

ARTICLE

An empirical analysis of US land-use change under multiple climate change scenarios

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Abstract

This study empirically estimates the effects of climate on land-use change across the conterminous United States and uses the empirical model to simulate the effects of a range of future climate change scenarios on the allocation of land to forestry, agriculture, and development. Ricardian estimation linking climate with the net returns to land production is integrated with a discrete-choice estimation of plot-level land-use change. Comparing projected land-use changes across scenarios, we find that drier and warmer climate scenarios favor forest land, wetter and cooler climate scenarios favor developed land, and wetter and warmer climate scenarios favor crop lands.

KEYWORDS

climate change, climate economics, land-use change, natural resource economics

JEL CLASSIFICATION

Q24, Q54, Q51

1 | INTRODUCTION

Large-scale land-use models are used to project trends in the stock of agricultural and forested lands (e.g., the US Forest Service's Resource Planning Act Assessment [U.S. Department of Agriculture, Forest Service, 2023]), to examine policies that sequester carbon (Lubowski et al., 2006), analyze changes in hydrology (Viger et al., 2011), and to anticipate changes in a broad range of ecosystem services such as food/fiber provision, wildlife habitat, and carbon sequestration (Lawler et al., 2014). Empirical research in land-use economics finds that the relative net economic returns to agriculture, forestry, and development strongly drive land-use changes across these broad uses (Lubowski et al., 2008).

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Recent climate economics research finds that climate change is widely expected to alter the growth of crops (Schlenker & Roberts, 2009), the growth of commercially valuable tree species (Davis et al., 2022), and the quality of life for urban populations (Albouy et al., 2016) in the United States. Spatially heterogeneous climate impacts on resource growth and quality of life are expected to spur a wide variety of adaptations in how land is managed and where people live (Mendelsohn & Massetti, 2017). The resulting impacts of climate-induced changes in the economic returns to agriculture, forestry, and development on broad land-use changes is not well understood.

The purpose of this paper is to empirically estimate the effects of climate on land-use change across the conterminous US, and to use the empirical model to simulate the effects of projected climate change on the allocation of broad land-use in forestry, agriculture, and development. An empirical analysis of climate-induced changes in broad land-uses must account for the potential economic value of adaptation in land management *within* each land-use. The relative climate impacts in forestry and agriculture drive land-use change between these land-uses and the ultimate outcome depends on the suite of management adaptation choices made within these systems.

Our empirical design is based on (a) developing empirical linkages between climate and the net economic returns to the major US land-uses of agriculture, forestry, and development, and (b) developing an empirical link between the net returns to each land-use and the choice to convert between land-uses. We combine previously estimated Ricardian functions of the effects of climate on the net returns to US forestry (Mihiar & Lewis, 2021) with new Ricardian estimations of crop and developed net returns to differentially link climate and net returns to these major land-uses. The Ricardian estimations generate county-level average net returns as functions of a set of climate variables that implicitly account for management adaptation within each land-use. We then develop a discrete-choice model of the plot-level choice of agriculture, forestry, and developed land-use as a function of the county-level net return measures, plot-level measures of soil quality, and a variety of spatial fixed effects that exploit the panel nature of the land-use data. The USDA's National Resources Inventory (NRI) provides the observed land conversion used to estimate our land-use change model. The effects of projected climate change on land-use arise by using the estimated Ricardian functions to adjust the net returns to each land-use based on projected climate, yielding plot-level land-use transition probabilities that capture landowners' revealed land-use behavior.

The primary contribution of this paper is the integration of empirically estimated climate-impacts on land-use returns and a nonlinear discrete-choice estimation of land-use change based on observed land conversion. Prior work in the econometric Ricardian literature has focused on estimating the effects of climate on net economic returns to agriculture (e.g., Mendelsohn et al., 1994; Schlenker et al., 2006), urban quality of life (Albouy et al., 2016) and forestry (Mihiar & Lewis, 2021) but has not gone further and linked projected climate induced changes in net returns to broad land-use changes. Conversely, there is an econometric literature focused on estimating the effects of net returns to land on changes across broad uses like agriculture, forestry, and development (e.g., Lewis & Plantinga, 2007; Lubowski et al., 2006; Wrenn et al., 2017). With three exceptions, the econometric land-use literature has not incorporated climate change into any land-use projections or policy analysis. One exception is Haim et al. (2011), who introduce climate change into Lubowski et al.'s (2006) econometric setup by projecting agricultural and forest yield changes using natural science projections that ignore management adaptation and linking land development returns to future population projections under climate change. As has been discussed extensively in the Ricardian literature (e.g., Mendelsohn et al., 1994), Ricardian functions have the advantage of explicitly accounting for adaptation in land management such as which crops to plant, the intensity of management in forestry, or the influence of climate on the relative attractiveness of housing location. Three additional exceptions include Fezzi et al. (2015) and Mu et al. (2017) who estimate econometric models of land-use decision-making *within* agriculture, and Hashida and Lewis (2019) who estimate an econometric model of management choices *within* forestry—rather than across broad land-uses—as a function of climate.

Our paper also makes two additional contributions to the literature. First, by explicitly linking climate change to land-use changes in a manner that accounts for management adaptation within land-uses, we provide the first econometric-based projection for how the composition of the US landscape will be affected by alternative climate change scenarios and climate adapting landowners. Second, we explicitly incorporate uncertainty arising from our approach to projecting land-use change—uncertainty from the selection of climate model and parameter uncertainty arising from econometric estimation of the impact of climate on land-use change. Following advice from Burke et al. (2015), we evaluate the sensitivity of our land-use projections to climate model and scenario selection by utilizing four global climate model outputs under two emissions scenarios (RCP 4.5 and RCP 8.5). Further, we use the Krinsky and Robb (1986) method of simulating confidence intervals to examine the sensitivity of results to the parameter uncertainty in the estimated models of net returns to land and corresponding land-use change.

Results indicate that developed land in the United States will continue to expand at an approximate average rate of 0.82 million acres per year, which translates to a 51% increase by 2070.¹ Our projected future development growth rates are much lower than the United States average of approximately 1.5 million acres per year observed from 1982 to 1997, and slightly lower than the US average of 0.93 million acres per year observed from 2000 to 2015.² The projected expansion of developed lands will come at the expense of net losses to all other land-uses, including a 5.6% loss in crop land, 7.9% loss in pasture land, and a 2.3% loss in forest land. Among the eight alternative climate change scenarios that we consider, we find that drier and warmer climate scenarios favor forest land (less projected loss), wetter and cooler climate scenarios favor development (higher gain), and wetter and warmer climate scenarios favor crop lands (less loss). However, while we find statistical differences in the simulated land-use distributions across the eight alternative climate change scenarios, the differences across scenarios are practically modest and never diverge from the overarching land-use trajectory of expanding development and falling amounts of all other land-uses. Thus, we find that the choice of climate change baseline makes little difference in the amount of projected net land-use change across the conterminous US.

2 | MATERIALS AND METHODS

2.1 | Land-use change with climate adaptation

An econometric model of the microlevel choice of changing plot-level land-use to adapt to climate change faces two primary challenges. First, the model must represent observable and unobservable information regarding the private net returns to land at the same scale in which the land-use choice varies (Plantinga & Lewis, 2014). Second, the model must account for climate adaptation that may induce the choice of management intensity and the private net returns to land-use. We build our framework off prior econometric work on discrete-choice land-use models (e.g., Bockstael, 1996; Lewis & Plantinga, 2007; Lubowski et al., 2006) and prior econometric work on Ricardian climate models (e.g., Albouy et al., 2016; Mendelsohn et al., 1994; Ortiz-Bobea, 2020) to develop a land-use change econometric model with climate adaptation.

Consider the owner of a homogeneous quality one-acre plot i that begins time period t in land-use j . The owner would receive annual revenue Rev_{ikt} from converting the plot to use k , but face annual management costs ($MgmtCost_{ikt}$) from use k and annualized costs ($ConvCost_{ijkt}$) from converting between use j and use k . The net economic returns to converting to use k are:

¹Alternative shared socioeconomic pathway (SSP) scenarios with higher income and population growth raise our projected future development from 0.82 million acres per year to approximately 1.05 million acres per year.

²See Bigelow et al. (2022) for an analysis of the reduction in US development patterns between the 1982–1997 and 2000–2015 time periods.

$$NR_{ikt} = Rev_{ikt} - MgmtCost_{ikt} - ConvCost_{ijkt}, \quad (1)$$

An issue with Equation (1) is that Rev_{ikt} , $MgmtCost_{ikt}$, and $ConvCost_{ijkt}$ are private information observable by the landowner of plot i , but not by the econometrician. Therefore, we rewrite NR_{ikt} based on factors that are both observable and unobservable to the econometrician:

$$NR_{ikt} = \beta_{0jk} + \beta_{1jk}NR_{c(i)kt} + \beta_{2jk}LQ_i + \mu_{R(i)k} + \varepsilon_{ijkt}, \quad (2)$$

where $NR_{c(i)kt}$ represents the time t average net economic return to land-use k in county c that contains plot i , LQ_i is an index representing an observable measure of land quality for plot i , $\mu_{R(i)k}$ is a fixed effect representing unobservable factors in region R that contains plot i and influence use k , ε_{ijkt} represents unobservable elements of the returns to land for plot i , and the β terms represent parameters to be estimated. Importantly, the alternative specific constant β_{0jk} will embed the annualized costs associated with converting the land from use j to use k ($ConvCost_{ijkt}$). Rewriting Equation (1) into Equation (2) effectively writes land-use returns for a plot as a deviation off the average returns for the county that contains that plot. For land starting in use j , the land-use k is chosen in time t if:

$$NR_{ikt} > NR_{ilt} \quad \forall l \neq k. \quad (3)$$

Equation (3) has been shown to be the optimal land-use decision rule when landowners have static expectations about future net returns to land (Plantinga, 1996). If the ε_{ijkt} is assumed to be IID type I extreme value, Equation (3) facilitates a discrete-choice Logit model (e.g., Train, 2009) of plot-level land-use change given a discrete choice set of plausible land-use alternatives, and the β parameters can be estimated by maximum-likelihood. An important feature of the above model is that Equation (3) is conditional on the land starting in use j , and so this is a land-use *change* model. Another feature of Equation (3) is that the nonlinear functions required to estimate it may preclude estimating the large set of fixed effects in $\mu_{R(i)k}$ due to the incidental parameters problem, and so BLP contraction-mapping may be required to numerically account for the large set of fixed effects in a logit framework (Berry et al., 1995; Train, 2009, ch. 13). The model developed here meets the first modeling challenge of representing observable and unobservable information regarding private returns to land at the plot-level scale in which the land-use choice is made.

To meet the second modeling challenge, we consider a simple model of climate adaptation in land management. Suppose there are M_k possible adaptation choices of land management that can be made within land-use k . For example, an owner of land in forestry could choose to plant their land in loblolly pine, shortleaf pine, hickory, or some other forest type. An owner of land in crop production could choose to plant corn, wheat, cucumbers, or some other crop. The net returns to use k under land management m are affected by climate and defined as:

$$NR_{ikt,m} = f_{km}(X_{it}, Climate_{it}; \gamma), \quad (4)$$

where X_{it} represents plot-level characteristics that affect economic production of land-use k , $Climate_{it}$ represents climatic characteristics around plot i in time t , and γ represents parameters to be estimated. The function f_{km} represents a hedonic price function that relates characteristics of the land and surrounding environment to the economic value of the land in use k which is managed with choice m . The resulting net return of plot i under use k in time t is the solution to the problem of choosing the land management system m that maximizes the value of the land:

$$NR_{ikt} = \max_m \{NR_{ikt,m}\}_{m=1}^{M_k}. \quad (5)$$

Since $NR_{ikt,m}$ is a function of $Climate_{it}$, then Equation (5) is a statement that the landowner will choose management action m to maximize the net economic returns to land-use k given the climate that they face. In turn, the observable county-average net economic return to use k in time t is:

$$NR_{ckt} = \frac{1}{A_{ckt}} \sum_{i=1}^{A_{ckt}} NR_{ikt}, \quad (6)$$

where A_{ckt} is the total acreage of land in county c devoted to use k in time t . Equation (6) indicates that the observable average net returns to use k in county c are a function of the independent management choices made by each landowner of use k land in response to their parcel characteristics and the climate that they face. We estimate the link between climate conditions and the county-mean net returns to use k land with a use- k specific linear Ricardian function:

$$NR_{ckt} = \gamma_{0k} + \gamma_{1k}X_{ct} + \gamma_{2k}Climate_{ct} + \mu_{ckt}, \quad (7)$$

where observable independent variables include county-aggregated land characteristics X_{ct} (e.g., percent of land with high quality soil) and county-aggregated climate characteristics $Climate_{ct}$ (e.g., county mean temperature, cooling degree days, etc.). Since observable county average net returns NR_{ckt} arise from many independent management choices made by landowners within that county in response to the climate they face, then estimation of Equation (7) implicitly accounts for how landowners have adapted their management to the climate conditions they face. And γ_{2k} maps changes in $Climate_{ct}$ to changes in NR_{ckt} , which then affect the optimal land-use choice in Equation (3). Therefore, the framework meets the second modeling challenge by accounting for climate adaptation that may induce management choices that affect the management intensity and the private net returns to land-use.

2.1.1 | Empirical specification and brief data description

Annualized county-level measures of net returns to land (NR_{ckt}) are constructed for k = crop, forest, and development for each year between $t = 1997$ and $t = 2014$ using a variety of mostly federal data sources described more fully in Supporting Information. Averaging NR_{ckt} over time creates cross-sectional measures that are used in three separate Ricardian models of Equation (7) which are estimated using three nonlinear representations of long-term climatic variables as independent variables that vary across each use k . The Ricardian estimation for k = development also includes county-level measures of population and income. The NRI provides the plot-level data³ for the land-use change models in Equation (3), which are used to estimate the discrete-choice that a plot in starting use j converts to use k in time period t . Following prior econometric studies using plot-level NRI data (e.g., Lewis & Plantinga, 2007; Lubowski et al., 2006), we separately estimate four distinct discrete-choice land-use change models (Equations 2 and 3) by starting use.⁴ We represent land quality LQ_i from Equation (2) with the NRI's land capability class (LCC) which is observable for each plot. A full discussion of econometric specification is provided in the supporting information. The estimated probability that each plot i transitions its land use from use k to use l in time t is defined by:

$$P_{iklt} = F[NR_{c(i)t}(X_{ct}, Climate_{ct}; \hat{\gamma}), LCC_i; \hat{\beta}_k, \hat{\mu}_{R(i)k}], \quad (8)$$

³National-level observed gross land-use changes from the NRI for our time period of 2000–2012 are found in Supporting Information: Table S1.

⁴Since almost no land leaves development, we do not model land-use change for plots starting in development.

where $F[]$ is the logistic function, $NR_{c(i)t}$ is the vector of all the time t net return variables in county c that contains plot i , $\hat{\mu}_{R(i)k}$ are the estimated regional fixed effect parameters, and $\hat{\beta}_k$ is the vector of estimated parameters (including alternative specific constants) for each land use k . The Ricardian functions for $NR_{c(i)t}$ are embedded into the logistic probability function in Equation (8), which defines the functional relationship between the land-use transition probabilities and the full set of climate variables $Climate_{ct}$.

2.2 | Landscape simulation

We simulate changes in broad land-uses across the conterminous US to the year 2070 under the range of climate scenarios presented in Figure 1a. The climate change scenarios alter the land-use transition probabilities in Equation (8) by altering $Climate_{ct}$ in each future period t , which then alters $NR_{c(i)t}$ through the estimated Ricardian functions (Equation 7) and parameter vector $\hat{y}$. The estimated logit land-use change functions and parameter vectors ($\hat{\beta}_k, \hat{\mu}_{R(i)k}$) then translate the resulting climate changes into the land-use transition probabilities (Equation 8). Each set of transition probabilities is defined by starting land-use k , county c , and the LCC rating of plot i (LCC_i).

We use the Krinsky and Robb (1986) approach to simulating confidence intervals for the full set of land-use projections under each climate scenario. The simulation works as follows. First, we take draws of the Ricardian ($\hat{y}$) and logit parameter vectors ($\hat{\beta}_k, \hat{\mu}_{R(i)k}$). Since the Ricardian and logit models are estimated independently, the draws are independent across models but reflect the estimated covariance structure of the parameters within each model. Second, we generate a

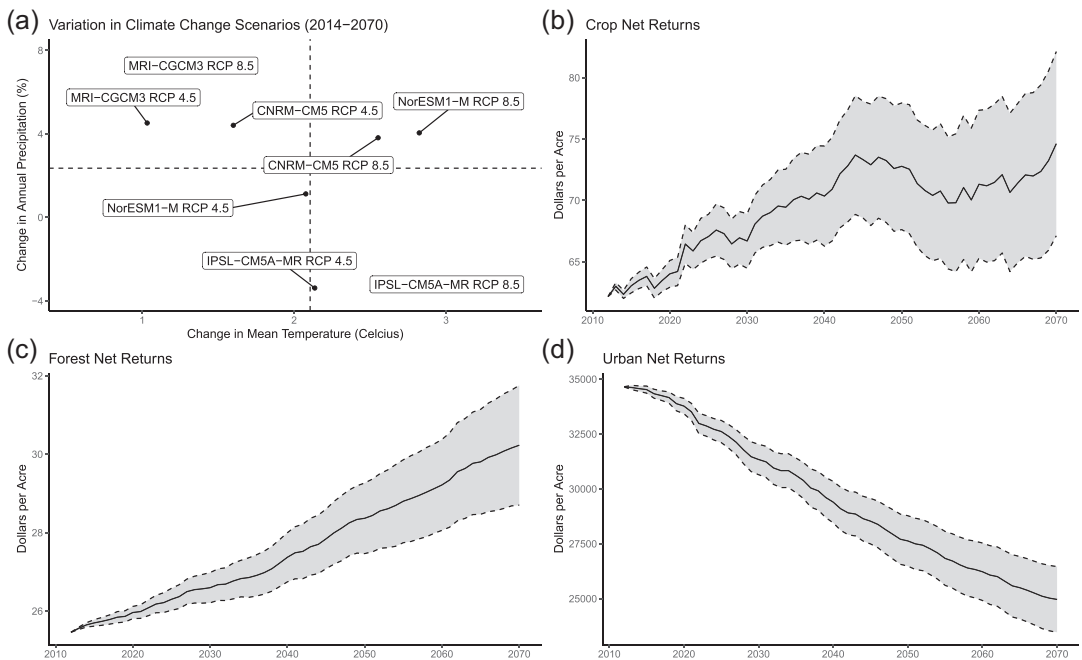


FIGURE 1 Climate model variation and projected net returns (2014–2070). Panel (a) shows variation in temperature and precipitation projections across all eight GCM-RCP scenarios. Dashed horizontal and vertical lines indicate mean climate change projection. Panels (b-d) plot projected net returns using mean projected change in temperature and precipitation. Shaded areas indicate 95% confidence intervals simulated with Krinsky-Robb method.

time-path of the net return variables out to 2070 using the estimated Ricardian functions. Third, using the time-path of net returns, we generate a time-path of land-use transition probabilities for each NRI plot i , and then scale them to the landscape level using the NRI's expansion factor for each plot. This process generates the full composition of each county's landscape across the broad land-uses. Repeating these steps many times provides a distribution of landscape outcomes.

We assume that the price of land in the different land uses will change over time according to the estimated Ricardian functions in Equation (7), but that commodity prices are held fixed. The assumption of fixed crop prices under climate change is supported by Hertel et al. (2016), who reviewed the widely diverging projected crop price studies that analyze future climate change impacts, and find that “crop prices are expected to be at roughly the same level in 2050 as in 2006” (p. 439). Sohngen and Tian's (2016) numerical study finds that climate change will lower timber prices by a modest 15% relative to a nonclimate change baseline. Further, recent work has found that carbon fertilization has already increased timber productivity in at least some areas (Davis et al., 2022), which would also exert downward pressure on future timber prices and potentially counter any supply-induced price increases arising from land-use change out of forests. Other complications for projecting future commodity prices include global forces such as international trade policy and economic growth and land-use change in other countries. Given our main interest in simulating how projected changes in temperature and precipitation influence broad land-use changes in the US, and the uncertainty and modest projected future crop and timber price impacts from climate change, we argue that holding commodity prices fixed is reasonable for this analysis.

3 | RESULTS

3.1 | Model estimation

The Ricardian function for each of the three land-uses (crop, forest, developed) is estimated using cross-sectional ordinary least squares, weighted by each county's acreage in that particular land-use.⁵ Full parameter estimates are presented in Supporting Information: Tables S2–S4. Estimates indicate that crop returns are sensitive to seasonal climate measures, as 15 out of 20 climate parameters are significantly different from zero using single parameter tests ($p < 0.1$). In the forest (Table S3) and development Ricardian (Table S4) models, all eight climate parameters are significantly different from zero in each model using single parameter tests ($p < 0.1$).

To examine how the different climate scenarios affect the projected future path of net returns to forestry, crops, and developed land-uses, we simulate the future time-path of net returns to each use under alternative climate change scenarios, where each climate scenario represents a combination of global climate model and representative concentration pathway and generates varying levels of precipitation and temperature. Temperature increases range from just over 1–3°C across the scenarios, while annual precipitation ranges from –3.4% to +7.4% (Figure 1a). Figure 1b–d present the time path for average net returns to each land-use using mean climate change, along with 95% confidence intervals.⁶ Average crop returns (Figure 1b) and forest returns (Figure 1c) increase moderately for most scenarios, with a mean increase of 23% for crops and 22% for forestry. While average forest returns increase in all eight climate scenarios, there are some climate scenarios in which crop returns fall (Supporting Information: Figure S1). In contrast, development returns (Figure 1d) have a declining time path for all scenarios, with a mean decrease of 32%. As seen in Supporting Information: Figure S1, there is variation in the magnitude of the Ricardian functions across climate

⁵Estimation data is described in the Supporting Information.

⁶See Supporting Information: Figure S1 for projected net returns under all modeled scenarios.

scenarios, but the qualitative trends are consistent. While the forest Ricardian comes from Mihiar and Lewis (2021), the crop and development Ricardian functions are new estimations. For context with prior Ricardian estimates, the projected trends in crop and development returns under climate change are consistent with Ortiz-Bobea (2020) Ricardian estimations of agriculture and housing prices, though our projected increases in crop returns are slightly larger. In addition, the projected declining trends in development returns are consistent with Albouy et al.'s (2016) projections that an urban quality-of-life metric is expected to decline under climate change across most US regions. Despite the declining trends in development returns, the level of projected average development returns remains far higher than the average returns to the other land-uses. Finally, while Figure 1 and Supporting Information: Figure S1 present average national net returns, there is substantial variation in projected net return paths across counties.

Parameter estimates for our land-use change models are presented in Table 1. Parameters are estimated using maximum likelihood, where the likelihood function is weighted by the NRI's expansion factor. Results are intuitive and indicate that increases in the net returns to a particular land-use will increase the probability of choosing that particular use ($p < 0.05$). We also find evidence that the LCC influences land-use transition probabilities. LCC is measured as an integer between 1 and 8, with 1 being the best quality for producing agricultural goods. Results indicate that landowners are more likely to convert low quality cropland (higher LCC) to other uses except development, and less likely to convert low quality land from other uses to crop land ($p < 0.05$). Results are consistent with prior land-use change models estimated from NRI data (e.g., Lewis & Plantinga, 2007; Lubowski et al., 2006).

TABLE 1 Parameter estimates for land-use change models.

	Starting land-use			
	Starts in crop	Starts in pasture	Starts in forest	Starts in range
Crop net return in \$1000s (Crop choice)	2.593*** (0.1610)	2.197*** (0.1213)	2.263*** (0.5928)	5.973*** (0.4399)
Forest net return in \$1000s (Forest choice)	0.217** (0.0916)	0.336*** (0.02724)	0.0812*** (0.5928)	-
Development net return in \$10,000s (Developed choice)	0.103*** (0.0141)	0.113*** (0.01082)	0.0867*** (0.01015)	0.107*** (0.01155)
LCC (Pasture choice)	0.263*** (0.00827)	0.392*** (0.009275)	0.0637** (0.03838)	-1.819*** (0.1600)
LCC (Forest choice)	0.086** (0.0506)	0.509*** (0.01490)	0.5024*** (0.03233)	-0.00896 (0.05030)
LCC (Rangeland choice)	0.438*** (0.0284)	1.116*** (0.009982)	0.4129*** (0.05587)	0.236*** (0.0390)
LCC (Developed choice)	-0.0683** (0.02735)	0.379*** (0.02559)	0.282*** (0.03462)	0.193*** (0.05114)
Alternative-specific constants	Yes	Yes	Yes	Yes
Regional and use-specific fixed effects	State	State	FIA region	No
Number of observations	1,077,732	392,294	1,211,500	609,443
Log-likelihood value	63,723.76	63,814.85	26,885.72	8972.08

TABLE 2 Projected net land-use change (2014–2070) in millions of acres.

	MRI-CGCM3		IPSL-CM5A-MR		CNRM-CM3		NorESM1-M	
	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5	RCP 4.5	RCP 8.5
Developed	46.79 (−11.76, −8.02)	46.4 (44.51, 48.58)	45.98 (44.22, 47.96)	46.16 (44.20, 48.45)	46.47 (44.68, 48.62)	45.85 (44.14, 47.76)	46.06 (44.21, 48.11)	45.5 (43.72, 47.55)
Forest	−9.88 (−11.76, −8.02)	−9.87 (−11.76, −8.01)	−8.99 (−10.87, −7.18)	−9.66 (−11.58, −7.79)	−9.41 (−11.30, −7.55)	−9.24 (−11.12, −7.40)	−9.75 (−11.66, −7.89)	−9.75 (−11.63, −7.93)
Crop	−20.09 (−22.61, −17.35)	−18.22 (−21.56, −14.41)	−23.07 (−25.74, −20.30)	−18.56 (−21.97, −14.78)	−23.85 (−26.75, −20.90)	−22.71 (−25.66, −19.54)	−18.11 (−21.17, −14.64)	−17.69 (−21.18, −13.61)
Pasture	−10.4 (−12.56, −8.28)	−11.29 (−13.67, −8.94)	−7.5 (−9.74, −5.33)	−10.3 (−12.75, −7.94)	−7.46 (−9.79, −5.17)	−7.93 (−10.30, −5.54)	−10.98 (−13.17, −8.79)	−10.74 (−13.14, −8.47)
Range	−6.43 (−8.04, −5.01)	−7.02 (−9.53, −5.28)	−6.42 (−7.88, −5.06)	−7.64 (−10.01, −5.91)	−5.75 (−7.17, −4.49)	−5.96 (−7.49, −4.63)	−7.22 (−9.48, −5.47)	−7.32 (−10.24, −5.43)

3.2 | Landscape simulation under alternative climate change scenarios

Mean net land-use change projections for the conterminous US are presented in Table 2 with 95% confidence intervals.⁷ Net land-use change projections are simulated across the eight climate change scenarios, each comprised of GCM-RCP combinations (Figure 1a).

A key finding of our simulations (Table 2) is that developed land is projected to increase by ~46 million acres through 2070 (~0.82 million acres per year), while all other uses are projected to experience net declines. As expected, our projected developed land-use growth rate of 0.82 million acres per year is similar to the mean growth rate observed from the 2000–2012 period (0.93 million acres per year), and much lower than the approximate 1.5 million acres per year from 1982 to 1997 that was used in previous national land-use projections (Lawler et al., 2014; Lubowski et al., 2006).⁸ When compared to the historical developed land-use growth rate of 0.93 million acres per year, the lower projected rate of developed land-use change of 0.82 million acres per year is largely driven by a) the projected decrease in developed net returns that arise from climate changes in temperature and precipitation (Figure 1b,d) and b) the modest projected increase in timber and crop net returns that arise from climate change (Figure 1b,c). Approximately 62% of newly developed acres occur in counties currently designated as nonmetropolitan,⁹ and nearly half (46%) of that development expansion is projected to occur in the Southern region of the United States.

The largest projected decline is in crop land (~−17.7 to −24 million acres) and the smallest projected decline is in range land (~−5.75 to −7.5 million acres). Forest land (~−9.5 million acres) and pasture land (~−7.5 to −11.3 acres) have moderate projected declines. The projected decline in

⁷See Supporting Information: Table S5 for projected land-use change as percent change.

⁸Using a land-use model based on the 1992–1997 NRI data, Lawler et al. (2014) project a baseline 71% increase in development over a 50-year horizon, which is much higher than our projected 50-year increase of 50%.

⁹The Rural–Urban Continuum system developed by USDA Economic Research Service classifies metro and Nonmetro US counties. Nonmetro counties are defined as having a population less than 250,000 and not containing a metro area.

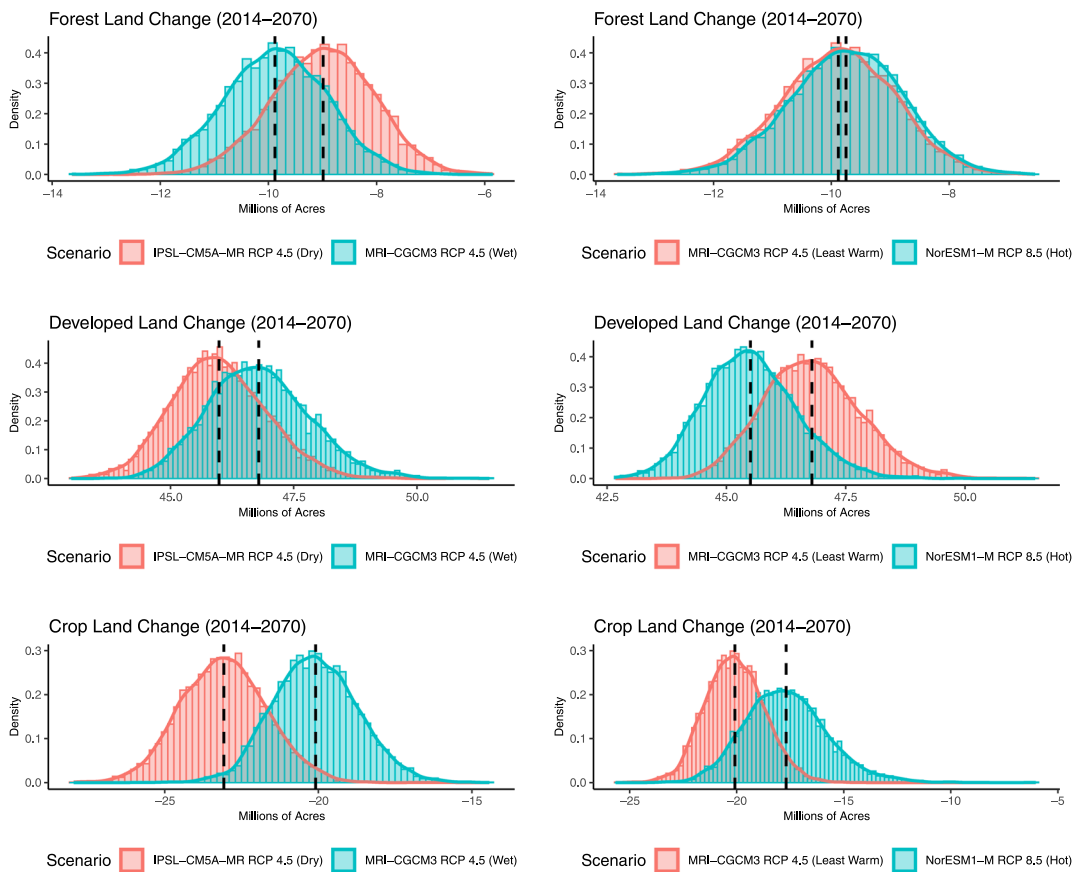


FIGURE 2 Projected net land-use change with parameter uncertainty. The distribution of projected land-use change is generated with the Krinsky–Robb method by incorporating variance–covariance from each estimated model. Dashed vertical lines indicate represents the mean projected change for each scenario and land-use type.

crop land is most sensitive to alternative climate scenarios, with the largest projected decline (–23.9 million acres) occurring in a relatively warmer and wetter scenario (CNRM-CM5 at RCP 4.5), while the lowest projected decline (–17.7 million acres) occurs in the middle scenario (NorESM1-M at RCP 8.5) where climate changes are relatively moderate as seen in Figure 1. Note however that the 95% confidence intervals overlap across all scenarios for the crop land projections. The projected changes in forest and developed land have much smaller variation across the eight climate scenarios.

Figure 2 presents distributions for the projected changes in forest, crop, and developed land. The first column compares the projected net land-use change distributions across relatively wet and dry climate scenarios. The drier scenario (IPSL-CM5A-MR RCP 4.5) has less forest land loss, a smaller expansion of developed land, and greater crop land loss when compared with the wetter scenario (MRI-CGCM3 RCP 4.5). The second column compares the least warm climate scenario (MRI-CGCM3 RCP 4.5) with a relatively hotter scenario (NorESM1-M RCP 8.5), with the hotter scenario having slightly less forest land loss, a smaller expansion of developed land, and lower crop land loss when compared with the least warm scenario. Thus, drier and warmer climate scenarios favor forest land (less projected loss), wetter and cooler climate scenarios favor development (higher gain), and wetter and warmer climate scenarios favor crop lands (less loss). But the overall pattern of development and corresponding losses in all other uses is unchanged across climate scenarios.

For a more rigorous comparison of the projected distributions, we employ the Kolmogorov–Smirnov (KS) test to compare the distribution of land-use outcomes between each of the eight climate change scenarios. In 26 out of 28 tests we reject the null hypothesis that the distribution of outcomes is the same ($p < 0.05$). The two exceptions where the KS test revealed no statistical difference in the distribution of outcomes occurred between NorESM1-M RCP 4.5 and RCP 8.5, and between MRI-CGCM RCP 4.5 and RCP 8.5.

3.3 | Robustness to including shared socioeconomic pathways (SSPs)

Future population and income are expected to play a significant role in how society manages the landscape. Although the present research is focused on the role of climate in driving land-use change, our framework allows for the inclusion of socioeconomic projections. To explore robustness of our land-use change projections, we investigate how alternative assumptions of future population and income affect landscape outcomes. We utilize downscaled SSP projections for population and income for counties in the conterminous US (Wear & Prestemon, 2019). The SSPs define a range of mitigation and adaptation challenges that society may face under a changing climate, and how those challenges translate to socioeconomic conditions (Riahi et al., 2017). We consider two SSPs for additional analysis. SSP1 describes a world where the global economy follows a path toward sustainability, and SSP2 assumes society continues along its current trajectory with slow, uneven progress towards sustainability. We pair SSP1 with the more modest climate change scenario RCP 4.5 and we pair SSP2 with the bigger climate changes in scenario RCP 8.5, consistent with Moss et al. (2010).

The population and income projections from the SSP scenarios are incorporated into our land-use change simulations through the developed land net return function (Equation 4, m = developed land) since that equation is an estimated function of county-level population and income. We project future developed net returns using county-level population and income changes from Wear and Prestemon's (2019) downscaling of SSP scenarios to the county level through 2070. As seen in Supporting Information: Figure S2, the increasing population and income in the SSP scenarios induce developed net returns to increase over time compared to our main projections of developed net returns from Figure 1. The higher rate of increase in developed net returns from the SSP scenarios raises the amount of land converted into developed uses (from approx. 0.82 million acres/year to approx. 1.05 million acres/year) and therefore, lowers the amount of land that remains in all other land uses (Supporting Information: Table S5). However, the relative effect of the *climate* variables from Equation (4) on net land-use change is robust to whether we include SSP scenarios or not. In comparing the net land-use changes from our main results in Table 2 to the corresponding net land-use changes from the SSP scenarios in Supporting Information: Table S5, the two sets of projections have a correlation coefficient of 0.998. Incorporating the SSP scenarios changes the level of land-use change, but not the pattern of changes under alternative climate scenarios. Drier and warmer climate scenarios continue to favor forestland, wetter and cooler climate scenarios continue to favor developed land, and wetter and warmer climate scenarios continue to favor cropland.

4 | DISCUSSION

There are limitations and caveats with our approach and results. First, our land-use change model embeds an assumption of static expectations—landowners are implicitly assumed to make decisions at any point in time by comparing the current level of net returns to each land-use. However, if landowners are forward looking and anticipate a changing path of net returns to each land-use, then they may make decisions in a more anticipatory fashion such as assumed in the numerical analyses of the global timber sector under climate change (Alig et al., 2002, Sohngen & Mendelsohn, 1998;

Sohngen & Tian, 2016). Second, our cross-sectional Ricardian functions may be subject to the common criticism that such models are sensitive to omitted variables (Blanc & Schlenker, 2017). Third, though our land-use projections capture three key forms of uncertainty—across four climate models and in parameter estimation of both the net return model and the land-use change model—there are many other forms of uncertainty that we do not incorporate including that deriving from downscaling climate change projections and uncertainty embedded within each of the four global climate models.

Prior numerical studies of climate impacts on land-use change are not directly comparable to our results because they focus on different scales and scenarios, such as how global agricultural area is impacted by climate change (Nelson et al., 2014) or how a climate stabilization policy affects broad US land-use change relative to a baseline without a stabilization policy (Beach et al., 2015). However, our finding that land development is the primary driver of US land-use change, and that the choice of climate scenarios leads to only small differences is consistent with the overall findings from Haim et al.'s (2011) study of US land-use change. In contrast to Haim et al. (2011), our empirical estimates reflect the large reduction in the rate of US development growth that occurred after the year 2000 (Bigelow et al., 2022) and we therefore project a much lower rate of development growth (at most 1.05 million acres/year) than Haim et al. (2011) (approx. 1.96–2.8 million acres/year), and correspondingly more land in undeveloped uses.

Finally, while our projections generate implicit changes in the price of land that would occur in response to temperature and precipitation changes, we do not model the resulting impact of land-use changes on the structural response that may arise in agricultural and timber markets that drive supply and demand for products generated from these land systems (e.g., crop prices, wood product prices, etc.). However, we can speculate as to how incorporating endogenous supply and demand shocks would alter the land-use change projections. Our projected losses in forest and agricultural land could lower the supply for timber and agricultural products that could increase net returns to forest and agricultural land, which would, in turn, reduce the amount of land converted away from these uses. Of course, technological advances in crop yields (Hertel et al., 2016) or carbon fertilization in forests (Davis et al., 2022) could counter-act such supply reductions. A future research advance could integrate the land-use change model here with scenarios from structural market models of commodity prices under climate change.

5 | CONCLUSION

In this paper, we generate empirically based projections of broad land-use changes for the conterminous US across multiple climate change scenarios. We develop a land-use change model with climate adaptation, consisting of a combination of Ricardian estimation of climate on net returns to land with discrete-choice estimation of net returns to land on land-use changes. Our approach is based on the microeconomic theory of how landowners adapt to climate change by choosing both the broad land-use and the management activity within each land-use that maximizes the value of their land. Eight climate change scenarios give us spatially-heterogeneous variation in warming (+1 to +3C) and precipitation (−4% to +7.5%) and our approach translates the projected climate changes to changes in net returns to each land-use, which are then embedded in our estimated plot-level land-use transition probabilities to project future landscape change conditional on the starting landscape and climate change path. Results indicate that developed land is projected to grow steadily along with corresponding declines in all other land uses. The projected declines are largest for crop land, smallest for range land, with moderate declines projected for forest and pasture. In comparing projected land-use changes across scenarios, we find that drier and warmer climate scenarios favor forest land (less projected loss), wetter and cooler climate scenarios favor development (higher gain), and wetter and warmer climate scenarios favor crop lands (less loss). However, the magnitude of land-use change is similar across climate change scenarios and the

overall pattern of development and corresponding losses in all other uses is unchanged across climate scenarios.

The natural sciences have examined how climate change may impact natural resource stocks through dynamic ecosystem changes, such as species range shifts (e.g., Lawler et al., 2009). However, ecosystems may also be affected by human decisions regarding the use of land, as people adapt to a changing climate. Adaptation that results in changes across broad land-uses can alter the supply of a range of nonmarket ecosystem services in addition to market changes in food and fiber production (Lawler et al., 2014). While the climate econometrics literature has made notable advances in the past decade in studying climate impacts on many sectors including sea level rise (Larsen et al., 2015), productivity (Zhang et al., 2018), agriculture (Ortiz-Bobea, 2020), forestry (Hashida & Lewis, 2019), and others, there is a notable gap in estimating climate impacts on broad land-use changes. This is all against a policy backdrop with considerable interest in encouraging tree planting on non-forested land (a broad land-use change) as a means of mitigating climate change (e.g., the Trillion Trees Act in the US House of Representatives). However, since climate is an input into the economic value of many land-uses, and since the climate is changing and widely expected to continue changing, the efficacy of encouraging tree planting must be evaluated against a baseline where climate change is ongoing and affecting land-use changes. In addition, the economics of dynamic conservation policy design requires information on how climate change may impact land-use decision making, which will in turn affect ecosystem service provision (Augustynczik et al., 2020; Lewis & Polasky, 2018). We view our results as providing foundational evidence of how an underlying baseline landscape change process in the United States is affected by alternative climate change scenarios.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in the Forest Service Data Archive at 10.2737/RDS-2023-0026. Land-use projections are available for scenarios used in the 2020 Resource Planning Act Assessment (10.2737/WO-GTR-102). The data used as inputs to land-use projections were derived from public sources with details provided in the associated metadata.

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SUPPORTING INFORMATION

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

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