Supplementary Material

Text summary

Supplementary Material includes seven sections of text, four table, and three figures. Sections S1, S2, S3, and S4 contain detailed descriptions of predicting future species distributions, predicting relative opportunity costs, estimating scenario-specific expected ROIs, and scenario design. In addition, sections S5, S6, and S7 provide detail descriptions of average elasticities of the efficient frontiers, sensitivity outcomes for the minimum constraint on portfolio weights, and sensitivity outcomes for alternative relative ecological quality of unprotected private forest, respectively. Table S1 shows the expected ROIs and their standard deviations (SD) for the counties selected in the first step and for the taxonomic groups in the selected counties in the second step at four risk-tolerances (i.e., 5%, 15%, 25%, maximum) represented by the four dashed vertical lines in Fig.3. Table S2 shows the optimal 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, 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 of unprotected forestland is 0.5. Table S3 represents the portfolio weights for the selected counties in the first step, portfolio weights for the four taxonomic groups in the second step with 10%-minimum portfolio weights required for each taxonomic group, 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. Fig. S1 displays 193 of 246 counties that are used in the two-step approach. Fig. S2 displays a schematic diagram of the empirical frameworks and their related scenarios. Fig. S3 displays the 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 selected counties at the four risk-tolerances in the first step represented by the four dashed vertical lines in Fig.1.

S1. 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 Fig. S2). 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.

S2. 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 Fig. S2). 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).

S3. 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 S7 (Supplementary Material).

S4. 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 S4, and relative opportunity costs, described in section S3. See Fig. S2 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 Fig. S2). The nine GCMs were selected based on the availability of climate-related variables and those with high statistical validation (Knutti et al. 2013).

S5. 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.

S6. Sensitivity outcomes for the minimum constraint on portfolio weights

Table S3 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.

S7. Sensitivity outcomes for alternative relative ecological quality of unprotected private forest

Table S2 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 1 and Table S2). 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 1 and Table S2). 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.

Table S1. 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 Fig.3, and for taxonomic groups in selected counties in the second step

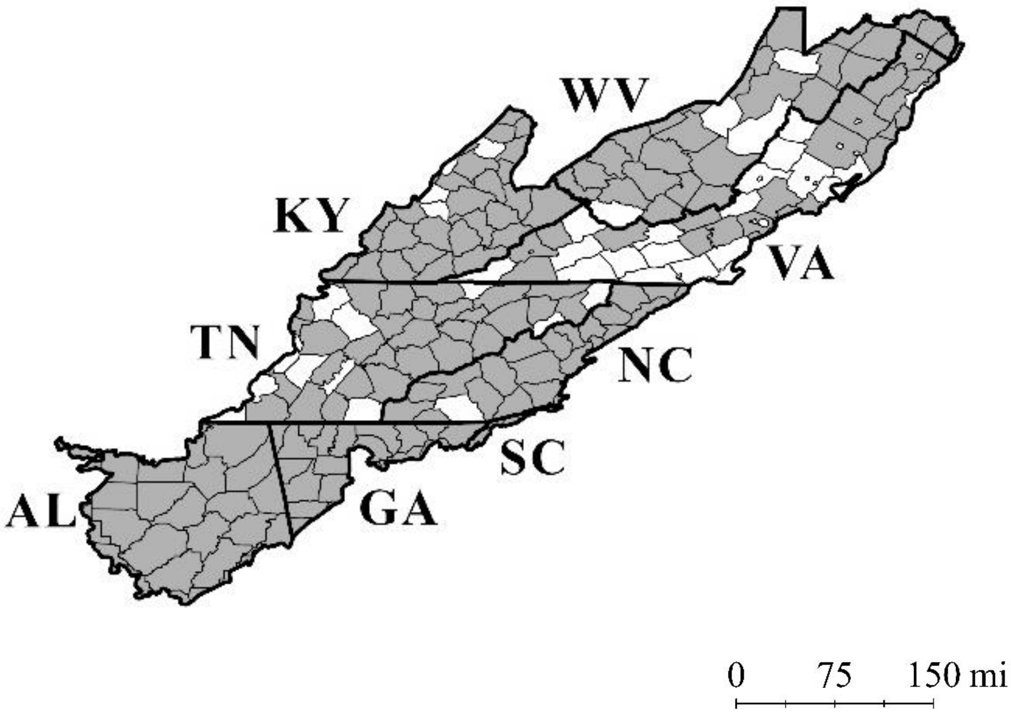
Risk-tolerances	Counties	Step 1 Expected ROIs (SD)	Step 1 Average	Step 2 Expected ROIs (SD) Amphibian	Bird	Mammal	Reptile
5%	Clay (AL)	0.0415 (0.0254)	0.0300 (0.0140)	0.01513 (0.01262)	0.00833 (0.00536)	0.00463 (0.00377)	0.01342 (0.00766)
	Jackson (KY)	0.0200 (0.0066)		0.00703 (0.00285)	0.00537 (0.00233)	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 S2. 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 S3. 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')

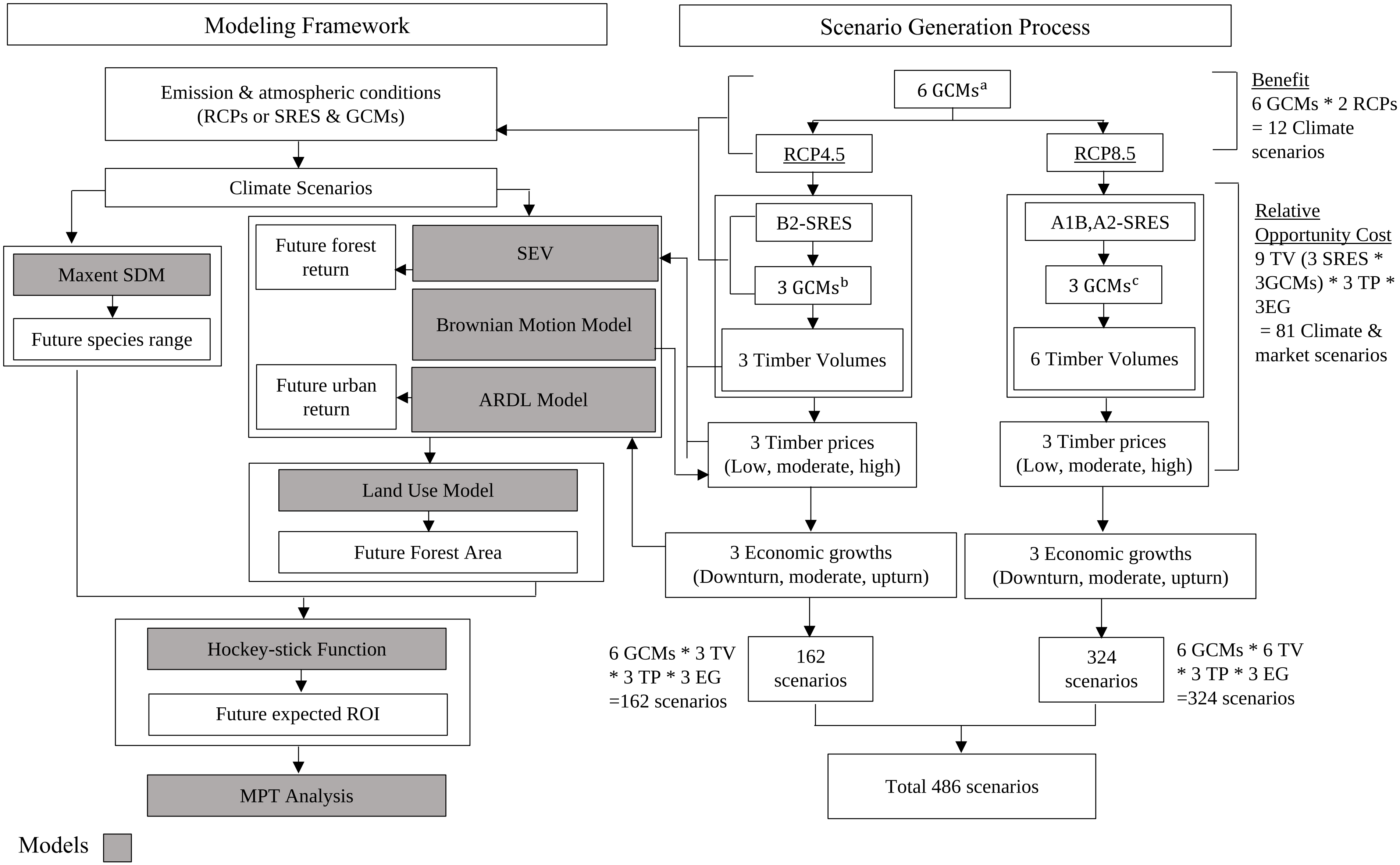
Four risk-tolerances	Counties	Portfolio weight 1	Alternative portfolio weights 2				Optimal budget distribution of US$1 million			
			Amphibian	Bird	Mammal	Reptile	Amphibian	Bird	Mammal	Reptile
5%	Bibb (AL)	5%	10%	32%	48%	10%	$5,000	$16,000	$24,000	$5,000
	Clay (AL)	18%	26%	10%	47%	17%	$46,800	$18,000	$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



193 counties

Filtered out counties (city-counties or counties without urban development pressure)

Fig. S1. Map of 193 of 246 counties that are used in the two-step approach



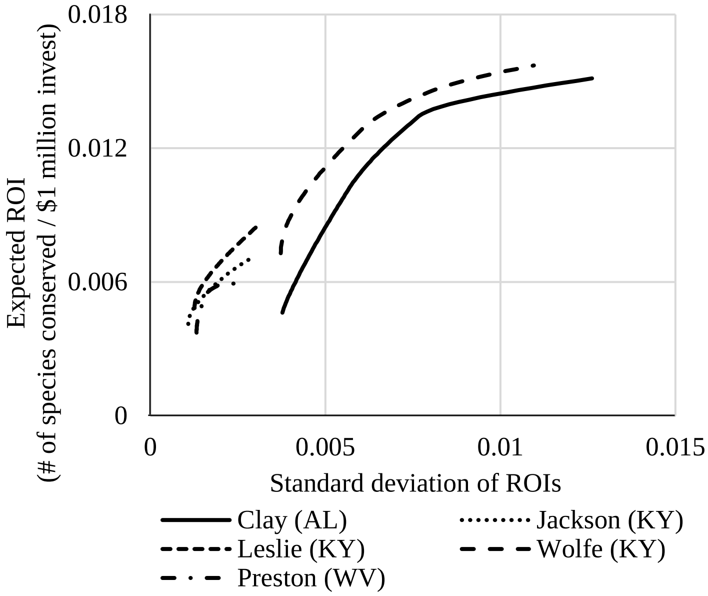
[a] 6 GCMs include ACCESS1-0, CanESM2, CCSM4, CNRM-CM5, CSIRO-Mk3, INM-CM4.

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

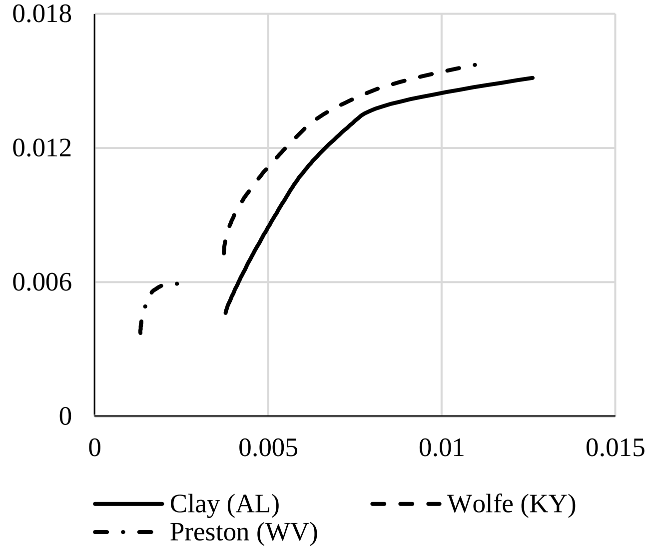
[c] 3 GCMs include MIROC32, CSIRO-Mk35, CGCM3

Fig. S2. Schematic diagram of the empirical frameworks and their related scenarios

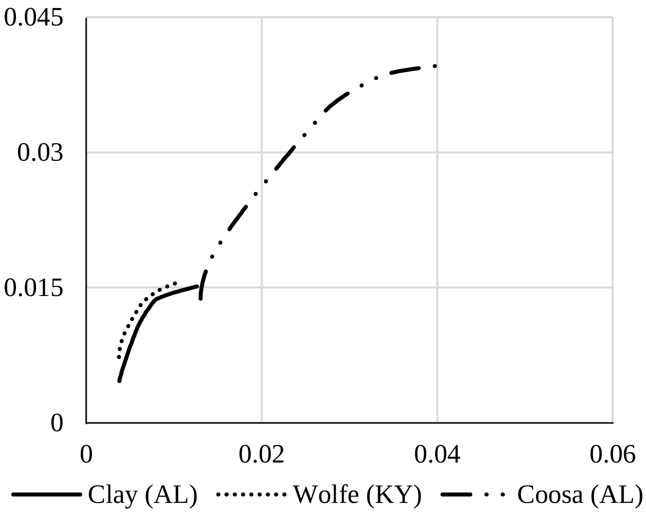
A – 5% risk-tolerance



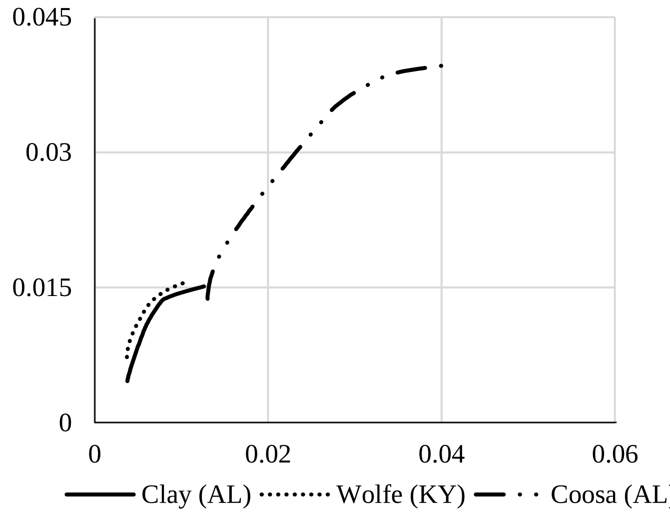
B – 15% risk-tolerance



C – 25% risk-tolerance



D – maximum risk-tolerance



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

Fig. S3. 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 Fig.1

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