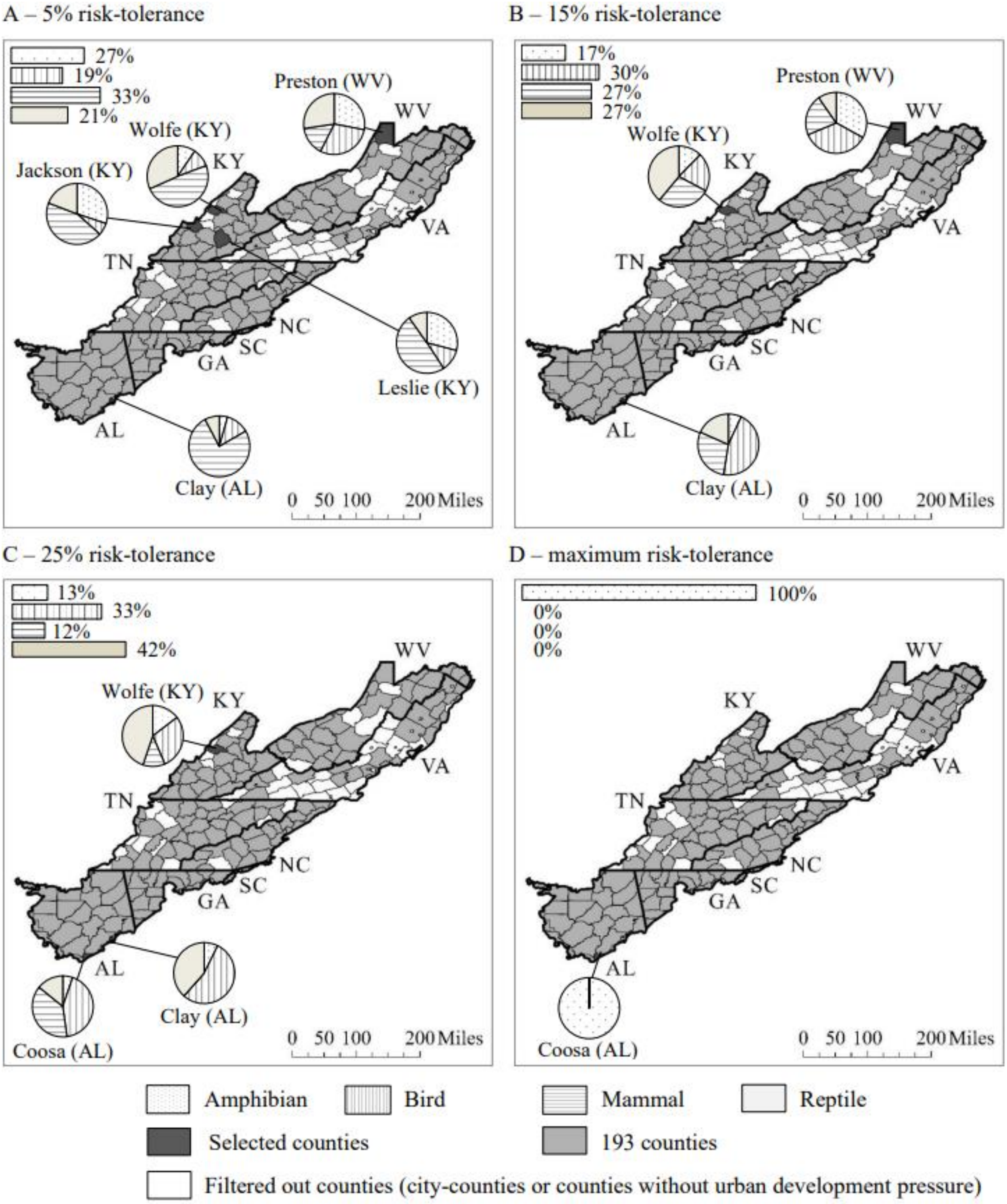


Figure 2.4. Portfolio weights for the four taxonomic groups identified in the second step in the counties selected in the first step at 5%, 15%, 25%, and maximum risk-tolerances. Bar graphs on the top left corner of each map show the overall portfolio weights for each taxonomic group at each risk-tolerance.

CHAPTER 3:
ACCOUNTING FOR LIMITATIONS ON AVAILABILITY OF DIFFERENT ASSETS IN RISK DIVERSIFICATION STRATEGIES FOR BIODIVERSITY CONSERVATION

Abstract

A risk-diversification strategy based on modern portfolio theory (MPT) takes advantage of heterogeneity in uncertainties to minimize risk associated with a portfolio of conservation investments. Despite its merits, to date, MPT has a major shortcoming— the portfolio optimization approach has been implemented without accounting for upper bounds of returns from conservation investments. For example, a conservation organization attempting to protect limited species habitat at a specific target site has a return on conservation investment that is clearly bounded by the species habitat available. The absence of an upper bound constraint may cause the allocation of all the investment to the target site, which may be above the availability of that site. However, this limitation has mainly been overlooked because the portfolio weight assigned to the target site is estimated without an upper bound constraint. The objective of this research is to identify the consequence of failing to account for the upper bound constraint in MPT framework and to understand the implications of correcting the failure. We use a case study focusing on the conservation of biodiversity at the county level in the central and southern Appalachian region. By comparing MPT outputs with and without upper bound constraints, we infer how the application of MPT without constraints generates misleading recommendations to conservation organizations and identify what may be the implications of correcting them. Consequently, we show that evaluating the impacts of ignoring upper bound constraints is an important task for conservation portfolio development in determining a conservation organization's ability to safeguard against the risks of climate and market uncertainties.

1. Introduction

Conservation investment has the potential to counter future uncertainties in climate and market change (Wessely et al. 2017, Cho et al. 2018, Newbold 2018). Due to these uncertainties, planning conservation investment based on purely historical data may yield misleading results (Holland et al. 2011, Snäll et al. 2021). In response to this concern, there have been various attempts to account for uncertainties in conservation investment. For example, species distribution models under different future climate scenarios have been adopted to prioritize regions for the conservation of various species (Adams-Hosking et al. 2015, Mukul et al. 2019, Fuentes-Castillo et al, 2020). A habitat-quality model has been applied to assess potential biodiversity impacts under alternative future land-use scenarios (Liang and Liu, 2017, Sharma et al. 2018). Fluctuating economic returns from different land uses resulting from different market conditions have been the focus of market-based cost uncertainty in the conservation literature (Lubowski et al. 2006; Cho et al. 2018).

While the literature that deals with various uncertainties related to conservation investment has provided plausible conservation scenarios, these studies do not help diversify risk associated with them. Modern Portfolio Theory (MPT), a quantified version of "Do not put all your eggs in one basket", developed by Markowitz (1952) and published in financial literature, has been applied to help diversify risk in conservation investment (Shipway, 2009). This tool accounts for heterogeneities in climate and market uncertainties to minimize risk associated with investing in portfolios targeting species, sites, and activities (Sanchirico et al. 2008, Ando and Mallory 2012, Eaton et al. 2019, Sierra-Altamiranda et al. 2020). Despite its merits, to date, MPT has a major shortcoming—the portfolio optimization approach has been implemented without accounting for upper bounds on returns from conservation investments. The absence of an upper bound constraint may cause the allocation of all the investment to the target site, which may be above the availability of that site (Ando and Mallory 2012).

For example, a conservation organization attempting to protect limited species habitat at a specific target site has a return on conservation investment that is clearly bounded by the total species habitat available. As a result, each target site has its own confined capacity on return which may be due to physical and/or economic limitations. The conservation organization faces a maximum investment constraint attributable to the physical limitation of the scope of target site and/or the economic limitation of conservation cost. Thus, the old saying “do not put all your eggs in one basket” makes sense only if the basket is sufficiently large enough to hold the distributed eggs. However, this limitation has been mainly overlooked since the portfolio weight assigned to a target site is customarily estimated without an upper bound constraint.

This limitation of MPT comes from its original application to financial investment, where returns do not face capacity limitations. The early applications of MPT to conservation problems do not consider the availability of each asset, and most of the subsequent literature has continued to overlook this issue (e.g., Figge 2004, Crowe and Parker 2008, Ando and Mallory 2012, Shah et al. 2017, Liang et al. 2018). For example, Figge (2004) suggests employing portfolio theory in environmental problem, by highlighting the importance of diversifying the gene species and mitigating the risk from intensive investment in individual gene and species. However, the author does not account for the limited availability of each gene and species. More recently, twenty-six case studies summarized by Ando et al. (2018) use MPT for risk diversifying allocation of investment for species-habitat conservation under climate uncertainty without considering an upper bound constraint in the MPT framework. Moreover, ignoring the upper bound constraint in these studies might have inaccurately estimated expected return and its standard deviation (risk), and the factors that determine the portfolio, since the conservation outcome for species habitat would have had clear constraints on their available size in the target site or region.

While MPT literature has not explicitly addressed the consequence of failing to account for the upper bound constraint of conservation investment, limited recent studies have sought to improve the application of MPT by adding such constraints (Jin et al. 2016, Beyer et al. 2018). Jin et al. (2016) apply portfolio theory to help implement ecosystem-based fishery management in different geographic regions. The authors consider the limited stock of each fish species to harvest in the MPT application with a constraint of maximum weight for the harvest of each species. In further addressing this issue, Eaton et al. (2019) integrate a multiple-objectives criteria analysis with MPT to evaluate spatial conservation planning under both unconstrained and budget-constrained scenarios, the latter reflecting more realistic management limitations. The authors assess optimal conservation risk-mitigation strategies under both scenarios and generally conclude that constrained optimization is more likely to provide better insights than unconstrained optimization. Similarly, Runting et al. (2018) reformulate an integer quadratic programming problem of MPT with binary decision variable representing whether each site is selected or not, to a reserve selection problem for landward migration of wetlands. By using binary decision variable, the authors account for sites' limited availability, alongside other consideration like connectivity for landward migration of wetland. This improvement of MPT allows identifying a risk diversified set of sites for preservation with consideration of an asset's availability under a fixed budget constraint.

The limited studies that account for the upper bound constraint on conservation investment to the application of MPT generate portfolios that help conservation organizations develop more realistic risk-mitigation strategies than those produced from MPT without the constraint. Despite the contributions of these studies, a major downside still exists in them—they did not pinpoint the specific downside of not including upper bound constraints in MPT. By not drawing attention to the consequence of failing to account for the upper bound constraint, the implications of correcting the failure are absent from the literature.

The objective of this research is to identify the consequences of failing to include upper bound constraints in the MPT framework and to understand the implications of correcting the failure. To achieve the objective, we first conceptually illustrate the consequences of failing to account for the upper bound constraint by comparing the MPT outcomes with and without the upper bound constraint for two hypothetical counties. Then, we illustrate the effects of constraints on species habitat for biodiversity protection by developing a quadratic programming model for a given risk level with and without the constraints. The two types of MPT models are applied at the county level in the central and southern Appalachian region under climate and market uncertainties. 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 (Milt et al. 2016, Rogers et al. 2016).

We estimate an investment portfolio represented by the percentage of conservation investment allocated to counties (referred to as ‘portfolio weights’). The optimal county-level portfolios constructed for biodiversity protection are identified, and expected returns on investment (ROIs) and their standard deviations (risks) are represented by corresponding optimal portfolio weights. We estimate the portfolio weights of counties by including a local budget constraint for each county, which refers to the amount of budget needed to protect all available habitat by protecting eligible forestland (i.e., unprotected private forestland) in a given county, and the overall budget available for all counties in the study area (referred to as ‘global budget’).

We hypothesize that efficient portfolio weights for conservation targets using MPT without upper bound constraints on available conservation return at each county (referred to as ‘naïve MPT’) diverge from MPT with the upper bound constraints (referred to as ‘constrained MPT’). By comparing MPT outputs with and without upper bound constraints, we infer how application of the naïve MPT generates misleading recommendations to conservation organizations and identify what may be the implications of correcting them. Our findings will contribute to the conservation literature by offering conceptual and empirical evidence of correcting the failure to account for upper bound constraints in the MPT framework. Understanding the impacts of upper bound constraints in the MPT framework is an important task for conservation portfolio development in determining a conservation organization’s ability to safeguard against the risks of climate and market uncertainties.

Below, in the method section, we conceptually illustrate the consequences of failing to include an upper bound on return from conservation investment by comparing the naïve and constrained MPT using a two-county hypothetical example. Then, we introduce two quadratic optimization programming frameworks for naïve and constrained MPT that are applied to biodiversity conservation in the central and southern Appalachian region. In the naïve and constrained MPT frameworks, we use the same expected ROIs of biodiversity conservation used in the first chapter (see 2. Method in the Chapter 1 for the details). Outcomes from the two MPT frameworks are discussed in the results section, which is followed by a conclusion that highlights key findings from the comparison of the MPT outcomes and their relevant policy implications.

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, and county A is assumed to have higher expected ROI than county B ($ROI_A > ROI_B$). The positively sloping diagonal line in the upper graph of Figure 3.1. shows the allocations of the efficient portfolio weights between the two counties (w_A and w_B for counties A and B, respectively) at different risk levels based on the naïve and constrained MPTs. The w_A and w_B are plotted in different directions on the same x-axis, with w_A going from left to right, and w_B from right to left. The w_A^M and w_B^M represent the weights assigned to counties A and B that reach their upper bound constraints. 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.

The two-county example based on the naïve and constrained MPTs illustrated in Figure 3.1. shows how the allocation of portfolio weights and corresponding risk levels and expected ROIs are different with and without the upper bound constraints. We first compare the risk level and corresponding portfolio's expected ROI between naïve and constrained MPTs and show the tradeoff between gains and losses incurred from accounting for the upper bound constraint in subsection 2.1.1. Next, we illustrate the impact of global budget amount on the difference in the efficient portfolios between the naïve MPT and constrained MPT with various hypothetical global budgets in subsection 2.1.2.

It is worth noting that our conceptual example only relates to the specific case of two counties with high risk-high return and low risk-low return, respectively. We consider these two counties as an example to illustrate the effects of risk levels and expected ROIs on naïve and constrained MPTs without the complication of considering their covariance structures. Furthermore, we assume that two counties are not perfectly correlated with each other, and thus the risk diversification strategy used has a feasible solution for both MPTs.

2.1.1. Comparison of risk levels and expected Return on Investments (ROIs)

Based on the naïve MPT outcome, a conservation organization with maximum risk level r_1 protects all of the conservation assets in county A (point P in the upper graph of Figure 3.1.), with the corresponding expected ROI being the area □*afho* in the lower graph. By comparison, the constrained MPT allocates weight, w_A^M, to county A with the remaining weight, $1 - w_A^M$, distributed to county B at the maximum risk level of r_2, corresponding to point P$'$. 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 based on the naïve MPT by $r_1 - r_2$ but sacrifices expected ROI by the area of □*f'fgg'* compared to the naïve MPT.

With the naïve MPT, the conservation investment would be divided between the two counties as their risk level decreases (< r_1). As the risk level reaches point Q 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, the constrained MPT would allocate weight, w_B^M, to county B and the remaining weight, $1 - w_B^M$, would be distributed to county A at the minimum risk level of r_3, corresponding to a point Q'. 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* by comparison with the naïve MPT because of the added weight to the high ROI county (i.e., county A) based on the constrained MPT.

While the naïve MPT does not consider the availability of resource such as forestland in each county, the constrained MPT limits the portfolio weight for each county with the upper bound constraints based on the availability of resource of each county. At the maximum risk level, the naïve MPT maximizes the risk and expected ROI by allocating the weight above the feasibility of county A (a point P 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 (a point 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.

2.1.2. Impact of global budget amount on difference of efficient portfolios

In this subsection, we illustrate that the amounts of deviations in risk level and expected ROI between the two models are affected by how efficiently the portfolio weights of the counties are bound by their available assets, which depend on the global budget amount. At the maximum risk of the constrained MPT, r_2, w_A^M (point P') shifts to the left to $w_A^{M\prime}$ at the risk level $r_2{}'$ (point P'') with greater global budget. The corresponding expected ROI for county A decreases by the area of □*f'''f'h'h'''* (shown by the difference between the areas of □*af'h'o* and □*af''h''o*) and the expected ROI for county B increases by the area of □*g''g'h'h''* (shown by the difference between the areas of □*g'ghh'* and □*g''ghh''*). As a result, the sum of expected ROI decreases by the area of □*f'''f'g'g''*, which deviates from the sum of the expected ROI based on the naïve MPT by the area of □*f''f'g'g''*. With the shift from P' to P'' at the maximum risk level, the share of budget assigned to county A decreases with greater global budget. The remaining global budget is allocated in county B, causing the maximum risk level and expected ROI to decrease.

By comparison, at the minimum risk level of the constrained MPT, r_3, w_B^M (point Q') shifts to the right to $w_B^{M\prime}$ at the risk level $r_3{}'$ (point Q'') with greater global budget. The corresponding expected ROI for county B decreases by the area of □*d'd''e''e'* (shown by the difference between the areas of □*d'ghe'* and □*d''ghe''*) and the expected ROI for county A increases by the area of □*c'c''e''e'* (shown by the difference between the areas of □*ac'e'o* and □*ac''e''o*). As a result, the sum of the expected ROIs increases by the area of □*c'c''d''d'*, which deviates from the sum of the expected ROIs based on the naïve MPT by the area □$cc''d''d$. At the minimum risk level, the share of the budget assigned to county B decreases as the global budget increases, shown by the shift from point Q' to point Q'' in the upper figure. The remaining budget is assigned to county A, causing the minimum risk level and expected ROI to increase.

The above comparative exercise suggests that the risk and expected ROI corrections made by the constrained MPT, relative to the naïve MPT, intensify with the increased global budget because the share of the budget assigned to each county, constrained by its upper bound, decreases with the higher global budget. Thus, we hypothesize that the global budget assigned to a conservation organization influences the degree of deviation of the risk level and corresponding expected ROI between the two models.

2.2. Naïve MPT framework

Following Runting et al. (2018), 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, $W^T \Sigma W$ 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^TM 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^TM) 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—global and local budget constraints. To account for global and local budget 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 across n counties as the decision variable, C is an $n \times 1$ vector of local budget constraints across n counties for the protection of eligible forestland (i.e., unprotected private forestlands) to maximize total species habitat, and B is a hypothetical global budget amount for the entire region.

The objective function in equation (4) maximizes the weighted sum of expected ROIs ($X^T\mathrm{M}$) and minimizes the portfolio's variance (i.e., $X^T\Sigma X$). Equation (5) constrains local budgets across n counties between 0 and C, and equation (6) constrains the global budget to B. For local budget constraints, we consider the product between size of eligible forestland and unit opportunity cost for conservation as the two together function as physical and economic limitations. The local budget constraints are fixed for counties under uncertainty scenarios, while the global budget constraint may change depending on the available budget for the entire region. To test the hypothesis found in the conceptual framework related to the impact of the global budget amount on the degree of deviation between naïve and constrained MPT, we compare outcomes based on the two models under three hypothetical global budget constraints (i.e., $3 million, $50 million, and $1 billion).

We calculate efficient portfolio weight W for constrained MPT by dividing efficient budget allocation X by global budget B to derive the efficient portfolio's expected ROI and corresponding variance as the weighted sum of expected ROIs ($W^T\mathrm{M}$) 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.

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. Results

Table 3.1. shows the portfolio's expected ROI for biodiversity conservation and risk reflected in its standard deviation at the maximum and minimum risk level from the naïve and constrained MPTs with three global budget constraints. The maximum risk level of 10.73 from the naïve MPT decreased to 2.77 and 0.39 from the constrained MPT with \$50 million and \$1 billion, respectively, as the expected ROI of 12.32 from the naïve MPT decreased to 5.04 and 1.53 from the constrained MPT with \$50 million and \$1 billion, respectively. This result represents that, at the maximum risk level, the constrained MPT compromised expected ROI while improving risk mitigation compared to the naïve MPT. The minimum risk level of 0.0038 from the naïve MPT and the constrained MPT with \$3 million increased to 0.0042 and 0.0092

from the constrained MPT with $50 million and $1 billion, respectively, as the expected ROI of 0.1046 from the naïve MPT and the constrained MPT with $3 million increased to 0.1134, and 0.1248 from the constrained MPT with $50 million, and $1 billion, respectively. Thus, at the minimum risk level, the constrained MPT gained higher expected ROI by reducing risk mitigation more than the naïve MPT.

The deviations in the 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 global budget did not deviate much from those from the naïve MPT because counties with optimal budgets above local budget 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 $3 million at the maximum risk level, as the efficient portfolios between the two models are exactly same: allocate all budget into a single county, Coosa County (AL). The upper bound constraint of Coosa County (AL) is less than the global 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 A1. for the detail portfolio weight allocation) 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 or is not considered. In contrast, the deviation was much more evident if the global budget for constrained MPT increased to $1 billion since counties with optimal budgets above local budget constraints (i.e., 81 of 85 counties selected for four risk tolerance levels) were much more frequent (see Table 3.1.). This finding shows that the local budget constraints create diversification among counties regardless of risk mitigation, especially with greater compared to lower global budgets.

Figure 3.2. shows four efficient frontiers of the expected ROI-risk tolerance relationship for portfolios from the naïve MPT and the constrained MPTs with three global budget constraints. The figure allows us to compare the efficient portfolios at four given risk tolerance levels. The four efficient frontiers have concave shapes implying higher return (i.e., expected ROI) with higher risk. Given the same risk tolerance level, expected ROIs are nearly indifferent between naïve MPT and constrained MPT with a $3 million global budget. In contrast, expected ROIs for constrained MPT with $50 million and $1 billion global budgets are compromised compared with those from naïve MPT because of the local budget constraints. Specifically, the portfolio's expected ROIs for the constrained MPT with $50 million and $1 billion global budgets at the 15% risk tolerance level are 2.11 and 0.53, which is lower than the 3.78 expected ROI for the naïve MPT at the same risk tolerance level (see Table 3.1.). The gap in the portfolio's expected ROI between the two approaches increases as the risk tolerance level increases. At the 25% risk tolerance level, the 2.54 and 0.70 expected ROIs from the constrained MPT with $50 million and $1 billion global budgets, respectively, are lower than the 5.01 expected ROI from naïve MPT (see Table 3.1.).

Figure 3.3. shows spatial distributions of portfolio weight allocations from the naïve MPT and the constrained MPT with $3 million and $1 billion global budgets at four different risk tolerance levels (i.e., minimum, 15%, 25%, and maximum risk tolerance levels). At the minimum risk tolerance level with a $1 billion global budget, we observe that the naïve MPT has 0.24, 0.15, 0.13, and 0.03 portfolio weights assigned to Henderson County (NC), Jackson County

(NC), Jefferson County (WV), and Randolph County (WV), respectively, while 0.12, 0.01, 0.03, and 0.00 portfolio weights are assigned to those respective counties for the constrained MPT (see Table A1.). The portfolio weight of 0.12 assigned to Henderson County (NC) based on constrained MPT with a $1 billion global budget implies allocating 12% of the $1 billion global budget ($120 million) to that county, whereas the same county's portfolio weight of 0.24 for the naïve MPT implies allocating 24% of an unidentified global budget to that county, both at the minimum risk tolerance level. The portfolio weight of 0.24 without an upper bound constraint would not exceed the local budget constraint of $120 million if the global budget constraint were $3 million since 24% of the budget constraint is only $0.72 million. Consequently, the portfolio weight of 0.24 would remain the same between the naïve MPT and constraint MPT with a $3 million global budget at the minimum risk tolerance level. However, if the budget constraint were $1 billion, 24% of $1 billion is $240 million, which would be well above the local budget constraint of the county. Consequently, under a global budget constraint of $1 billion, if naïve MPT were applied, $120 million ($240 million – $120 million) would have been over allocated to Henderson County, NC, whereas the constrained MPT binds the local budget constraint and corrects the misleading portfolio weight. (See Table A1. and S.8. in the Supplementary material for all the details of portfolio weights between the two models with three hypothetical global budgets at the four risk levels, and highlights of their analysis.)

Our empirical findings together confirm the conceptual illustration and provide new insights as following: (1) 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, (2) the amount of correction in risk and expected ROI made by the constrained MPT is greater with higher global budgets, (3) greater diversification among counties regardless of risk mitigation is generated especially with greater global budgets compared to lower global budgets, (4) the gap between the expected ROIs of the naïve and constrained MPT increases as risk tolerance level increases, and (5) the correction of misleading portfolio weights by the constrained MPT occurs only if the optimal budget assigned to a county without a global budget constraint is above the county's local budget constraint.

4. Discussion

We identified the consequences of failing to account for the upper bound constraint in the MPT framework using a case study involving the conservation of biodiversity under uncertainty in the central and southern Appalachian region. The comparison of MPT outputs with and without upper bound constraints has implications for conservation strategies with different targets. For example, the constrained MPT is more capable of finding an optimal budget allocation for an urban area, which is highly fragmented at a small scale not typical for a rural area (Zhou and Wang 2010, Rissman 2012, Norton et al. 2016), as a small-scale site is likely to be bound by its local budget constraint for both physical and economic limitations. Similarly, the constrained MPT is 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, 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 up to $150,000. By applying the constrained MPT to CEPF's grant allocation decision, the optimal solution would take greater advantage of the portfolio of eligible sites for biodiversity conservation within the limit of the assigned budget.

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 also is necessary. For example, if the application of MPT for biodiversity conservation involves creating portfolios of species, instead of creating portfolios of sites similar to our case study, the possibility of zero or extremely small portfolio weights is concerning. The reason for concern is that such possible outcome implies that species are completely fungible, which would lead to poor ecological outcomes if an entire species were 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 naïve MPT that does not account for upper bounds of returns from conservation investments. However, our findings suggest that such a correction is only needed if the global budget is large enough so that portfolio weights from naïve MPT allocate beyond local budget constraints 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 global budget for constrained MPT is higher, and the degree of the divergence depends on how the local budget constraint binds and corrects 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 naïve and constrained MPT outcomes under various global constraint levels illustrates the vulnerability of naïve MPT and helps conservation organizations evaluate risk-diversifying strategies that are specific to different available global budget levels. The constrained MPT for a given risk tolerance level and a specific global budget can identify a risk- and budget-specific portfolio of target sites for biodiversity conservation. This implication means the portfolio weights that suggest the risk-mitigating allocation of conservation investment can be adjusted by the conservation organization's risk tolerance and the level of global budget it manages. This flexible nature of constrained MPT encourages conservation organizations make the risk-diversification strategy as an usable interface to be incorporated into their decision-making processes.

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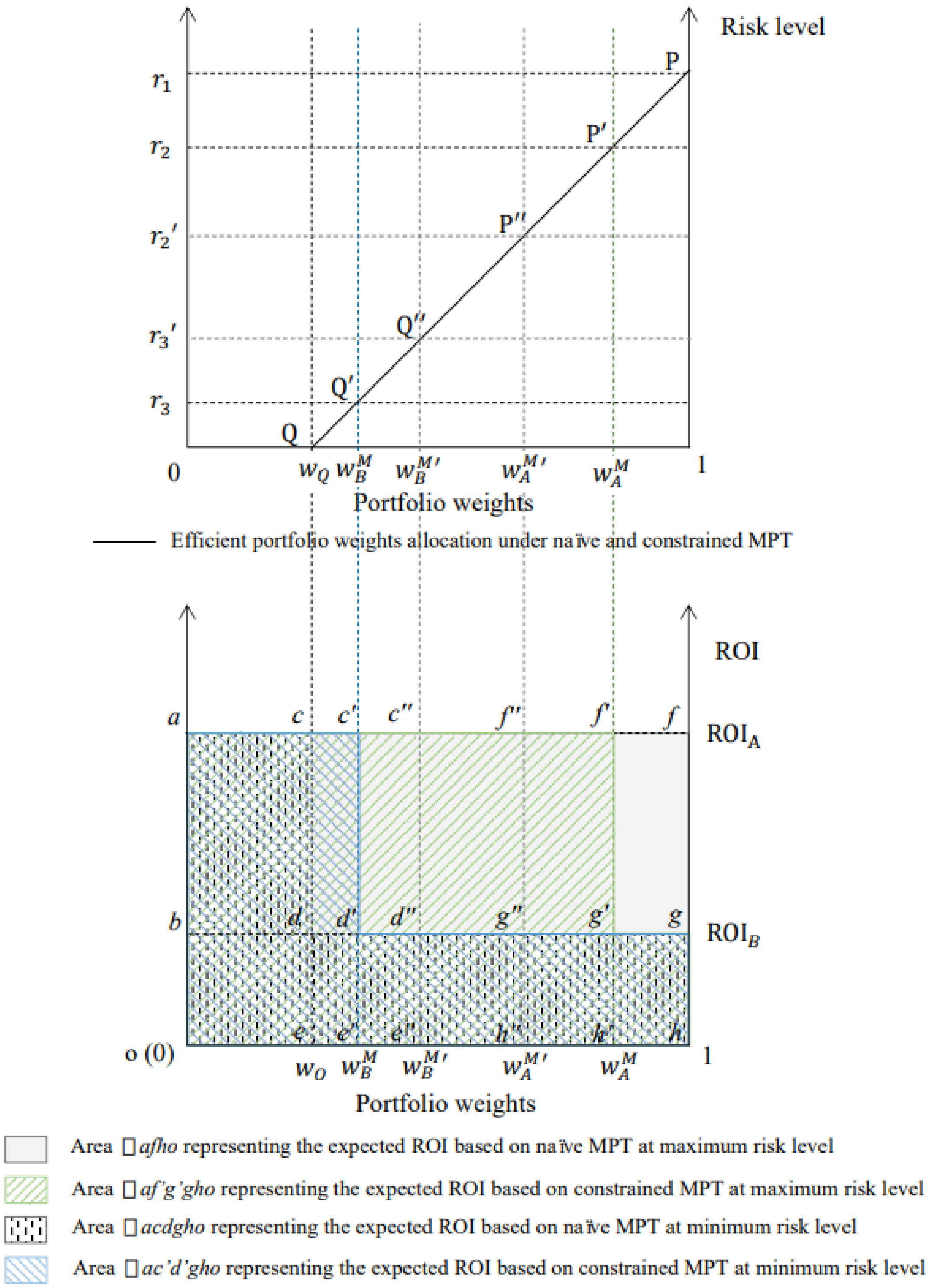
Appendix

Table 3.1. The portfolio's expected ROI for biodiversity conservation, 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 MPTs with three global budgets under minimum and maximum risk levels.

		Naïve MPT	Constrained MPTs		
			$3 million	$50 million	$1 billion
Minimum risk level	Portfolio's expected ROI	0.10456	0.10456	0.11339	0.12475
	Portfolio's standard deviation	0.00382	0.00382	0.00418	0.00921
	# of counties selected	12	12	12	16
	# of counties bound by upper bound constraints	-	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	3.78276	3.76641	2.10546	0.52629
	Portfolio's standard deviation	1.59987	1.62243	0.47094	0.06526
	# of counties selected	3	4	8	35
	# of counties bound by upper bound constraints	-	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	5.00882	4.92338	2.54659	0.69811
	Portfolio's standard deviation	2.67907	2.75664	0.69317	0.10444
	# of counties selected	3	4	9	43
	# of counties bound by upper bound constraints	-	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	12.32435	12.32435	5.04343	1.53150
	Portfolio's standard deviation	10.73443	10.73443	2.76939	0.39036
	# of counties selected	1	1	9	59
	# of counties bound by upper bound constraints	-	0	8	58
	Average cost of selected counties	$3,645,232	$3,645,232	$5,588,646	$17,942,059



The upper graph of the figure shows the allocations of the efficient portfolio weights between the two counties (w_A and w_B 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 3.1. Allocation of portfolio weights and corresponding risk levels and expected ROIs with and without the upper bound constraints using two-county example

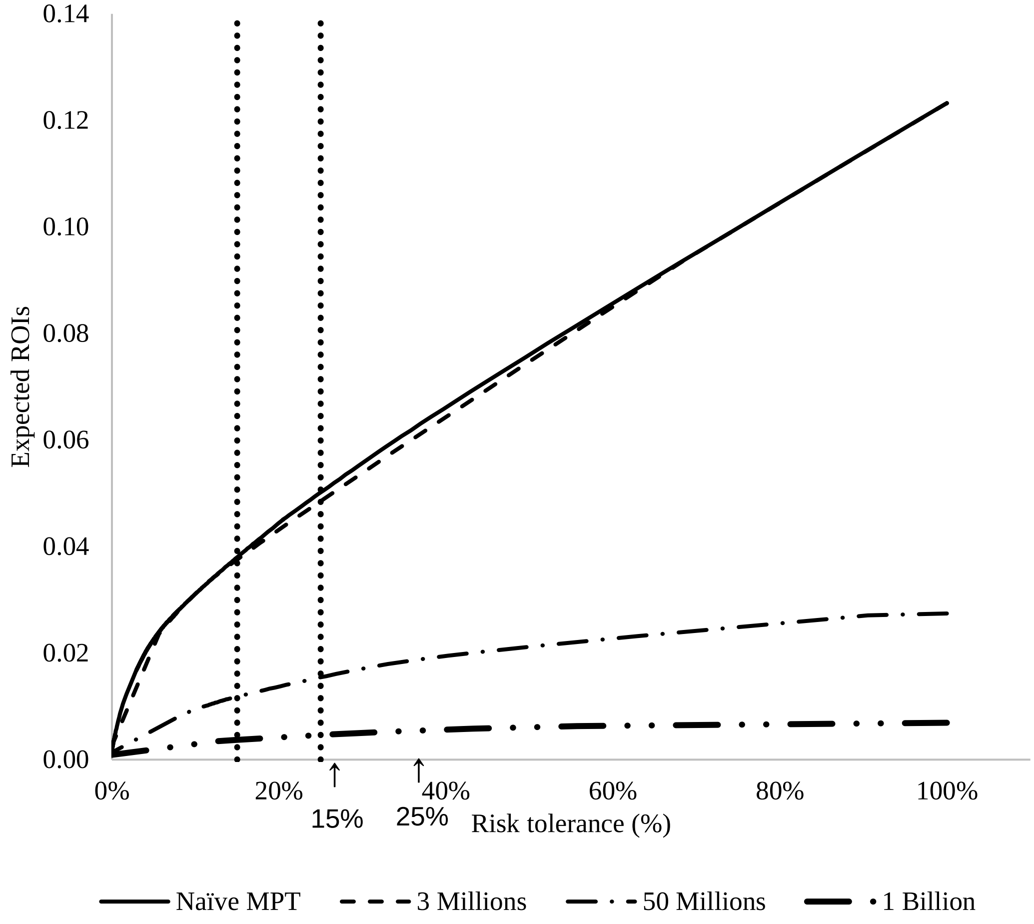


Figure 3.2. Four efficient frontiers of the expected ROI-risk tolerance relationship for portfolios from the naïve MPT and the constrained MPTs with three global budget constraints (i.e., \$3 million, \$50 million, and \$1 billion)

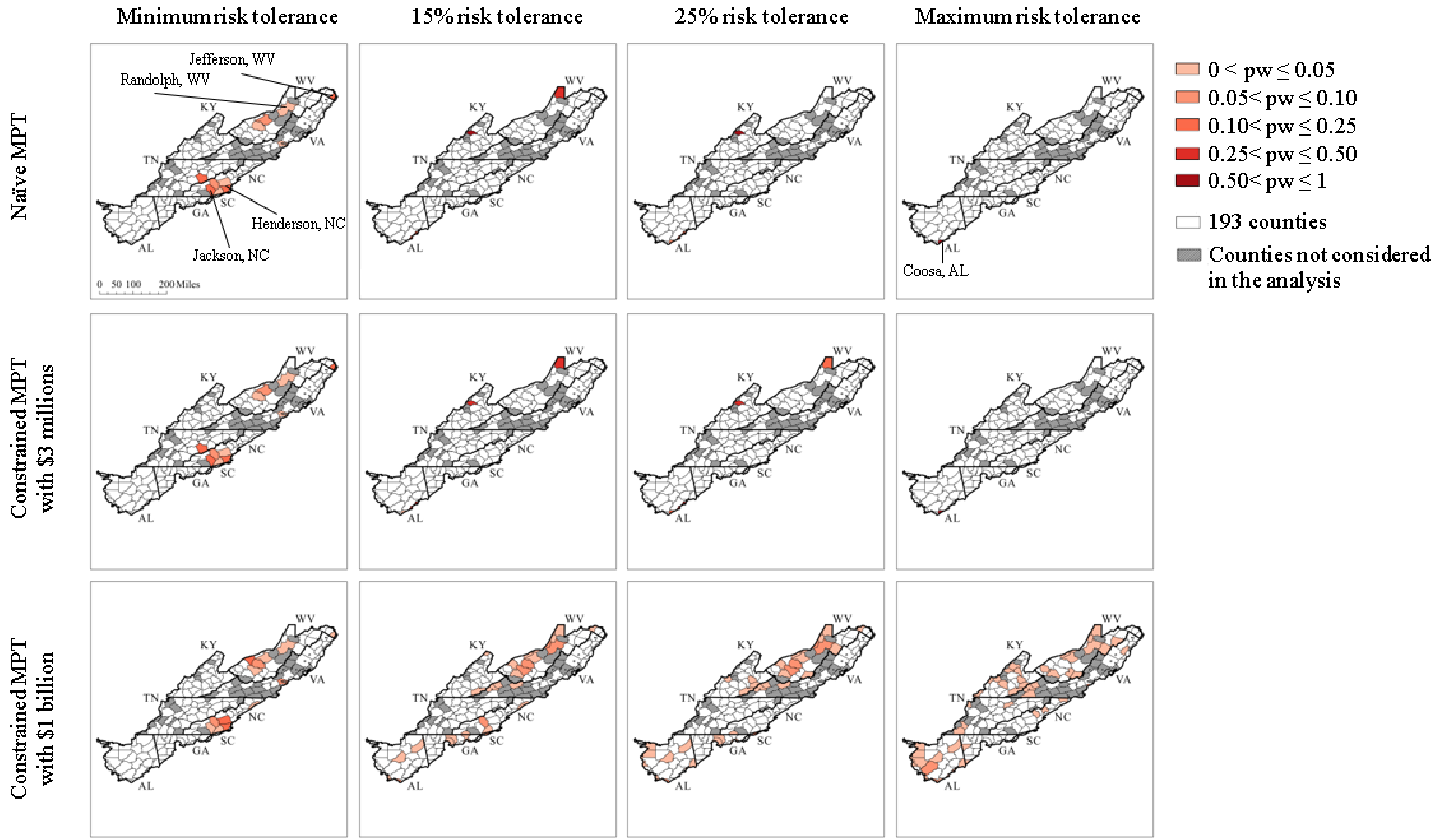


Figure 3.3. Spatial distributions of portfolio weight allocations from the naïve MPT and the constrained MPT with $3 million and $1 billion global budgets at four different risk tolerance levels (i.e., minimum, 15%, 25%, and maximum risk tolerance levels)

CHAPTER 4:
CONCLUSION

Conclusion

The two essays examine the efficient portfolio allocation for biodiversity conservation under the future uncertainties. Through the two-step approach using MPT in the first essay, we estimate an investment portfolio of counties and taxonomic groups in the central and southern Appalachian region under climate and market uncertainties. In the first step, optimal target counties are identified and corresponding portfolio weights for biodiversity protection are estimated at four portfolio risk-tolerance levels represented by the standard deviation of expected return on investment (ROI). The four sets of portfolio weights indicate optimal percentages of budget allocation at the county level for the protection of overall biodiversity at four different risk-tolerance levels. In the second step, taxonomic group portfolio weights are estimated for each individual target county chosen at each risk-tolerance level in the first step. The taxonomic group portfolio weights indicate optimal percentages of budget allocation that benefit the biodiversity of four particular taxonomic groups for each individual target county. In the second essay, we identify the consequence of failing to account for the upper bound constraint in MPT framework and to understand the implications of correcting the failure. To achieve the objective, we first conceptually illustrate the consequences of failing to account for the upper bound constraint in MPT by comparing the MPT outcome that accounts and not accounts for the upper bound constraint using two-county example. Then, we illustrate the effects of constraints on species habitat for biodiversity protection by developing a quadratic programming model for a given risk amount with and without constraints.

In the result from the first essay, the optimal portfolio weights for the counties and taxonomic groups from our two-step approach offer risk-diversification information to help conservation organizations determine which taxonomic groups to protect in which counties and the shares of the total investment budget to allocate for given market and climate risk levels. Further, our two-step MPT approach can identify different optimal target counties and taxonomic groups along a continuum of assumed risk levels. These optimal risk diversification strategies can be presented to conservation organizations, who can then choose a strategy that matches their risk-tolerances. The outcome from each step has a vital implication in its own right. For example, conservation decisions that allow for selecting sites for risk diversification fit the purpose of the first step of our MPT approach. Likewise, conservation investments that benefit biodiversity for particular species for a selected site are made based on the relative importance among species in diversifying risk in that site, fitting the purpose of our MPT second step. The two-step MPT approach as a whole allows the greatest flexibility on where and what to protect for conservation investment under uncertainty, and thus would be applicable for the distribution of general conservation funds without prior motivation to protect either specific sites or species.

By accounting the upper bound constraints in MPT in the second essay, the constrained MPT model is structured to correct potentially misleading portfolio weights from naïve MPT that does not account for upper bounds of returns from conservation investments. However, our findings suggest that such a correction is only needed if the global budget is large enough so that portfolio weights from naïve MPT allocate beyond local budget constraints 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 global budget for constrained MPT is higher, and the degree of the divergence depends on how the local budget constraint binds and corrects 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 naïve and constrained MPT outcomes under various global constraint levels illustrates the vulnerability of naïve MPT and helps conservation organizations evaluate risk-diversifying strategies that are specific to different available global budget levels. The constrained MPT for a given risk tolerance level and a specific global budget can identify a risk- and budget-specific portfolio of target sites for biodiversity conservation. This implication means the portfolio weights that suggest the risk-mitigating allocation of conservation investment can be adjusted by the conservation organization's risk tolerance and the level of global budget it manages. This flexible nature of constrained MPT encourages conservation organizations make the risk-diversification strategy as an usable interface to be incorporated into their decision-making processes.

APPENDIX:
SUPPLEMENTARY MATERIAL

S.1. Predicting future species distributions

We projected future species distributions by estimating climatically suitable areas for 258 forest-dependent vertebrate species (75 amphibians, 89 mammals, 40 reptiles, and 54 birds) that are of policy concern for the U.S. Fish and Wildlife Service (2020), Landscape Conservation Cooperative Network (2020), and USGS Science Analytics and Synthesis program (2020). We used suitable areas to measure biodiversity because vast primary biodiversity data are established based on species' spatial distributions under the assumption that the spatial distributions of species are direct functions of the areas where species can be found and are protected (Fuentes-Castillo et al. 2019, Zhu et al. 2021). We used Maxent as the species distribution model (SDM) algorithm under climate scenarios from six General Circulation Models (GCMs, Phillips 1956, Flato et al. 2014) under two representative concentration pathways (RCPs) (see schematic diagram in Figure S.2.). The twelve future climate scenarios were established using data from the ClimateNA database (Wang et al. 2016).

Maxent estimates the association between locations where species are known to occur today and a range of relevant biophysical characteristics of sites, including temperature, precipitation, and elevation (Phillips & Dudík 2008, Abdelaal et al. 2019). Then, the model projects the probability of future climatic suitability at sites for species under 12 future climate scenarios (i.e., 6 GCMs × 2 RCPs). Projections take the form of predicted probabilities that a species will be found in different locations in the future given a particular climate scenario. The predicted probabilities of climate suitability were transformed into binary variables using a 10% training presence threshold, which means that the top 90% are considered suitable and the remaining 10% unsuitable. The binary suitability variables of species within a particular taxonomic group at the 1-km^2 pixel level are aggregated at the county level for the benefit measure of all species within that taxonomic group. The benefit measures for the four taxonomic groups are then combined to provide the county-level overall biodiversity measure. See Zhu et al. (2021) for the details of the methodology used to generate the future estimated distributions for the 258 forest-dependent vertebrate species.

S.2. Predicting relative opportunity costs

To predict the forest landowners' relative opportunity costs (i.e., urban return minus forest return), we needed forecasts of annualized forest and urban returns (see schematic diagram in Figure S.2.). We first estimated future annualized forest return using the Soil Expectation Value (SEV) based on forecasted timber prices, per-hectare timber harvest volume, an infinite series of identical harvest rotations with lengths of 50-75 years depending on the tree species, and a discount rate of 5%, assuming the same timber management practices. A Brownian motion model was used to forecast future timber prices. The stumpage prices used in the model came from Timber Mart-South (Timber Mart-South 2015) and the State Division of Forestry in 8 states (AL, GA, KY, NC, SC, TN, VA, WV). To account for timber price uncertainty, three timber price scenarios (high, moderate, low) were introduced. The high, moderate, and low scenarios were specified by projected mean price plus its standard deviation, mean price, and mean price minus its standard deviation, respectively, all at the state level. To predict the future timber harvest volumes, forest rotation models (Sims et al. 2021) were applied using the historic timber harvest volumes from the Forest Inventory and Analysis (FIA) database (USDA Forest Service 2018) under future climate scenarios (see Cho et al. 2018 for more details).

To predict the urban return, we estimated the annualized median assessed land value roughly following Lubowski et al. (2006). First, we estimated the ratio of assessed land value per hectare to total assessed value at the parcel level as land value ratios per hectare for sample counties where data were available. Then, we converted the land value ratio at the parcel level to the census block group (CBG) level by regressing the land value ratio per hectare on socioeconomic and location data at the CBG level (see Liu et al. 2019 for more details). We multiplied the predicted land value ratio per hectare by the median housing price for three market scenarios (upturn, moderate, downturn) to estimate the median assessed land value per hectare for three market conditions. Then, we used the median assessed land value as a proxy for urban return, which was averaged at the county level and annualized (see Mingie & Cho 2020 for more details).

S.3. Estimating scenario-specific expected ROIs

We estimated scenario-specific ROIs for overall biodiversity and four individual taxonomic groups for each county in 2050 by employing a modeling framework developed by Armsworth et al. (2020). First, we considered the marginal change in hectares of unprotected forest resulting from conservation investment in each county using a share-based, county-level land use model that explains the shifting of counties from one type of land use to another over a transition period (Plantinga & Wu 2003, Du et al. 2014, Plantinga 2017). The share-based, county-level land use model quantifies the relationship between shares of land allocated to different uses and hypothesized determinants of land use such as the net return of a particular use at the county level (Plantinga 2017). The estimation results specify which land-use determining factors are important in explaining land-use changes and are commonly used to estimate how land use will change if determinants of land use change (Plantinga 2017).

In the absence of specific location information from the share-based, county-level land use model, we simply assumed that the increase in forest within the future species distributions predicted by the SDMs (Zhu et al. 2021) was proportional to both the amount of future distributions of the species and the forest area within a relevant county. Furthermore, we assumed the probability that each species would survive and persist was independent across species and was also an increasing function of aggregate forest area within the area of future species distribution based on the species overall distribution range size (Polak et al. 2016, Armsworth et al. 2020). The dependence of persistence probabilities on remaining private forest and protected forest was assumed to be a linear, piecewise continuous, hockey-stick function (Armsworth et al. 2020). By using these assumptions, we allowed species to go extinct if there was no forest, while we let the persistence probabilities increase linearly with greater amounts of forest area within its range until a species-specific saturation threshold

(Armsworth et al. 2020). The species-specific saturation threshold was assigned for each species based on the thresholds used in Armsworth et al. (2020), which are broadly comparable to those used in other studies and to those used in the IUCM Red list (Rodrigues et al. 2004, IUCN 2012). While we assumed the whole range for the small range species ($<10^6$ hectares) would be needed to ensure its persistence, persistence of large range species ($>10^8$ hectares) would be guaranteed once only 10% of the range of that species was protected (Armsworth et al. 2020). The threshold on the size of species range for intermediate cases was assumed to be a decreasing linear function.

Finally, we defined the scenario-specific future ROIs (i.e., the expected marginal benefit of investing in a county) as the change in the expected number of species that will persist calculated by summing the relevant probabilities. We aggregated the relevant probabilities for each of the four taxonomic groups, which are accumulated for the overall biodiversity measure, to represent the benefit of the scenario-specific ROIs for the four taxonomic groups and overall biodiversity, respectively. We differentiated protected and unprotected private forests by assigning relative weights of 1 to 1 hectare of protected forest land and α to 1 hectare of unprotected private forest land, based on the subjective assumption that the ecological quality of usable habitat is different in protected forest than unprotected private forest, following Armsworth et al. (2020). Because we could not exclude development pressure when unprotected private forest and protected forest are equally valuable, α should be less than 1. Hence, we analyzed the MPT outcome under the assumption that ecological quality of unprotected private forest is one quarter of the protected forest (i.e., $\alpha = 0.25$). For the sensitivity analysis, we also presented the MPT outcome under the assumption that the ecological quality of unprotected private forest is one-half of the protected forest (i.e., $\alpha = 0.5$). The sensitivity outcomes for relative ecological quality of unprotected private forest are presented in section S.7. (Supplementary Material).

S.4. Scenario design

The scenario-specific expected ROIs for a total of 486 scenarios were structured by combining the scenarios of the predicted benefits, described in section S.4., and relative opportunity costs, described in section S.3. See Figure S.2. for the schematic diagram that shows how these scenarios are organized and are linked to the empirical frameworks. The scenarios for predicting overall biodiversity and for taxonomic-group benefits were only related to climate changes, and thus we considered 12 climate scenarios from six GCMs under RCP4.5, representing an intermediate stabilization emission scenario, and six GCMs under RCP 8.5, representing a high emission scenario. In comparison, the relative opportunity costs were forecasted under 81 scenarios associated with both climate and market changes from scenarios for nine timber volumes derived from three GCMs and three Special Report on Emission Scenarios (SRES, Nakicenovic et al. 2000), three timber prices, and three economic growth rates. As the relative opportunity costs are specified by urban return minus forestland return, the urban return was forecasted by an autoregressive distributed lag (ARDL) model under three economic growth scenarios (USDA Forest Service 2012), while the forestland return was forecasted using the stochastic forest rotation model under twenty-seven scenarios with nine timber volumes based on three GCMs, three SRES and three timber price scenarios (Wear & Greis 2013).

Among the three SRES, the A1B-SRES and A2-SRES scenarios assume rapid economic and technological growth, while scenario B2-SRES represents more sustainable practices (Nakicenovic et al. 2000). Thus, we matched RCP 8.5 with A1B-SRES and A2-SRES, and RCP 4.5 with B2-SRES for consistency between climate and market scenarios. As a result, a total of 162 scenarios were created for each of the two SRES (A1B and A2) under RCP 8.5 with six GCMs for the benefits and three GCMs, three timber price scenarios, and three economic growth scenarios for the relative opportunity costs. Likewise, a total of 162 scenarios were created for B2-SRES under RCP 4.5 with six GCMs for the benefits, and three GCMs, three timber price scenarios, and three economic growth scenarios for the relative opportunity cost. Note that the six GCMs used for predicting the overall biodiversity and taxonomic-group benefits and the three GCMs for forecasting the relative opportunity costs were different from each other (see Figure S.2.). The nine GCMs were selected based on the availability of climate-related variables and those with high statistical validation (Knutti et al. 2013).

S.5. Average elasticity of the efficient frontier

The rate of change in the slope of the efficient frontier from the first step and the 8 unique efficient frontiers from the second step represent the effectiveness of MPT at mitigating portfolio risk (referred to as 'MPT effectiveness'). We quantified MPT effectiveness by estimating the percentage of a portfolio's expected ROI that must be foregone to lower its standard deviation by 1% from the riskiest points to the most conservative points on the frontier (referred to as 'average elasticity'). The average elasticity of the frontier from the first step for spatial diversification of overall biodiversity is 0.983, which is interpreted as an average decrease in a portfolio's expected ROI by 0.98% resulting from a decrease of its standard deviation by 1% from the riskiest point to the most conservative point on the frontier.

The means of the average elasticities for taxonomic diversification of the efficient frontiers from the second step for the 5, 3, 3, and 1 counties selected at 5%, 15%, 25%, and maximum risk-tolerances in the first step are 0.74, 0.81, 0.89, and 0.93, respectively. The higher means of the average elasticities for taxonomic diversification of the selected counties at higher risk-tolerances can be explained by their higher average pairwise covariance among taxonomic groups. For example, the average pairwise covariances among taxonomic groups for the selected counties at 5%, 15%, 25%, and maximum risk-tolerances in the first step are 0.000010, 0.000016. 0.000177, and 0.00484, respectively. These relationships suggest that the lower average pairwise covariances among taxonomic groups for the selected counties at lower risk-tolerances result in higher average elasticities for taxonomic diversification within those counties.

The inverses of the average elasticities at the four risk-tolerances suggest that a 1% decrease in a portfolio's expected ROI decreases its standard deviation from the riskiest point to the most conservative point on the frontier by 1.35%, 1.23%, 1.12% and 1.08%, respectively, for the counties selected in the first step at the 5%, 15%, 25%, maximum risk-tolerances. The higher inverses of the average elasticities suggest sacrificing in the same unit of expected return mitigates more risk (or simply, higher MPT effectiveness).These findings imply that taxonomic diversification from the second step works better for portfolios of counties targeted for spatial diversification of biodiversity at lower risk-tolerances in the first step. With the same average elasticity of the frontier from the first step for spatial diversification of biodiversity, this result further implies that the two-step MPT approach as a whole works better at lower risk-tolerances.

S.6. Sensitivity outcomes for the minimum constraint on portfolio weights

Table S.2. shows alternative portfolio weights for the four taxonomic groups with a minimum portfolio weight of 10% required for each taxonomic group in all counties to avoid yielding zero or extremely small portfolio weights for any of the four taxonomic groups. We note that changes in the portfolio weights triggered by the constraint can be mostly explained by covariance structure among taxonomic groups. For example, at 5% risk-tolerance without the minimum constraint, portfolio weights of 30%, 6%, 44%, and 19% were assigned to amphibian, bird, mammal, and reptile groups, respectively, while at the same risk-tolerance level with the minimum constraint, portfolio weights of 26%, 10%, 47%, and 17% were assigned to the respective taxonomic groups. With the minimum constraint, the portfolio weights for bird and mammal groups increased, whereas those for amphibian and retile groups decreased. As the portfolio weight for the bird group increased from 6% to 10% to meet the minimum constraint, the portfolio weight for the mammal group, which has a negative covariance with the bird group (i.e., -0.0000004) increased to mitigate risk, and the portfolio weights for the other taxonomic groups, which have positive covariance with the bird group (i.e., 0.0000046 and 0.0000014, respectively, with the amphibian and reptile groups) decreased to mitigate the portfolio's risk.

S.7. Sensitivity outcomes for alternative relative ecological quality of unprotected private forest

Table S.1. shows portfolio weights for the four taxonomic groups when we assume relative ecological quality of unprotected private forest is one-half of that for protected forest instead of one-quarter as described in the main text. The sensitivity outcomes for spatial diversification for biodiversity in the first step show some differences and similarities to the optimal portfolio weights at previously stated risk-tolerances. For example, Clay County (AL), Preston County (WV), and Coosa County (AL) were commonly selected for both optimal solutions. In contrast, Jackson County (KY), Leslie County (KY), and Wolfe County (KY) were selected at least once for 5%, 15%, 25% and maximum risk-tolerances when $\alpha = 0.25$, but were not selected at any risk-tolerance when $\alpha = 0.5$. Furthermore, Bibb County (AL), which was not selected when $\alpha = 0.25$, was selected when $\alpha = 0.5$ at 5% risk-tolerance (compare Table 2.1. and Table S.1.). The difference in county selection can be explained by a pattern of counties with larger areas of unprotected private forest receiving larger portfolio weights, relative to other counties, as the weight on unprotected private forest increases from $\alpha = 0.25$ to $\alpha = 0.5$. For example, the area of unprotected private forest in Bibb County (AL) (151,628 hectares), which was selected at 5% risk-tolerance when $\alpha = 0.5$ but not $\alpha = 0.25$, is relatively larger than areas in Jackson County (KY) (51,330 hectares), Leslie County (KY) (255 hectares), and Wolfe County (KY) (53,030 hectare), which were selected when $\alpha = 0.25$ but never when $\alpha = 0.5$.

In addition, the sensitivity outcomes for taxonomic diversification in different counties for the second step are similar to the overall optimal portfolio weights for each taxonomic group at the previously stated risk-tolerance. Even though different counties were selected in the first step at different risk-tolerance levels, the overall portfolio weights at 5%, 15%, 25%, and maximum risk-tolerance were focused on the mammal group, bird group, reptile group, and amphibian group, respectively, for both optimal solutions. Conversely, when comparing optimal portfolio weight among taxonomic groups in Clay County (AL), Preston County (WV), and Coosa County (AL), commonly selected counties for both optimal solutions, the amphibian group and the reptile group were not selected for Clay County (AL) and Coosa County (AL), respectively at the 25% risk-tolerance level. Moreover, while the largest portfolio weight was assigned to the bird group at 5% and 15% risk-tolerance levels when $\alpha = 0.25$, the largest weight was assigned to the mammal group when $\alpha = 0.5$ (compare Table 2.1. and Table S.1.). Similar to the discussion above, differences in taxonomic group allocation can be explained by the size of predicted species ranges in unprotected private forest areas.

S.8. The pattern of portfolio weight distribution

Figure 3.3. 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 A1. 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 global budget (see Table 1 for the details).

In contrast to naïve MPT and constrained MPT with a $3 million global budget, Table 1 shows that the number of counties with positive portfolio weights from constrained MPT, with a $1 billion, increases with higher risk tolerance levels. 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 global budget. This pattern of results is interesting in 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 global 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 global 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 global 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 levels for constrained MPT with a $1 billion global 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 global budget constraints. As a result, a greater number of counties are selected at lower risk tolerance levels or vice versa using naïve MPT. In contrast, the portfolio of maximum expected ROIs for constrained MPT exhausts the global 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 global budget constraint.

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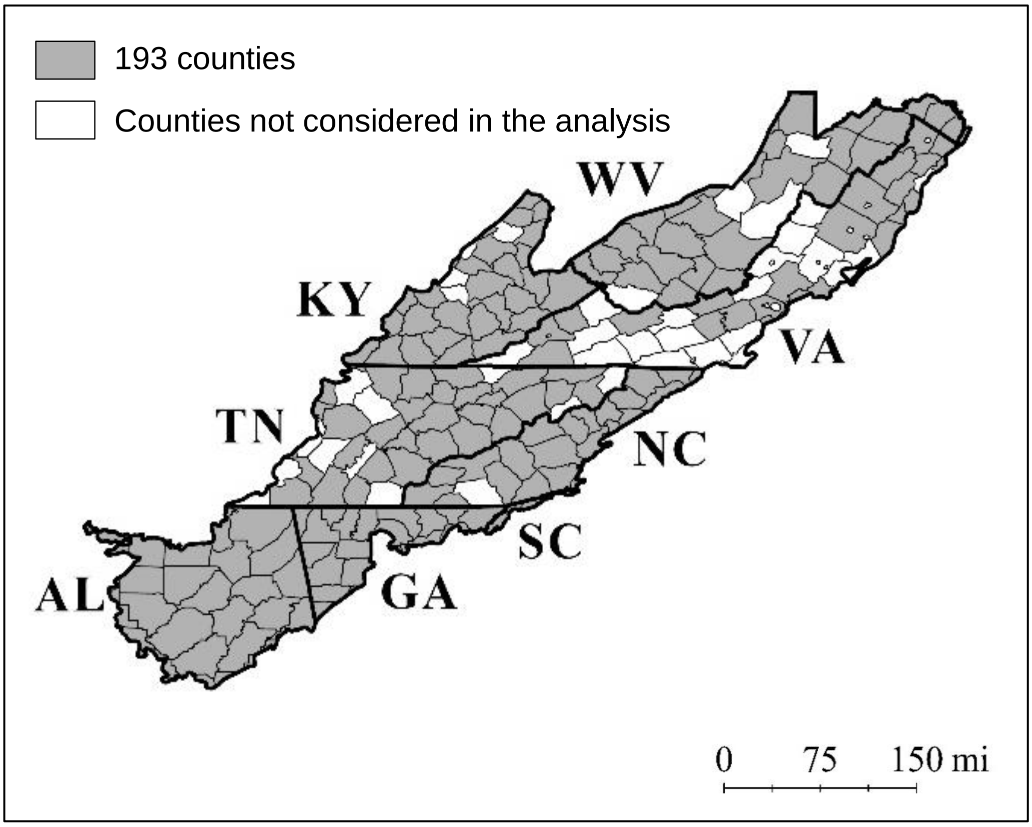
Table S.1. The optimal portfolio weights for the counties in the first step (referred to as 'Portfolio weights 1'), portfolio weights for the four taxonomic groups in the second step, and the portion of total budget optimally distributed to the counties for conservation investments that benefit biodiversity of particular taxonomic groups under four risk-tolerances using a hypothetical total budget of US$1 million (referred to as 'Optimal budget distribution of US$1 million') when the relative weight on unprotected forest land is 0.5.

Four risk-tolerances	Counties	Portfolio weights 1	Alternative portfolio weights 2				Optimal budget distribution of US$1 million			
			Amphibian	Bird	Mammal	Reptile	Amphibian	Bird	Mammal	Reptile
5%	Bibb (AL)	51%	40%	15%	45%	0%	$204,000	$76,500	$229,500	$0
	Clay (AL)	9%	1%	52%	29%	18%	$900	$46,800	$26,100	$16,200
	Coosa (AL)	2%	4%	19%	77%	0%	$800	$3,800	$15,400	$0
	Preston (WV)	38%	5%	34%	45%	16%	$19,000	$129,200	$171,000	$60,800
15%	Clay (AL)	26%	4%	53%	0%	43%	$10,400	$137,800	$0	$111,800
	Coosa (AL)	10%	8%	42%	50%	0%	$8,000	$42,000	$50,000	$0
	Preston (WV)	64%	19%	23%	37%	21%	$121,600	$147,200	$236,800	$134,400
25%	Clay (AL)	41%	0%	25%	0%	75%	$0	$100,524	$0	$309,476
	Coosa (AL)	16%	11%	61%	28%	0%	$17,600	$97,600	$44,800	$0
	Preston (WV)	43%	31%	13%	31%	25%	$133,300	$55,900	$133,300	$107,500
maximum	Coosa (AL)	100%	100%	0%	0%	0%	1,000,000	$0	$0	$0

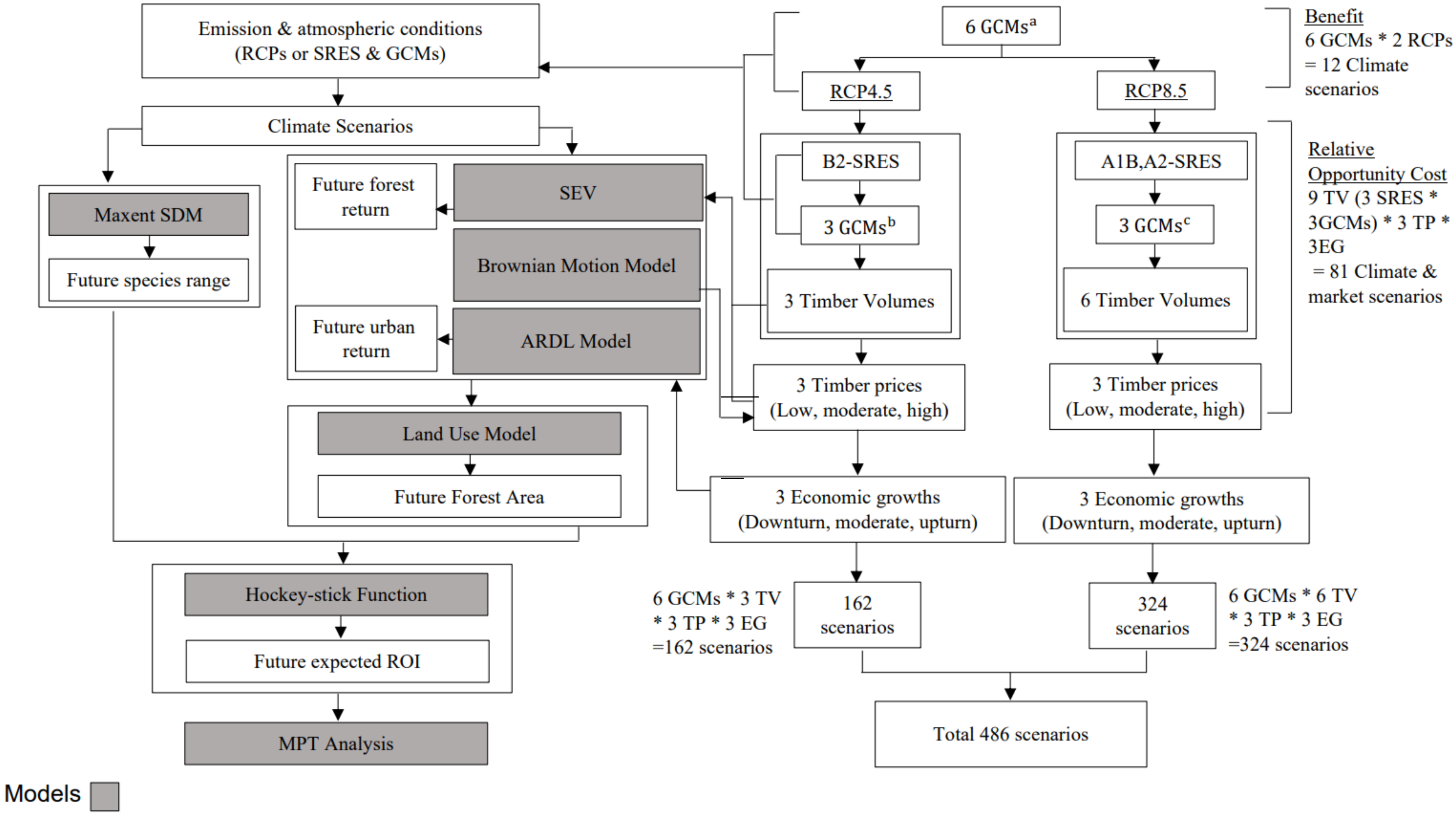
Table S.2. Portfolio weights for the counties in the first step (referred to as 'Portfolio weights 1'), portfolio weights for the four taxonomic groups in the alternative second step (referred to as 'Alternative portfolio weights 2') with 10% of minimum of portfolio weight required for each taxonomic group, and the portion of total budget optimally distributed to the counties for the conservation investments that benefit biodiversity of particular taxonomic groups under four risk-tolerances using a hypothetical total budget of US$1 million (referred to as 'Optimal budget distribution of US$1 million').

Four risk-tolerances	Counties	Portfolio weight 1	Alternative portfolio weights 2				Optimal budget distribution of US$1 million			
			Amphibian	Bird	Mammal	Reptile	Amphibian	Bird	Mammal	Reptile
5%	Bibb (AL)	5%	10%	32%	48%	10%	$5,000	$16,000	$24,000	$5,000
	Clay (AL)	18%	26%	10%	47%	17%	$46,800	$18,000	$84,600	$30,600
	Coosa (AL)	25%	25%	13%	52%	10%	$62,500	$32,500	$130,000	$25,000
	Preston (WV)	49%	26%	28%	13%	33%	$127,400	$137,200	$63,700	$161,700
15%	Clay (AL)	21%	10%	56%	17%	17%	$21,000	$117,600	$35,700	$35,700
	Wolfe (KY)	53%	11%	17%	35%	37%	$58,300	$90,100	$185,500	$196,100
	Preston (WV)	26%	30%	31%	17%	22%	$78,000	$80,600	$44,200	$57,200
25%	Clay (AL)	13%	10%	45%	10%	35%	$13,000	$58,500	$13,000	$45,500
	Coosa (AL)	6%	10%	39%	37%	14%	$6,000	$23,400	$22,200	$8,400
	Wolfe (KY)	81%	13%	23%	23%	41%	$105,300	$186,300	$186,300	$332,100
maximum	Coosa (AL)	100%	70%	10%	10%	10%	$700,000	$100,000	$100,000	$100,000



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 concerns

Figure S.1. Map of 193 counties used for naïve MPT and constrained MPT



[a] 6 GCMs include ACCESS1-0, CanESM2, CCSM4, CNRM-CM5, CSIRO-Mk3, INM-CM4.

[b] 3 GCMs include HadCM3, CSIRO – Mk2, CGCM2.

[c] 3 GCMs include MIROC32, CSIRO-Mk35, CGCM3

Figure S.2. Schematic diagram of the empirical frameworks and their related scenarios

VITA

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