An Econometric Analysis of the Impact of Climate Change on Broad Land-Use Change in the Conterminous United States

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Abstract

Climate change affects the choice of land-use not only through its direct effect on the productive potential of land, but also through human actions that alter the landscape. In this study, we estimate current climate's effect on the economic net returns to alternative land-use systems in the conterminous United States. Then we model the conversion between these alternative uses to analyze how future climate change may alter future landscapes. This research contributes to the general knowledge of natural resource and environmental economics by i) conducting the first study to model broad land-use change as an explicit function of climate variables for the conterminous U.S., and iii) constructing a novel and flexible framework for analyzing alternative future climate and demographic scenarios and their effect on land-use change. We model climate's impact on the economic net returns to four major U.S. land-use systems: crop, pasture, forest, and urban. Each climate model is specified separately to capture the distinct ways that climate drives land rents. The climate models are used to predict the impact of climate change on the profitability of the alternative land-uses. Predicted climate change impacts on land rent are the inputs to a discrete choice logit model, facilitating estimation of transition probabilities for land starting in crop, pasture, and forest. A functional relationship is established between climate and the probability of land-use change. Although climate change increases the amount of forest land, the magnitude of impact is small relative to non-climatic drivers of land-use change. The models constructed here have the potential to test numerous climate change scenarios with significant implications for land-use policy.

JEL classification: Q23, Q51, Q54, Q57
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1. Introduction

Climate change presents many research challenges to environmental and resource economists, including the problem of how to estimate the economic value of the numerous costs and benefits arising from a changing climate. The past two decades has seen an increasing number of empirical studies analyzing the effects of climate on various types of economic activity, including agricultural production [47, 48], labor allocation [17], war [26], and electricity demand [4]. Within the recent strand of empirical studies on human-climate linkages is the Ricardian method that is commonly used to estimate the effects of climate on agricultural land values using cross-sectional data on agricultural net returns and climate [36, 37, 47]. Ricardian analyses suggest that current climate change projections will generate a range of impacts on agricultural land values, from costly declines in low latitudes of the globe to potential gains in higher latitudes. The key advantage of Ricardian analyses is that they implicitly account for privately optimal adaptation to climate, by empirically relating a regions climate to the land-use specific economic net returns that arise from private management decisions under that climate.

Climate affects economic outcomes in two ways [25]. First, climate has a direct effect on economic outcomes by affecting the biophysical conditions that humans face. For example, warmer winters can increase growth of a forest landowners trees by extending the growing season. Second, climate has a belief effect on economic outcomes by influencing people's decisions through adaptive measures. For example, a forestland owner located in the inter-mountain western United States plants ponderosa pine trees because the landowner believes ponderosa will be more profitable than Douglas-fir trees given the region's dry climate and cold winters, or the landowner could leave forest use entirely in favor of an alternative land system such as rangeland. Both direct and belief effects are important when analyzing the effects of climate on economic outcomes. The framework developed in this paper allows analysis of climate impacts on land-use in a manner that accounts for both the direct and belief effects of climate.

This paper fills a gap in the literature between climate's impact within single systems and the drivers of land-use change across broad systems. A limitation of the Ricardian approach is that potential adaptations are restricted by the choice of economic outcome to measure. Recent results for climate's impact on agriculture indicate climate change will have significant negative impacts on agriculture, with little evidence of adaptation [9]. A possible explanation for the lack of predicted adaptation may be the omission of adaptations out of agriculture into substitute land systems such as forestry or urban use. In order to encompass the full range of climate change adaptation across and within each broad land-use system I develop a discrete choice model where separately estimated Ricardian functions drive land-use change incentives under alternate climate change scenarios.

The model developed and executed here is the first discrete choice land-use model that predicts the probability of broad land-use change as an explicit function of climate. A major strand of the literature on land-use and climate is concerned with how land-use change alters local climate [42], species habitat [32], and species diversity [28]. Feddema et al [13] demonstrate how changes in agricultural land cover alter the results of climate change simulations. Kalnay & Cai [29] estimate the impact of urbanization on near surface warming, finding a significant influence of land-use change on local climate. My work differs from the aforementioned literature by studying the counter relationship: how climate drives land-use change. To accomplish my objective, I build on a rich literature on the economic and climatic drivers of land-use change. Lawler et al [32] use a discrete choice model to generate projections of future land-use change under alternative crop demand scenarios. Fezzi & Bateman [15, 5] use a spatially explicit structural approach to the economic modeling of agricultural land-use change as determined by economic, policy, and environmental factors, and further consider how the resulting adaptive response further alters environmental impacts [16]. My land-use change model differs by establishing an empirical link between climate and the determinants of land-use choice, and using that relationship to simulate future changes in land cover that result from discrete changes to temperature and precipitation.

Developing a model of climate's impact on land-use change is accomplished by i) estimating the effects of climate on the net returns to alternative land-uses in the manner of the existing Ricardian literature (e.g. [36]) and ii) estimating the effects of net returns to land on observed land-use decisions in the manner of the existing econometric land-use literature (e.g. [35]). This paper is laid out as follows. In section 2, we describe construction of the economic net returns to alternative land-uses that define the broad systems. In section 3, we present the discrete choice modeling framework used to predict land-use transitions for land starting in crop, pasture, range, and forest use. The analysis accounts for conversion to crops, pasture, range, forest, and urban use. These four systems define the major land-uses in the U.S. and are parameterized by climate in section 4 using the Ricardian framework. Finally, these frameworks are integrated to analyze the impact of climate change on land-use change probability and the future landscape.

2. The Economic Net Return to Alternative Land-uses

The land-use model developed and estimated here relies on the economic incentives that drive land-use management decisions. We assume that the suite of choices faced by landowners is revealed by the current choices observed across the landscape, and the resulting spatial distribution of the economic net return to land. This section describes the development of measures for the economic net return to four broad land-use systems: forest, crop, pasture, and urban. A strength of this economic approach is that the drivers of land-use change are measured in a common unit, annualized dollars per acre of land, allowing comparison of value across systems.

2.1 Forest Net Return

This analysis features a novel construction of current county-level annualized net economic returns to forestland for the conterminous U.S., which comprises the primary dependent variable in the forest Ricardian function. Classical forest economics posits that forest land values depend on timber growth, stumpage prices, a discount rate, and the rotation period with which harvests occur [12]. In contrast to agriculture, forestry rotations occur over decades rather than annually requiring a novel approach to forest net return construction. The aim is to construct a measure of the current annual profitability of U.S. timberland at the county-level. Development of land rents builds from the strategy in [34] by constructing annualized county-level net returns to forestry. Relative to [34], the present approach captures far greater spatial and species heterogeneity in timber yields, and avoids imposing belief effects about future climate by using empirically-derived rotation lengths from the FIA data rather than basing rotation lengths on Faustmann optimized cut periods.

We rely on a model of rotational forestry consisting of periodic harvests with subsequent replanting. The landowner only earns profit at harvest, and the landowners value function can be written in dynamic programming form as follows [20]:

$$V_t(a, s, C_t) = max \begin{cases} P(s,t) \cdot vol^s(a, C_t) - R + \rho V_{t+1}(1, s_1, C_{t+1}) \\ P(s,t) \cdot vol^s(a, C_t) - R + \rho V_{t+1}(1, s_2, C_{t+1}) \\ \vdots \\ P(s,t) \cdot vol^s(a, C_t) - R + \rho V_{t+1}(1, s_S, C_{t+1}) \\ \rho V_{t+1}(a+1, s, C_{t+1}) \end{cases}$$

Where $P(s,t)$ is the stumpage price of species *s* at time *t*, $vol^s(a, C_t)$ is the species *s* timber volume of age *a* trees growing in climate conditions C_t, R is a replanting cost, and ρ is a discount factor. At each point in time *t*, the landowner chooses whether to harvest and earn a one-time profit of $P(s,t) \cdot vol^s(a, C_t) - R$, with subsequent replanting optimized over the choice of which tree species s_j to plant. If the landowner chooses not to harvest, then their trees grow by $vol^s(a+1, C_{t+1}) - vol^s(a, C_t)$ over the next period. Indexing the climate conditions variable by *t* accounts for the fact that climate may change across time. The optimized land value function $V_t(a, s)$ can be used to construct an annualized net return (rental value) of forestland as$NR = V_t(a, s) \cdot \delta$, where δ is the discount rate embedded in ρ.

Past natural science literature has shown examples of how climate affects the tree growth functions for selected species and regions, $vol^s(a, C_t)$ (e.g. Latta et al. 2010; Rehfeldt et al. 2014). Given the substantial climate variability across the contiguous U.S., we want tree growth functions that differ across fine spatial scales to capture fine-scale climate differences. We estimate approximately 59,000 county-species specific timber growth equations[2] at the forest type and species group level using a permutation of von Bertalanffy's function for organic growth (von Bertalanffy 1938).

[2]We estimate 58,626 growth equations from observations on public and private forestland. Since the current research is focused on private landowner's profit objective, we use the 27,889 county-species pairs for which private forestland is observed.

$$vol_i^s(a) = \alpha_{is}(1 - e^{-\beta_{is}a})^3$$

Where a is average stand age, and α_{is} and β_{is} are parameters to be estimated which vary across county i and forest species group s. von Bertalanffy growth functions have been used extensively in natural resource sciences and apply generally to any organic life. For example, Van Deusen and Heath (2016) use von Bertalanffy functions to estimate growth for the measurement of carbon characteristics on U.S. forestland. The growth parameter estimates rely on over 32 million FIA observations of stand age (in years) and growing stock volume (cubic feet per tree). Since (8) is estimated from observed data in recent years, then $vol_i^s(a)$ implicitly embeds the current climate at location i.

With an available price P_{is}, replanting cost R_i, and estimated volume functions $vol_i^s(a)$ for each county (i) –species (s) pair, we need a harvest age (i.e. rotation length) to be able to determine a one-rotation forestry profit. We focus on one rotation to get a good measure of current profitability of timberland. As noted above, Guo and Costello (2013) and Lubowski et al. (2006) solve for optimal rotation time given an assumed belief effect about future climate. In order to avoid assuming a belief effect, we instead use empirical harvest ages derived from FIA plots that recorded timber harvesting activities. In particular, we use the state average age of all recent harvests of species s to calculate a rotation length T_{is}, and then calculate the present value of a one-rotation profit from harvesting $vol_i^s(T_{is})$ in T_{is} years:

$$[\overline{P_{is}} \cdot vol_i^s(T_{is}) - R_i]\rho^{T_{is}} = PVProfit_{is}$$

Where $\overline{P_{is}}$ is the average stumpage price for forest species s in county i over the period 1997 to 2014, $vol_i^s(T_{is})$ is the estimated von Bertalanffy volume of timber for species s evaluated at age $a = T_{is}$, and R_i and ρ are replanting cost and discount factors as defined previously. Our measure of annualized net returns is the annual payment NR_i^s, in which a landowner would be indifferent to receiving $PVProfit_{is}$ today or a series of annual payments NR_i^s for T_{is} years:

$$NR_i^s(\rho^1 + \rho^2 + \cdots + \rho^{T_{is}}) = PVProfit_{is}$$

Finally, we construct a county average net return NR_i through a species-weighted average:

$$NR_i = \sum_{s=1}^{S_i} NR_i^s \cdot share_i^s$$

Where $share_i^s$ is the share of county *i*'s private timberland in forest species *s*, and S_i is the total number of observed forest species in county *i*. Our approach differs from Lubowski et al.'s (2006) construction of NR_i in that i) our volume functions were disaggregated by county i and species s, as opposed to aggregated functions over broad regions, and ii) we use observed state-average rotation ages T_{is} rather than solving a Faustmann formula with an assumed belief effect. Our final measure of NR_i is comparable across counties and interpreted as the *current* average annual net return to forestry for an acre of bare forestland.

2.2 Urban Net Return

Following the work of Lubowski [35], county-specific proxies are constructed to serve as the net return to urban land. The proxy is derived from the average price per acre of recently developed land. Annualized net returns to urban 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 backed out by subtracting from property value the value of newly constructed single family homes from Survey of Construction (SOC) reports. The SOC also reports the average lot size which is used to generate per acre land price. This per acre land price serves as proxy for net returns.

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, their overlaps with county boundaries vary 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. I 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. This scaling introduced measurement error when the PUMA boundary was large relative to the county boundary. This is particularly acute in the western US because there are large areas of open space with very little population from which to survey households.

2.3 Crop and Pasture Net Returns

The economic net return to crop and pasture 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 time 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. Livestock operations are comprised of ranches, farms, and feedlots whose purpose is to keep and raise animals for the products they yield.

The BEA reports farm income separately for crop and livestock production. However, not all of the farm expense variables are clearly divided between those related to crop and those related to pasture. Therefore, total net farm income for each county is partitioned into two parts: net income deriving from crop production and net income deriving from livestock production. In addition to cash receipts, the total net income measure also includes other income such as government payments, labor expenses, and the value of changes in inventory. Income is included for both sole proprietors and corporate farms.

A crop-livestock ratio is derived using the cash receipts data from crop and livestock operations. This ratio is applied to total net income to yield separate measures for crop and livestock net revenue. All values are converted to per acre measures in 2010 dollars in order to make then comparable across land-use systems (i.e. to match forest and urban net returns).

3. Land-use Model

We employ an econometric model of the revealed preferences of landowners based on detailed micro-data of land-use and land quality spanning five major land-uses. Because the choice of land-use on an individual parcel can be described by a finite discrete set, the conversion decision can be modeled with a discrete choice framework. 8 Land owners are assumed to choose the productive use k that maximizes the net present discounted return to land.

$$R_{inkt} = \int (P_{inkt} * Q_{inkt} - S_{inkt} * Z_{inkt}) e^{-rt} dt$$

Where R is the economic net return to land-use k on parcel i located in county n in time t, P is the output price, Q is the output quantity, S is a vector of input prices, Z is a vector of inputs, and r is the discount rate. Following the land-use conversion framework outlined by [49], we assume land owners have static expectations of conversion costs and future net returns so that land owner's will convert from land-use j to k in time t when the net returns less conversion costs C_{jkt} for use k exceed the net returns from the current land-use j.

$$argmax_k\left(R_{kt} - rC_{jkt}\right) \geq R_{jt}$$

Assuming the factors that determine R are additively separable into observable and unobservable components, we can decompose R into a deterministic portion V_{inkt} and a random portion ϵ_{inkt} so that

$$R_{inkt} = V_{inkt} + \epsilon_{inkt}.$$

And define V_{inkt} linearly as

$$V_{inkt} = \beta_k' X_{inkt}.$$

Where X_{inkt} is a vector of observable characteristics of the land-use k (e.g. net returns, land quality, etc.), and β_k' is a vector of unobserved parameters to be estimated. If we further assume that land-use conversion follows a Markovian process then the probability of conversion between land-uses can be modeled as a function of the parcel's current land-use and exogenous parcel and county level attributes [53]. Then the probability that a land parcel converts from use j to use k in time t is

$$\Pr(\beta_k' X_{inkt} - \beta_j' X_{injt} > \epsilon_{injt} - \epsilon_{inkt}).$$

If the ϵ_{inkt} are assumed to be IID according to a type I extreme value distribution then the probability that land owner i converts from land-use j to k is given by the logit structure where

$$P_{injkt} = \frac{\exp(\beta_j' X_{inkt})}{\sum_{m=1}^{K} \exp(\beta_m' X_{inmt})}.$$

The specification in above embodies the property of Independence of Irrelevant Alternatives (IIA). Specifically, IIA restricts the idiosyncratic error terms (ϵ_{inkt}) to be uncorrelated across choice options for a given land owner.

By substituting net returns parameterized by climate variables and land quality into the above probability function, we define a function P_{injk} that returns the probability of plot i converting from land-use j to k given the economic net returns to alternative land-uses as determined by local climate and land quality.

$$P_{injk} = f(NR^{k_1}(C), NR^{k_2}(C), \dots, NR^{K}(C) | LC \quad _i)$$

The total derivative of P with respect to climate is composed of the sum of the partial effects relative to each land-use assuming that the probability function is evaluated near the current level of net returns, climate, and land quality distribution.

$$dP_{injk} = \frac{\partial f}{\partial N \quad ^{k_1}} \cdot \frac{\partial N \quad ^{k_1}}{\partial C} + \dots + \frac{\partial f}{\partial NR^K} \cdot \frac{\partial NR^K}{\partial C}$$

The total increment of P is derived from a linear approximation of the derivative defined above.

$$\Delta P_{injk} = f(\Delta\, NR^{k_1}, \Delta\, NR^{k_2}, \dots, \Delta\, NR^{K}) - f(NR^{k_1}, NR^{k_2}, \dots, NR^{K})$$

Where $\Delta\, NR^{k_1} = NR^k(\Delta C) - NR^k(C)$ is the difference in net return between the future and present climate levels holding all other net return determinants fixed. The partial increment in probability with respect to use k deriving from climate's impact on the net returns to use j can be stated as:

$$\Delta_{\mathrm{j}} P_{injk} = f\left(\Delta\, NR^{j}, \Delta\, NR^{2}, \ldots, \Delta\, NR^{K}\right) - f(NR^{j}, NR^{2}, \ldots, NR^{K})$$

A set of partial increments (effects) can be calculated for each starting land-use, and represent climate's effect isolated on one land-use system at a time, holding its effect on the other uses fixed. Construction of the probability function ensures that before and after any changes in probability, the sum of the probabilities for each starting use must sum to one, and that the sum of changes to those probabilities must equal zero.

4. Climate Impact Models

The United States comprises many distinct regions with varying demographic and institutional differences. By establishing a functional relationship between climate and the net returns to land, the impacts of potential climate changes can be inferred by the estimated parameters of a statistical model. This section presents Ricardian models of four distinct but related land-uses: crop, pasture, forest, and urban use. The Ricardian approach, regressing local climate on economic returns to land, captures the ability of landowners to adapt to climate variability within the suite of choices unique to the modeled system. In a study by Polsky et. al. [43], a county's ability to adapt was not only influenced by its local climate but also by social factors, their result was revealed by estimating an agricultural Ricardian at multiple spatial scales. For example, the forest Ricardian function captures the ability of forest owners to adapt to climate changes by changing the species planted, intensifying management practices, adjusting rotation length, among many other decisions on their forest land. However, a forest Ricardian does not account for adaptations outside of the forest system such as converting their land to an urban use. A primary goal of this paper is to account for intensive margin adaptations within each land system, then combine the climate functions into a non-linear land-use choice model that captures adaptation across land-use systems.

4.1 Ricardian Analytic Framework

Climate plays a significant role in determining the value of land in each of its potential uses because landowners are assumed to maximize net returns to land given their local climactic conditions. Climate change impacts and the suite of adaptation strategies vary significantly by region and system requiring different econometric treatment for each land-use. Many variables affect land-use decisions including the market return associated with each system. A key driver of these market returns is climate and weather. Where weather describes the current realizations of variables such as temperature or precipitation, and climate describes the distribution of weather over time.

This section formalizes the concept of adaptation and develops the intuition behind our empirical strategy using a forest system as motivation, although the theory applies to any land-use system. Consider an alteration of the Ricardian climate model from the seminal work of Mendelsohn, Nordhaus, and Shaw [36]. Suppose there exists a functional relationship between the net return to land in forest use and a climate variable such as temperature. Consider figure 1, the curve labeled species 1 represents net economic returns as an optimized function over climate, whereby small changes in climate induce the landowner to make small decisions continuously to maximize the return to having the land planted in species 1. We refer to these continuous management decisions as actions on the intensive margin. Intensive margin decisions may include altering the rotation age, thinning out the parcel to encourage growth, or treating the parcel to reduce fire risk, all while continuing to keep the land planted in species 1.

[FIGURE 1 HERE]

In addition to small continuous adaptations, there is a set of discrete management choices that can characterized by a threshold that defines the extensive margin. An important extensive margin choice in forestry is the decision to switch from species 1 to species 2. A key insight from [36] was that regressing land value on climate implicitly captures all continuous and discrete land owner adaptations by tracing out a function akin to the upper envelope of the curves in figure 1. Guo and Costello [20] extend Mendelsohn et. al's setup, and develop an analytic framework for valuing climate change adaptation on the extensive margin. Consider figure 2, where climate begins at C and changes to C'. At C, the landowner optimally replants species 1 and their net return is found at point a. At C', the landowner optimally plants species 2 and their net return is found at point b. If they had remained in species 1 with new climate C', then their net return would have been found at point c. The impact of the discrete change in climate from C to C' in figure 2 is the difference in net returns from point a to point b, and implicitly includes the value of adaptation on the extensive margin. The value of adaptation in figure 2 is the difference between the net returns at point b and the net returns at point c. The value of adaptation is contingent on the level of climate [20].

[FIGURE 2 HERE]

The flexibility of the Ricardian model to capture extensive margin adaptation increases as the land value measure encompasses more potential land-uses. For example, if I define value as the net return to pine forests only, then we capture adaptations within a pine system. However, if we define net returns as that accruing to forestry in general (i.e. all potential species) then we capture adaptations both within each forest type system and across multiple substitute tree species. The net return functions in figure 2 would capture the ability to switch between species 1 and species 2, but they would not capture the ability to adapt by switching to a species other than species 1 or species 2, or leaving forestry entirely. The preceding thought exercise can also be applied to agricultural and urban land values and their associated adaptation strategies.

Hsiang [25] formalizes the econometric study of climate and weather effects on economic outcomes. Applying Hsiang's framework to land-use choice, climate affects economic outcomes through a direct effect on the productive capacity of land (e.g. warmer temperatures increase tree growth rate). Further, climate affects decisions by landowners that are driven by their expectation of how climate and weather affects their production, known as the belief effect. The net returns to a land-use system are a function of the direct and belief effects of climate. If we assume that landowners have a good sense of climate at their location, then it is reasonable to assume they have adapted their current land-use practices to best fit their local climate. Therefore, data on observed net returns will reflect both direct effects and belief effects. The cross-sectional (Ricardian) approach uses spatial variation in climate variables to identify the total effect of climate on net returns. The goal is to identify the total effect of climate on net returns in an econometric estimation of adaptation. The empirical problem is to estimate the average treatment effect for a change in climate on the net returns to land. That is, the difference in expected outcomes given all non-climactic factors under two different climates. We cannot directly observe the treatment because counties can never be in both climate states at the same time, which is known as the fundamental problem of causal inference [23]. If two counties were identical in every way except for their climate then the unit homogeneity assumption holds. Unit homogeneity is the identifying assumption for the Ricardian approach and assumes that no unobserved drivers of net returns are also correlated with climate. We estimate a variant of the following equation to recover the functional relationship between climate and the net return to land-use k.

$$NR_n^k = \alpha_n^k + \beta_n^k \boldsymbol{C}_n^k + \gamma_n^k \boldsymbol{x}_n + \epsilon_n^k$$

Where C is a vector of climate variables specific to county n and land-use k, and $\boldsymbol{x}_n$ is a vector of non-climactic variables that also affect net returns. The remainder of this section describes estimation of four Ricardian functions that serve as determinants in the land-use choice estimation that follows.

4.2 Forest Ricardian

Globally climate change is expected to shift potential vegetation zones north as new areas in the tundra become suitable for growth [30]. Perez et al [41] implement an integrated assessment model to analyze the impacts of climate change on the global forest sector, finding net positive changes to welfare, but identify significant regional variation where some regions gain while other lose. Using FIA data from the U.S. Forest Service, Huang [27] performs a two-stage estimation of climate's effect on Loblolly pine trees in the southern U.S. They find that productivity increases, and the magnitude of increase varies spatially across the region. Latta et. al. [31] find similar results for forests in the pacific northwest U.S., their predictions of increased forest productivity are robust to multiple climate models and scenarios. Because the U.S. spans such a large area with vastly different climate regimes, we can expect there to be a corresponding spatial variation in forest impact. This paper exploits the spatial variation in climate and forest rents to empirically identify climate's effect on forest net returns. In contrast, most numerical analyses of climate-forest linkages assume specific belief effects through adaptation. Sohngen and Mendelsohn's [50] dynamic optimization model of the global timber market assumes adaptation, and finds that climate change projections will benefit many timber markets, especially in the U.S. as result of increased supply, even when accounting for price effects. Perez-Garcia et. al's [41] integrated assessment model also finds net positive changes to global welfare from changes in global timber markets, but with significant regional variation where some regions gain while others lose.

More recent numerical analyses of global timber markets largely confirm the positive productivity effects of climate change on forestry [51]. In a parcel-level approach, Guo and Costello [20] use numerical dynamic programming techniques to examine the value of adaptation on California timberlands using an approach that assumes all landowners have homogeneous beliefs about how a particular climate change scenario affects tree growth, and respond optimally.

The following specification for the economic net returns to timberland is used to capture climate's role in the determination of forest land value. Net returns in county n for species group s is weighted by the observable shares of a county's timberland in species group s to obtain an estimable function explaining weighted average net returns to timberland.

$$NR_n^f = \alpha_n + \beta_n f(T_n, P_n) + \gamma_n LCC_n + \delta_r + \epsilon_n$$

Where $f(T_n, P_n)$ is a polynomial function of temperature and precipitation that includes an interaction, T_n is an annual measure of temperature on forested land in county n, P_n is the total annual precipitation on forested land in county n, LCC_n is the measure of land quality, and δ_r is a set of region r fixed effects. All climate variables are weighted by forest area.

I assume that climate enters the model exogenously. That is, climate is not correlated with some unobservable that directly drives the net returns to forestland. The agricultural-climate literature has identified irrigation infrastructure as a problematic omitted variable that has spurred numerous panel data applications [6]. However, irrigation is not used for timberland. Further supporting the use of cross-sectional analysis is the long-term nature of timber management decisions. A key difference between agriculture and timber is the way timber managers respond to short run fluctuations in weather versus long run fluctuations. Timber harvest decisions are made on much longer time horizons than those in agriculture. According to the data constructed for this dissertation, observed harvest and replanting decisions are made over 15-100 year horizons on average. The panel solutions advanced in the agricultural-climate literature that rely on a climate binning approach do not apply to a forestry model since the variation of year-to-year weather shocks on timber growth is averaged out by the broader climate over the multi-decade period.

Drought or fire risk indices are omitted in the model of forest net returns because including these measures result in a bad control problem [3]. Including a variable such as fire risk is challenging because fire risk is a direct function of climatic measures like precipitation. There is no ceteris paribus nature to a regression function that includes both climate and fire risk as separate variables. However, fire risk is implicitly captured in the forest Ricardian function through the observed impact of fire occurrence on average timber growth used in constructing the dependent variable.

We estimate a forest system Ricardian for the conterminous U.S. to recover the total impact of climate on the economic net returns to forestry. Predictions made using the national Ricardian model approximate the outer envelope from figure 1 and implicitly account for the total impact (direct plus belief effects) of climate change on annualized net returns to U.S. forestland. That is, the Ricardian models estimated impact of climate change implicitly includes all potential forestland adaptations, including intensive margin changes to management practices for particular species and extensive margin changes involving switching plantings to alternative tree species and forest types. Climate change impact on the net returns to forestry are evaluated using global circulation model projections for the period (2021-2050) versus a baseline period (1983-2012). The main result of this section uses the multi-model mean from 20 Global Climate Models under emissions scenario RCP 8.5.

Given the quadratic specifications, I focus on the estimated average marginal effects of the key climate variables in table 1. Average estimated marginal effects indicate that a 100 mm increase in annual precipitation increases forestland value by approximately \$3.11/acre. A marginal increase in maximum temperature of 1 degree C generates an increase in net returns of \$5.25/acre. The marginal effects of maximum temperature and precipitation are significant at the 1% level. Parameter estimates for minimum temperature and its square are statistically significant, although the marginal effect is not significantly different from zero. The impact of projected climate change to the year 2050 on annualized net returns to forest production is positive on average across the U.S. Climate change impact predictions vary significantly over space, where some counties will experience a loss in forest net returns, and others experience a gain. Using the multi-model mean change in climate we find that forest net returns will increase on average by approximately \$22.31/acre, an increase of 57% from the baseline value.

4.3 Crop and Pasture Ricardian

The goal of this section is not to advance the literature on the structure of climate's impact on agricultural yields nor profit, but rather to estimate a tractable function for the relationship between long term climate and agricultural net returns to be used as an input to a broad land-use change model. Therefore, I implement a standard OLS Ricardian function. A principle difference between existing Ricardian studies is the choice of dependent variable. The dependent variable that I have chosen is a broadly defined measure of net farm revenue including that accruing to fruit trees and livestock production. The choice of dependent variable sets the scope of system being modeled, and therefore the set of intensive margin adaptations faced by owners of crop and pasture land. The take away from the current literature is that direction and magnitude of climate change's impact on agriculture depends on the choice of dependent variable, the functional form of climate's relationship to the outcome, and the spatial aspect of the analysis.

The crop and pasture Ricardian functions estimated here take the following form where NR_n^k, the net economic return per acre in county n and land-use k, is the outcome of interest.

$$NR_n^k = \alpha_n^k + \beta_n^k f\left(T_{n\xi}, P_{n\xi}\right) + \gamma_n^k LCC_n + \epsilon_n^k$$

. Where $f\left(T_{n\xi}, P_{n\xi}\right)$ is a quadratic specification of seasonal temperature and precipitation that includes an interaction, $T_{n\xi}$ is the mean temperature in county n and season ξ measured in degrees Celsius, and $P_{n\xi}$ is the total precipitation in county n and season ξ measured in millimeters. The year is broken into four seasons: winter, spring, summer and fall. Climate variables enter as the 30-year historical average taken over the years 1975 - 2004. LCC_n is the share of a county's land in each of eight Land Capability Classes as defined and reported by the National Resource Inventory.

4.4 Urban Ricardian

In this section, the impact of climate on urban net returns is estimated and predictions made under climate scenario NorESM1-M RCP 8.5. Land-use decisions in an urban setting are nearly irreversible so that year-to-year weather fluctuations are unlikely to influence urban net returns. However, it is plausible to expect long term shifts in the distribution of weather (i.e. climate) to impact urban rents.

Albouy et. al. [2] estimate the willingness to pay for climate using a hedonic framework (similar to the approach employed here), finding that households are responsive to changes in temperature. They find that households prefer temperatures close to 65 degrees Fahrenheit, and are willing to pay more to avoid extreme heat relative to extreme cold. This result, that households are willing to pay more to live in places where the climate amenities are greater given their preferences naturally extends to climate's effect on the net returns to urban land.

The following specification is used to estimate the functional relationship between climate and urban net returns.

$$NR_n^u = \alpha_n + \beta_n f(HD_n, CD_n, P_n) + \gamma_n X_n + \epsilon_n$$

Where $f(HDD_n, CD_n, P_n)$ is a quadratic function of temperature and precipitation that includes and full set of interactions. Precipitation is measured as the annual total. The term X_n is comprised of county-level demographic control variables including population density, median income, racial composition, and educational attainment. Temperature enters the specification in the form of heating degree days (HDD) and cooling degrees days (CDD). HDD is a measure of cold relative to 65 ◦F (i.e. days that require expending energy on heating). CDD measures warmth relative to 65 ◦F (i.e. days that require expending energy on cooling). The temperature 65 ◦F can be thought of as a bliss point for human comfort and this threshold is confirmed through non-linear estimation in the work by [2]. In the current context, degree days measure deviations away from the most desirable temperatures so the sign of marginal effects is expected to be negative on both HDD and CDD.

The average marginal effect of a one unit increase in HDD is −$3.90, suggesting that cooler temperatures decrease urban rents. The average marginal effect of a one unit increase in CDD is −$5.96, suggesting that warmer temperatures also decrease urban rents. The negative sign affirms the construction of degree days, as the further away the temperature is from the bliss point, the less attractive an urban area is. More revealing is that urban rents are more sensitive to heat than to cold, confirming the finding in [2] that Americans are willing to pay more to avoid excess heat than extreme cold. The model implicitly accounts for adaptation possibilities within an urban system, implying that there exist fewer adaptations to heat than cold. The average marginal effect of precipitation on urban rents is negative, implying that people prefer relatively dryer locations.

5. Logit Estimation and Simulation Results

This section presents the explicit modeling of the effects of climate on land-use conversion (i.e. adaptation) through climate's impact on the economic net returns to land. Plot-level land-use data on privately owned land for the period 1981-2012 were obtained from the National Resource Inventory (NRI) of U.S. Department of Agriculture. The NRI is a longitudinal panel survey of land-use, land cover and soil characteristics in 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. For each transition period a pooled cross-section is taken capturing the current distribution of a particular land-use within a defined spatial region. The current land-use chosen on a parcel embeds all of the characteristics that drove that parcel to end up in that land-use system.

Combining the climate driven net return predictions from section 4 with the plot-level land quality data from the NRI, we specify the alternative specific utility that enters into our logit model as

$$U_{inkt} = \alpha_k + \beta_k LCC_i + \gamma_k NR_{nkt} + \epsilon_{inkt}$$

Where α_k is an alternative specific constant. The parameters to be estimated are β_k and γ_k. The constant and LCC variables are estimated relative to crop use by normalizing their values to zero in the crop utility equation. The LCC measure ranges from 1 to 8, where LCC 1 is the most productive and LCC 8 is the least productive. Assuming that conversion costs are strongly correlated with land quality, the sum of the first two terms on the right hand side of representative utility serve as proxy for conversion costs [35].

Land-use conversion is modeled using two-year transition periods starting in 2008 and ending in 2012 creating 2 transition periods. The observed transitions for each period create three choice data sets used for estimation, one for each starting use (crop, pasture, and forest). The structure of the response to an extra dollar of rents is assumed to be the same today as it will be in the future so that parameters estimated by observing recent land transitions remain relevant for predicting land transitions under a future climate scenario. Landowner i in county n converts from use j to k when $U_{inkt} > U_{injt}$ for $j \neq k$.

All estimations are weighted according to how many acres each observation represents relative to the whole sample. This avoids bias that may be caused because some plots are more intensively sampled than others, that is, some plots represent a greater number of acres than other plots. Each plot's weight is the number of acres it represents divided by the total number of acres in the sample, and then the weight is scaled by the total number of plots in the sample. This plot weighting structure allows the resulting predicted probability to be interpreted as the probability of an acre of land either remaining in its current use or converting to an alternative. Tables [] present the full set of parameter estimates. This set of models is defined by starting uses crop, pasture, forest and ending uses crop, pasture, forest, and urban for the period 2008-2012. The economic net return to land enters the full model set in four alternative specifications; the mean level over the two-year period prior to the starting year, the change in net return over the transition period, the mean level over the period of my net return data (1998-2012), and the mean transition period change between 1998 and 2012.

For land starting in crop across all regions, the results indicate, as expected, that plots in higher LCC categories (i.e. lower quality land) are more likely to convert from crop to pasture. That is, crop systems are more likely to be found on higher quality land. This result is consistent in all 55 model estimates presented here. Conversions to forest land are also more likely to occur on lower quality land. The parameter on LCC in the forest utility equation is always greater than LCC in the pasture utility equation. Taken together the models capture the fact that from high to low quality land, we can expect to find relative movements from crop to pasture to forest. Lower quality land is also positively correlated with urban land, but its impact relative to pasture and forest is less clear.

In a logit model, the parameter estimate and the marginal effect will have the same sign [53]. Further, the law of demand implies that as net returns to land-use k increase, so too should the probability of converting to or remaining in that particular use. The coefficient on crop net returns is positive and significant for all levels only models. There is a positive effect of crop rents on the probability of remaining in crops, given that the land started in crop use. Land starting in pasture is more likely to convert to forest use when forest net returns increase in all regions. Higher forest net returns drive conversions to forestry from both pasture and crop systems. The relationship between urban rents and the probability of conversion is clear: positive and significant in all models.

6. Simulation of the Southeastern U.S. Landscape

The eastern United States has long experienced an active margin between agriculture and forestry, and past research has shown that increases in net returns to forestry will increase land-use changes from agriculture to forestry (e.g. [35, 33]). Further, in a Ricardian analysis of agriculture in the eastern U.S., Schlenker et al. [48] found that climate change can result in reductions in agricultural returns by 2050. Since agriculture and forestry are substitute land-uses in the eastern U.S., climate changes that are more favorable to forestry than agriculture suggest potential afforestation, and prior studies have shown that afforestation from agriculture to forestry can have potentially large effects on many non-market ecosystem services, from carbon sequestration to wildlife habitat [32].

To begin answering the broader question of whether climate will drive more conversions along the agricultural-forestry land-use margin, I present here a single scenario of the potential impact of climate change on land-use in the southeastern U.S. Of the numerous specifications estimated above, three models are chosen to analyze the impact of climate change on the probability of converting between alternative land-uses. Parameter estimates for the models of interest are presented in table []. In the climate change scenario evaluated below, the focus is on showing how climate induced change in the level of net returns affects the probability of conversion.

For this analysis, geography is restricted to counties in the southeast U.S. for which all three starting uses were present in the respective estimation data (867 counties). Transition periods are restricted to the final two periods of the sample, 2008-2010 and 2010-2012. The model includes three starting uses, and four ending uses. Land starting in urban use is not modeled as these parcels so rarely leave the urban system. The preferred models include only the level of net returns, parcels located east of the 100th meridian and in the southern region as defined by the U.S. Forest Service.

As a reference point for exploring the many impacts of climate on land-use conversion, consider the observed rates of conversion in the selected southeastern counties over the final transition period (table []). For land starting in crop use, the share of crop acres remaining in crop use is approximately 98.8%. The percentage of acres converting to pasture is 0.93%, to forest is 0.089%, and to urban is 0.089%. For land starting in pasture use, the share of pasture land remaining in pasture use is approximately 97.84%. The percentage of acres converting to crop use is 1.21%, to forest is 0.667%, and to urban is 0.134%. Movement out of pasture is relatively more fluid than movements out of crop use. For land starting in forest use, the percentage of forest acres remaining in forest is approximately 99.71% with 0.0167% converting to crop land, 0.0844% to pasture land, 0.117% to urban use. The alternative specific constants included in all of the land-use models ensures that the predicted shares in each land-use matches the observed shares over the estimation period. The most active land-use margins in the southeast U.S. over the period 2000-2012 have been crop-pasture (9.5 million acres), pasture-forest (4.6 million acres, and forest to urban (3 million acres).

The ultimate impact of climate change on the future landscape is driven by the starting land-use, land quality distribution, and path of predicted climate changes. In addition, non-climatic factors define a baseline trend in each land-use such that the number of acres in each system is either increasing, decreasing, or remains unchanged on net. Further, climate change can amplify, dampen, or have no effect on the baseline trend.

Consider four possible impacts of climate change on land-use change. Figure [] illustrates the four cases. An accelerated decline is characterized by a declining baseline trend that is amplified by the total effect of climate. Inhibited decline occurs when a declining trend in land area is slowed by climate change. An increasing baseline may be accelerated or inhibited depending on climate's total effect. Each of these scenarios assumes that climate's impact is small relative to non-climatic drivers of land-use change such that the trend is monotonic.

From these relationships between future land area and climate change impact, we define a climate change impact factor that describes climate's impact on land-use change relative to the non-climatic drivers embedded in the baseline trend.

$$ccfact = \frac{\Delta C}{\Delta B}$$

Where ΔB is the percentage change between future land area and today's land area under the baseline (i.e. without climate change), and ΔC is the percentage difference between future land area under climate change and future land area under the baseline. The sign of ΔB indicates the direction of the baseline trend, and the sign of $ccfact$ indicates whether climate change accelerates (positive) or inhibits (negative) the baseline trend.

In this section, consider the path that climate takes and how that translates into a path of land-use change. The climate data is re-formulated to trace out changes from today's climate to the climate in 2050 under scenario NorESM1-M RCP 8.5. The set of transition probabilities calculated from table [] satisfy the Markov property, so that the probability of conversion depends only on the current state and the transition period. Markov processes are said to be memory-less in the sense that earlier states are independent because information about the past is embedded in the current state. I employ a discrete time Markov chain at two-year time steps from 2014 to 2050 with four states evolving according to the estimated transition probabilities. The four states to be traced out are crop, pasture, forest, and urban. Acreage in each land-use system begins at the observed level in 2012. Under the baseline, the acreage for each land-use is determined by the predicted probability held fixed at its 2012 level. Under the climate change scenario, the transition matrix is a function of climate variables that evolve along a climate changed future path.

The goal of this exercise is to calculate how much climate change adds (or takes away from) the baseline trend in land area. The results presented below are driven by the starting land distribution in the chosen study area, and do not generally apply to other regions in the U.S. There are four potential scenarios arising from climate's impact on land area; i) accelerated increase, ii) accelerated decline, iii) inhibited increase, and iv) inhibited decline. Within each county, land in a particular use is either increasing or decreasing under the baseline trend. Climate change impact will either amplify or dampen the non-climatic pressures of land-use change. When the climate impact factor is positive (negative), land-use change is accelerated (inhibited).

The baseline land-use and climate changed trend, and the climate impact factors for each broad land-use type are mapped in figures []. To explore the changes underlying these figures we have selected a small set of counties and land-uses that help to illustrate the range of potential climate change impacts in this study region.

In Washington County, Oklahoma where pasture is the dominant land-use type (50% of county acres) climate change impact is positive for all four land-use types implying that climate accelerates the baseline acreage trends in this county. Forest acres in Washington County decline under the baseline, and climate change accelerates this by approximately 3.42%. Pasture is predicted to decline, while crop and urban land area is predicted to experience accelerated increase.

In Lee County, Mississippi climate change accelerates baseline losses in both pasture and forest land area by 1.88% and 0.46%, relatively minor impacts. Crop acres 100 are declining under the baseline, but climate change inhibits this loss by 21.1%. This is a relatively large impact for Lee County, where 89,000 acres (33%) of land is in crop use. A similar impact on crop land is predicted for Baldwin County, Alabama where crop declines are slowed by 21.4%. While cropland in Baldwin is comparable to Lee at 81,000 acres, this land-use comprises only 8.4% of total county land area. Baldwin county pasture land provides an example of inhibited increase, with gains to pasture land reduced by 7.66% under climate change.

Finally, consider St. Lucie, Florida where an example of accelerated increase can be found. Crop land comprises the greatest share of land area in this county at 35% and is predicted to increase in the future with climate change accelerating that increase by 9.68%. Urban land, which is increasing across the region, is slowed by climate change in St Lucie by approximately 1.04%.

The regionally aggregated climate impact results are presented in table 5.14. Urban land is increasing under the baseline trend and climate change is accelerating the increase by 0.33%, a minor impact relative to the overall changes expected to occur in urban land area. Forest land experiences an accelerated decline, but the magnitude is only 0.005% across the study region.

Pasture land trends are mixed spatially, but in aggregate pasture experiences an accelerated decline in acres. Crop land is generally increasing under the baseline trend. However, current crop areas are on an increasing trend, and climate change will result in relatively more crop acres over a large portion of the southeastern U.S (figure []). The aggregate climate impact factor for crop land is positive implying that crop gains are accelerated by climate change.

Forest acres are decreasing in most counties, and the declining trends are predicted to be amplified by future climate. Climate impact follows a south to north gradient, lower in the south and increasing as you move northward (figure []). Notice that the counties experiencing the greatest decline in baseline acres have the highest level of climate impact. Predictions also indicate that relatively more crop land will convert to pasture land, and that climate change will slow urban growth in the northern part of the study area and amplified urban growth in the southern portion.

7. Discussion

The analyses in this paper provide multiple contributions to the literature on the economic costs and benefits of climate change. We develop and implement a land-use change model that is driven by climate's simultaneous impact on broad land-use alternatives. My analysis further contributes to the broad inquiries into how society may adapt to future climatic conditions. Haim et al. [21] estimate an econometric land-use model similar to my own where climate's impact on net returns enter exogenously as the output of global models of urban population and income, and crop and timber. This research extends the work in [21] by i) incorporating intensive margin adaptation through the Ricardian estimation of net returns, ii) parameterizing urban rents directly by climate variables in addition to population and income, iii) modeling the growth of forest species to implicitly account for climate's effect on yield at a highly dis-aggregated level. In addition, the independent variables that enter the land-use choice model are constructed at a high spatial resolution without down-scaling measures from global models.

While land-use decisions and adaptation to climate are driven by land owners incentive to maximize their private economic returns, decisions based on private economic returns have consequences for landscape composition, and therefore, ecosystem services that have public goods characteristics. For example, the distribution and abundance of forest and agricultural lands directly affect the habitat suitability for numerous wildlife species [32]. In addition, the aggregate stock of land devoted to timber and agriculture is affected by the relative net returns to both substitute land-uses, and influences local water quality and the amount of carbon sequestered from the atmosphere [34].

A new finding from our national forest Ricardian analysis is that average U.S. forest rents are increasing in precipitation and average maximum summer temperature and decreasing in average minimum winter temperature. Results are robust to numerous alternative specifications of climate variables, regional fixed effects, and soil quality controls. When examining simultaneous changes in multiple climate variables through projected climate change scenarios to 2050, I find that forest net returns are projected to increase by an average of $22/acre, which is a sizable increase over the current average of $39/acre. However, there is significant spatial variation in projected climate change impacts as some regions are expected to lose while others are expected to gain. Projected gains in forest rents from climate change could be driven by uniformly higher growth effects of climate on all tree species or by differential growth effects of climate across tree species and corresponding extensive margin adaptation by landowners across planted tree species.

The results from my discrete choice land-use model are used to simulate the future southeastern U.S. landscape. My simulation accounts for net changes in land area as land moves between alternative productive systems, and how these transitions are affected by climate change. The results suggest that under climate change crop land is far more likely to move into urban use, and that crop land that would otherwise have converted to pasture is more likely to convert to forest use. Analysis of land starting in forest and pasture imply that this margin will be more active under climate change relative to current rates of conversion. Growth in urban development will be slowed near the major cities of the southeast including Houston, Atlanta, and Charlotte as the probability of converting from pasture and forest into urban use is less likely. There is a clear spatial pattern of climate's impact along the gulf coast states where urban development is accelerated at the expense of forest and pasture.

Regional aggregation of simulation results reveals that the magnitude of impact is small relative to a baseline scenario of land-use change that holds climate fixed at today's level. The baseline trend is driven by the non-climatic factors that influence land-use change. Although climate change impacts are relatively small, the spatial pattern of changes may have implications for the distribution of the costs and benefits of climate change. Understanding the linkages between broad land-use choice, climate change, and natural systems is vital for understanding the non-market economic costs of climate change. The models constructed and parameterized in this dissertation provide a foundation to explore numerous questions regarding the interaction between climate change, land-use, ecosystem services, and conservation policy

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Figures

Figure 1: The Ricardian Climate Function

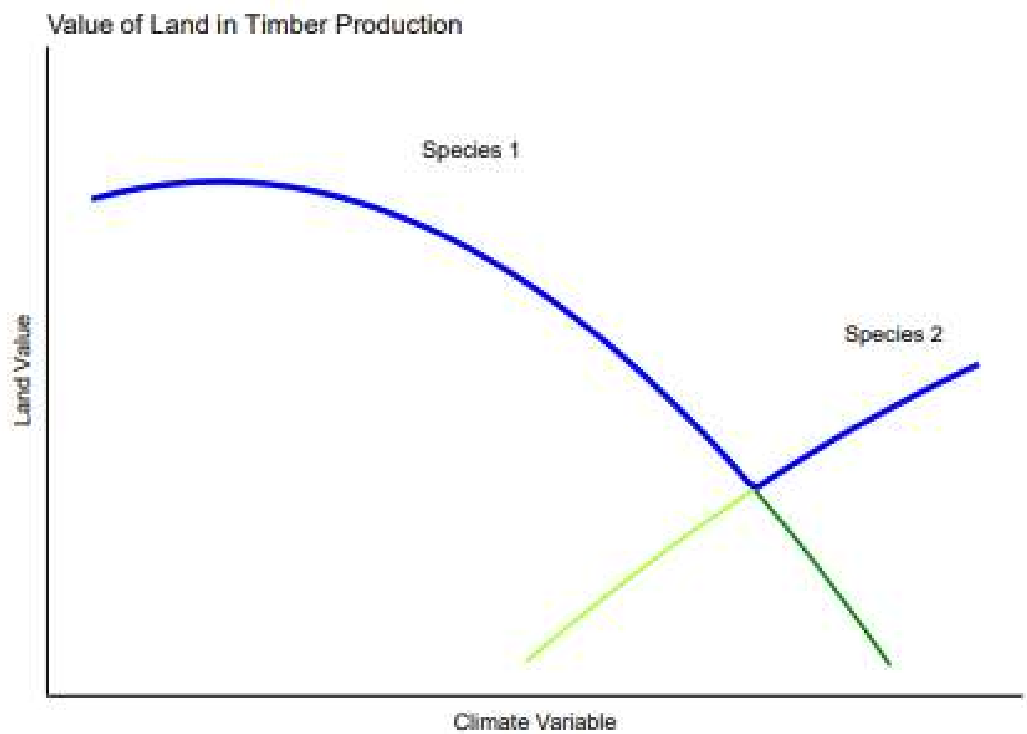


Figure 2: Climate Change Impact under the Ricardian Framework

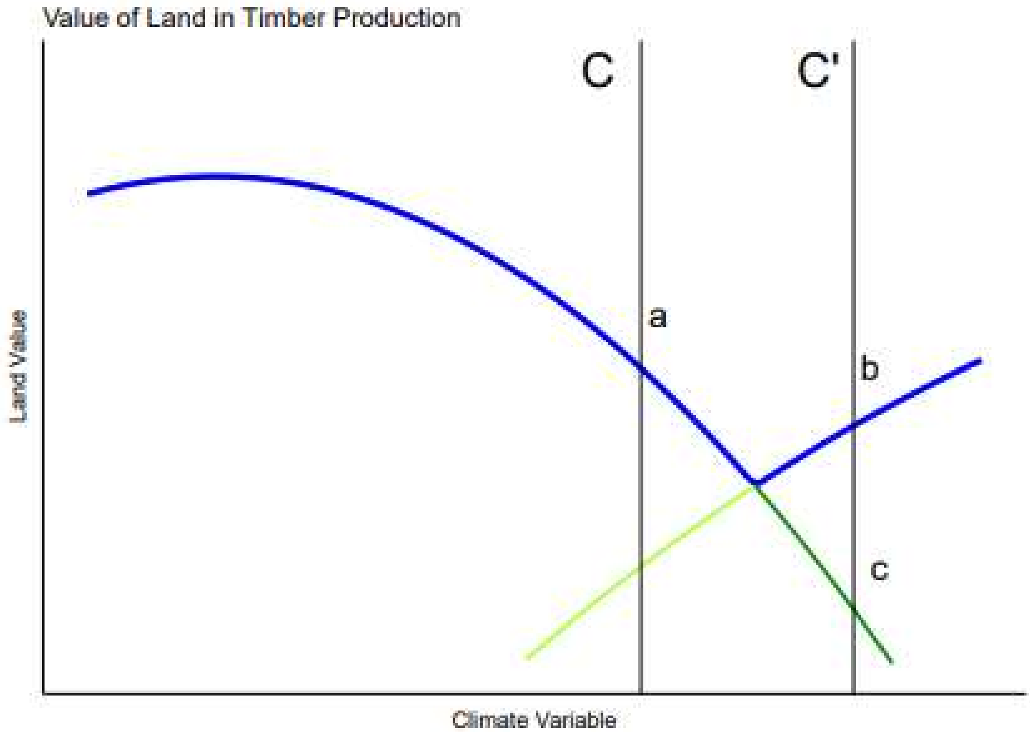


Figure 3: Climate Change Impact Factor

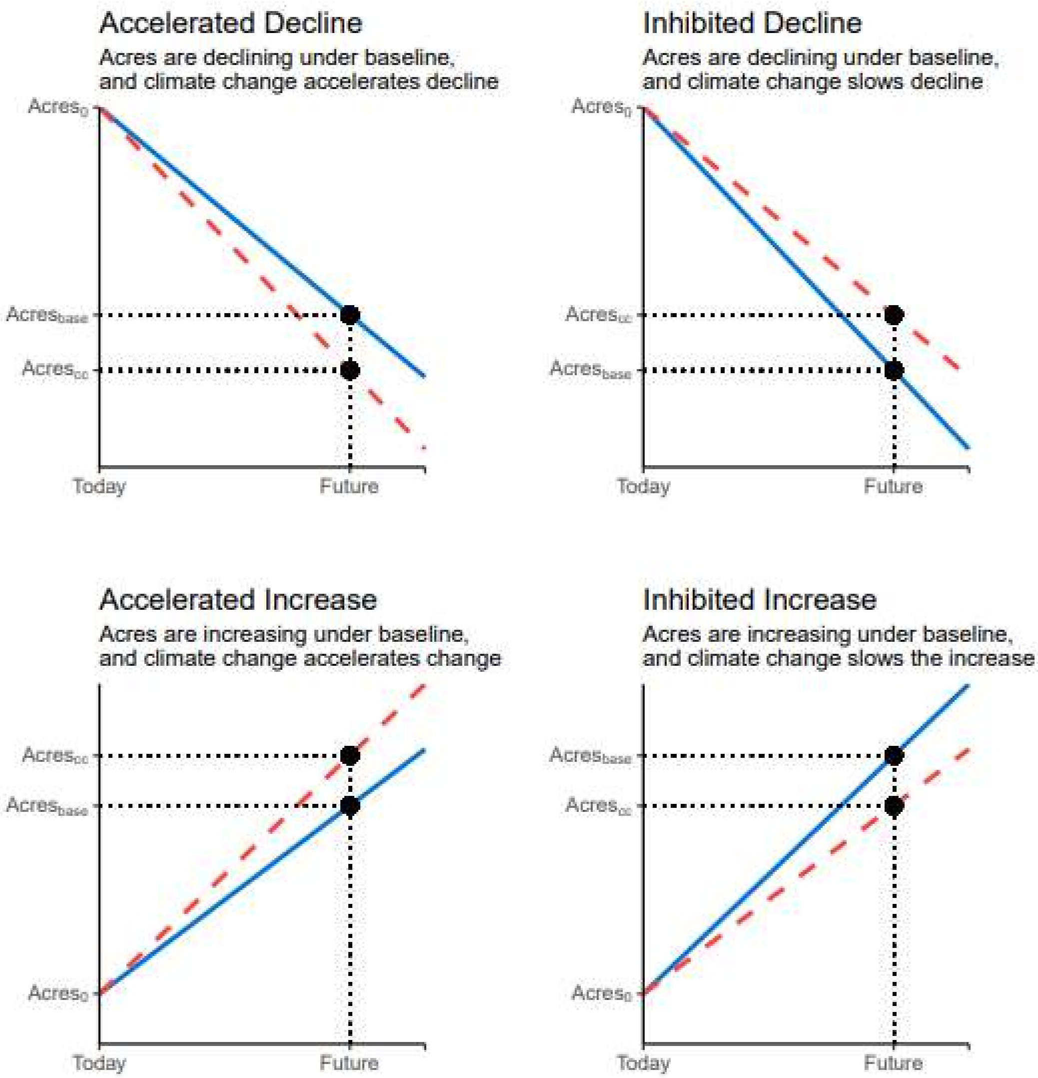


Figure 4: Tree Growth Heterogeneity

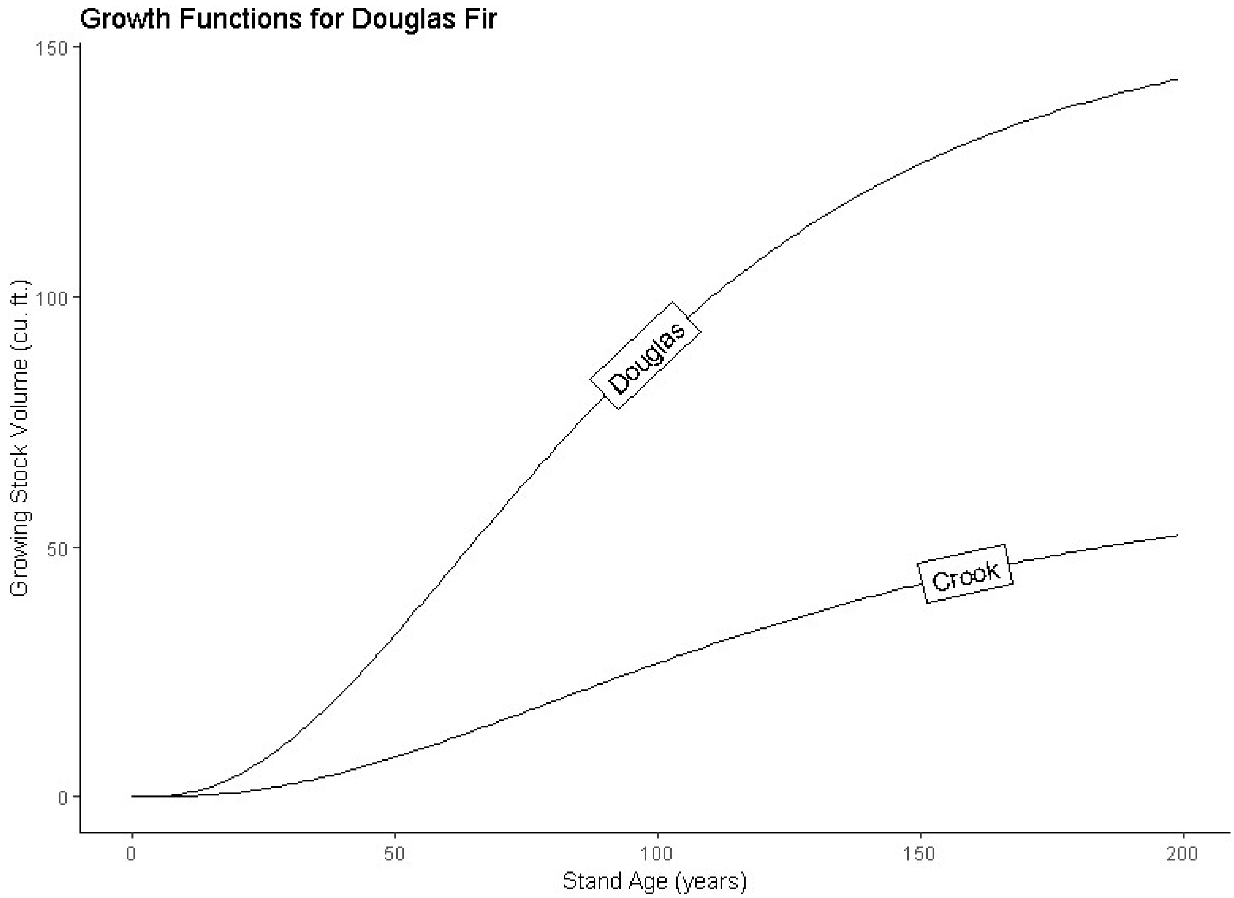


Figure 5: Climate Change Impact on Future Crop Acres

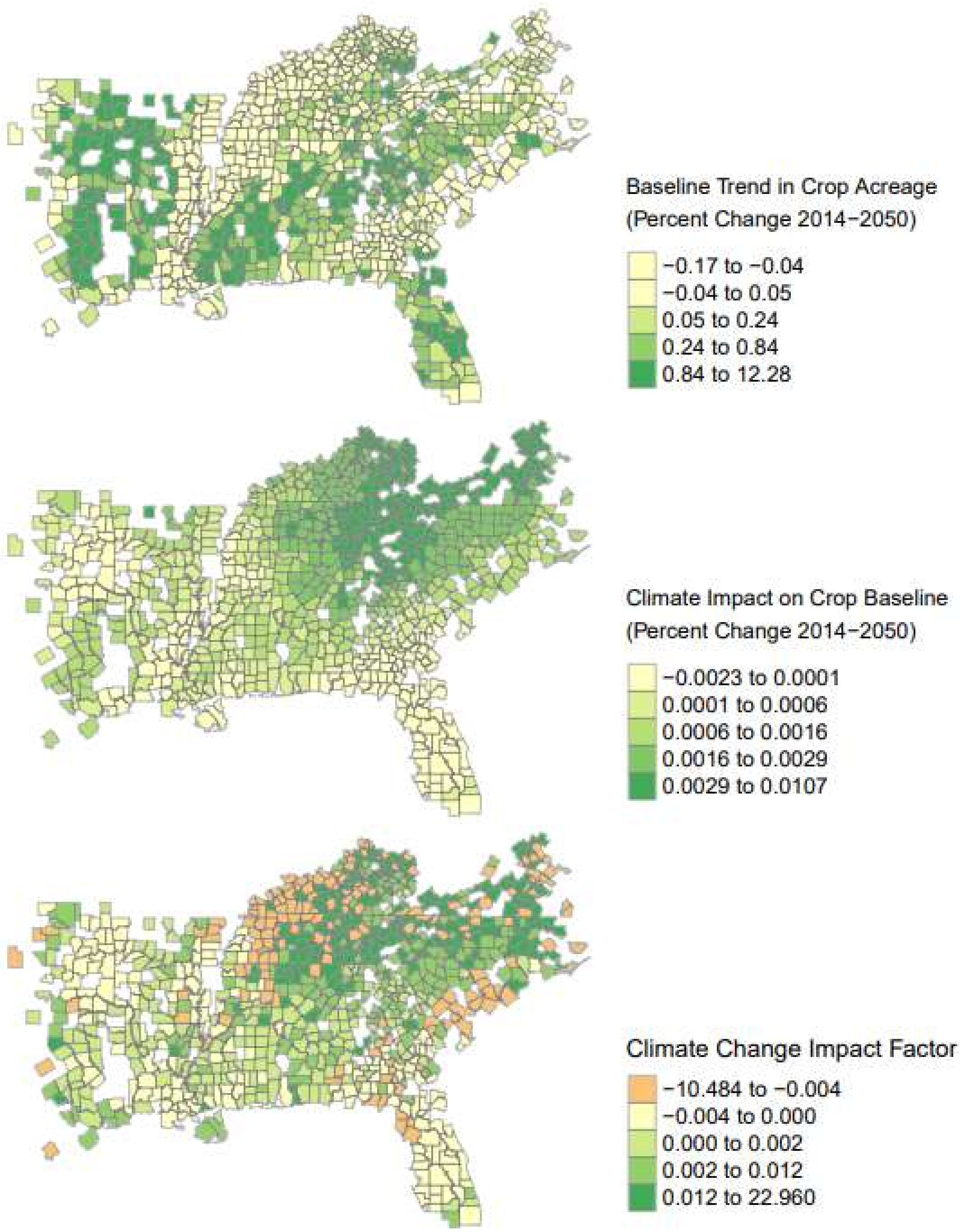


Figure 6: Climate Change Impact on Future Pasture Acres

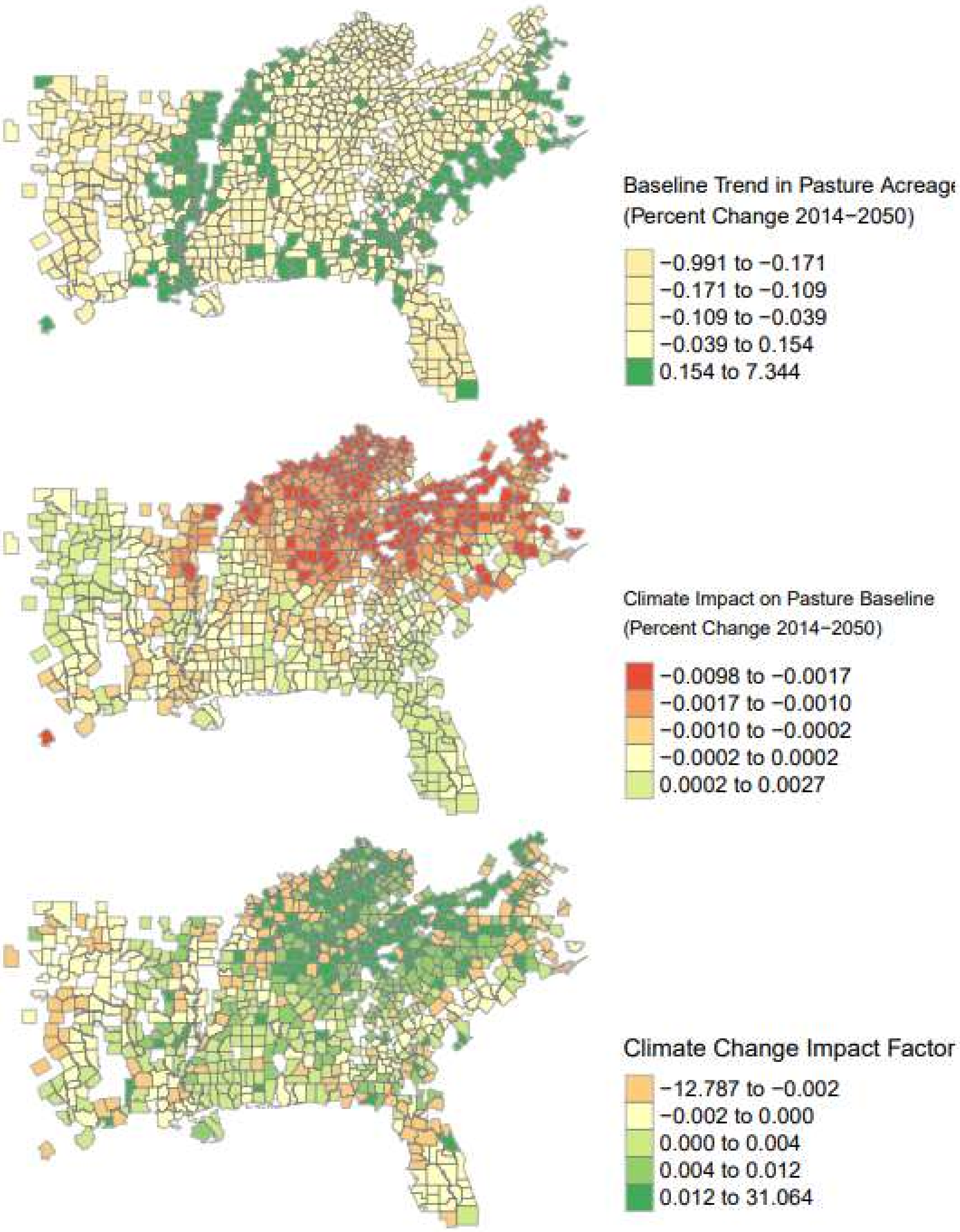


Figure 7: Climate Change Impact on Future Forest Acres

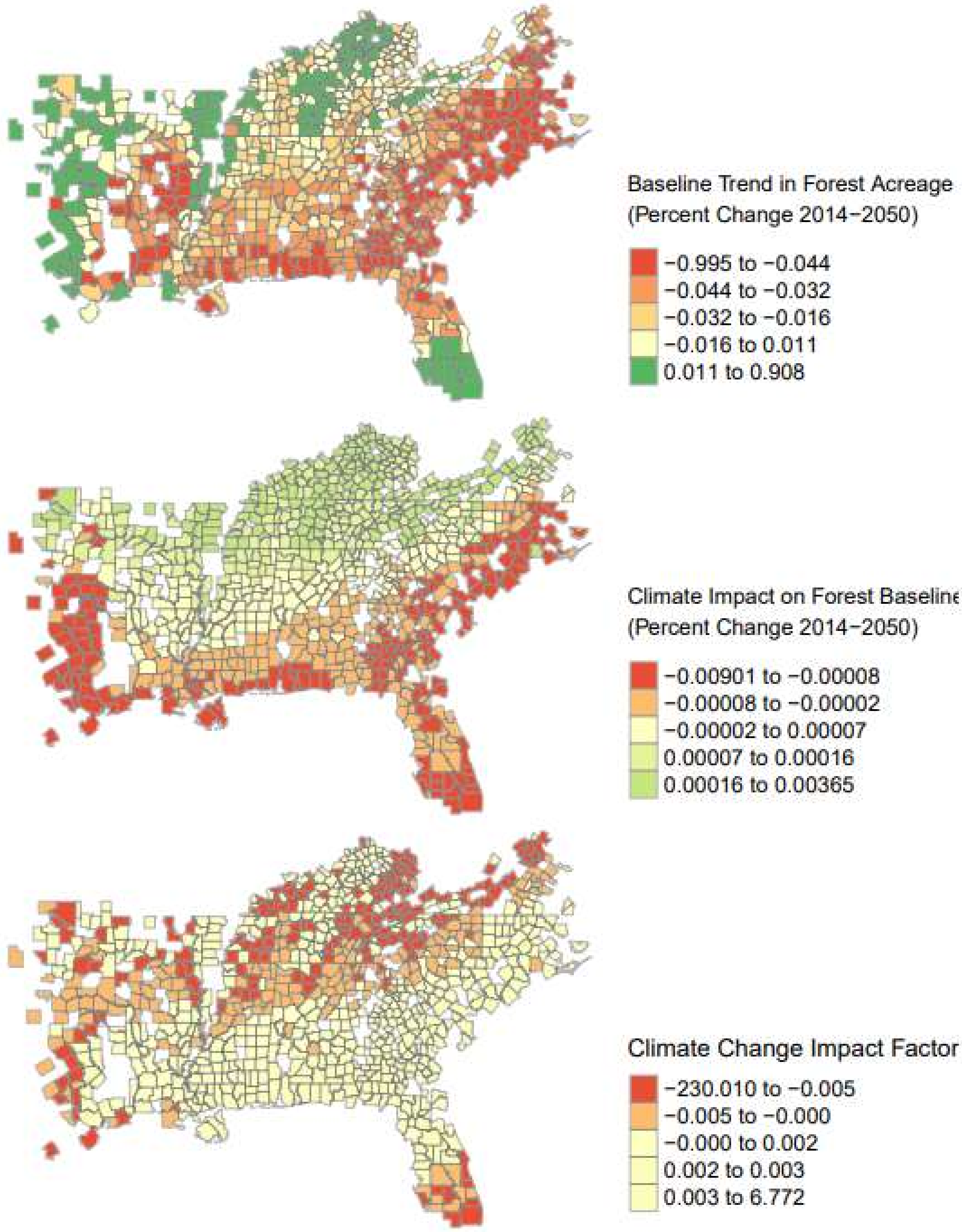
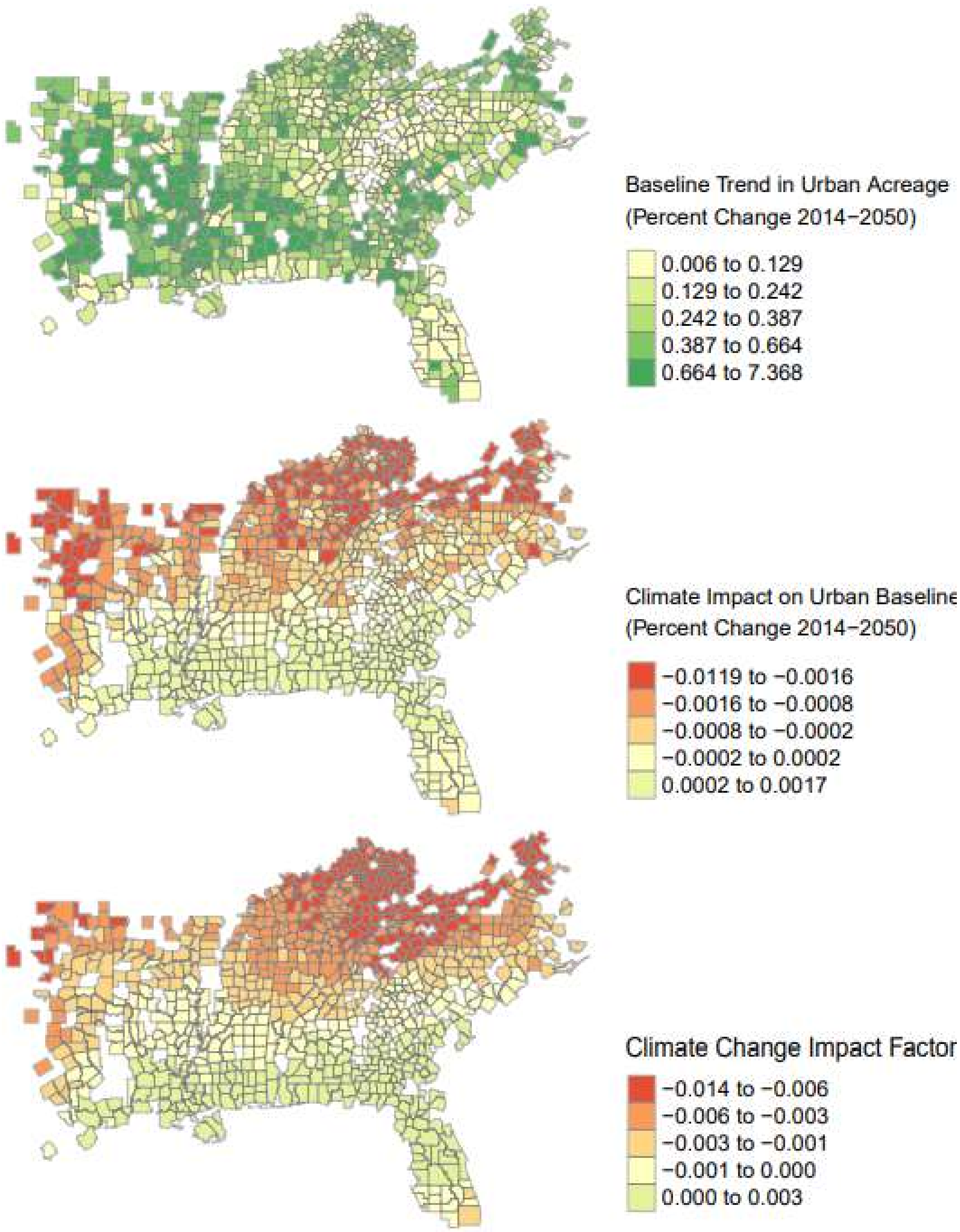


Figure 8: Climate Change Impact on Future Urban Acres



Tables

Table 1: Forest Ricardian Parameter Estimates

	Conterminous U.S.	Eastern U.S.	Northeast	Southeast
Max Temp	-17.401^{***}	-23.408^{***}	4.716	40.483^{**}
	(2.883)	(5.153)	(5.322)	(19.867)
Max Temp Squared	0.283^{***}	0.713^{***}	-0.476^{***}	-1.878^{***}
	(0.077)	(0.166)	(0.157)	(0.519)
Min Temp	2.988^{**}	-9.070^{**}	1.780	25.539^{**}
	(1.291)	(4.341)	(2.990)	(12.258)
Min Temp Squared	-0.182^{***}	-0.714^{***}	0.207^{**}	-0.722^{**}
	(0.053)	(0.124)	(0.088)	(0.293)
Precip	-0.209^{***}	-0.010	0.013	-0.192
	(0.029)	(0.067)	(0.050)	(0.248)
Precip Squared	0.00002^{***}	-0.0001^{*}	-0.0001^{***}	-0.0003^{***}
	(0.00001)	(0.00003)	(0.00003)	(0.0001)
Max Temp:Precip	0.010^{***}	0.005	0.010^{**}	0.050^{***}
	(0.001)	(0.005)	(0.004)	(0.016)
Min Temp:Precip	-0.002	0.011^{***}	-0.002	-0.014
	(0.001)	(0.004)	(0.003)	(0.011)
Constant	171.861^{***}	115.089^{*}	-33.075	-669.661^{**}
	(33.800)	(60.802)	(47.310)	(273.967)
Soil Control (LCC)	Yes	Yes	Yes	Yes
Regional Fixed Effect	Yes	Yes	Yes	Yes
Observations	2,390	2,130	957	1,058
R^2	0.380	0.396	0.115	0.361
Adjusted R^2	0.374	0.391	0.099	0.351
Residual Std. Error	39.762 (df = 2366)	38.422 (df = 2110)	14.290 (df = 939)	47.796 (df = 1041)
F Statistic	62.983^{***} (df = 23; 2366)	72.846^{***} (df = 19; 2110)	7.191^{***} (df = 17; 939)	36.743^{***} (df = 16; 1041)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 2: Crop Ricardian Parameter Estimates

	Conterminous U.S.	Eastern U.S.	Northeast	Southeast
Winter Temp	1.136	11.361***	−24.560***	−60.402***
	(2.662)	(3.745)	(8.939)	(17.252)
Winter Temp Squared	0.518***	1.186***	−1.074*	4.826***
	(0.143)	(0.250)	(0.627)	(0.920)
Spring Temp	47.267***	−3.174	30.473	252.052***
	(6.641)	(14.539)	(20.705)	(55.848)
Spring Temp Squared	−2.660***	−1.466***	−2.673*	−10.023***
	(0.269)	(0.534)	(1.446)	(1.620)
Summer Temp	12.851	123.782***	−58.350	−74.057
	(11.997)	(34.740)	(79.688)	(89.126)
Summer Temp Squared	−0.473*	−2.453***	2.033	2.418
	(0.271)	(0.654)	(1.871)	(1.624)
Fall Temp	−35.366***	−3.912	−51.477	−50.181
	(10.246)	(22.592)	(41.829)	(91.309)
Fall Temp Squared	2.553***	1.376	4.387**	3.844
	(0.439)	(0.860)	(1.782)	(2.755)
Winter Precip	0.346***	0.450***	0.479	1.952***
	(0.048)	(0.106)	(0.485)	(0.255)
Winter Precip Squared	−0.0004***	−0.001***	−0.0003	−0.003***
	(0.0001)	(0.0002)	(0.001)	(0.0004)
Spring Precip	−0.199	0.356	1.039*	−4.885***
	(0.134)	(0.300)	(0.605)	(1.200)
Spring Precip Squared	0.001***	−0.0005	−0.001	0.003**
	(0.0002)	(0.001)	(0.001)	(0.001)
Summer Precip	−0.826***	0.189	−0.295	5.931***
	(0.154)	(0.386)	(1.175)	(1.149)
Summer Precip Squared	0.0001	−0.001***	0.0001	−0.002***
	(0.0001)	(0.0003)	(0.001)	(0.0004)
Fall Precip	0.397**	0.094	−0.010	1.652**
	(0.172)	(0.265)	(0.675)	(0.742)
Fall Precip Squared	0.0004**	0.002***	0.001	0.003***
	(0.0002)	(0.001)	(0.001)	(0.001)
Winter Temp:Precip	0.008	0.002	0.045	0.003
	(0.005)	(0.008)	(0.032)	(0.021)
Spring Temp:Precip	−0.019**	0.011	−0.065	0.187***
	(0.009)	(0.016)	(0.056)	(0.047)
Summer Temp:Precip	0.032***	0.021	0.005	−0.170***
	(0.008)	(0.015)	(0.032)	(0.044)
Fall Temp:Precip	−0.058***	−0.097***	−0.059	−0.221***
	(0.009)	(0.016)	(0.047)	(0.032)
Constant	−81.950	−1,560.684***	322.409	−1,128.314
	(96.809)	(351.045)	(680.346)	(810.688)
Soil Control (LCC)	Yes	Yes	Yes	Yes
Observations	3,070	2,489	1,036	1,229
R^2	0.343	0.282	0.370	0.350
Adjusted R^2	0.337	0.274	0.353	0.335
Residual Std. Error	62.547 (df = 3042)	61.386 (df = 2461)	43.729 (df = 1008)	71.773 (df = 1201)
F Statistic	58.753*** (df = 27; 3042)	35.740*** (df = 27; 2461)	21.903*** (df = 27; 1008)	23.931*** (df = 27; 1201)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3: Pasture Ricardian Parameter Estimates

	Conterminous U.S.	Eastern U.S.	Northeast	Southeast
Winter Temp	164.791***	290.259***	−28.959	23.246
	(33.246)	(36.191)	(98.961)	(146.336)
Winter Temp Squared	1.772	2.282	−3.028	−0.079
	(1.821)	(2.533)	(6.825)	(8.013)
Spring Temp	307.800***	−690.623***	−593.245***	−1,206.320**
	(87.105)	(137.906)	(222.026)	(555.494)
Spring Temp Squared	−22.658***	18.943***	9.783	29.066*
	(3.844)	(5.277)	(16.050)	(15.328)
Summer Temp	−451.612***	1,615.620***	134.674	1,694.014**
	(162.537)	(349.337)	(896.967)	(797.137)
Summer Temp Squared	21.052***	−21.542***	5.202	−23.981*
	(3.670)	(6.515)	(20.867)	(14.436)
Fall Temp	−381.764***	−55.001	138.657	1,002.977
	(141.971)	(235.262)	(474.148)	(883.121)
Fall Temp Squared	9.128	−15.737*	−15.812	−32.263
	(6.113)	(8.850)	(20.711)	(25.963)
Winter Precip	4.695***	−0.366	1.971	6.192***
	(0.607)	(1.001)	(5.275)	(2.193)
Winter Precip Squared	−0.007***	0.001	−0.001	−0.004
	(0.001)	(0.002)	(0.012)	(0.003)
Spring Precip	−8.767***	4.219	42.512***	−50.630***
	(1.832)	(2.876)	(6.436)	(10.559)
Spring Precip Squared	0.029***	−0.005	−0.071***	0.031***
	(0.003)	(0.005)	(0.016)	(0.010)
Summer Precip	8.886***	16.982***	−3.471	54.614***
	(1.963)	(3.742)	(12.623)	(10.182)
Summer Precip Squared	0.006***	0.003	0.012	−0.004
	(0.002)	(0.002)	(0.015)	(0.003)
Fall Precip	−1.042	−4.363*	−23.769***	7.359
	(2.203)	(2.465)	(7.188)	(6.386)
Fall Precip Squared	0.0004	0.004	0.031**	−0.014
	(0.002)	(0.005)	(0.015)	(0.009)
Winter Temp:Precip	0.353***	0.029	0.830**	−0.720***
	(0.065)	(0.081)	(0.356)	(0.185)
Spring Temp:Precip	−0.876***	−0.219	−0.028	1.639***
	(0.129)	(0.157)	(0.622)	(0.410)
Summer Temp:Precip	−0.415***	−0.685***	−0.185	−1.766***
	(0.099)	(0.149)	(0.359)	(0.385)
Fall Temp:Precip	0.009	0.212	0.676	0.243
	(0.112)	(0.155)	(0.521)	(0.282)
Constant	3,804.552***	−17,917.030***	−3,583.881	−23,804.610***
	(1,329.320)	(3,409.255)	(7,724.579)	(7,188.718)
Soil Control (LCC)	Yes	Yes	Yes	Yes
Observations	2,620	2,180	917	1,076
R^2	0.281	0.228	0.348	0.185
Adjusted R^2	0.274	0.218	0.329	0.164
Residual Std. Error	713.191 (df = 2592)	529.178 (df = 2152)	433.697 (df = 889)	573.821 (df = 1048)
F Statistic	37.573*** (df = 27; 2592)	23.563*** (df = 27; 2152)	17.601*** (df = 27; 889)	8.832*** (df = 27; 1048)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4: Urban Ricardian Parameter Estimates

	Conterminous U.S.	Eastern U.S.	Northeast	Southeast
Heating Degree Days (HDD)	−83.118***	40.475***	8.085	70.618***
	(5.067)	(7.131)	(20.011)	(19.694)
HDD Squared	0.005***	−0.003***	0.001	−0.018***
	(0.001)	(0.001)	(0.001)	(0.003)
Cooling Degree Days (CDD)	−199.232***	−21.771*	51.675	−184.142***
	(8.428)	(11.171)	(38.489)	(31.820)
CDD Squared	0.030***	0.014***	−0.008	0.054***
	(0.003)	(0.003)	(0.019)	(0.007)
Annual Precipitation	−154.521***	195.345***	103.864	90.104
	(16.685)	(30.559)	(114.495)	(64.436)
Annual Precipitation Squared	0.026***	−0.060***	−0.007	−0.056***
	(0.003)	(0.007)	(0.029)	(0.010)
HDD:Precip	0.021***	−0.025***	−0.022*	−0.012
	(0.003)	(0.004)	(0.013)	(0.013)
CDD:Precip	0.043***	−0.005	−0.042	0.053**
	(0.007)	(0.009)	(0.044)	(0.021)
Constant	312,735.400***	−172,768.500***	−125,209.100	−33,679.940
	(18,480.760)	(30,744.630)	(95,477.290)	(64,721.410)
Demographic Controls	Yes	Yes	Yes	Yes
Observations	3,089	2,506	1,038	1,244
R^2	0.531	0.362	0.439	0.383
Adjusted R^2	0.528	0.357	0.430	0.375
Residual Std. Error	25,292.360 (df = 3071)	13,795.180 (df = 2488)	12,694.290 (df = 1020)	14,776.840 (df = 1226)
F Statistic	204.417*** (df = 17; 3071)	82.862*** (df = 17; 2488)	47.018*** (df = 17; 1020)	44.818*** (df = 17; 1226)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5: Climate Change Impact on Net Returns

	East U.S.			*Southeast U.S.*			*Northeast U.S.*		
	Current Climate	Climate Changed	Percent Change	Current Climate	Climate Changed	Percent Change	Current Climate	Climate Changed	Percent Change
Crop	68.11	-51.11	-75%	83.24	-74.25	-89.2%	66.19	2.16	+3.36%
Pasture	174.75	650.61	+372%	139.14	465.03	+334.2%	194.44	1027.7	+528%
Forest	49.76	31.60	+63.5%	80.78	43.76	+54.2%	13.58	17.21	+126.7%
Urban	33575	-1726	-5.1%	34638	684	+1.97%	32932	-4084	-12.4%

Table 6: Logit Parameter Estimates

	Land Starting in Crop			Land Starting in Pasture			Land Starting in Forest		
	(East)	(South)	(North)	(East)	(South)	(North)	(East)	(South)	(North)
fr:(intercept)	−8.411***	−6.481***	−11.848***	−2.276***	−1.988***	−2.709***	6.188***	6.278***	5.843***
	(0.279)	(0.383)	(0.585)	(0.105)	(0.144)	(0.156)	(0.227)	(0.357)	(0.296)
ps:(intercept)	−5.757***	−4.916***	−6.483***	3.270***	3.635***	2.829***	0.074	0.464	−1.676***
	(0.061)	(0.088)	(0.092)	(0.057)	(0.086)	(0.076)	(0.267)	(0.388)	(0.482)
ur:(intercept)	−7.222***	−6.912***	−7.404***	−2.823***	−2.406***	−3.393***	0.055	0.346	−0.761**
	(0.198)	(0.327)	(0.254)	(0.189)	(0.240)	(0.313)	(0.252)	(0.380)	(0.359)
fr:lcc	0.078	−0.390***	0.793***	0.378***	0.348***	0.425***	0.538***	0.611***	0.533***
	(0.097)	(0.150)	(0.129)	(0.026)	(0.037)	(0.039)	(0.065)	(0.111)	(0.081)
ps:lcc	0.239***	0.114***	0.333***	0.252***	0.232***	0.277***	0.243***	0.336***	0.347***
	(0.020)	(0.029)	(0.029)	(0.017)	(0.025)	(0.023)	(0.074)	(0.118)	(0.114)
ur:lcc	−0.025	−0.081	0.0003	0.148***	0.133**	0.173**	0.390***	0.449***	0.441***
	(0.073)	(0.117)	(0.095)	(0.052)	(0.066)	(0.086)	(0.069)	(0.115)	(0.090)
cr:nrchange	0.003***	0.003***	0.001	0.001	−0.0003	0.0003	0.003**	0.001	0.003
	(0.0004)	(0.0004)	(0.001)	(0.0004)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
fr:nrchange	−0.003***	−0.003***	−0.002**	−0.002***	−0.003***	−0.001*	0.001***	0.0005**	−0.00001
	(0.0004)	(0.001)	(0.001)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0004)
ps:nrchange	0.001***	0.0004**	0.0004**	−0.0002	−0.00004	−0.0002	0.001***	0.001***	0.001
	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.001)
ur:nrchange	−0.00000	0.00000	−0.00000	−0.00000	0.00000	−0.00001	0.00001***	0.00001*	0.00001**
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00000)	(0.00001)	(0.00000)
Observations	273,825	82,461	191,364	126,364	75,296	51,068	427,707	236,980	190,727
R^2	0.354	0.286	0.467	0.085	0.194	−0.088	0.755	0.737	0.786
Log Likelihood	−12,160.890	−5,680.374	−5,711.711	−16,748.930	−8,727.510	−8,050.187	−7,165.345	−4,818.789	−2,320.083
LR Test (df = 10)	13,353.160***	4,555.732***	10,008.550***	3,100.831***	4,214.246***	−1,306.482	44,222.990***	26,994.440***	17,084.750***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 7: Logit Parameter Estimates Used in Simulation

	Dependent variable:		
	Land Starting in:		
	(Crop)	(Pasture)	(Forest)
fr:(intercept)	-6.406^{***}	-2.421^{***}	6.622^{***}
	(0.395)	(0.152)	(0.386)
ps:(intercept)	-4.613^{***}	3.716^{***}	0.840^{**}
	(0.093)	(0.088)	(0.415)
ur:(intercept)	-7.341^{***}	-2.788^{***}	0.286
	(0.367)	(0.273)	(0.412)
fr:lcc	-0.403^{***}	0.360^{***}	0.609^{***}
	(0.152)	(0.037)	(0.111)
ps:lcc	0.102^{***}	0.235^{***}	0.335^{***}
	(0.029)	(0.026)	(0.118)
ur:lcc	-0.092	0.146^{**}	0.448^{***}
	(0.120)	(0.067)	(0.115)
cr:nr	0.003^{***}	0.002^{***}	0.005^{***}
	(0.0004)	(0.0003)	(0.001)
fr:nr	0.001^{***}	0.001^{***}	0.0001
	(0.0002)	(0.0001)	(0.0001)
ps:nr	-0.001^{***}	-0.0003^{**}	0.0005^{**}
	(0.0001)	(0.0001)	(0.0002)
ur:nr	0.00002^{***}	0.00001^{***}	0.00002^{***}
	(0.00000)	(0.00000)	(0.00000)
Observations	82,461	75,296	236,980
R^2	0.291	0.205	0.739
Log Likelihood	$-5,645.650$	$-8,618.243$	$-4,783.248$
LR Test (df = 10)	$4,625.179^{***}$	$4,432.779^{***}$	$27,065.520^{***}$
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 8: Climate Change Impact on Landscape in Southeast U.S.

	Current Acres (in 1000s)	Future Acres (no CC)	Baseline Trend ΔB	Future Acres (w/ CC)	Climate Impact ΔC	Climate Impact Factor
Crop	43,241	46,202	0.0685	46,211	0.00084	0.0123
Pasture	45,138	41,240	−0.0863	41,214	−0.00063	0.0073
Forest	149,122	144,687.9	−0.0297	144,688.1	0.000006	−0.000047
Urban	27,253	32,605	0.1964	32,592	−0.0004	0.0033