# An empirical analysis of U.S. land-use change under multiple climate change scenarios


Christopher Mihiar[1]

USDA Forest Service Southern Research Station

David J. Lewis

Department of Applied Economics, Oregon State University


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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, land-use change, discrete choice, Ricardian

**JEL Codes:** Q24, Q54, Q51



[1] Mihiar (christopher.mihiar@usda.gov) is Research Economist, USDA Forest Service Southern Research Station. https://orcid.org/0000-0002-9832-5262. Lewis (lewisda@oregonstate.edu) is Professor, Department of Applied Economics, Oregon State University, Corvallis, OR 97331. https://orcid.org/0000-0002-2161-4189.


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## Introduction

Large-scale land-use models are used to project trends in the stock of agricultural and forested lands (e.g. the U.S. Forest Service's Resource Planning Act), 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). Recent climate economics research finds that climate change is widely expected to alter the growth of crops (Schlenker and Roberts 2009), the growth of commercially valuable tree species (Restaino et al. 2015), 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 (Massetti and Mendelsohn 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 United States, and to use the empirical model to simulate the effects of future 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 of the land-uses. For example, consider the middle of the eastern U.S., a region where climate changes are expected to increase the profitability of pine forests when compared to the current climate (Mihiar and Lewis 2021). The net economic returns to forestry would rise and reflect the value of adapting to pine forest systems rather than simply reflecting the value of pre-climate change forestry. Whether owners of agricultural lands would respond and convert their land to forestry depends on how those same climate changes affect the profitability of crops, which depend on any adaptations made to crop management (e.g. crop switching). The relative climate impacts on both forestry and agriculture should drive land-use changes across these land-uses and will critically depend on potential land management adaptation choices that could be made within both forestry and agriculture.

The empirical design of our research is based on a) developing empirical linkages between climate and the net economic returns to the major U.S. 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 change land-uses across agriculture, forestry, and development conditional on land quality and the current landscape allocation. We combine previously estimated Ricardian functions of the effects of climate on the economic returns to U.S. forestry (Mihiar and Lewis 2021) with new Ricardian estimations of the effects of climate on the returns to crop land and development in order to differentially link climate and net returns to the major land-uses. The Ricardian estimations generate county-level average net economic returns as functions of a set of climate variables. As with all Ricardian models, the results 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 land-use change model is estimated from hundreds of thousands of repeated plot-level land-use choices as observed in the USDA's National Resources Inventory (NRI) dataset from 2000 to 2012. The estimated land-use change model generates transition probabilities that are functions of the county-level net returns to land. The effects of climate change on land-use change arise because we use the estimated Ricardian functions to adjust the net returns to each land-use to future climate changes, ultimately yielding plot-level land-use transition probabilities that are functions of various climate measures based on landowners' revealed land-use behavior, and which account for management adaptation within each land-use.

The primary contribution of this paper is an integration of Ricardian estimation of climate-impacts on land-use returns combined with discrete-choice estimation of land-use change as a function of land-use returns. 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 and 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. Lubowski et al. 2006; Lewis and Plantinga 2007; 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), estimating Ricardian functions has the advantage of explicitly accounting for adaptation in land management such as the choice of crops to plant, the choice of trees to grow, or the influence of climate on the relative attractiveness of locations as a place to live. 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 U.S. landscape will be affected by different climate change scenarios. This evidence complements other non-econometric land-use studies based on numerical methods like the FASOM model (e.g. Alig et al. 2002). An advantage of the econometric approach over numerical approaches is the ability to use evidence on landowners' revealed behavior combined with statistical theory to generate confidence intervals for estimates. Second, we explicitly incorporate two primary forms of uncertainty that arise from our approach to projecting land-use change – uncertainty arising from the selection of climate model to generate future climatic conditions, and uncertainty arising from econometric estimation of parameters describing both net returns to land and corresponding land-use change. We follow advice from Burke et al. (2015) and consider the effects of different climate change projections by examining sensitivity of results to the choice from among four different climate models across both RCP 4.5 and RCP 8.5. Further, we use the Krinsky-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 U.S. will continue to expand at an approximate average rate of 0.82 million acres per year, which translates to a 51% increase by 2070.[2] Our projected future development growth rates are much lower than the U.S. average of approximately 1.5 million acres per year observed from 1982-1997, and slightly lower than the U.S. average of 0.93 million acres per year observed from 2000-2015.[3] 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 we consider, 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 a climate change baseline makes little difference in the amount of projected net land-use change across the conterminous U.S.

This paper is structured as follows. Section 2 describes the theory underpinning the econometric land-use change model with climate adaptation. Section 3 describes the data on net returns, land-use change and climate, along with the various econometric specification choices that we make. Section 4 presents econometric parameter estimates while section 5 uses the parameter estimates to simulate the effects of climate change on U.S. land-use change up to

[2] Alternative shared socio-economic 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.
[3] See Bigelow et al. (2022) for an analysis of the reduction in U.S. development patterns between the 1982-1997 and 2000-2015 time periods.

2070. Finally, section 6 offers concluding thoughts on the intersection between climate change and broad land-use changes.

**Materials & Methods**

Theoretical Framework: An econometric land-use change model with climate adaptation

An econometric model of the micro-level 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 and 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; Lubowski et al. 2006; Lewis and Plantinga 2007) and prior econometric work on Ricardian climate models (e.g. Mendelsohn et al. 1994; Albouy et al. 2016; 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:

$$NR_{ikt} = Rev_{ikt} - MgmtCost_{ikt} - ConvCost_{ijkt} \tag{1}$$

An issue with Eq. (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 re-write $NR_{ikt}$ 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*, $\varepsilon_{ijkt}$ represents unobservable elements of the returns to land for plot *i*, and the $\beta$ terms represent parameters to be estimated. Importantly, the alternative specific constant $\beta_{0jk}$ will embed the annualized costs associated with converting the land from use *j* to use *k* ($ConvCost_{ijkt}$). Re-writing Eq. (1) into Eq. (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:

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

Eq. (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 $\varepsilon_{ijkt}$ is assumed to be IID type I extreme value, Eq. (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 $\beta$ parameters can be estimated by maximum likelihood. An important feature of the above model is that Eq. (3) is conditional on the land starting in use *j*, and so this is a land-use *change* model. Another feature of Eq. (3) is that the non-linear 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:

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

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 $\gamma$ 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:

$$NR_{ikt} = max_m\{NR_{ikt,m}\}_{m=1}^{M_k} \tag{5}$$

Since $NR_{ikt,m}$ is a function of $Climate_{it}$, then Eq. (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:

$$NR_{ckt} = \frac{1}{A_{ckt}}\sum_{i=1}^{A_{ckt}} NR_{ikt} \tag{6}$$

Where $A_{ckt}$ is the total acreage of land in county *c* devoted to use *k* in time *t*. Eq. (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:

$$NR_{ckt} = \gamma_{0k} + \gamma_{1k}X_{ct} + \gamma_{2k}Climate_{ct} + \mu_{ckt} \tag{7}$$

Where observable independent variables include county-aggregated land characteristics $X_{ct}$ (e.g. percent of land in 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 that they face, then estimation of Eq. (7) implicitly accounts for how landowners have adapted their management to the climate conditions they face. And $\gamma_{2k}$ maps changes in $Climate_{ct}$ to changes in $NR_{ckt}$, which then affect the optimal land-use choice in Eq. (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.

<u>Data sources and econometric specification</u>

In this section, we describe the construction of the private economic returns to productive land-use and the estimation of our climate Ricardian functions. We construct net returns measures for three distinct land-use systems: crop, forest, and development. The Ricardian approach econometrically links the net returns to each land-use with exogenous climate variables that are heterogeneous across space. Spatial variation in net returns and climate allow us to identify how local climate, conditioned on land quality, determines the optimal set of intensive margin management decisions.

*Data sources on net returns to land*

The economic net return to crop land is derived from regional economic accounts reported by the U.S. Department of Commerce's Bureau of Economic Analysis (BEA). The BEA's regional program tracks the geographic distribution of economic activity, providing data on farm income and expenses at the county level for the period 1969 - 2014. The BEA defines farms as including both crop and animal production. Crop establishments include farms in the production of food and fiber, including orchards, groves, greenhouses, and nurseries, primarily engaged in growing crops, plants, vines or trees and their seeds. In addition to cash receipts, the total net income measure also includes government payments, labor expenses, and the value of changes in inventory. Income is included for both sole proprietors and corporate farms. All values are converted to per acre measures in 2010 dollars to make then comparable across land-use systems (i.e. to match forest and development net returns).

County-specific proxies are constructed to serve as the net return to developed land using a residual-based approach. The proxy is derived from the average price per acre of recently developed land used for home construction. Annualized net returns to developed land are constructed from data in the PUMS survey conducted by the U.S. Census. For the year 2000, the data comes from the decennial census. Starting in 2005, the PUMS survey was conducted as part of the American Community Survey (ACS). The ACS is done annually and collects owner-reported property value. The value of land is the difference between the value of newly constructed single-family homes from Survey of Construction (SOC) reports and the Census reported property value. The SOC also reports the average lot size which is used to generate per acre land price.

Data on property value, including land and structures, is compiled from the U.S. Census' Public Use Microdata Samples (PUMS 5% sample). The PUMS data is reported at the Public Use Microdata Area (PUMA) geographic unit. PUMA boundaries lie completely within state boundaries; however, the overlap between PUMA boundary and county boundary varies across the country. In some cases, multiple PUMAs will be contained within a single county, while other PUMAs may have multiple counties falling within a single PUMA. We developed an algorithm that scaled the PUMS data according to neighbor relationships using a GIS to estimate the county-level sales price of recently developed homes. County sales price is the weighted average of the PUMS property value, where the weight is the area of overlap between county and PUMA boundary.

Lastly, the net economic return to timber production is taken from Mihiar and Lewis (2021). Measured in annualized dollars per acre of forestland, this variable is constructed by combining stumpage prices, forest establishment costs, and timber yield functions estimated with data from the U.S. Forest Service's Forest Inventory and Analysis (FIA) data. Timber yield functions were estimated at the county and species group level and capture the spatial heterogeneity of forest productivity across the U.S. The current forested landscape is used to combine species level net returns into a composite measure of county level forest net returns.

*Data sources for climate*

Historically observed weather and climate data are obtained from Oregon State University's PRISM Climate Group (PRISM 2017). PRISM daily data was obtained for three climate variables: precipitation, minimum temperature, maximum temperature. Mean temperature is derived from the minimum and maximum values. Because we are interested in the impact of climate on the net return to land, we use the long-term average (normal) of each locations' weather variable. We use various measures of temperature and precipitation for the period 1981-2010 measured in degrees Celsius and millimeters (mm), respectively. We aggregate the PRISM data to the level of U.S. counties for each variable. These historically observed climate data are used to estimate parameters for the Ricardian functions. We discuss the specific climate measures used for each net return function below.

Predictions of future climate are obtained from the University of Idaho, MACA Statistically Downscaled Climate Data for CMIP5. MACAv2- METDATA (Multivariate Adaptive Constructed Analogs) was developed by Abatzoglou et al (2013). Climate variables are reported at a 4km (1/24-deg) resolution, and include mean daily maximum temperature, mean daily minimum temperature, and daily total precipitation (mm). As part of the Resource Planning Act (RPA) assessment for 2020, the U.S. Forest Service has identified a subset of MACA scenarios to represent a full range of future climates (e.g. wet, dry, etc.) (Joyce and Coulson 2020). Models were evaluated on the basis of their strength at predicting the historically observed climate. We evaluate the future landscape across four GCMs at RCP 4.5 and RCP 8.5[4].

*Data source for land-use change*

We use the plot-level 2012 National Resources Inventory (NRI) data from the USDA Natural Resources Conservation Service as the source for land-use change data. The NRI is a

[4] Global climate models used in our analysis include MRI-CGCM3 (Least Warm), IPSL-CM5A-MR (Dry), CNRM-CM5 (Wet), and NorESM1-M (Hot).

longitudinal dataset comprised of land-use, land cover and soil characteristics on non-Federal lands across the conterminous U.S. The 2012 NRI data set used here is comprised of 1,362,936 unique plots covering 3,096 U.S. counties and includes annual observations of land-use after the year 2000.[5] Land-use conversion is modeled using two-year transition periods starting in 2000 and ending in 2012, creating six transition periods that comprise starting and ending land-uses. Table 1 presents the observed land-use changes between each broad land-use between 2000 and 2012 in the NRI, and figure 1 shows the land-use to which converted land transitioned over the observation period.. The largest net-change in land-use was a loss of almost 11 million acres of crop land, and a gain of almost 11 million acres of developed land. However, other uses had minimal net changes but much larger gross changes to and from other uses. For example, almost 2 million acres of forest were converted to pasture while nearly 6 million acres of pasture was converted to forest. We also use the plot-level variable land capability class (LCC) as an indicator of the quality of land (i.e. $LQ$ in Eq. 2).

*Econometric specification of climate in Ricardian models*

Given the above sources of data, we specify Eq. (7), the function that relates vectors of climate variables to the net returns for each land-use. The dependent variable is the county average net return to land use $k$, which is averaged over the time period 1997-2014 to create a cross-sectional dataset consistent with the traditional Ricardian approach. We build off prior research and define the functional form and the choice of climate variables differently for the three different Ricardian functions that represent net returns to the major land-uses of forest land, crop land, and development. Each of the three Ricardian functions uses U.S. counties as the unit

[5] Between 1982 and 1997, land use is observed in 5-year increments.

of observation, and we use ordinary least-squares to estimate parameters for each function. A key finding of past literature is that climate variables have a non-linear effect on net returns to various land-uses, and our specification choices reflect this finding.

For the forest Ricardian ($k$=forest), we employ the Ricardian function specification used by Mihiar and Lewis (2021) including climate variables representing average annual temperature and total annual precipitation in each county. Temperature and precipitation are specified as polynomial functions with a $4^{th}$ order polynomial. Mihiar and Lewis (2021) present an extended analysis of specification, including robustness checks with an alternative specification for counties west of the $100^{th}$ meridian and seasonal climate measures. In addition to climate, variables capturing average county soil quality and regional fixed effects are included to specify Eq. (7) for forestland.

For the crop land Ricardian ($k$=crop), we build off the voluminous literature on agricultural Ricardian models (Mendelsohn et al. 1994; Schlenker et al. 2005; Ortiz-Bobea 2020) and specify a new model using our county-average crop land net returns data as the dependent variable. In contrast to earlier analyses built on farm land values, we follow Ortiz-Bobea (2020) and use a quasi-rent measure for the dependent variable that is consistent with the theoretical setup of the econometric land-use model. For specifying climate in the crop land Ricardian, we follow Massetti et al. (2016) and choose seasonal average temperatures and seasonal total precipitation for our set of climate variables, along with interactions between temperature and precipitation. All climate variables are specified with a $2^{nd}$ order polynomial function to capture the non-linear relationship between climate and crop land returns. We also include variables representing the proportion of county crop land in each of the eight primary land capability classifications (LCC).

For the development Ricardian (*k*=developed), we build off Albouy et al.'s (2016) cross-sectional analysis of climate impacts on urban quality of life and specify a new model using our county-average developed land net returns data as the dependent variable. Since Albouy et al. (2016) found strong support for using heating and cooling degree days to explain urban quality of life, we represent climate in the developed land Ricardian with $2^{nd}$ order polynomial functions of heating and cooling degree days, a $2^{nd}$ order polynomial of total annual precipitation, and interactions between precipitation and the heating/cooling degree days variables. Heating and cooling degree days represent deviations from the bliss point of 65 degrees Fahrenheit. The Ricardian model for developed land estimates the link between climate amenities and developed land prices, thereby providing us an avenue in which to link climate change to development land-use change.

In addition to climate, we include several standard explanatory variables in the development Ricardian that have historically been shown to influence developed land values, including population, income, racial composition, and population shares in various education levels. We do not include factors like population and income in our timber or crop Ricardian models since our dependent variable is an annualized net return to those uses rather than a land price that capitalizes all expected future rents, including those from conversion to future developed land. This is consistent with Ortiz-Bobea (2020), who found that non-farm influences like population and income have no effect on agricultural cash rents.

*Econometric specification in land-use change models*

The econometric land-use models estimate the probability of conversion between different choices in the land-use choice set. Our choice set includes the major broad land-uses of forest, crop, pasture, range, and development. The choice set differs by county and is determined by the observed choices made during the study period, e.g. there is no range land in the northeastern U.S. therefore range is not a choice in those counties. Following prior econometric studies using NRI data (Lubowski et al. 2006; Lewis and Plantinga 2007), we separately estimate four different land-use change models by starting use, creating separate models for land starting in forest, crop, pasture, and range. Since almost no land leaves developed use, we do not model land-use change for existing developed land and instead assume all developed land remains developed with probability of one. Development is a potential land-use choice in all four land-use change models. The key independent variable is a net return to land measure, $NR_{ckt}$, that varies by county *c*, land use *k*, and time *t*. The net return variable is a rolling average of the five years preceding each land-use transition period.

By including a set of use-$k$ fixed effects in the land-use change model that are specific to region *R* that contains plot *I*, $\mu_{R(i)k}$, we effectively shift the model's alternative specific constants in a way that captures regional unobservables (e.g. regulations) that influence the choice of use *k*. For the crop and pasture starting uses, we define region to represent state fixed effects separately for each possible land-use choice, creating a total of 192 separate fixed effects (crop is the omitted use). Given this large number fixed effects, we use the BLP contraction mapping approach (Berry et al. 1994) to numerically account for the fixed effects in the non-linear logit framework. For the model based on forest starting use, we have a coarser fixed effect structure and simply include a dummy variable indicating whether the forest is located in one of four U.S. regions (northeast, southeast, rocky mountain, and pacific coast) in order to capture the structural difference in forest type composition and distribution. One final specification choice is that we omit the forest net returns variable, $NR_{c(i)kt}$, for *k*=forest from the model with range as a starting use due to lack of variation in observed range-to-forest transitions.

Our econometric model is based on all observed land-use changes during the 2000-2012 time-period, and so our estimates implicitly embed the land-use change process that occurred during this period. For example, urban economics has long argued that urban expansion is driven by growth in population and income, as well as commuting costs (Brueckner 2000; Nechyba and Walsh 2004). Therefore, since maximum likelihood estimation of Eq. (2) guarantees that the estimated land-use model can reproduce the sample land-use shares (Train 2009 Ch. 3), then our estimates embed factors that influenced development patterns from 2000-2012, such as commuting costs, population and income growth rates that occurred during this time period. In addition, our estimates will embed the recent reduction in U.S. development rates that occurred between the last two decades of the 20th century and the first fifteen years of the 21st century (Bigelow et al. 2022).

*Landscape simulation approach*

We simulate changes in broad land-uses across the conterminous U.S. to the year 2070 under the range of climate scenarios presented in Fig. 1A. According to our model, the estimated probability that each plot *i* transitions from use *k* to use *l* in time *t* is defined by:

$$P_{iklt} = F\left[\boldsymbol{NR}_{\boldsymbol{c(i)t}}(X_{ct}, Climate_{ct}; \hat{\boldsymbol{\gamma}}), LCC_i;\ \widehat{\boldsymbol{\beta}_{\boldsymbol{k}}}, \hat{\boldsymbol{\mu}}_{\boldsymbol{R(i)k}}\right] \tag{8}$$

Where F[] is the logistic function and $\boldsymbol{NR}_{\boldsymbol{c(i)t}}$ is the vector of all the time *t* net return variables in county *c* that contains plot *i* . The Ricardian functions for $\boldsymbol{NR}_{\boldsymbol{c(i)t}}$ are embedded into the logistic probability function in Eq. (8), which defines the functional relationship between the land-use transition probabilities and the full set of climate variables $Climate_{ct}$. The climate change scenarios alter the land-use transition probabilities by altering $Climate_{ct}$ in each future period *t*, which then alters $\boldsymbol{NR_{c(i)t}}$ through the estimated Ricardian functions and parameter vector $\widehat{\boldsymbol{\gamma}}$. The estimated logit land-use change functions and parameter vectors $(\widehat{\boldsymbol{\beta}_k}, \widehat{\boldsymbol{\mu}}_{\boldsymbol{R(i)k}})$ then translate the resulting climate changes into the land-use transition probabilities. Each set of transition probabilities is defined by starting land-use *k*, county *c*, and the land capability class rating of plot *i* ($LCC_i$).

We use the Krinsky-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 ($\widehat{\boldsymbol{\gamma}}$) and logit parameter vectors ($\widehat{\boldsymbol{\beta}_k}, \widehat{\boldsymbol{\mu}}_{\boldsymbol{R(i)k}}$). 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 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.

An assumption in our simulation is that the price of land in the different land uses will change over time according to the estimated Ricardian functions in Eq. (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 they find that "crop prices are expected to be at roughly the same level in 2050 as in 2006" (p. 439). Projections of future timber prices under climate change have received less attention, but Sohngen and Tian's (2016) numerical study finds that climate change will lower timber prices by a modest 15% relative to a non-climate 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 deal changes 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 U.S., 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. We leave a study of scenarios with commodity price changes for future research.

## Results

### Ricardian functions

The Ricardian function for each of the three land-uses (crop, forest, developed) is estimated using cross-sectional OLS, weighted by each county's acreage in that particular land-use. Full parameter estimates are presented in Tables S1 – S3. In the crop Ricardian (Table S1), 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 S2) and development Ricardian (Table S3) 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. Supplementary Fig. S1 presents projected paths for each scenario. Temperature increases range from just over 1℃ to 3℃ across the scenarios, while annual precipitation ranges from -3.4% to +7.4% (Fig. 1A). Fig. 1B-1D presents the time path for the average net return for each land-use using mean climate change, along with 95% confidence intervals. Average crop returns (Fig. 1B) and forest returns (Fig. 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 (Fig. S1). In contrast, development returns (Fig. 1D) have a declining time path for all scenarios, with a mean decrease of 32%. As seen in Fig. S1, there is variation in the magnitude of the Ricardian functions across climate 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's (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 U.S. 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 Fig. 1 and Fig. S1 present average national net returns, there is substantial variation in projected net return paths across counties.

Land-use change functions

Parameter estimates from the land-use change equations for each of the four starting land-uses are presented in Table 2. All estimates are derived from 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 land capability class (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 the NRI (e.g. Lubowski et al. 2006; Lewis and Plantinga 2007).

Landscape simulations under climate change scenarios

Mean net land-use change projections for the conterminous U.S. are presented in Table 3 along with 95% confidence intervals in parentheses. Net land-use change projections are simulated across the eight climate change scenarios comprised of GCM-RCP combinations visually depicted in Fig. 1A.

The key finding of our simulations (Table 3) is that developed land is projected to increase on net by around 46 million acres by 2070 (~0.82 million acres per year), while all other uses are projected to experience net declines. As expected, our projected future developed land-use growth rates of 0.82 million acres per year is similar to the average rate from the 2000-2012 period used for estimation (0.93 million acres per year), and much lower than the approximate 1.5 million acres per year from 1982-1997 that was used in previous national land-use projections (Lubowski et al. 2006; Lawler et al. 2014).[6] When compared to the historical developed land-use change 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 i) the projected decrease in developed net returns that arise from climate changes in temperature and precipitation (Fig. 1D) and ii) the modest projected increase in timber and crop net returns that arise from climate change (Fig. 1B and 1C). Approximately 62% of newly developed acres occur in counties currently designated as non-metropolitan[7], and nearly half (46%) of that development expansion is projected to occur in the Southern region of the U.S.

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 crop land is most sensitive to the different 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 Fig 1. Note however that the 95% confidence intervals overlap across all scenarios for

[6] Using 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%.

[7] The Rural-Urban Continuum system developed by USDA Economic Research Service classifies metro and non-metro U.S. counties. Non-metro counties are defined as having a population less than 250,000 and not containing a metro area.

the crop land projections. The projected changes in forest and developed land have much smaller variation across the eight climate scenarios.

Fig. 3 presents Krinsky-Robb distributions for the projected changes in forest, crop, and developed land. The first column in Fig. 3 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 in Fig. 3 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.

<u>Robustness to including shared socio-economic pathways (SSPs)</u>

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 socio-economic 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 Shared Socio-Economic Pathways (SSP) projections for population and income for counties in the conterminous U.S. (Wear and 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 (Eq. 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 up to the year 2070. As seen in Supplementary Fig. 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 Fig. 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 (Supplementary Table S4). However, the relative effect of the *Climate* variables from Eq. (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 3 to the corresponding net land-use changes from the SSP scenarios in Table S4, the two sets of projections have a correlation coefficient of 0.998. So, incorporating the SSP scenarios changes the level of land-use change, but not the pattern of changes in response to climate. 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.

**Conclusion**

The purpose of this paper is to generate empirically-based projections of broad land-use changes for the conterminous U.S. across multiple climate change scenarios. Climate econometrics research has estimated how climate affects farm land values (Mendelsohn et al. 1994; Schlenker et al. 2006; Massetti et al. 2016), agricultural rents (Ortiz-Bobea 2020), forestry returns (Mihiar and Lewis 2021), and urban quality of life (Albouy et al. 2016). Econometric land-use research has estimated how net returns to land affect discrete changes across broad land-uses (Bockstael 1996; Lubowski et al. 2008; Wrenn et al. 2017; Bigelow et al. 2017). We contribute to this literature by developing 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 land-use change model with climate adaptation provides the basis for a land-use projection 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.

We project broad land-use changes as a function of eight climate change scenarios that consist of four different global climate models (GCMs) and two different representative concentration pathways (RCPs). These eight climate change scenarios give us variation in warming (+1 to +3C) and precipitation (-4% to +7.5%). These climate change scenarios generate spatially-heterogeneous time paths of temperature and precipitation changes across a landscape that itself is spatially-heterogeneous in both starting land-use distributions and net returns to alternative uses. 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 continue growing at a rate of approximately 0.82 million acres per year 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. In a robustness check that examines incorporating alternative population and income growth scenarios from shared socio-economic pathways (SSPs), we find that the SSP scenarios raise the amount of land converted into developed uses and lower the amount of land that remains in all other land uses, though the relative effect of climate on the different land-uses remains the same whether we include SSP scenarios or not.

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 (Sohngen and Mendelsohn 1998; Sohngen and Tian 2016). Second, our cross-sectional Ricardian functions may be subject to the common criticism that such models are sensitive to omitted variables (Blanc and 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. In particular, we do not incorporate uncertainty that arises from downscaling the climate change projections, or uncertainty embedded within each of the four global climate models.

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 commodity prices (e.g. crops, timber, etc.). However, we can speculate as to how incorporating endogenous commodity prices would alter the land-use change projections. Since all our projections result in net losses in timber and agricultural lands, it is possible that reductions in supply of timber and agricultural commodities may occur. If land-use change leads to such supply reductions, then it would be reasonable to expect corresponding price increases for timber and agricultural commodities that would increase the net returns to forest and crop lands. Since our results show that higher net returns in a particular land use raise the probability of choosing that use, then endogenizing timber and agricultural commodities should reduce the amount of land that is converted out of timber and agricultural uses and our current results would overstate forest and agricultural land losses. However, a full consideration of changing commodity prices would be complicated by other factors that might lower commodity prices over time, such as technology-induced crop yield increases (Hertel et al. 2016) and timber productivity increases resulting from carbon fertilization (Davis et al. 2022). A future research advance could integrate the land-use change model here with scenarios from market models of commodity prices under climate change.

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 non-market 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 and 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 U.S. 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 (Lewis and Polasky 2018; Augustynczik et al. 2020). We view our results as providing foundational evidence of how an underlying baseline landscape change process in the U.S. is affected by alternative climate change scenarios.

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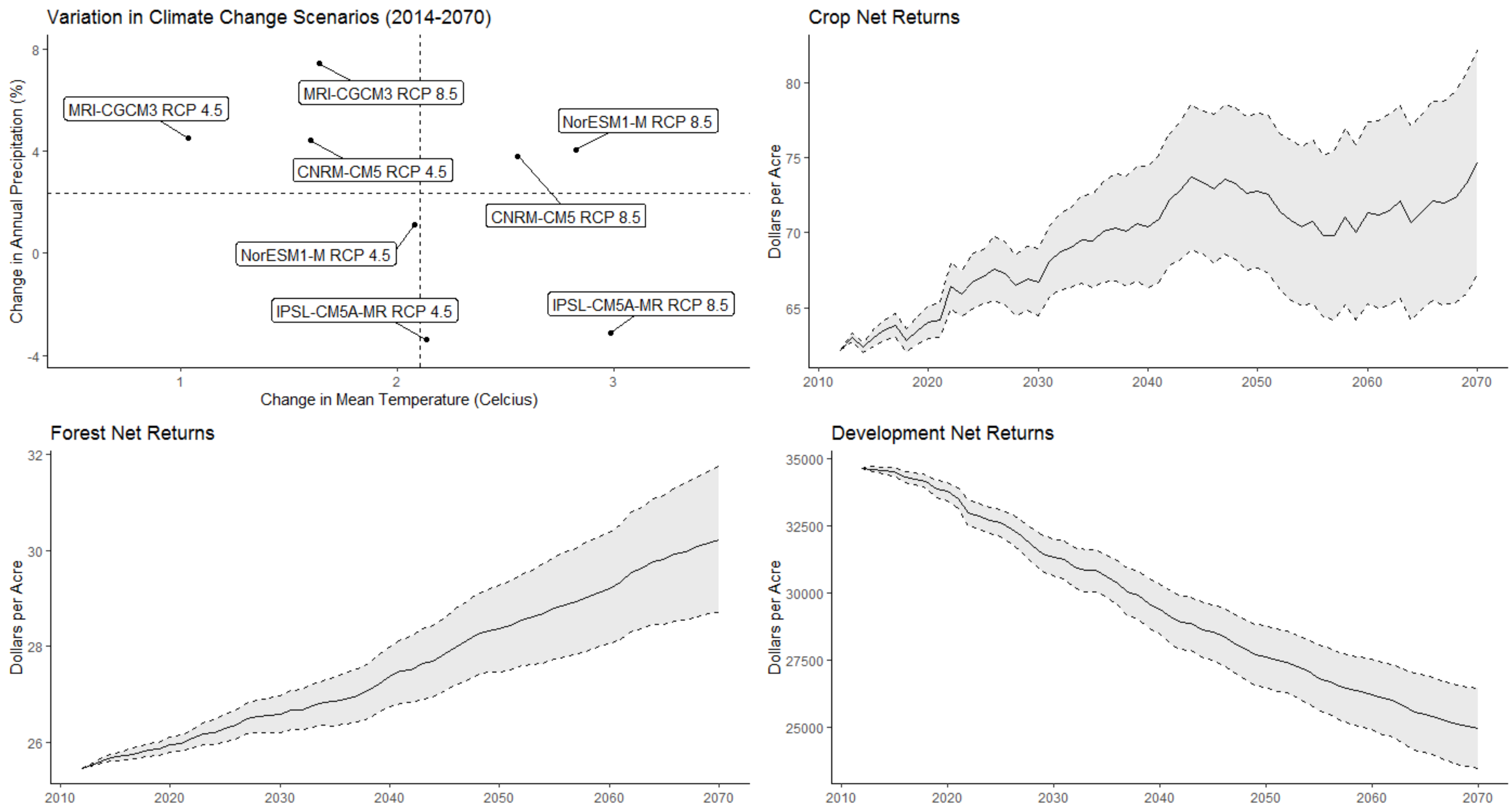
## Tables and Figures

Figure 1: Projected Net Returns Using the Mean Climate Projection Through 2070 with Krinsky-Robb Confidence Bounds




Notes: 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. Panel (b-d) plot projected net returns using mean change in temperature and precipitation.

Table 1: Observed Gross Land-use Change (2000-2012) in thousands of acres

| | End in Forest | End in Developed | End in Crop | End in Pasture | End in Range | Total in 2000 |
|---|---|---|---|---|---|---|
| **Start in Forest** | 402,376<br>98.03% | 4,957<br>1.21% | 455<br>0.11% | 1,998<br>0.49% | 682<br>0.17% | 410,468<br>100% |
| **Start in Developed** | 200<br>0.25% | 79,407<br>99.51% | 103<br>0.13% | 58<br>0.07% | 32<br>0.04% | 79,841<br>100% |
| **Start in Crop** | 1,628<br>0.44% | 2,712<br>0.74% | 343,655<br>93.75% | 17,171<br>4.68% | 1,383<br>0.38% | 366,549<br>100% |
| **Start in Pasture** | 5,938<br>5.10% | 1,773<br>1.52% | 9,811<br>8.43% | 97,044<br>83.36% | 1,856<br>1.59% | 116,442<br>100% |
| **Start in Range** | 732<br>0.18% | 1,735<br>0.43% | 1,527<br>0.38% | 505<br>0.12% | 400,074<br>98.89% | 404,573<br>100% |
| **Total in 2012** | 410,674<br>(+406) | 91,018<br>(+10,784) | 355,448<br>(-10,998) | 116,718<br>(+354) | 403,995<br>(-546) | 1,377,583 |

Note: Observed land-use transitions on non-Federal lands in the conterminous U.S. obtained from the National Resources Inventory (NRI) survey conducted by U.S. Department of Agriculture's Natural Resources Conservation Service.

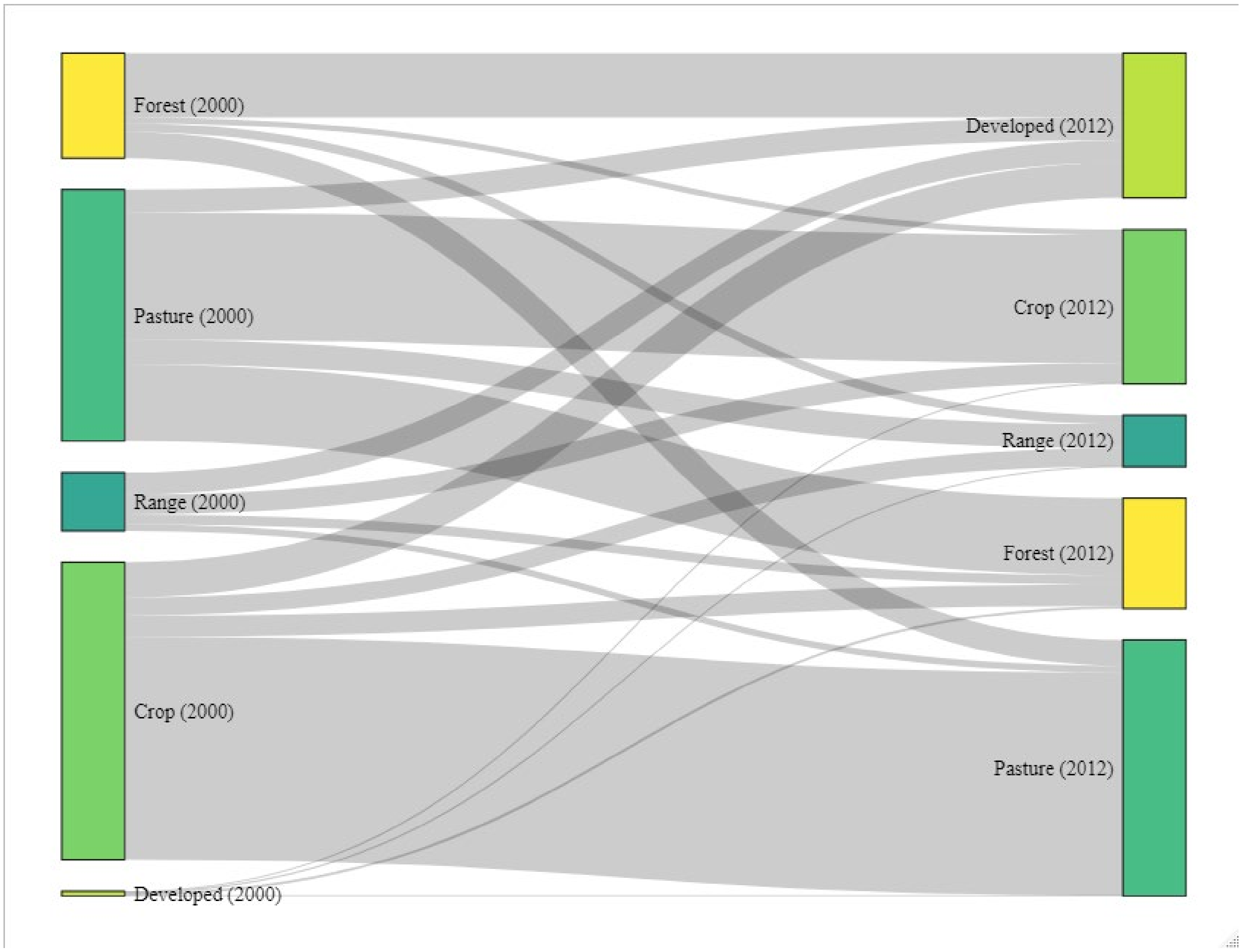
Table 2: Logit Parameter Estimates for Land-use Choice Models

| | **Starting Land-Use** | | | |
|---|---|---|---|---|
| | **Starts in Crop** | **Starts in Pasture** | **Starts in Forest** | **Starts in Range** |
| **Crop Net Return in $1,000s (Crop Choice)** | 2.593***<br>(0.1610) | 2.197***<br>(0.1213) | 2.263***<br>(0.5928) | 5.973***<br>(0.4399) |
| **Forest Net Return in $1,000s (Forest Choice)** | 0.217**<br>(0.0916) | 0.336***<br>(0.02724) | 0.0812***<br>(0.5928) | - |
| **Development Net Return in $10,000s (Developed Choice)** | 0.103***<br>(0.0141) | 0.113***<br>(0.01082) | 0.0867***<br>(0.01015) | 0.107***<br>(0.01155) |
| **LCC (Pasture Choice)** | 0.263***<br>(0.00827) | 0.392***<br>(0.009275) | 0.0637**<br>(0.03838) | -1.819***<br>(0.1600) |
| **LCC (Forest Choice)** | 0.086**<br>(0.0506) | 0.509***<br>(0.01490) | 0.5024***<br>(0.03233) | -0.00896<br>(0.05030) |
| **LCC (Rangeland Choice)** | 0.438***<br>(0.0284) | 1.116***<br>(0.009982) | 0.4129***<br>(0.05587) | 0.236***<br>(0.0390) |
| **LCC (Developed Choice)** | -0.0683**<br>(0.02735) | 0.379***<br>(0.02559) | 0.282***<br>(0.03462) | 0.193***<br>(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** | 63723.76 | 63814.85 | 26885.72 | 8972.08 |

Table 3: Projected Net Land-use Change (2014-2070) in millions of acres

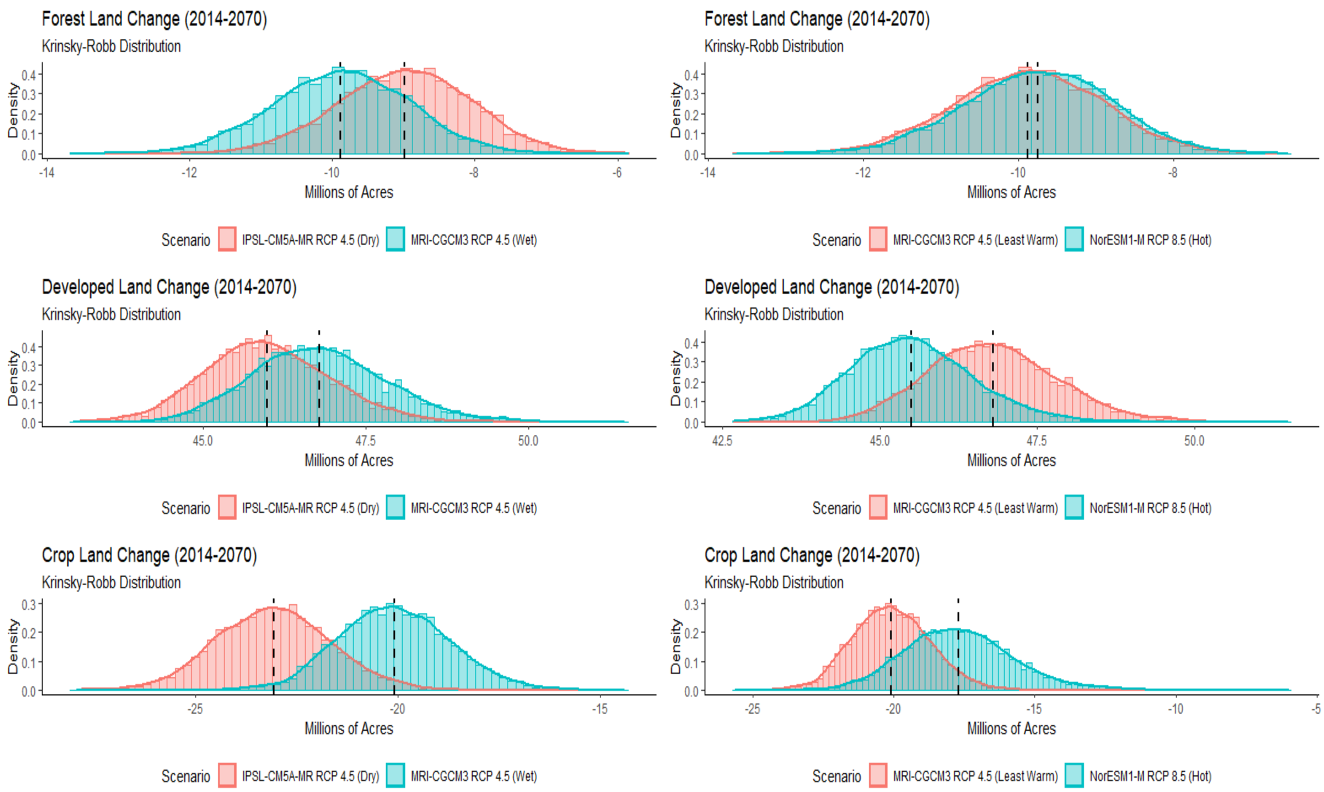
| | ***MRI-CGCM3*** | | ***IPSL-CM5A-MR*** | | ***CNRM-CM3*** | | ***NorESM1-M*** | |
|---|---|---|---|---|---|---|---|---|
| | **RCP 4.5** | **RCP 8.5** | **RCP 4.5** | **RCP 8.5** | **RCP 4.5** | **RCP 8.5** | **RCP 4.5** | **RCP 8.5** |
| ***Developed*** | 46.79 | 46.4 | 45.98 | 46.16 | 46.47 | 45.85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

Figure 2: Observed Land-use Transitions for the Conterminous United States (2000-2012)




Note: This network flow diagram shows land that starts in one land-use in 2000 and moves to an alternative land-use in 2012.

Figure 3: Krinsky-Robb Distribution of Selected Landscape Outcomes



## Supplemental Tables and Figures

Table S1: Parameter Estimates for Crop Ricardian

| | **Crop Net Return** |
|---|---|
| **Winter Temperature** | 1.136<br>(2.662) |
| **Winter Temp Squared** | 0.518***<br>(0.143) |
| **Spring Temperature** | 47.267***<br>(6.641) |
| **Spring Temp Squared** | -2.660***<br>(0.269) |
| **Summer Temperature** | 12.851<br>(11.997) |
| **Summer Temp Squared** | -0.473*<br>(0.271) |
| **Fall Temperature** | -35.366***<br>(10.246) |
| **Fall Temp Squared** | 2.553***<br>(0.439) |
| **Winter Precipitation** | 0.346***<br>(0.048) |
| **Winter Precip Squared** | -0.0004***<br>(0.0001) |
| **Spring Precipitation** | -0.199<br>(0.134) |
| **Spring Precip Squared** | 0.001***<br>(0.0002) |
| **Summer Precipitation** | -0.826***<br>(0.154) |
| **Summer Precip Squared** | 0.001<br>(0.001) |
| **Fall Precipitation** | 0.397***<br>(0.172) |
| **Fall Precip Squared** | 0.001***<br>(0.0002) |
| **Winter Temp x Precip** | *0.008*<br>*(0.005)* |
| **Spring Temp x Precip** | *-0.019***<br>*(0.009)* |
| **Summer Temp x Precip** | *0.032****<br>*(0.008)* |
| **Fall Temp x Precip** | *-0.058****<br>*(0.009)* |
| **County Proportion in LCC 1** | *240.314****<br>*(25.669)* |
| **County Proportion in LCC 2** | *32.437**** |

| | |
|---|---|
| | *(10.762)* |
| **County Proportion in LCC 3** | *14.812*<br>*(11.498)* |
| **County Proportion in LCC 4** | *-19.401*<br>*(13.930)* |
| **County Proportion in LCC 5** | *128.080****<br>*(28.912)* |
| **County Proportion in LCC 6** | *-19.456***<br>*(11.754)* |
| **County Proportion in LCC 7** | *-41.014****<br>*(11.313)* |
| **Constant** | *-81.950*<br>*(96.809)* |
| | |
| **Observations** | 3,070 |
| **Adjusted R-squared** | 0.337 |
| **Residual SE** | 62.547 (df = 3042) |
| **F Statistic** | 58.753*** (df = 27; 3042) |
| | **p<0.1;* ****p<0.05;** ***p<0.01 |

| Table S2: Parameter Estimates for Forest Ricardian | |
|---|---|
| | **Forest Net Return** |
| **Mean Temperature** | 17.123***<br>(4.011) |
| **2nd Order Temp** | -2.875***<br>(0.543) |
| **3rd Order Temp** | 0.207***<br>(0.030) |
| **4th Order Temp** | -0.005***<br>(0.001) |
| **Annual Precipitation** | 0.151***<br>(0.058) |
| **2nd Order Precip** | -1.996e-04***<br>(6.628e-05) |
| **3rd Order Precip** | 1.096e-07***<br>(2.997e-08) |
| **4th Order Precip** | -1.842e-11***<br>(4.721e-12) |
| **Temp-Precip Interaction** | -0.002***<br>(0.001) |
| **Constant** | -59.905***<br>(20.406) |
| | |
| **Observations** | 2,442 |
| **Adjusted R-squared** | 0.374 |
| **Residual SE** | 8598 (df = 2431) |
| **F Statistic** | 146.8*** (df = 10; 2431) |
| | **p<0.1;* ****p<0.05;** ***p<0.01 |

| Table S3: Parameter Estimates for Development Ricardian | |
|---|---|
| | **Development Net Return** |
| **Heating Degree Days (HDD)** | -83.118***<br>(5.067) |
| **HDD Squared** | 0.005***<br>(0.001) |
| **Cooling Degree Days (CDD)** | -199.232***<br>(8.428) |
| **CDD Squared** | 0.030***<br>(0.003) |
| **Annual Precipitation** | -154.521***<br>(16.685) |
| **Precip Squared** | 0.026***<br>(0.003) |
| **HDD x Precip** | 0.021***<br>(0.003) |
| **CDD x Precip** | 0.043***<br>(0.007) |
| | |
| **Population Density** | 2.077***<br>(0.352) |
| **Median Household Income** | 1.274***<br>(0.120) |
| **Black Share of Population** | 4630.074<br>(4288.274) |
| **Hispanic Share of Population** | 21549.930***<br>(6395.196) |
| **Share of Population with High School Education** | -369.457**<br>(148.465) |
| **Some College** | 1894.851***<br>(153.170) |
| **Associate degree** | 191.326<br>(244.882) |
| **Bachelor's Degree** | 443.895**<br>(186.117) |
| **Graduate Degree** | -471.710*<br>(246.183) |
| **Constant** | *312735.400****<br>*(18480.760)* |
| | |
| **Observations** | 3,089 |
| **Adjusted R-squared** | 0.528 |
| **Residual SE** | 25292.360 (df = 3071) |
| **F Statistic** | 204.417*** (df = 17; 3071) |
| | *p<0.1; **p<0.05; ***p<0.01 |

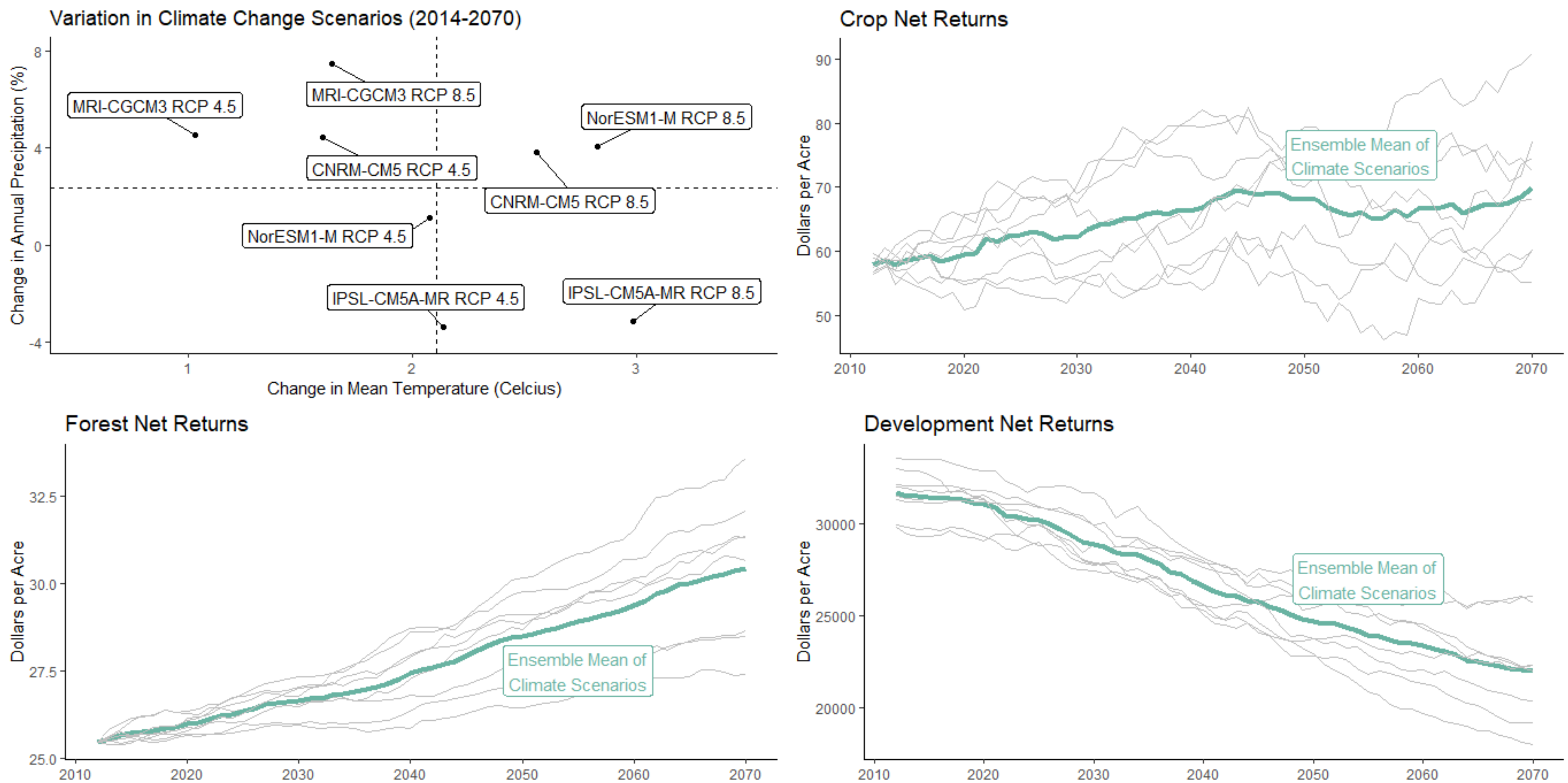
Table S4: Alternative Projected Net Land-use Change (2014-2070) in millions of acres with SSP Scenarios

| | *MRI-CGCM3* | | *IPSL-CM5A-MR* | | *CNRM-CM3* | | *NorESM1-M* | |
|---|---|---|---|---|---|---|---|---|
| | **RCP 4.5 - SSP1** | **RCP 8.5 - SSP2** | **RCP 4.5 - SSP1** | **RCP 8.5 - SSP2** | **RCP 4.5 - SSP1** | **RCP 8.5 - SSP2** | **RCP 4.5 - SSP1** | **RCP 8.5 - SSP2** |
| ***Developed*** | 60.05 | 57.84 | 58.46 | 56.51 | 60.44 | 58.21 | 58.19 | 55.81 |
| | (54.65, 65.68) | (53.03, 63.31) | (53.19, 63.82) | (51.75, 61.83) | (54.90, 66.20) | (53.42, 63.31) | (53.50, 63.56) | (51.22, 60.93) |
| ***Forest*** | -14.9 | -14.37 | -13.74 | -13.61 | -14.64 | -13.81 | -14.28 | -13.79 |
| | (-18.31, -11.82) | (-17.31, -11.46) | (-16.60, -11.05) | (-16.50, -10.88) | (-17.97, -11.32) | (-16.75, -10.92) | (-17.39, -11.32) | (-16.64, -10.99) |
| ***Crop*** | -23.81 | -21.23 | -26.4 | -21.33 | -27.82 | -26.27 | -21.38 | -20.43 |
| | (-29.12, -19.06) | (-26.45, -15.46) | (-31.54, -21.49) | (-26.90, -15.86) | (-33.09, -22.77) | (-31.23, -21.40) | (-26.76, -16.50) | (-25.81, -14.58) |
| ***Pasture*** | -12.39 | -12.98 | -9.42 | -11.74 | -9.74 | -9.82 | -12.76 | -12.09 |
| | (-16.05, -8.69) | (-16.79, -9.23) | (-13.21, -5.52) | (-16.02, -7.84) | (-13.69, -5.77) | (-13.96, -5.94) | (-16.54, -8.98) | (-16.03, -8.47) |
| ***Range*** | -8.96 | -9.25 | -8.9 | -9.83 | -8.25 | -8.31 | -9.78 | -9.48 |
| | (-11.47, -6.55) | (-12.42, -6.69) | (-11.23, -6.54) | (-12.53, -7.41) | (-10.65, -6.15) | (-10.72, -6.23) | (-12.64, -7.27) | (-12.65, -6.96) |

Table S5: Projected Net Land-use Change (2014-2070) in Percent Change from 2012 Baseline

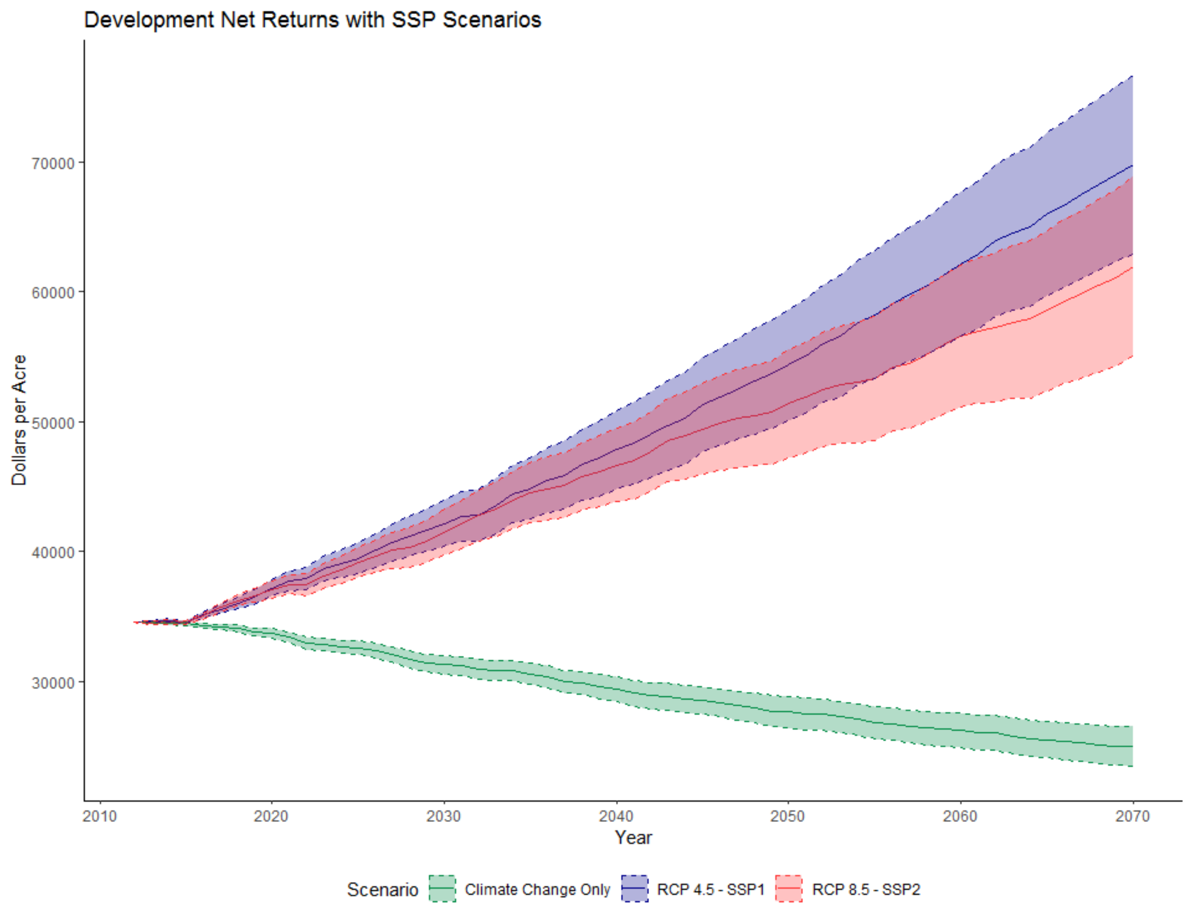
| | *MRI-CGCM3* | | *IPSL-CM5A-MR* | | *CNRM-CM3* | | *NorESM1-M* | |
|---|---|---|---|---|---|---|---|---|
| | **RCP 4.5** | **RCP 8.5** | **RCP 4.5** | **RCP 8.5** | **RCP 4.5** | **RCP 8.5** | **RCP 4.5** | **RCP 8.5** |
| ***Developed*** | 51.91% | 51.48% | 51.01% | 51.21% | 51.55% | 50.87% | 51.10% | 50.48% |
| ***Forest*** | -2.40% | -2.40% | -2.19% | -2.35% | -2.29% | -2.25% | -2.37% | -2.37% |
| ***Crop*** | -5.55% | -5.03% | -6.37% | -5.12% | -6.58% | -6.27% | -5.00% | -4.88% |
| ***Pasture*** | -8.62% | -9.36% | -6.22% | -8.54% | -6.18% | -6.57% | -9.10% | -8.90% |
| ***Range*** | -1.59% | -1.74% | -1.59% | -1.89% | -1.42% | -1.48% | -1.79% | -1.81% |

Figure S1: Projected Net Returns Across Eight Alternative Climate Scenarios




Note: Panel (a) shows mean climate change across all eight scenarios with dashed horizontal and vertical lines. Net returns are projected into the future using mean change in temperature and precipitation.

Figure S2: Alternative Projections of Development Net Returns




Note: Projected time path of US average developed net returns under i) mean for all GCMs (Climate Change Only), ii) shared socio-economic pathway 1 with mean projections for RCP 4.5 (RCP 4.5 – SSP1), and iii) shared socio-economic pathway 2 with mean projections for RCP 8.5 (RCP 8.5 – SSP2). 95% confidence intervals presented.