AN ABSTRACT OF THE DISSERTATION OF

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Title: An Econometric Analysis of the Impact of Climate Change on Forest Land Value and Broad Land-use Change

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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 dissertation, I estimate current climate's effect on the economic net returns to alternative land-use systems in the United States. Then I model the conversion between these alternative uses to analyze how future climate change may alter future landscapes. My research contributes to the general knowledge of natural resource and environmental economics by i) developing the first national scale application of the Ricardian method to the economic return to forestry, ii) 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. I 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. The full model is used to examine the impact of climate change on the southeastern U.S. landscape. The national analysis of forest rents indicates significant increases to forest profitability across most of the U.S. under climate change projections to 2050. However, there is limited evidence that higher forest rents in the southeast will induce large shifts in the forest land area. 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.

An Econometric Analysis of the Impact of Climate Change on Forest Land Value and Broad Land-use Change

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I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

Christopher Mihiar, Author

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Chapter 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 peoples decisions through adaptive measures. For example, a forest-land 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 regions dry climate and cold winters, or the landowner could leave forest use entirely in favor of an alternative land system. Both direct and belief effects are important when analyzing the effects of climate on economic outcomes. The framework developed in this dissertation allows analysis of climate impacts on land-use in a manner that accounts for both the direct and belief effects of climate.

This dissertation fills a gap 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 significant 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.

A novel Ricardian analysis is conducted that estimates the effects of climate on the annualized net economic returns to forestry across the conterminous United States. Climate has been shown to affect the forestry sector of the economy through its effects on the biological growth and productivity of trees [31, 27, 45]. Recent numerical analyses have highlighted the potential economic value of extensive margin adaptation in forestry, particularly through replanting choices [20]. However, there have been no large-scale empirical analyses that link observable measures of the net economic returns to forestry in a region with climate conditions in that region [10].

The foundation of my forest Ricardian analysis is a novel county-level database of net returns to forestry for the conterminous United States compiled and estimated from numerous data sources. Unlike U.S. agriculture − the focus of many Ricardian analyses − there is no readily available national database of net economic returns to forestry. Two primary data products are brought together to develop the full database. First, stumpage price data is compiled for numerous tree species across dozens of public and private data sources across the country encompassing the years 1998 to 2014. Second, highly localized timber growth equations are developed and estimated by exploiting a big data set comprised of over 32 million observations of growing stock volume and stand age from the U.S. Forest Services Forest Inventory and Analysis (FIA) data across the conterminous U.S. My unique database includes approximately 59,000 separately estimated timber growth equations that generate timber yields which vary by county and by tree species group. The relatively fine-scale variation in the estimated timber growth equations embed localized climatic factors such as direct productivity impacts and belief effects arising from landowners intensive margin adaptation decisions from managing particular tree species.

My dissertation is organized as follows. Chapter 2 characterizes the analytic framework used to construct and analyze the functional relationship between climate and land-use change. In chapter 3, measures of the economic net returns to alternative land-uses are developed for the conterminous U.S. including the novel estimation of tree growth equations used to construct forest rents. Chapter 4 presents the results for separately estimated Ricardian functions of crop, pasture, forest, and urban land-use types. In chapter 5, climate impact results from chapter 4 are integrated into a broad land-use choice model. Climate's impact on broad land-use change is analyzed for the southeastern U.S. in section 5.2.2. Chapter 6 concludes.

Chapter 2: Analytic Framework

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 chapter is laid out as follows. First, I present the discrete choice modeling framework used to predict land-use transitions for land starting in crop, pasture, and forest use. The analysis accounts for conversion to crops, pasture, forest, and urban use. These four systems define the major land-uses in the eastern U.S., the region examined in great detail in section 5.2. Second, I describe the framework underlying chapter 4's estimation of separate Ricardian functions, uniquely specified to describe climate's affect on the economic net returns to each alternative land-use system. In chapter 5 these frameworks are integrated to analyze the impact of climate change on land-use change. Finally, later analysis of climate impact on transition probability and the future landscape are motivated in sections 2.3 and 2.4.

2.1 Land-use Change Model

This analysis builds on an extensive body of research concerned with land-use choice and the resulting impacts to ecosystem services. Stavins and Jaffe [52] demonstrated how relative economic returns to land drive land-use change, recognizing the significant difference between agricultural land and forest land in terms of the provision of ecosystem services, and that policies that incentivize one land system over another can have unintended consequences. Bockstael [7] highlighted the inherently spatial nature of land-use and ecosystem services, presenting the necessary framework for modeling land owner decisions and simulating landscape changes. The key insight in [7] was that the choice probabilities resulting from a discrete choice model must be updated each period so as to account for the influence of land supply on the decision to convert from one system to another. Lubowski built on that earlier work by extending the spatial scale of the land-use change problem to the U.S. national level, analyzing the market and land quality drivers of land-use change [35], and studying the potential costs associated with a national carbon sequestration policy [34]. Radeloff et al [44] simulate, at the national level, the future U.S. landscape under alternative policy scenarios. It is from this rich base of knowledge that the current study begins.

I employ an econometric model of the revealed preferences of landowners based on detailed micro-data of land-use and land quality spanning four 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.

Land owners are assumed to choose the productive use k that maximizes the net present discounted return to land.

$$R_{inkt} = \int (P_{inkT+t} Q_{inkT+t} - S_{inkT+t} Z_{inkT+t}) e^{-rt} dt \tag{2.1}$$

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.

$$\arg\max_{k}(R_{kt} - rC_{jkt}) \geq R_{jt} \tag{2.2}$$

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

$$R_{inkt} = V_{inkt} + \epsilon_{inkt}, \tag{2.3}$$

and define V_{inkt} linearly as

$$V_{inkt} = \beta_k^{'} X_{inkt}. \tag{2.4}$$

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

$$Pr(\beta_k^{'} X_{inkt} - \beta_j^{'} X_{injt} > \epsilon_{injt} - \epsilon_{inkt}). \tag{2.5}$$

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

$$P_{injkt} = \frac{exp(\beta_k^{'} X_{inkt})}{\sum_{m=1}^{K} exp(\beta_m^{'} X_{inmt})}. \tag{2.6}$$

The specification in equation 2.6 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. In the next section I lay out the framework for identifying the effect of climate on the value of land which enter as independent variables in equation 2.6.

2.2 Climate Econometrics & the Ricardian 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 my empirical strategy using a forest system as motivation. 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 2.1, the curve labeled species 1 presents 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.

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 in figure 2.1. 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 2.1. 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 2.2, 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 2.2 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 2.2 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].

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 ponderosa pine forests only, then we capture adaptations within a ponderosa 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. For example, the net return functions in figure 2.2 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 forestry, 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. Let NR^k be the net economic return to production in land-use k, and C be a vector containing temperature and precipitation.

$$NR^k(\mathbf{C}) = NR^k(\mathbf{c}(\mathbf{C}), \mathbf{b}(\mathbf{C})) \tag{2.7}$$

The net returns to a land-use system k are a function of the direct $c(C)$ and belief $b(C)$ effects of climate. If we assume that landowners have a good sense of C 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, which is the differential of NR^k with respect to C.

$$\frac{dNR(C)}{dC} = \nabla_c NR(C) \cdot \frac{dc}{dC} + \nabla_b NR(C) \cdot \frac{db}{dC} \tag{2.8}$$

$$= \sum_{k=1}^{K} \frac{\partial NR(C)}{\partial c_k} \frac{dc_k}{dC} + \sum_{n=1}^{N} \frac{\partial NR(C)}{\partial b_n} \frac{db_n}{dC} \tag{2.9}$$

Equation 2.8 provides an expression where the total marginal effects of climate are equal to the sum of the direct effects and the belief effects. 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 β for a change in climate $\delta C_{n\tau}$ on the net returns to land.

$$\beta = E[NR_{n\tau} \mid C_{n\tau} + \Delta C_{n\tau}, x_{n\tau}] - E[NR_{n\tau} \mid C_{n\tau}, x_{n\tau}] \tag{2.10}$$

That is, the difference in expected outcomes given all non-climactic factors under two different climates. We cannot directly observe β because county n 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 n and m were identical in every way except for their climate then the unit homogeneity assumption holds. This assumption is represented by the equality

$$E[NR_{n\tau} \mid C, x_{n\tau}] = E[NR_{m\tau} \mid C, x_{m\tau}]. \tag{2.11}$$

Unit homogeneity is the identifying assumption for the Ricardian approach and assumes that no unobserved drivers of NR^k are also correlated with climate. When the unit homogeneity assumption holds we can use the following unbiased estimator which compares net returns in different locations which differ by climate

$$\begin{aligned}\hat{\beta} &= E[NR_{m\tau} \mid C_{n\tau} + \Delta C_{n\tau}, x_{m\tau}] - E[NR_{n\tau} \mid C_{n\tau}, x_{n\tau}] \\ &= E[NR_{n\tau} \mid C_{n\tau} + \Delta C_{n\tau}, x_{n\tau}] - E[NR_{n\tau} \mid C_{n\tau}, x_{n\tau}] \\ &= \beta.\end{aligned}$$

I rely on the extensive revealed preference literature to estimate a variant of the following equation to recover the functional relationship between climate and the net return to land-use k.

$$NR_n^k = \alpha_n^k + \beta_n^k \mathbf{C}_n^k + \gamma_n^k \mathbf{x}_n + \epsilon_n^k \tag{2.12}$$

Where C is a vector of climate variables specific to county n and land-use k, and x_n is a vector of non-climactic variables that also affect net returns. Four Ricardian functions are developed and estimated in chapter 4, corresponding to the four broad land-uses modeled in chapter 5.

2.3 The Effects of Climate Change on Land-use Change Probability

By substituting equation 2.12 into equation 2.6, I 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.

$$P_{injk} = f(NR^{k_1}(C), NR^{k_2}(C), \cdots, NR^{K}(C)|LCC_i) \tag{2.13}$$

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.

$$dP_{injk} = \frac{\partial f}{\partial NR^{k_1}} \cdot \frac{\partial NR^{k_1}}{\partial C} + \cdots + \frac{\partial f}{\partial NR^{K}} \cdot \frac{\partial NR^{K}}{\partial C} \tag{2.14}$$

The total increment of P is derived from a linear approximation from the derivative defined in 2.13.

$$\Delta P_{injk} = f(\Delta NR^{k_1}, \Delta NR^{k_2}, \cdots, \Delta NR^{K}) - f(NR^{k_1}, NR^{k_2}, \cdots, NR^{K}) \tag{2.15}$$

Where $\Delta NR^k = NR^k(\Delta C) - NR^k(C)$ 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:

$$\Delta_j P_{injk} = f(\Delta NR^j, NR^2, \cdots, NR^K) - f(NR^j, NR^2, \cdots, NR^K) \tag{2.16}$$

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 it's effect on the other uses fixed. Construction of the probability function ensures that before and after any changes in probability, the sum of the probabilites for each starting use must sum to one, and that the sum of changes to those probabilites must equal zero. Such that $\sum_{j=1}^{J} P_{injk} = 1$ and $\sum_{j=1}^{J} \Delta_j P_{injk} = 0$.

2.4 The Impact of Climate Change on Future Land Area

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 2.3 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 as defined in equation 2.15. 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, I 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.

$$ccfact = \frac{\Delta C}{\Delta B} \tag{2.17}$$

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.

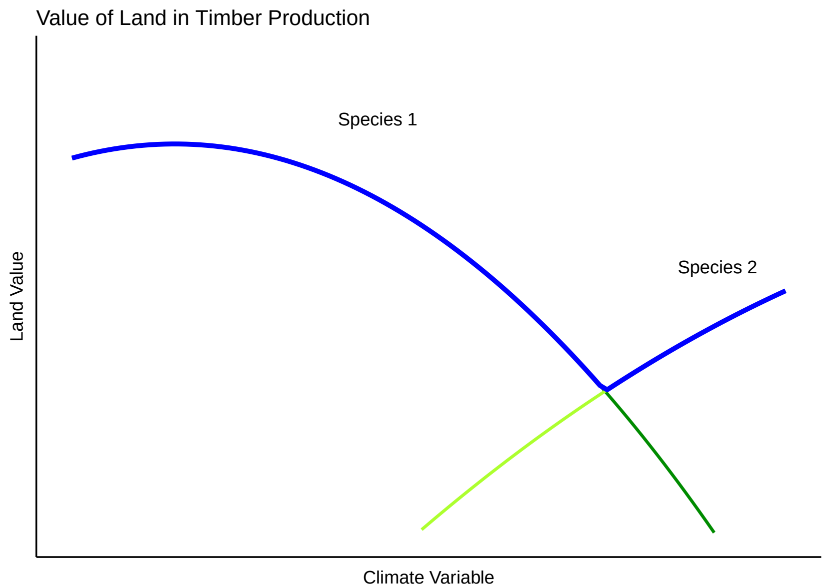

Figure 2.1: Stylized Ricardian Value Function

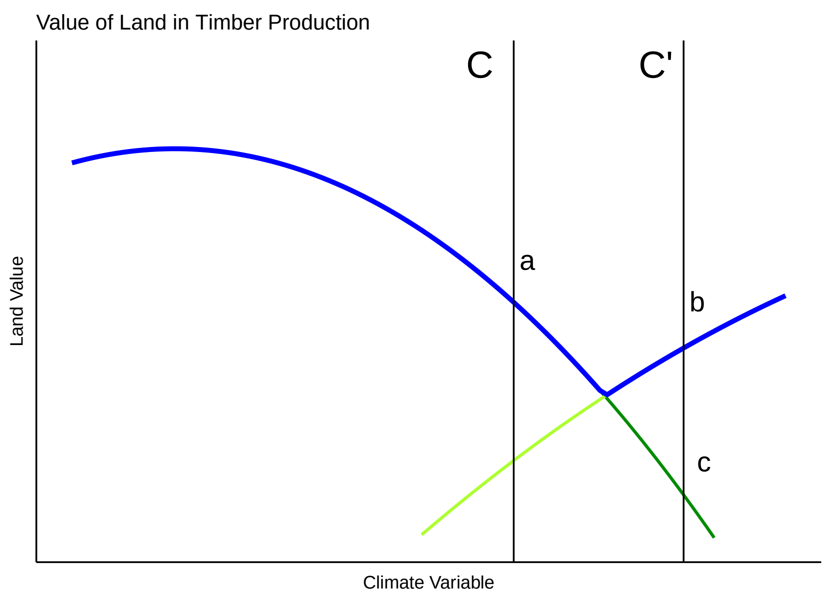

Figure 2.2: Stylized Climate Change Adaptation

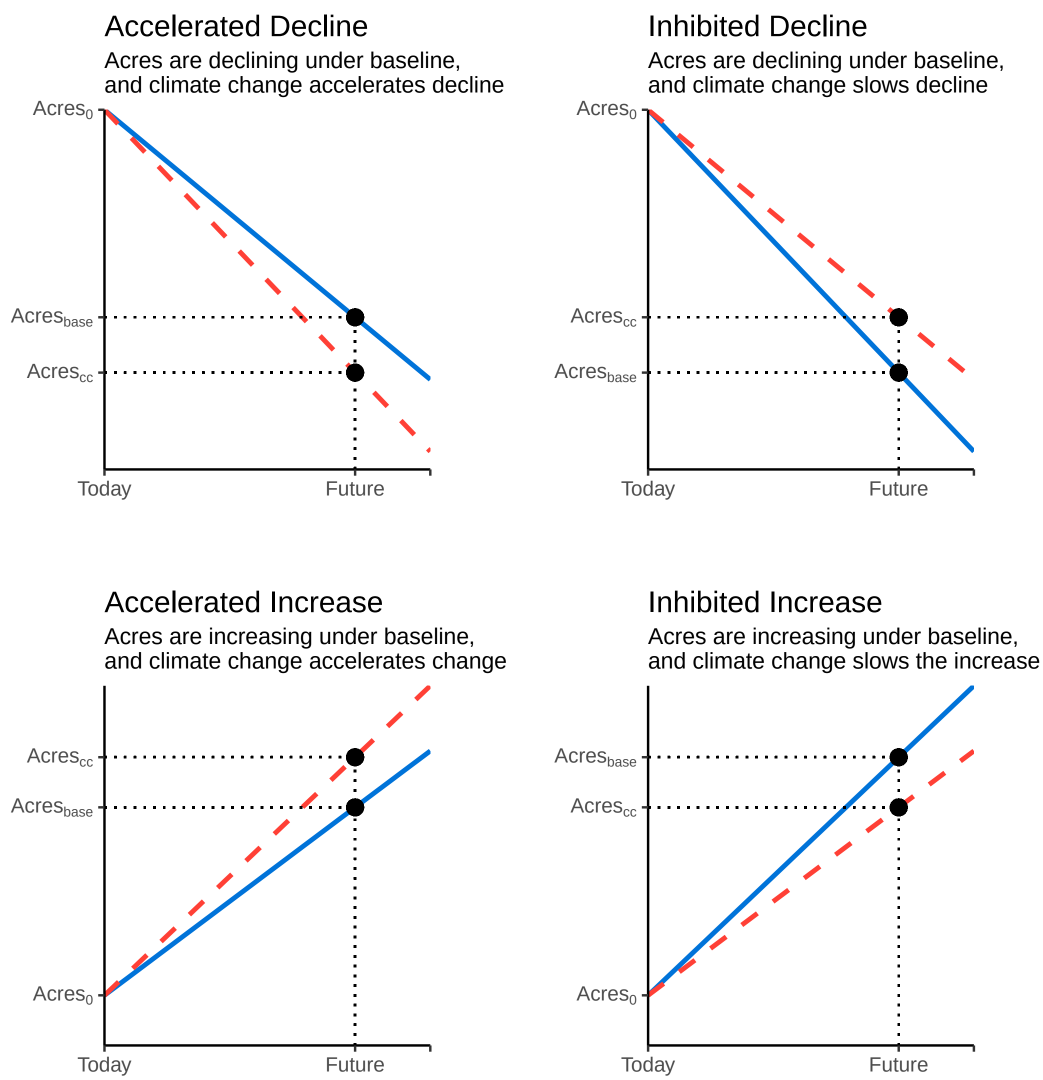

Figure 2.3: Stylized Climate Change Impact on Land Area

Chapter 3: The Economic Net Return to Land

The land-use model developed and estimated in chapter 5 relies on the economic incentives that drive land-use management decisions. I 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. The present chapter 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, dollars per acre of land, allowing comparison of value across systems. Special attention is given to the novel construction of forest net returns.

3.1 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 variation 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.

3.1.1 Basic theory of forestry land values and net returns

Rotational forestry consists 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]:

$$V_t(a,s) = max \begin{cases} P(s,t) \cdot vol(a,t,s) - C + \rho V_{t+1}(1,s_1) \\ P(s,t) \cdot vol(a,t,s) - C + \rho V_{t+1}(1,s_2) \\ \quad \vdots \\ P(s,t) \cdot vol(a,t,s) - C + \rho V_{t+1}(1,s_S) \\ \qquad\qquad \rho V_{t+1}(a+1,s) \end{cases} \tag{3.1}$$

Where $P(s,t)$ is the stumpage price of species s at time t, $vol(a,t,s)$ is the timber volume of age a trees, C is the cost of afforestation, 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 $P(s,t) \cdot vol(a,t,s) - C$, with subsequent replanting optimized over the choice of which tree species s to plant. If the landowner chooses not to harvest, then their trees grow by $vol(a+1,t+1,s) - vol(a,t,s)$ over the next period. The volume function has time t as an argument to capture the fact that climate change might alter tree growth. The classic Faustmann version of the problem is embedded in 3.1 and emerges when landowners have static expectations and expect no future changes in price, the timber volume function, nor afforestation costs.

Guo and Costello [20] show how climate change can be introduced into the forestry land value function in 3.1 when timber volume functions for alternative tree species are a function of climate, and so the landowners optimal replanting choice and harvest time depend on climate change. In particular, their approach assumes that landowners have knowledge about climate change into the future as well as the functional link between $vol(a,t,s)$ and climate. The optimized land value function $V_t(a,s)$ can be used to construct an annualized net return (rental value) of forestland as $V_t(a,s) \cdot \delta$, where δ is the discount rate embedded in ρ. Lubowski et. al. [34] constructed county-level annualized net returns to forestry by collecting data on stumpage prices P and afforestation costs C, incorporating regional aggregated timber volume functions from U.S. Forest Service reports to approximate $vol(a,t,s)$, and then derived a fixed rotation time T by solving the maximization problem in 3.1 for each county under a static expectations Faustmann assumption. Guo and Costello [20] and Lubowski et al. [34] impose different belief effects on landowners. Guo and Costello impose a belief about a climate change trajectory and dynamically optimized responses by landowners to climate change. Lubowski et al. [34] imposes a belief that nothing changes in the future, and so the same rotation length T occurs in perpetuity. My approach is to construct county-level net return measures that impose as little as possible about landowners belief effects with respect to climate change.

3.1.2 Stumpage price and afforestation cost data

Analysis of forestry rents at the national level has been limited by the lack of a centralized and consistently reported data source for stumpage prices. I compile a unique national level stumpage price data set from numerous sources including state-level departments of natural resources, University extension services, the US Forest Service, and private reporting services (see appendix B for a complete list). In locations where price data is not observed, either because it was not reported and/or collected, or when the there is little-to-no market activity, county-species price is extrapolated by taking advantage of correlation across space using neighboring counties and regions.

All stumpage prices are georeferenced to the county level, and the reported species were mapped to species groups defined by the U.S. Forest Service. Missing years for each county-species pair are interpolated linearly using the observed values. Observed stumpage prices are used to spatially interpolate missing prices for counties that did not have a reported stumpage price. The interpolation is executed whenever the observed species was present in large enough volumes to estimate growth in that county. The spatial interpolation algorithm first looks for the missing price in neighboring counties that share a boundary. If multiple prices are found, then the volume weighted average price is used. This is repeated for 2nd and 3rd degree neighbors (i.e. two and three counties away). Finally, when county-neighbor price is unavailable, the state or regional weighted average is used.

Forest establishment costs were econometrically estimated by Nielsen et al [40] for each county in the contiguous United States. Their estimation is based on enrollment data from the USDAs Conservation Reserve Program.

3.1.3 Tree Growth Functions

Past natural science literature has shown examples of how climate affects tree growth for particular species and regions, $vol(a, t, s)$ [31, 45]. Given the substantial climate variability across the conterminous U.S., tree growth functions that differ across space are ideal. I estimate approximately 59,000 county-species specific timber growth equations specific to county, forest type and species group using a permutation of von Bertalanffys function for organic growth [56, 54].

$$V(a)_{ns} = \alpha_{ns}(1 - e^{-\beta a})^3 \tag{3.2}$$

Where a is stand age as defined above, and α_{ns} and β_{ns} are parameters to be estimated which vary across county n and forest species s. The α parameter is interpreted as the asymptotic limit of tree volume, the volume at which growth is zero, and the β parameter is the rate of growth. The FIA observations also include information on stand size, site class (i.e. land productivity), and land disturbance (e.g. clear cutting, fire occurrence, etc.). The inclusion of these variables in the sample implicitly incorporates their effects into the growth function. The growth function $V(a)_{ns}$ for each ns is estimated using a non-linear least squares algorithm where the observed FIA data is fit to a growth curve by minimizing the sum of the squared deviations using the quasi-Newton method BFGS.

Bertalanffy growth functions have been used extensively in natural resource sciences and apply generally to any organic life. For example, Van Deusen and Heath [54] use von Bertalanffy functions to estimate growth for the measurement of carbon characteristics in 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). Variation within species group between individual trees identifies the functional relationship between volume and age given the unique characteristics of each county-species pairing.

The complete FIA data set covers 52 forest species groups that combine to form 167 different forest types. When averaged across all county-species equations in the conterminous U.S., estimated values for α and β are 39.9 and 0.068, respectively. Figure 3.1 contrasts two estimated von Bertalanffy growth functions for Douglas-fir for two different Oregon counties Deschutes county (α = 124.4, β = 0.023) in the semi-arid central portion of Oregon, and Benton county (α = 753.6, β = 0.021) in a much wetter and more temperate portion of western Oregon. The difference in estimated growth functions across these two climates within the same state is a striking example of how climate affects tree growth at relatively fine spatial scales.

3.1.4 An annualized net returns to forestry measure for one rotation

With an available price P_{ns}, afforestation cost C_n, and estimated volume functions $vol(a)_{ns}$ for each county (n) species (s) pair, what remains is to choose a harvest age (rotation length) to determine the one-rotation forestry profit for an acre of land. Focus is placed on the first rotation to obtain a reasonable measure for the current profitability of timberland. The belief effect assumptions of [20, 34] are relaxed by deriving an observed harvest age from FIA plots that recorded timber harvesting activities. In particular, the average age of all recent removals of species s at the state level are used to calculate a rotation length T_{ns}. The present value of the one-rotation profit from harvesting $vol(T_{ns}, s)_{ns}$ in T_{ns} years is given by:

$$[\bar{P_{ns}} \cdot vol(T_{ns}, s) - C_n]\rho^{T_{ns}} = PVProfit_{ns} \tag{3.3}$$

Where $\bar{P_{ns}}$ is the average stumpage price for forest species s in county n over the period 1997 to 2014, $vol(T_{ns}, s)$ is the estimated von Bertalanffy volume of timber for species s evaluated at age T_{ns}, and C_n and ρ are cost and discount factors. This measure of annualized net returns is the annual payment NR_{ns}, in which a landowner would be indifferent to receiving $PVProfit_{ns}$ today or a series of annual payments NR_{ns} for T_{ns} years:

$$NR_{ns}(\rho^1 + \rho^2 + \ldots + \rho^{T_{ns}}) = PVProfit_{ns} \tag{3.4}$$

Finally, the composite net return NR_n for all species and forest types is constructed using the species-weighted average volume observed in each county.

$$NR_n = \sum_{s=1}^{S_n} NR_{ns} \cdot Share_{ns} \tag{3.5}$$

Where $Share_{ns}$ is the share of county n's private timberland in forest species s, and S_n is the total trees of the observed forest species in county n. Average net returns from equation 3.5 are presented in tables 4.1 - 4.4, and the spatial distribution of the composite net return is presented in figure 3.2.

As a robustness check, the Faustmann T_{ns} solution is applied where the rotation period is optimal and rent is derived from perpetual harvests. The corresponding assumption is that landowners have static expectations, do not expect climate change, and are pure profit maximizers. The Faustmann optimized net return exhibits a comparable numerical and spatial distribution as the net returns derived from the observed rotation periods.

3.2 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. When measurement error is correlated with the size of the PUMA, it may be appropriate to scale the weights with the size of the county. Where-by larger PUMAs are given a systematically lower property value relative to smaller PUMAs. This may be explored in future iterations of this data set, especially for analysis of the western U.S. This error is apparent when looking at the spatial distribution of urban net returns in figure 3.3, and results from the relatively large size of western counties. For this reason, Ricardian analysis of urban land is restricted to the eastern U.S.

Net returns to urban land are calculated as follows:

$$NR_n^{ur} = (SalesPrice)_n * (LotShare)_d / (LotAcres)_d$$

Where net returns in county n equals the sales price times the average lot share in census division d divided by the average lot size in acres in division d. Lot share is derived from SOC data by dividing the sales price of the lot by the total sales price including the house. Dividing by average lot size converts the measure to a per acre unit. Finally, urban net returns are annualized using a 5% discount rate.

3.3 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. The resulting measures comprise the dependant variable in the associated Ricardian functions defined and estimated in chapter 4. 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). The spatial distribution of crop and pasture net returns is presented in figures 3.4 and 3.5.

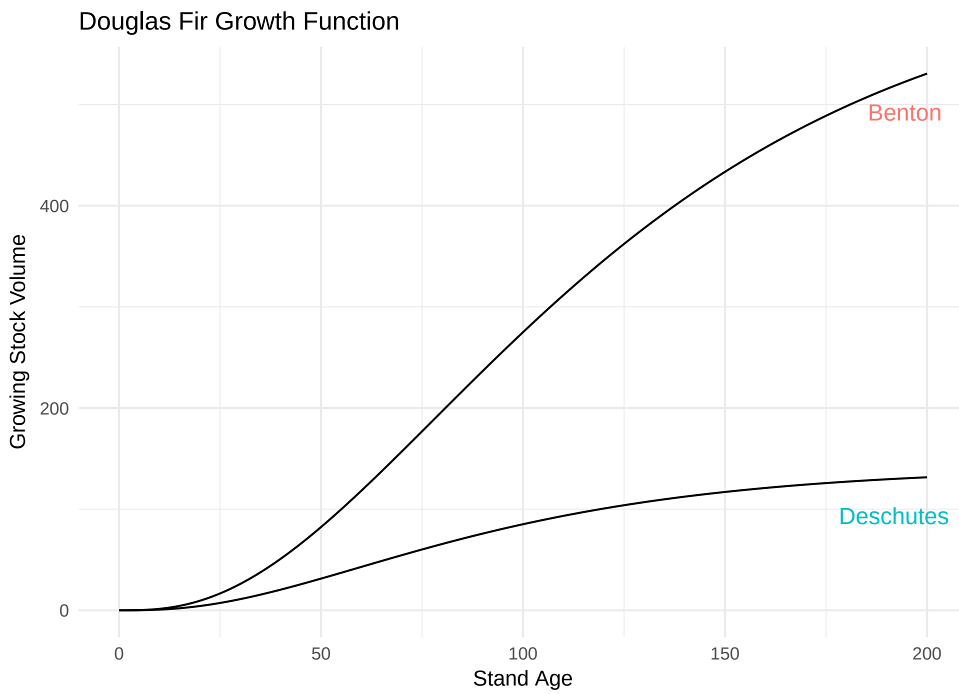

Figure 3.1: Spatial Variation in Douglas-fir Growth

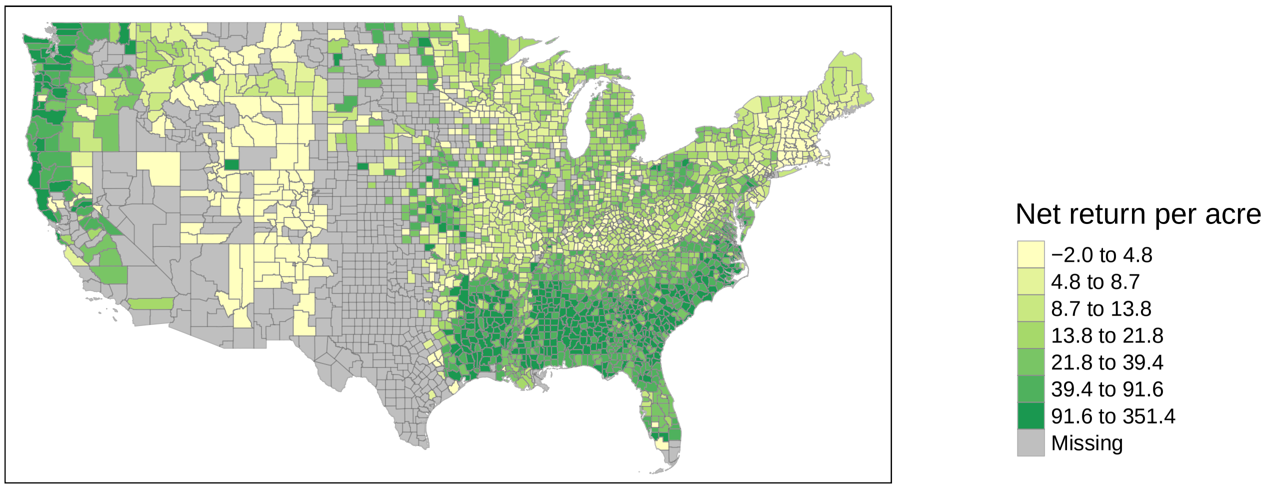

Figure 3.2: Map of Forest Net Returns

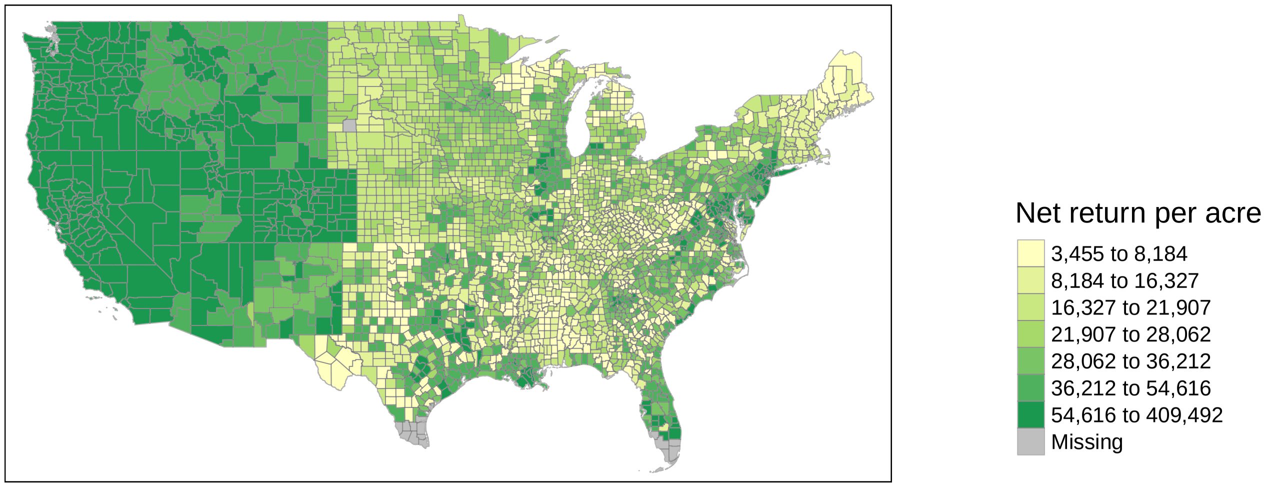

Figure 3.3: Map of Urban Net Returns

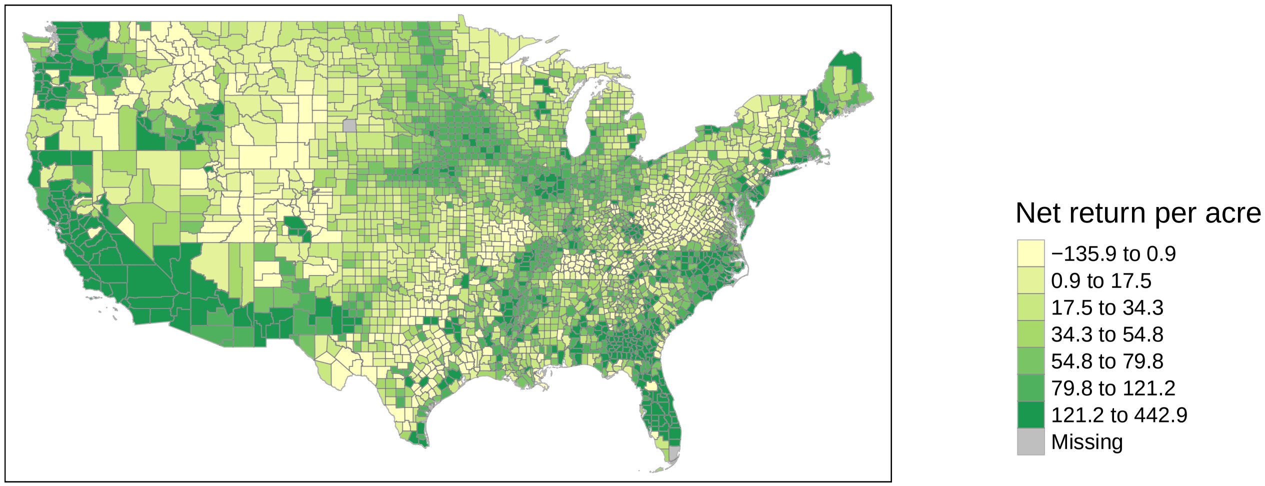

Figure 3.4: Map of Crop Net Returns

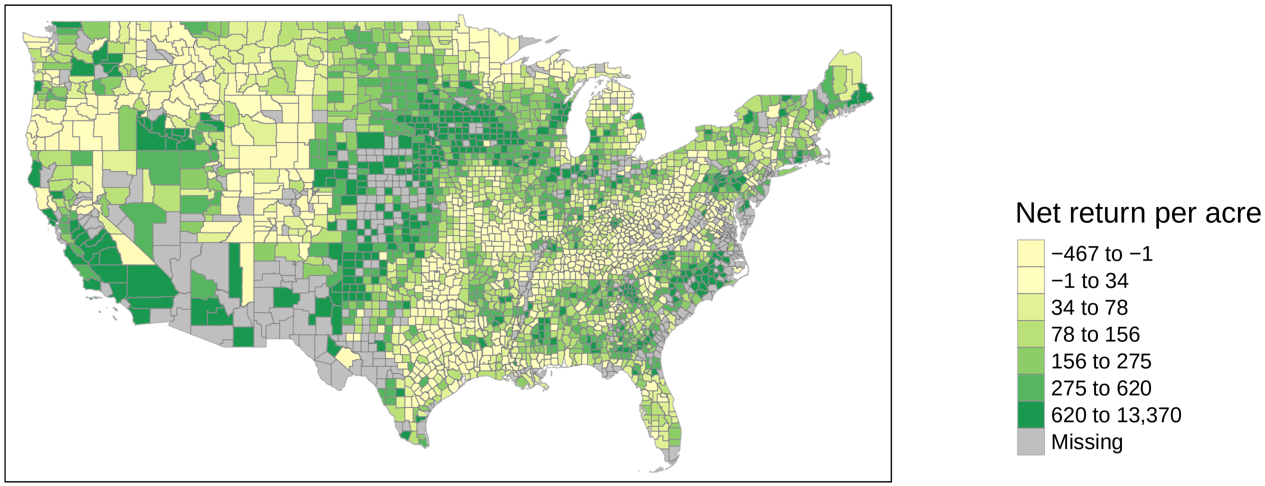

Figure 3.5: Map of Pasture Net Returns

Chapter 4: Ricardian Analysis of the Economic Net Return to Land

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 chapter 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 spacial 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. The goal of this chapter then, is to account for intensive margin adaptations within each land system, and in chapter 5 combine the climate functions into a non-linear land-use choice model that subsequently captures adaptation across land-use systems.

4.1 Forest Ricardian and the Impact of Climate Change

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. My analysis will exploit this spatial variation in climate and forest rents to identify climate's effect on forest net returns.

The forest Ricardian analysis presented here uses empirical methods with observed data to reveal the combined direct and belief effects of climate on forestland 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 United States 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.

4.1.1 Econometric Estimation

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 countys timberland in species group s to obtain an estimable function explaining weighted average net returns to timberland. See section 3.1 for more information on the construction of forest net returns.

$$NR_n^f = \alpha_n + \beta_n f(T_n, P_n) + \gamma_n LCC_n + \delta_r + \epsilon_n \tag{4.1}$$

Where $f(T_n, P_n)$ is a quadratic 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, x_n is a set of county control variables such as soil quality, and δ_r is a set of region r fixed effects. Summary statistics for the forest Ricardian estimations are presented in tables 4.1 - 4.4. All climate variables are weighted by forest area (see appendix A). Identification relies on variation in net returns and climate so that including δ_r may soak up the necessary variation when the study region is too small.

The cross-sectional operationalization employed here to estimate climates effect on land rents builds on the framework popularized by Mendelsohn et al [36]. The Ricardian approach remain popular, with many follow-up articles examining agricultural-climate Ricardian models throughout the world [37]. This is the first application of the Ricardian approach for U.S. forestry.

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.

4.1.2 National Forest Ricardian

In this section, the national forest Ricardian is critically examined by i) estimating a forest system Ricardian for the conterminous U.S. to recover the total impact of climate on the economic net returns to forestry, and ii) checking the robustness of the results to functional form and climate scenario choice. Predictions made using the national Ricardian model approximate the outer envelope from figure 2.1 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 annualized net returns to an acre of private forestland in county n is the dependent variable. Maximum and minimum temperatures enter separately to account for the difference between extreme heat and extreme cold, which has been the focus of some past natural science literature on forests and climate [57, 45]. Annual precipitation and its square are also included. Finally, an interaction between precipitation and temperature extremes is included. FIA defined sub-regions serve as fixed effects to control for unobservable factors that vary across regions and are correlated with net returns and climate. Within state variation is too low to find significance using a state fixed effect. Land quality is controlled for by using county shares of forestland in alternative categories of the land capability class (LCC) measure. LCC is used to approximate soil quality effects on each countys forests, where LCC is derived from the USDAs 2012 National Resource Inventory (NRI) observed LCC data on each countys forestland.

The main result of this section uses the multi-model mean from 20 Global Climate Models under emissions scenario RCP 8.5. Predictions are calculated for 2,390 U.S. counties. Warming is predicted to occur across the entire U.S. and under every GCM as presented in figure 4.1. Temperature increases are relatively greater in the northern region as compared to the south. The distribution of changes in annual precipitation is presented in figure 4.2. Most areas of the U.S. are expected to see increased precipitation at the median for all GCMs except one. However, the majority of climate models predict both wetter and drier conditions across space. The multi-model mean predicts the eastern U.S. getting wetter relative to the west, with the exception of the northern Pacific coast region.

The base estimates in table 4.5 include maximum temperatures, minimum temperatures, and annual precipitation specified as a quadratic, temperature and precipitation interactions, and separate variables indicating shares of each countys forests in the eight alternative LCC soil quality classes, and sub-regional spatial fixed effects. U.S. Forest Ricardian parameter estimates include White's robust standard errors. LCC is a measure of the soils capability to produce commonly cultivated crops and pasture where LCC 1 is the most productive for agriculture and LCC 8 is the least productive. Sub-regions are defined by the FIA as northeast, northern lake states, northern prairie states, pacific northwest, pacific southwest, rocky mountain north, rocky mountain south, south central, and southeast. Given the quadratic specifications, I focus on the estimated average marginal effects of the key climate variables in table 4.6. 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.

There are numerous possible alternative specifications of climate impacts on forest net returns, and the existing natural science literature has not found a consistent functional form in which tree growth is influenced by climate [31, 27, 57]. Therefore, twenty-six alternative specifications of the national Ricardian model are estimated differing by i) the functional form in which climate is specified, ii) whether soil controls (measured as LCC shares) are included, and iii) whether regional fixed effects are included. Table 4.7 presents average marginal effects of the principal climate measures across all twenty-six alternative specifications. Clear robustness is found in the estimated marginal effects of annual precipitation, mean temperature, and maximum temperature, with very little variation across the alternative specifications. Some sensitivity to the estimated marginal effects are found for minimum temperature. The base model in table 4.5 is model number 17 in table 4.7. Comparison of model 17 with models 8 and 14 in table 4.7 indicate that the estimated marginal effects vary across models that do and do not include soil controls. Since estimated parameters on the individual soil control measures are strongly significant (see appendix C), then omitting soil controls appears to induce bias in measuring the effects of minimum temperatures on forest net returns, which suggests correlation between soil quality and minimum temperatures (e.g. colder climates have poorer soils). However, results in table 4.7 suggest minimal bias from omitting soil variables when modeling mean temperature alone, rather than maximum and minimum temperatures separately.

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.

Following Burke et. al.'s [8] suggestion to incorporate uncertainty in climate model predictions, I estimate changes in U.S. forestland returns across twenty alternative global circulation models and find robust positive aggregate impacts of future climate on U.S. forest returns. The national Ricardian function is used to make predictions under each of the 20 available down-scaled GCMs to explore how the projected climate change impact results vary by choice of model. The median change in forest net returns ranges from \$11.58 to \$33.52 (mean change ranges from \$12.64 to \$32.00) per acre, remaining positive regardless of the GCM chosen (figure 4.3).

4.1.3 Under the hood of the national Ricardian: extensive versus intensive margin adaptation in forestry

Projected increases in average forestry returns from climate change using the national Ricardian model could be explained by many direct and belief effects. For example, climate change may have a direct effect by positively affecting the biophysical yield of tree growth across all tree species, and so projected net return increases may occur without any extensive margin adaptations across planted tree species. Alternatively, some tree species may experience biophysical growth from climate change that is larger than the growth experienced by other tree species, and so projected net return increases are driven by landowners adapting along the extensive margin (e.g. replanting different species).

However, the Ricardian models implicit assumption about no barriers to extensive margin adaptation may be problematic in the forestry sector where replanting decisions on a stand occur once over multiple decade harvest rotation cycles. I explore the extent to which extensive margin adaptations are likely driving the national Ricardian model results by separately estimating Ricardian functions for the overlapping major forest types of Douglas-fir and ponderosa pine in the U.S. northwest, and loblolly and shortleaf pine in the U.S. southeast. By using observed growing stock data, each forest type-specific Ricardian function implicitly accounts for adaptation along the intensive margin within each forest type (e.g. rotation length, site preparation, seeding strategies etc.). By comparing separately estimated Ricardian functions across forest types, we are then able to examine whether the projected changes from the national model may be explained by intensive margin changes within each tree species, or whether extensive margin changes across tree species are needed to explain the national model projections.

The national Ricardian model from section 4.1.2 presented estimates of the impacts of climate change on the net annual returns to forestry with the implicit assumption that an unrestricted set of intensive and extensive margin adaptations can occur by 2050. Since the national model approximates the outer envelope of forestry returns from 2.1, the drivers of projected changes in net returns can be explored. One hypothesis is that net returns to forestry may change with climate change because the volume functions for all species change such that natural growth is increased, and only intensive margin adaptations are needed to re-optimize. In contrast, an alternative hypothesis is that net returns to forestry may change with climate change because some forest species experience relatively higher natural growth changes and provide extensive margin adaptation possibilities for existing forest species that experience lower (and potentially negative) growth effects from climate change.

The stylized example in figures 2.1 and 2.2 showed climate ranges where returns to one tree species decline with climate change while returns to another species may increase with climate change. Either of the above two hypotheses could be consistent with results from the national model. Therefore, in this section Ricardian net return functions are separately estimated for four commercially important forest types in two distinct regions: Douglas fir and ponderosa pine in the western U.S., and loblolly and shortleaf pine in the southern U.S. By estimating Ricardian functions that differ across forest types, I can examine whether extensive margin adaptations are likely to explain the predictions of the national model.

Loblolly & shortleaf pine Separate Ricardian net return functions are estimated for two of the primary timber species in the southern U.S., loblolly and shortleaf pine. An analysis is conducted to explore whether the projected gains in net returns to forestry in the southeast from the national Ricardian model could be explained by growth in the value of these two pine species, or whether some of the projected gains are from some type of extensive margin adaptation. Summary statistics for this restricted sample are presented in table 4.8. The average county contains approximately 46,000 acres of land classified as either loblolly or shortleaf pine. Of the southern U.S. forest types included in the national Ricardian, loblolly and shortleaf forest types account for 39.2% and 2% of the forest acres, respectively. Mean net returns for loblolly and shortleaf pine are about 2.4 times higher than the national average of all species, and the southern U.S. is generally warmer, wetter, and has more productive soils relative to the national average.

Parameter estimates for mean temperature and its square are significant at the 1% level for both loblolly and shortleaf pine (table 4.10). Estimated marginal effects of both mean temperature and precipitation for shortleaf pine are approximately double the effects for loblolly (table 4.11). Using the multi-model mean climate change projections the model predicts that net returns to loblolly production will remain roughly unchanged on average, while the projected net returns to land in shortleaf pine production will increase by about 38% on average. Loblolly and shortleaf pine are projected to experience both losses and gains in net returns across space, with losses in the southern latitudes and gains in the northern latitudes (see figures 4.4 and 4.5). Since climate change is predicted to reduce net returns to both loblolly and shortleaf pine in the southern region of their range, the national Ricardian models positive projected gains in net returns in this region illustrate incentives for extensive margin adaptation away from loblolly/shortleaf to an alternative forest type.

To further explore the potential for extensive margin adaptation, consider the difference between the currently observed net returns to loblolly and the average net returns to all forest types in the same region, defined here as the loblolly premium. For the 651 counties currently home to loblolly forests, nearly all of them (647) have a positive loblolly premium. By 2050, the premium is predicted to be positive in only 559 of those counties. On average, loblolly remains the more profitable species under future climate, but its value relative to all forest types will shrink. By differencing the predicted future loblolly premium from its current level, I find that climate change lowers the loblolly premium by $37/acre. As with each of our results, there is significant spatial variation in premium change. The loblolly premium change increases in 111 counties and decreases in the remaining 540 counties. The current premium to shortleaf pine is positive on average with a mean of approximately $5/acre. Under future climate change the model predicts that the shortleaf premium will be reduced by $9.15/acre. Over the range of shortleaf, 131 counties are predicted to experience gains in the shortleaf premium, but not enough to outweigh the premium decreases in the remaining 240 counties.

By comparing the estimated climate impacts between the forest type Ricardian and the composite forest Ricardian that includes all potential forest types, the model can explain how the projected total impact of climate change on the net returns to forestry are likely driven by extensive margin adaptations in loblolly and shortleaf production. Consider the 299 southern U.S. counties where both loblolly and shortleaf forest types are currently observed. Loblolly net returns decrease by $2.48/acre, and shortleaf net returns increases by $20.20/acre. However, since loblolly forests represent a much greater share of forest land, the acreage weighted impact of climate change on loblolly/shortleaf net returns is only $1.04/acre. In contrast, the climate change impact on the net returns to all forest types is $35.97/acre, implying significant incentives for extensive margin adaptation out of loblolly and shortleaf pine in the southern latitudes of the southeast.

Douglas-fir & ponderosa pine Ricardian functions are separately estimated for two of the most commercially important forest species in the American west: Douglas-fir and Ponderosa pine. These two species overlap for most of their observed range.

However, by restricting the sample to these specific forest types, much of the climate variation within LCC classes that the full national model relied on are lost. This requires modeling climate′s effect using a simplified functional form that excludes LCC shares. Climate enters the species-specific Ricardian model as mean annual temperature and its square, total annual precipitation and its square, and an interaction between mean temperature and precipitation. This specification is supported by robustness checks of the national model which found that the marginal effects of mean annual temperature are unaffected by the inclusion of soil quality variables. Summary statistics for the restricted sample are presented in table 4.9. Average net returns are about 40% lower for Douglas-fir and ponderosa pine than the national average across all forestland. The western U.S. counties included here are generally colder, dryer, and have less productive soil relative than the national average.

Parameter estimates for the western Ricardian models are presented in table 4.10 and marginal effects are shown in table 4.11. Although many of the individual climate parameter estimates are insignificant in table 4.10, the average marginal effect of precipitation on Douglas-fir and ponderosa pine is positive and significant at the 1% level. The average marginal effect of mean temperature is positive and significant at the 1% level for ponderosa pine, and at the 10% level ($p = 0.053$) for Douglas-fir (table 4.11). While both forest types have positive marginal effects for mean temperature, marginal effects for ponderosa pine are larger than Douglas-fir. Further, the marginal effect of precipitation on ponderosa pine net returns is almost double the effect for Douglas-fir.

Using the multi-model mean climate change projections, the net returns to Douglas fir production are predicted to increase by approximately \$10.93/acre (44%) on average, and the net returns for ponderosa pine are predicted to increase by about \$23.28/acre (101%). The spatial distribution of projected climate impacts are presented in figures 4.6 and 4.7, and indicate the largest positive effects for Douglas-fir (in level form) are found in the northern Rocky Mountain sub-region, and the highest gains to ponderosa are concentrated in the Pacific coast region. Even though the range of these two forest types overlap in many places, extensive margin adaptations may not be necessary in order to get to the net return gain found when including all forest types because the relative gains and losses occur in distinct regions.

Consider the difference between the currently observed net returns to Douglas-fir and the average net returns to all forest types, defined here as the Douglas-fir premium. For the 133 western counties currently home to Douglas-fir forests, approximately 52% have a positive premium indicating Douglas-fir is the most profitable species in its range. By 2050, the share of counties with a positive Douglas-fir premium is predicted to remain nearly unchanged. However, climate change is projected to increase the premium for ponderosa pine by \$9.01/acre on average across the west. For the 99 counties that currently have both Douglas-fir and ponderosa forests, Douglas-fir net returns are projected to increase by \$11.48/acre while ponderosa net returns increase by \$22.17/acre. The acreage weighted average climate impact for Douglas-fir/ponderosa production is \$13.94/acre, which is almost identical to the average projected increase in net returns from the U.S. national Ricardian model for this same region. In contrast to the southeastern U.S., there does not appear to be large economic incentives for extensive margin adaptation out of the currently dominant

Douglas-fir and ponderosa forests of the west to other species. However, there may be some incentive for extensive margin adaptation between Douglas-fir and ponderosa forests.

Further Discussion The role of extensive margin adaptations in forestry is an important consideration when examining the national results. The national Ricardian model essentially assumes no constraints or hysteresis in adaptation, whereas there are reasons to think that extensive margin adaptations in forestry may happen sluggishly. Forest landowners do not make harvest and replanting choices annually, but rather once over several decades. In an econometric analysis and dynamic simulation of replanting choices in forestry along the U.S. west coast, Hashida and Lewis [22] found that landowner-driven changes in forest landscapes occur slowly under projected climate change, primarily due to the periodic nature of when replanting choices are made over multiple decades. It can take time to radically convert a forested landscape from one dominant tree species to another. Therefore, the national results should be treated as an upper bound on the potential gains to U.S. forestry under climate change because the Ricardian framework assumes that the full set of optimal adaptation can and will happen by 2050. The results also suggest numerous new research questions. For example, how quickly can extensive margin adaptation in forestry occur, and what barriers exist? Do current landowners anticipate future climate change by planting species that may grow better in the future than today? Guo and Costellos (2013) numerical analysis of extensive margin adaptation in forestry assume that landowners anticipate future climate, but a study of family foresters in the northwestern U.S. found little evidence that landowners are making management decisions in response to climate change forecasts (Grotta et al. 2013).

4.2 Crop and Pasture Ricardians and the Impact of Climate Change

There is a rich and extensive body of research concerned with the impact of climate and climate change on agricultural outcomes [10]. The modern literature on climate adaptation and agriculture begins with [36] who conceptualized how agricultural land owners would adapt to changes in climate and analyzed the impact of temperature and precipitation on future farm values by establishing a statistical relationship between current climate and land value. Deschenes et. al. [11] exploit random year-to-year weather fluctuations to develop a fixed effects model of climate's impact on agricultural profits. Schlenker et. al. [48] quantify the non-linear relationship between temperature and crop yields. Burke et. al. [9] combine the cross-sectional and time series approaches of earlier work to begin explicitly measuring adaptation in U.S. agriculture.

A large strand of the current literature on agricultural climate impact examine particular crops or small groups of crops (e.g. corn, wheat, soybeans), and focus on yield as the dependant variable [10]. When studying a single crop's yield, the researcher can choose a form of temperature that better captures non-linear climate impacts. Measures of this type, known as growing degree days, have been developed for several major food crops in the U.S. [48]. The gain in climate specification comes at the cost of limiting adaptation possibles. By studying climate change impact on corn yield, adaptations to non-corn crops are not accounted for.

A common dependent variable in Ricardian analyses is land value, which closely parallels the hedonic approach of valuing climate as an amenity that is capitalized into the sale price of agricultural land [36, 37, 55]. An advantage of the land value measure is that the full range of land adaptations are included. A drawback is that land near urban areas capitalizes the value of urban development potential requiring far greater spatial information to control for proximity to the urban boundary. My measure of net returns combines the strength of the two most prominent methods, yield and land value, by encompassing a broader suite of adaptations options and abstracting away from the market capitalized value.

The goal of this dissertation 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 as described in section 2.2. A principle difference between existing Ricardian studies is the choice of dependant 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 dependant variable sets the scope of system being modeled, and therefore the set of intensive margin adaptations faced by owners of crop and pasture land.

In a study of climate change impact on corn and soybean profits, [11] found that climate change would increase annual profits significantly. Burke & Emerick [9] come to a different conclusion, finding that crop and soybeans will suffer productivity losses under future climate, and they provide evidence that adaptation to mitigate losses among the top six U.S. crops will be limited. In a recent Ricardian analysis of the U.S. Great Plains region, Polsky et al [43] found that higher July temperature increased agricultural land value at currently observed levels while the functional relationship exhibited an inverted u-shape which is consistent with the results presented below for crop and pasture Ricardian functions as shown in tables 4.17 and 4.24. The take away from the current literature is that direction and magnitude of climate change's impact on agriculture depends on the choice of dependant 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. Ricardian functions are estimated for crop and pasture uses. See section 3.3 for details on the construction of the dependant variables.

$$NR_n^k = \alpha_n^k + \beta_n^k f(T_{n\xi}, P_{n\xi}) + \gamma_n^k LCC_n + \epsilon_n^k \tag{4.2}$$

Where $f(T_{n\xi}, P_{n\xi})$ 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.

Crop and pasture Ricardian functions are estimated at four spatial scales: the conterminous U.S., the eastern U.S. counties east of the 100th meridian, the southeastern U.S., and the northeast U.S. Notable differences are apparent in the summary statistics presented in tables 4.12 - 4.15 and 4.19 - 4.22, respectively. Although the mean crop net return in the east is comparable with that in all conterminous U.S. counties, the distribution is quite different. Negative crop net returns are observed for western counties over the period of this analysis, whereas the minimum eastern crop net return is relatively high at $135 per acre. The highest average net returns are observed in the southeastern region while the lowest average is found in the northeastern region. Within each of these regions there is significant spatial variation as demonstrated by the map of crop net returns in figure 3.4.

The climate in the southeast is warmer and wetter in every season relative to the northeast. These differences in climate and net returns help to identify the effect of climate on net returns in the Ricardian estimation. Average soil quality is markedly higher in the northeast relative to the southeast, the local climate results in different crops being produced with consequently differing levels of net return. The share of land in the top three soil classes (LCC 1-3) is approximately 52.2% in the northeast and 42.7% in the southeast. Despite the higher average land quality of the northeast, the net return to crop land is higher on average in the southeast. The opposite is true for pasture rents, with higher values observed in the northeast relative to the southeast.

Twenty climate parameters are estimated for each region and agricultural system including temperature and precipitation for each of four seasons, a squared term for each climate variable-season, and an interaction between temperature and precipitation for each season. For the crop model, 15 of 20 parameters are significant at the U.S. level, 10 of 15 for the east, 5 of 20 for the northeast, and 15 of 20 in the southeast (table 4.16). Identification varies according to the level of variation in climate. Even though the significance varies across regions for the crop model parameter estimates, average marginal effects are significant for the majority of climate variables and regions as seen in table 4.17.

With the exception of the northeast, the pasture model's estimated average marginal effects are highly significant for all climate variables except fall precipitation in the U.S. and eastern U.S., and fall and summer temperature in the southeast (table 4.24). In the northeast, pasture net returns appear to be driven exclusively by winter and spring climate. In the U.S. and eastern U.S., cool dry spring seasons and warm wet summers are highly correlated with greater pasture rents.

The crop model results suggest that locations with higher winter precipitation are correlated with greater crop net returns. The average marginal effect of spring precipitation is significantly positive in the eastern region, but insignificant elsewhere. Across all regions, higher fall precipitation is associated with lower net returns. Warmer summers are beneficial to crop net returns in the east and northeast, but insignificant in the southeast and conterminous U.S.

The impact of climate change on crop and pasture net returns is analyzed by restricting attention to the Ricardian model of the eastern U.S. presented in tables 4.16 and 4.23. Average regional impact varies over the study area. The full spatial distribution of climate change impact on agriculture is shown in figure 4.8. The predictions represent the potential impact of a discrete change in climate from the 1983 - 2012 baseline to a possible future climate from 2021 - 2050 under climate model NorESM1-M scenario RCP 8.5. Pasture net returns per acre increase for nearly all counties, while crop returns increase in northeast but decrease in the southeast. Average climate impacts are reported in table 4.18. On average, the impact of climate change on pasture net returns is positive. The south to north gradient of pasture impacts observed in figure 4.8, mirrors the spatial pattern of projected future temperature increases. Pasture in the southern region starts at a lower level than the north, and experiences a subsequent decline. This suggests that the likelihood of remaining in pasture and converting to pasture from other uses will be relatively lower under climate change. Although, as explored in chapter 5, the ultimate effect of climate change on land-use will depend on the simultaneous impact of climate on all substitute land-uses.

4.3 Urban Ricardian and the Impact of Climate Change

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.

$$NR_n = \alpha_n + \beta_n f(T_n, P_n) + \gamma_n X_n + \epsilon_n \tag{4.3}$$

Where $f(T_n, P_n)$ is a quadratic function of temperature and precipitation that includes and full set of interactions. The unit of analysis is the county. 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.

Parameter estimates for the urban Ricardian and average marginal effects are presented in tables 4.29 and 4.30, respectively. Consider the eastern urban Ricardian. 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.

The impact of a discrete change in climate under scenario NorESM1-M RCP 8.5 is mapped in figure 4.9. Predicted increases occur across much of the far south and along the Canadian border with Wisconsin and Minnesota, but losses are predicted for large areas of the great plains and northeast. Negative impacts to urban rents are also present in the counties surrounding Atlanta, Georgia. Regional average impacts are reported in table 4.18. Predicted urban rents are negatively impacted by a discrete climate shock across the east, balanced by an average increase when looking at the southeastern counties only.

Figure 4.1: Change in Mean Temperature Across 20 Global Climate Models

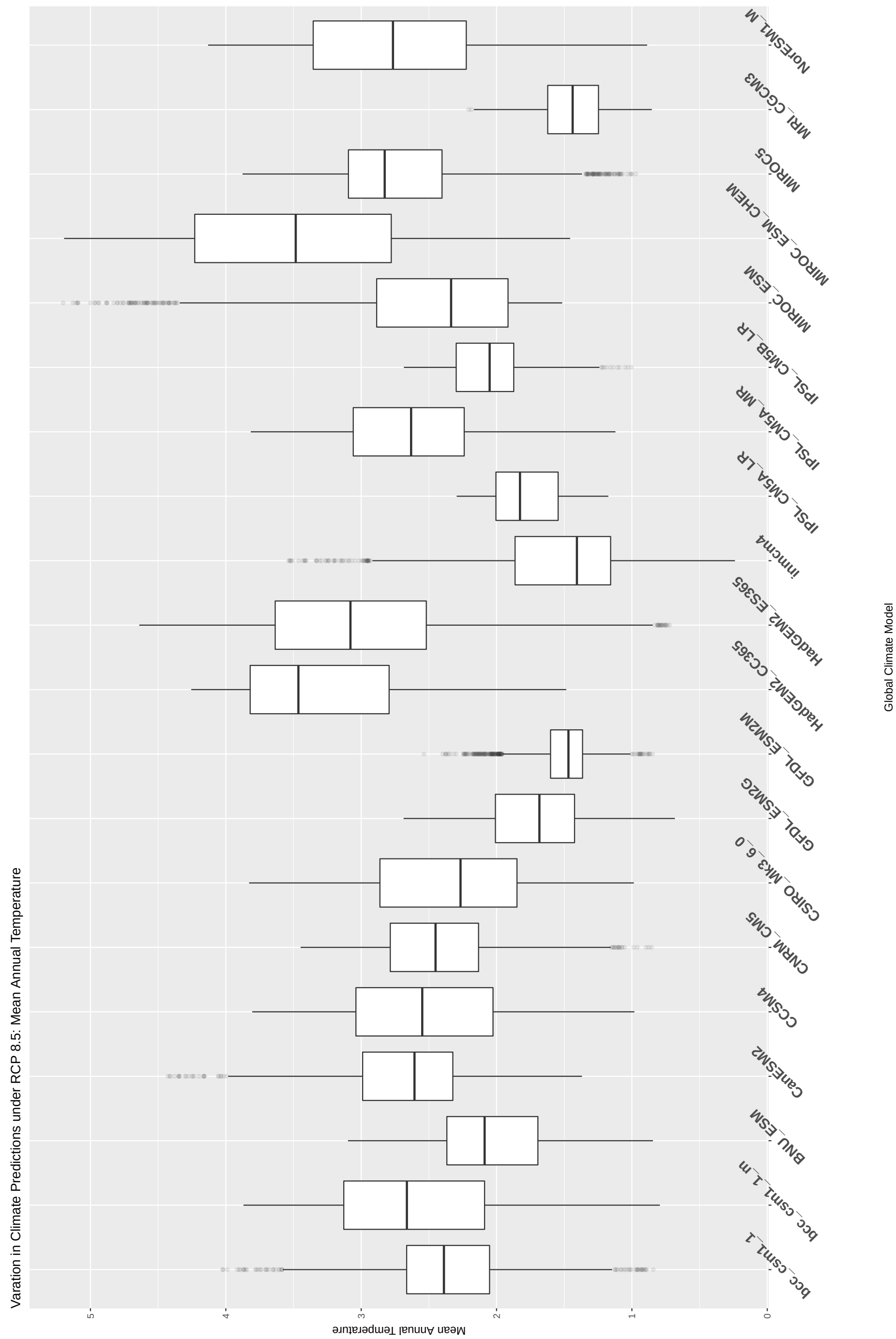

Figure 4.2: Change in Annual Precipitation Across 20 Global Climate Models

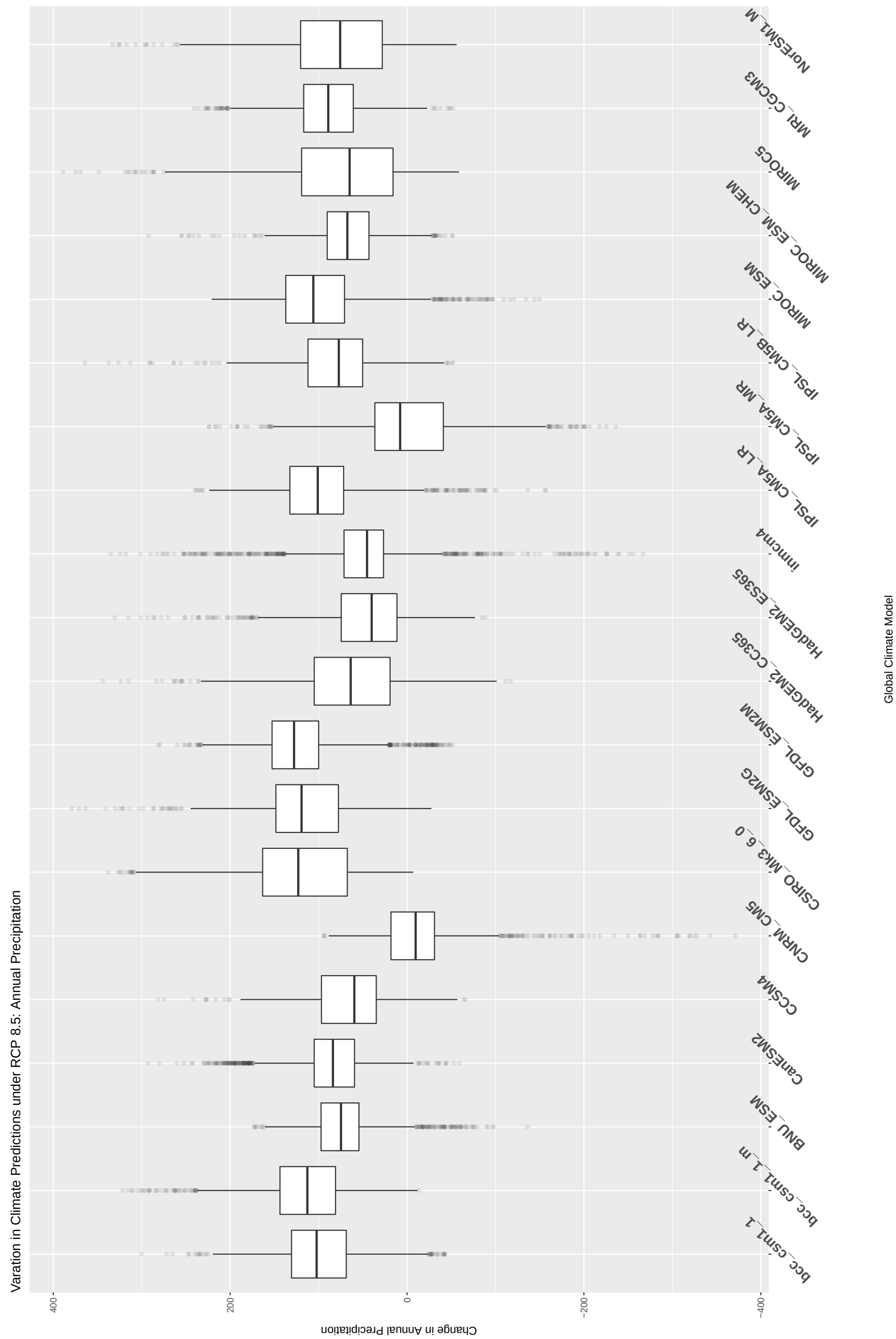

Table 4.1: Summary of Estimation Data for Forest Ricardian: Conterminous U.S.

Statistic	Mean	St. Dev.	Min	Max
Net return per acre	38.908	50.244	−2.000	351.353
County forest acres	211,041.700	193,205.100	1,561.122	3,751,603.000
Max Temp (Celsius)	19.418	4.224	9.150	31.330
Min Temp	5.241	5.051	−9.520	17.230
Mean Temp	12.371	4.464	1.406	23.724
Precip (mm)	1,111.566	293.810	315.036	3,039.402
Share of forest in LCC 1	0.008	0.031	0.000	0.741
Share of forest in LCC 2	0.162	0.174	0.000	1.000
Share of forest in LCC 3	0.182	0.155	0.000	1.000
Share of forest in LCC 4	0.148	0.130	0.000	1.000
Share of forest in LCC 5	0.050	0.100	0.000	0.909
Share of forest in LCC 6	0.193	0.182	0.000	1.000
Share of forest in LCC 7	0.242	0.243	0.000	1.000
Share of forest in LCC 8	0.016	0.060	0.000	0.803

Table 4.2: Summary of Estimation Data for Forest Ricardian: Eastern U.S.

Statistic	Mean	St. Dev.	Min	Max
Net return per acre	39.601	49.222	0.188	312.835
County forest acres	216,674.400	192,282.400	2,398.417	3,751,603.000
Max Temp (Celsius)	19.628	4.263	9.610	30.080
Min Temp	6.267	4.150	−5.460	17.230
Mean Temp	13.015	4.172	2.750	23.724
Precip (mm)	1,136.132	220.204	490.400	1,821.994
Share of forest in LCC 1	0.009	0.033	0.000	0.741
Share of forest in LCC 2	0.180	0.175	0.000	1.000
Share of forest in LCC 3	0.197	0.152	0.000	1.000
Share of forest in LCC 4	0.154	0.128	0.000	1.000
Share of forest in LCC 5	0.055	0.104	0.000	0.909
Share of forest in LCC 6	0.178	0.162	0.000	0.974
Share of forest in LCC 7	0.215	0.223	0.000	1.000
Share of forest in LCC 8	0.013	0.055	0.000	0.803

Table 4.3: Summary of Estimation Data for Forest Ricardian: Northeastern U.S.

Statistic	Mean	St. Dev.	Min	Max
Net return per acre	15.341	15.056	0.188	148.522
County forest acres	194,899.400	229,976.600	2,398.417	3,751,603.000
Max Temp (Celsius)	16.055	2.544	9.610	21.240
Min Temp	3.155	2.767	−5.460	8.870
Mean Temp	9.644	2.552	2.957	15.165
Precip (mm)	1,010.642	157.929	565.831	1,439.869
Share of forest in LCC 1	0.009	0.030	0.000	0.418
Share of forest in LCC 2	0.196	0.197	0.000	1.000
Share of forest in LCC 3	0.200	0.155	0.000	1.000
Share of forest in LCC 4	0.143	0.122	0.000	0.969
Share of forest in LCC 5	0.037	0.082	0.000	0.909
Share of forest in LCC 6	0.191	0.163	0.000	0.974
Share of forest in LCC 7	0.213	0.212	0.000	1.000
Share of forest in LCC 8	0.011	0.041	0.000	0.632

Table 4.4: Summary of Estimation Data for Forest Ricardian: Southeastern U.S.

Statistic	Mean	St. Dev.	Min	Max
Net return per acre	62.359	59.333	0.551	312.835
County forest acres	254,201.600	147,392.900	6,844.573	847,860.000
Max Temp (Celsius)	23.096	2.381	17.850	30.080
Min Temp	9.309	2.901	0.440	17.230
Mean Temp	16.302	2.580	8.977	23.724
Precip (mm)	1,287.061	148.160	830.486	1,821.994
Share of forest in LCC 1	0.007	0.021	0.000	0.374
Share of forest in LCC 2	0.156	0.135	0.000	0.835
Share of forest in LCC 3	0.205	0.145	0.000	0.929
Share of forest in LCC 4	0.167	0.121	0.000	0.814
Share of forest in LCC 5	0.067	0.112	0.000	0.783
Share of forest in LCC 6	0.156	0.146	0.000	0.960
Share of forest in LCC 7	0.227	0.235	0.000	0.999
Share of forest in LCC 8	0.015	0.067	0.000	0.803

Table 4.5: Parameter estimates for forest Ricardian function

	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 4.6: Average marginal effects of climate on forest net returns

Variable	Conterminous U.S.	Eastern U.S.	Northeast	Southeast
Max Temp	5.252^{***} (0.735)	10.160^{***} (1.004)	-0.039 (0.683)	17.572^{***} (1.992)
Min Temp	-0.785 (0.6439)	-5.483^{***} (0.942)	0.0701 (0.591)	-5.340^{***} (1.799)
Precip	0.031^{***} (0.006)	0.037^{***} (0.008)	-0.009 (0.007)	0.057^{***} (0.013)

Table 4.7: Functional Form Sensitivity Analysis

Model	Specification	Precip	Mean Temp	Max Temp	Min Temp
1	Linear precip & mean temp	0.0396*** (0.0038)	3.8121*** (0.2473)		
2	Linear climate & interaction	0.0599*** (0.0041)	3.3156*** (0.2457)		
3	Quadratic climate	0.0269*** (0.0042)	4.6863*** (0.2662)		
4	**Quadratic climate & interaction**	0.0392*** (0.0048)	4.3416*** (0.2731)		
5	Linear precip, max temp, & min temp	0.0411*** (0.0037)		3.5415*** (0.3572)	0.5456* (0.3025)
6	Linear climate & interaction	0.0458*** (0.0045)		5.0822*** (0.4575)	−0.8875** (0.3530)
7	Quadratic climate	0.0303*** (0.0042)		4.0035*** (0.4928)	0.7179 (0.4584)
8	Quadratic & interaction	0.0289*** (0.0051)		5.3611*** (0.5238)	−0.3313 (0.4719)
9	Quadratic, interaction & sub-region FE	0.0331*** (0.0054)	4.5513*** (0.3890)		
10	Quadratic, interaction, & region FE	0.0397*** (0.0054)	4.2271*** (0.3385)		
11	Quadratic, interaction, & lcc share	0.0436*** (0.0048)	3.9232*** (0.2936)		
12	Quadratic, interaction, sub-region FE, & lcc	0.0367*** (0.0054)	3.7961*** (0.4170)		
13	Quadratic, interaction, region FE, & lcc	0.0491*** (0.0054)	3.0716*** (0.3702)		
14	Quadratic, interaction, sub-region FE	0.0247*** (0.0058)		4.0090*** (0.7300)	1.0805* (0.5970)
15	Quadratic, interaction, & region FE	0.0397*** (0.0059)		2.4924*** (0.6554)	1.5229*** (0.5224)
16	Quadratic, interaction, & lcc	0.0387*** (0.0052)		6.5177*** (0.5332)	−2.0695*** (0.5209)
17	**Quadratic, interaction, sub-region FE, & lcc**	0.0311*** (0.0058)		5.2520*** (0.7350)	−0.7851 (0.6439)
18	Quadratic, interaction, region FE, & lcc	0.0497*** (0.0059)		3.5149*** (0.6534)	−0.3056 (0.5677)
19	Quadratic, interaction, sub-region FE, & 2 lcc groups	0.0280*** (0.0057)		5.1056*** (0.6527)	−0.0548 (0.5466)
20	Quadratic, interaction, region FE, & 2 lcc groups	0.0488*** (0.0059)		3.3114*** (0.6527)	−0.0548 (0.5466)
21	Quadratic, interaction, east/west FE, & lcc	0.0471*** (0.0053)		4.9051*** (0.5853)	−0.4274 (0.5763)
22	Quadratic, interaction, east/west FE, & 2 lcc groups	0.0434*** (0.5832)		4.7166*** (0.5832)	−0.1509 (0.5600)
23	Quadratic, interaction, & 4 lcc groups	0.0451*** (0.0048)	3.7737*** (0.2798)		
24	Quadratic, interaction, & 2 lcc groups	0.0420*** (0.0047)	3.8583*** (0.2787)		
25	Quadratic, interaction, & 4 lcc groups	0.0391*** (0.0051)		6.4421*** (0.5296)	−2.0172*** (0.5002)
26	Quadratic, interaction, & 2 lcc groups	0.0353*** (0.0051)		6.3141*** (0.5298)	−1.8018*** (0.4993)

Figure 4.3: Climate Change Impact on Forest Rents Across 20 Global Climate Models

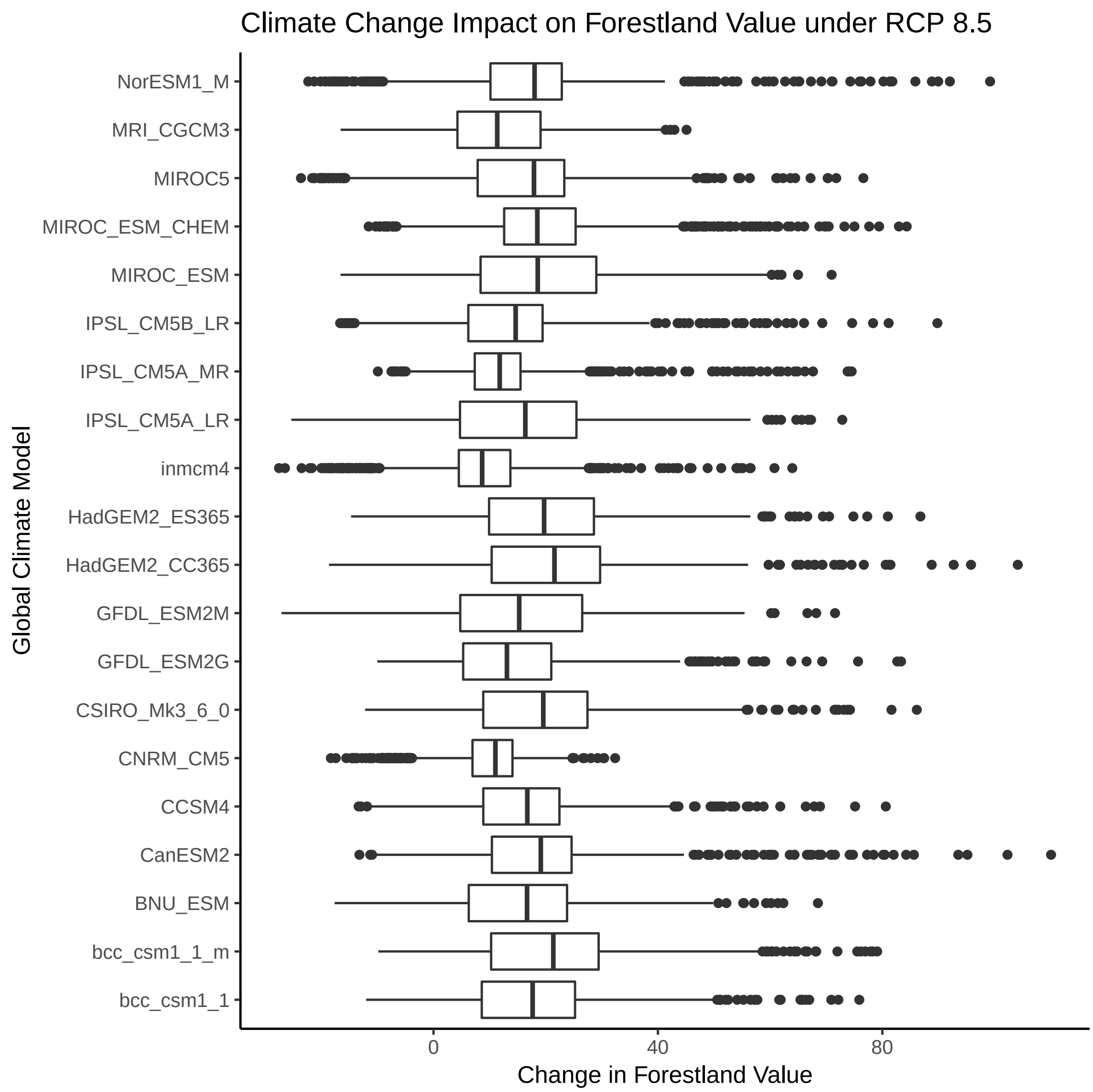

Table 4.8: Summary of Estimation Data for Loblolly / Shortleaf Pine Ricardian

Statistic	Mean	St. Dev.	Min	Max
Net return per acre	131.62	107.11	0.105	481.89
County forest acres (1000s)	46	55	0.671	334
Max Temp (Celsius)	23.57	1.855	18.06	28.46
Min Temp	9.649	2.174	2.81	15.24
Mean Temp	16.717	1.940	11.208	21.803
Precipitation (mm)	1,305	137	982	1,769
Share of forest in LCC 1	0.008	0.022	0.000	0.374
Share of forest in LCC 2	0.190	0.133	0.000	0.643
Share of forest in LCC 3	0.227	0.133	0.000	0.801
Share of forest in LCC 4	0.176	0.110	0.000	0.792
Share of forest in LCC 5	0.066	0.092	0.000	0.597
Share of forest in LCC 6	0.151	0.130	0.000	0.643
Share of forest in LCC 7	0.176	0.191	0.000	0.976
Share of forest in LCC 8	0.006	0.028	0.000	0.436

Table 4.9: Summary of Estimation Data for Douglas-fir / Ponderosa Pine Ricardian

Statistic	Mean	St. Dev.	Min	Max
Net return per acre	23.56	56.13	0.001	373.91
County forest acres (1000s)	76	105	0.948	827
Max Temp (Celsius)	17.751	2.929	11.4	29.350
Min Temp	-3.421	3.312	-9.52	6.57
Mean Temp	6.918	2.632	1.406	14.631
Precipitation (mm)	956	595	359	3,039
Share of forest in LCC 1	0.0003	0.002	0.000	0.030
Share of forest in LCC 2	0.009	0.021	0.000	0.118
Share of forest in LCC 3	0.051	0.089	0.000	0.733
Share of forest in LCC 4	0.106	0.131	0.000	0.577
Share of forest in LCC 5	0.007	0.028	0.000	0.250
Share of forest in LCC 6	0.325	0.257	0.000	0.999
Share of forest in LCC 7	0.471	0.264	0.000	1.000
Share of forest in LCC 8	0.031	0.060	0.000	0.313

Table 4.10: Forest Type Ricardian Parameter Estimates

	All Species	Douglas-fir	Ponderosa	Loblolly	Shortleaf
Mean Temperature	-4.407^{***}	5.185	-27.0977^{***}	169.7557^{***}	80.5597^{***}
	(1.066)	(7.625)	(6.186)	32.651)	(37.142)
Mean Temp Squared	0.119^{**}	-0.165	0.650	-4.2217^{***}	-3.8027^{***}
	(0.051)	(0.650)	(0.401)	(0.953)	(1.080)
Annual Precipitation	-0.105^{***}	0.060	-0.136^{**}	0.903^{*}	-0.093
	(0.105)	(0.045)	(0.054)	(0.501)	(0.571)
Precip Squared	0.00004^{***}	-0.00002	-0.00003	-0.0002	-0.0002
	(0.00000)	(0.00001)	(0.00002)	(0.0002)	(0.0002)
Mean temp · precip	0.005^{***}	0.001	0.031^{***}	-0.016	0.042^{***}
	(0.001)	(0.005)	(0.004)	(0.016)	(0.015)
Constant	66.298^{***}	-52.243	128.8087^{***}	-1931.3757^{***}	-713.614
	(9.762)	(35.737)	(37.657)	(357.323)	(467.243)
Observations	2,390	135	107	651	371
Adjusted R^2	0.316	0.163	0.668	0.080	0.199
Residual Std. Error	41.563	53.074	31.049	99.309	75.163
	(df = 2384)	(df = 129)	(df = 101)	(df = 645)	(df = 365)
F Statistic	221.450^{***}	6.218^{***}	43.616^{***}	12.280^{***}	19.410^{***}
	(df = 5; 2384)	(df = 5; 129)	(df = 5; 101)	(df = 5; 645)	(df = 5; 365)

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

Table 4.11: Average marginal effects for forest type Ricardian models

Variable	All Species	Douglas-fir	Ponderosa	Loblolly	Shortleaf
Mean Temp	4.342^{***} (0.273)	4.290^{**} (2.216)	5.759^{***} (1.424)	5.034^{**} (2.189)	11.63^{***} (2.223)
Precip	0.039^{***} (0.005)	0.034^{***} (0.013)	0.037^{***} (0.014)	0.071^{**} (0.033)	0.167^{***} (0.033)

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

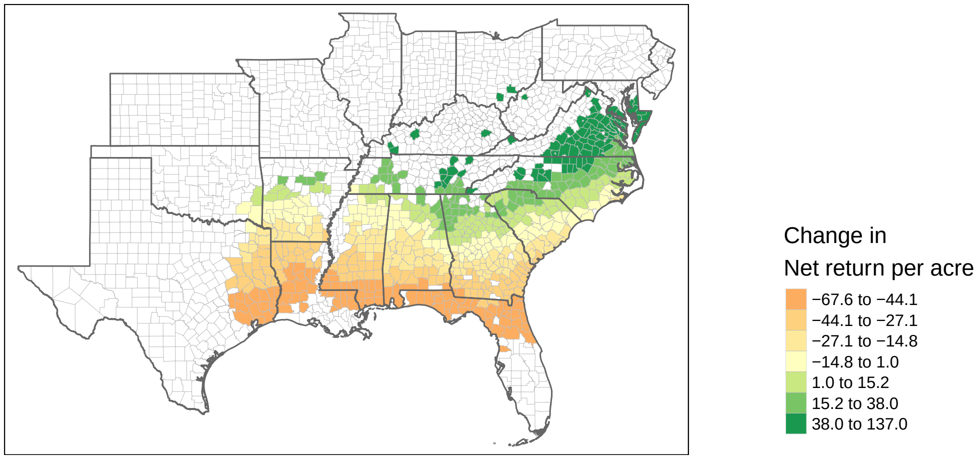

Figure 4.4: Map of Climate Change Impact on Loblolly Pine

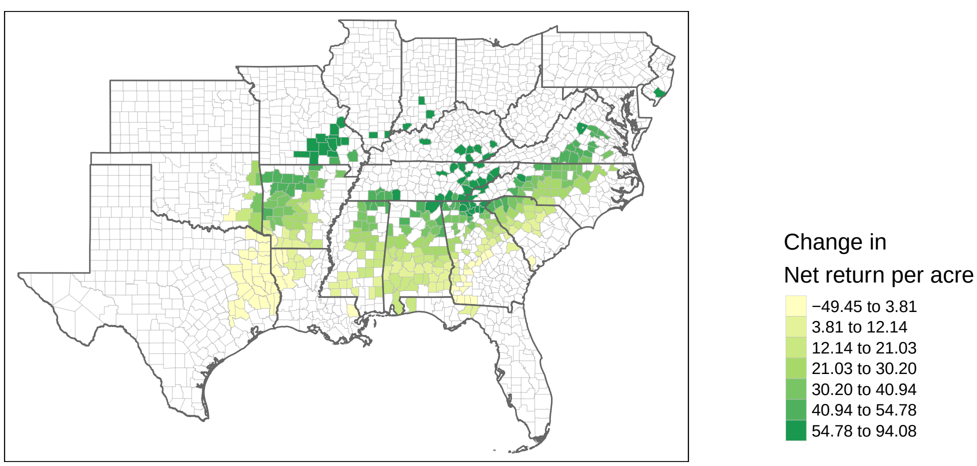

Figure 4.5: Map of Climate Change Impact on Shortleaf Pine

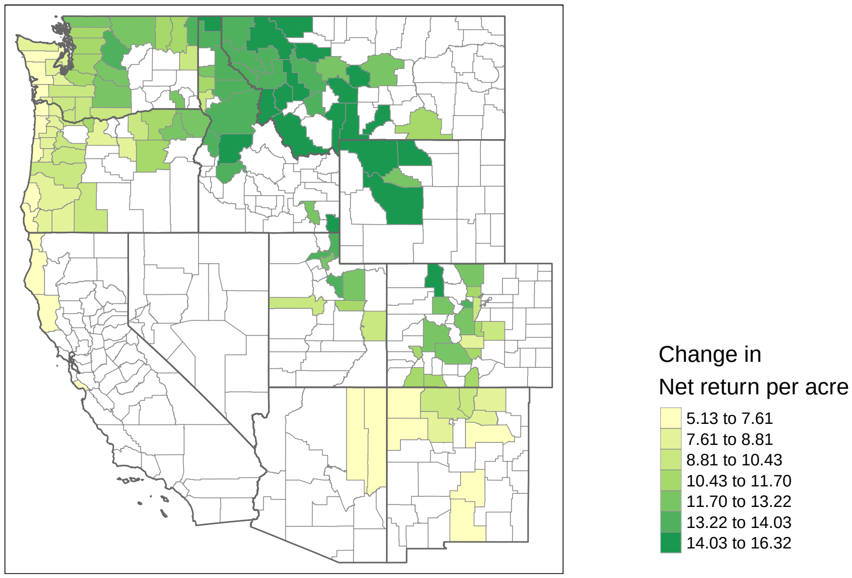

Figure 4.6: Map of Climate Change Impact on Douglas-fir

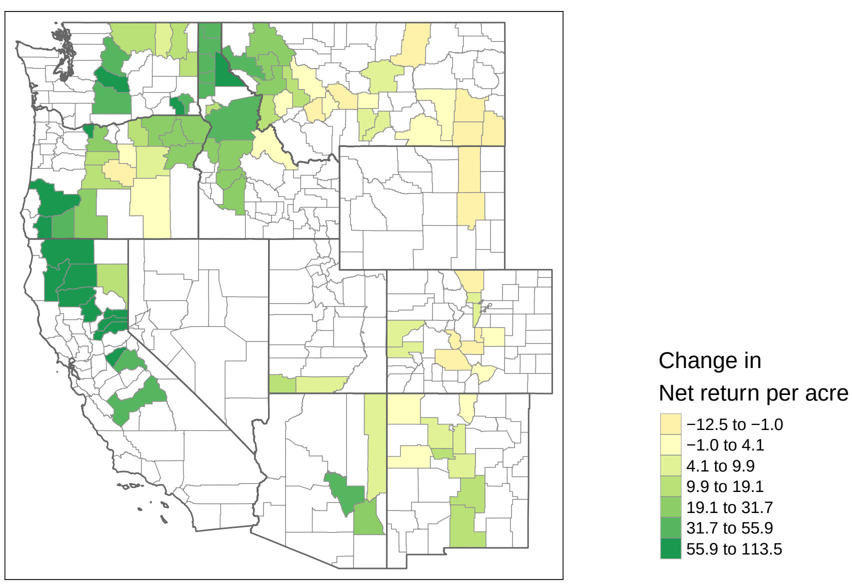

Figure 4.7: Map of Climate Change Impact on Ponderosa Pine

Table 4.12: Summary of Estimation Data for Crop Ricardian: Conterminous U.S.

Statistic	Mean	St. Dev.	Min	Max
Net return per acre	62.171	76.811	−135.929	442.939
Winter Temp	1.280	6.158	−13.783	20.205
Winter Precip	210.477	139.773	18.871	1,294.182
Spring Temp	11.954	4.707	−1.095	24.104
Spring Precip	261.422	88.871	12.679	707.270
Summer Temp	23.099	3.386	9.903	32.454
Summer Precip	280.402	98.012	2.814	709.614
Fall Temp	13.257	4.379	1.305	25.778
Fall Precip	238.601	89.417	17.661	851.605
Share of land in LCC 1	0.023	0.052	0.000	0.563
Share of land in LCC 2	0.222	0.196	0.000	0.936
Share of land in LCC 3	0.196	0.142	0.000	0.900
Share of land in LCC 4	0.124	0.103	0.000	0.852
Share of land in LCC 5	0.025	0.047	0.000	0.418
Share of land in LCC 6	0.142	0.146	0.000	0.954
Share of land in LCC 7	0.148	0.184	0.000	0.954
Share of land in LCC 8	0.015	0.051	0.000	0.807
Share of land w/o LCC	0.105	0.140	0.002	1.000

Table 4.13: Summary of Estimation Data for Crop Ricardian: Eastern U.S.

Statistic	Mean	St. Dev.	Min	Max
Net return per acre	61.843	72.034	−135.929	442.939
Winter Temp	1.620	6.277	−13.783	20.205
Winter Precip	221.124	109.580	30.196	484.220
Spring Temp	12.628	4.480	2.157	24.104
Spring Precip	285.954	63.666	105.307	436.401
Summer Temp	23.754	2.827	16.298	30.478
Summer Precip	315.504	65.951	147.518	709.614
Fall Temp	13.914	4.107	4.216	25.778
Fall Precip	261.911	59.539	90.907	451.851
Share of land in LCC 1	0.026	0.054	0.000	0.563
Share of land in LCC 2	0.254	0.194	0.000	0.936
Share of land in LCC 3	0.206	0.134	0.000	0.900
Share of land in LCC 4	0.120	0.095	0.000	0.654
Share of land in LCC 5	0.028	0.050	0.000	0.418
Share of land in LCC 6	0.116	0.120	0.000	0.849
Share of land in LCC 7	0.122	0.167	0.000	0.954
Share of land in LCC 8	0.012	0.051	0.000	0.807
Share of land w/o LCC	0.116	0.147	0.004	1.000

Table 4.14: Summary of Estimation Data for Crop Ricardian: Northeastern U.S.

Statistic	Mean	St. Dev.	Min	Max
Net return per acre	54.377	54.359	−94.699	387.933
Winter Temp	−3.241	3.561	−13.515	3.768
Winter Precip	172.676	70.780	44.739	317.795
Spring Temp	9.042	2.613	2.157	15.287
Spring Precip	270.260	51.243	120.945	392.332
Summer Temp	21.495	1.954	16.298	26.280
Summer Precip	306.769	31.823	211.889	425.589
Fall Temp	10.780	2.277	4.405	15.971
Fall Precip	251.198	43.665	128.823	368.677
Share of land in LCC 1	0.032	0.060	0.000	0.484
Share of land in LCC 2	0.294	0.223	0.000	0.936
Share of land in LCC 3	0.196	0.132	0.000	0.714
Share of land in LCC 4	0.103	0.093	0.000	0.501
Share of land in LCC 5	0.016	0.030	0.000	0.250
Share of land in LCC 6	0.107	0.121	0.000	0.849
Share of land in LCC 7	0.111	0.159	0.000	0.896
Share of land in LCC 8	0.008	0.024	0.000	0.361
Share of land w/o LCC	0.132	0.169	0.008	1.000

Table 4.15: Summary of Estimation Data for Crop Ricardian: Southeastern U.S.

Statistic	Mean	St. Dev.	Min	Max
Net return per acre	69.520	88.026	−135.929	442.939
Winter Temp	6.761	3.710	−1.386	20.205
Winter Precip	291.610	90.599	56.269	484.220
Spring Temp	16.239	2.779	8.419	24.104
Spring Precip	312.559	59.269	110.553	436.401
Summer Temp	25.829	1.861	18.919	30.478
Summer Precip	330.133	84.113	147.518	709.614
Fall Temp	17.172	2.733	9.952	25.778
Fall Precip	289.896	48.210	127.113	451.851
Share of land in LCC 1	0.016	0.033	0.000	0.346
Share of land in LCC 2	0.199	0.143	0.000	0.810
Share of land in LCC 3	0.212	0.136	0.000	0.900
Share of land in LCC 4	0.135	0.096	0.000	0.654
Share of land in LCC 5	0.041	0.062	0.000	0.418
Share of land in LCC 6	0.116	0.111	0.000	0.774
Share of land in LCC 7	0.148	0.179	0.000	0.954
Share of land in LCC 8	0.017	0.069	0.000	0.807
Share of land w/o LCC	0.116	0.132	0.004	1.000

Table 4.16: Parameter estimates for crop Ricardian function

	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 4.17: Average marginal effects of climate on crop net returns

Variable	Conterminous U.S.	Eastern U.S.	Northeast	Southeast
Winter Temperature	4.185 (2.850)	15.564*** (3.900)	−9.820** (5.009)	5.809 (11.440)
Winter Precipitation	0.190*** (0.038)	0.108** (0.053)	0.239*** (0.100)	0.067 (0.086)
Spring Temperature	−21.290*** (3.366)	−37.039*** (5.487)	−35.559*** (8.219)	−15.091 (14.664)
Spring Precipitation	0.006 (0.053)	0.235*** (0.077)	0.118 (0.126)	−0.043 (0.149)
Summer Temperature	0.111 (3.405)	13.983*** (5.809)	30.710*** (10.113)	−5.340 (13.313)
Summer Precipitation	−0.006** (0.025)	0.090 (0.057)	−0.098 (0.091)	0.344*** (0.089)
Fall Temperature	18.394*** (4.993)	8.908 (7.445)	28.355*** (10.034)	17.814 (15.097)
Fall Precipitation	−0.202*** (0.050)	−0.248*** (0.061)	−0.217** (0.103)	−0.334*** (0.099)

Table 4.18: Climate Change Impact on the Economic Net Return to Land

	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%

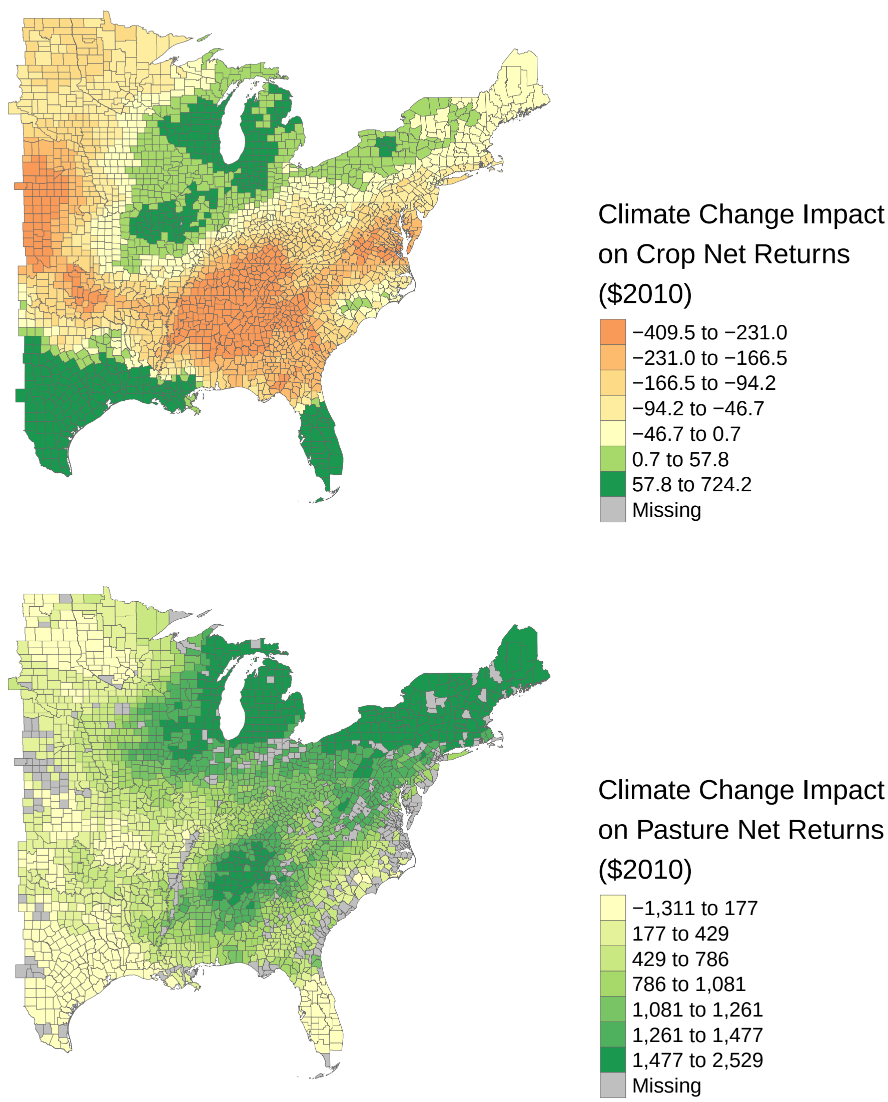

Figure 4.8: Climate Change Impact Map: Crop and Pasture Rents

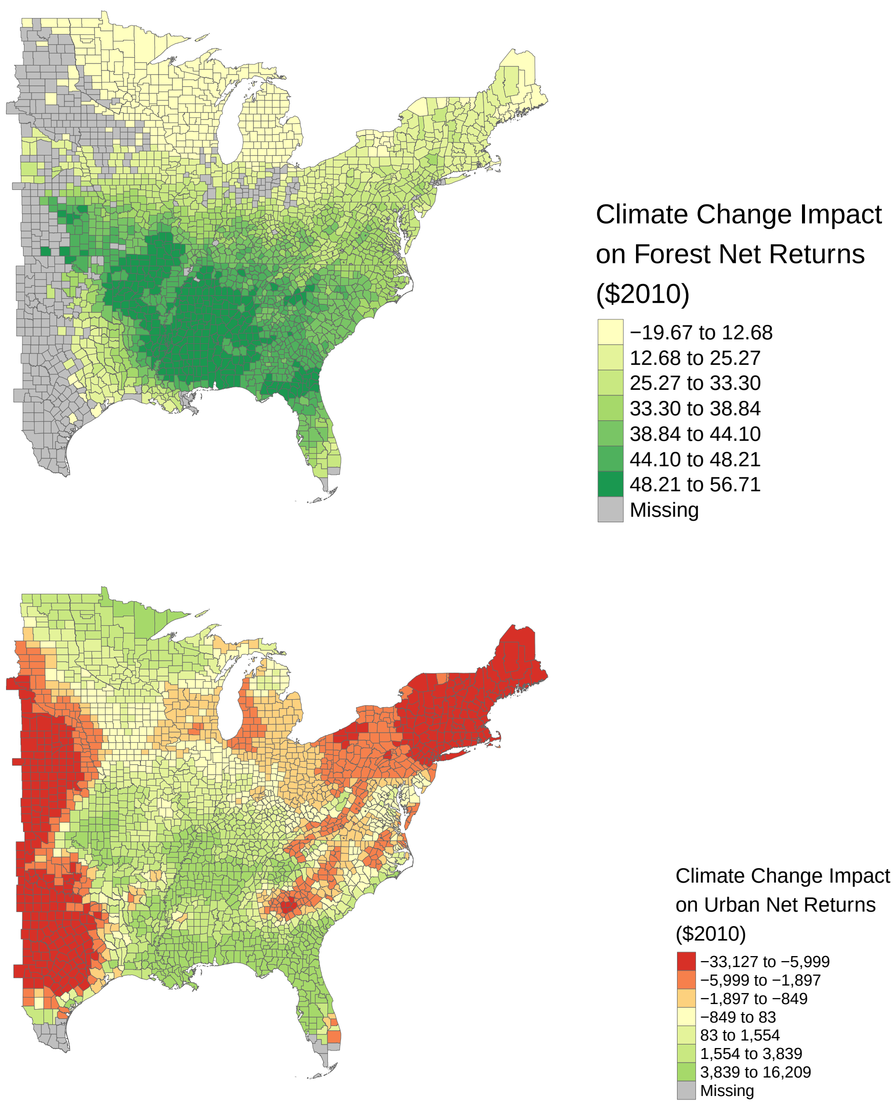

Figure 4.9: Climate Change Impact Map: Forest and Urban Rents

Table 4.19: Summary of Estimation Data for Pasture Ricardian: Conterminous U.S.

Statistic	Mean	St. Dev.	Min	Max
Net return per acre	343.237	836.911	−467.488	13,369.660
Winter Temp	1.098	6.226	−13.783	19.891
Winter Precip	212.925	140.218	18.871	1,294.182
Spring Temp	11.898	4.713	−0.163	24.104
Spring Precip	266.550	86.971	36.019	707.270
Summer Temp	23.066	3.361	10.774	31.443
Summer Precip	282.195	94.938	2.814	709.614
Fall Temp	13.170	4.395	2.173	25.587
Fall Precip	242.175	88.056	29.187	851.605
Share of land in LCC 1	0.022	0.049	0.000	0.563
Share of land in LCC 2	0.229	0.192	0.000	0.904
Share of land in LCC 3	0.205	0.136	0.000	0.900
Share of land in LCC 4	0.131	0.102	0.000	0.852
Share of land in LCC 5	0.025	0.046	0.000	0.415
Share of land in LCC 6	0.138	0.135	0.000	0.812
Share of land in LCC 7	0.140	0.171	0.000	0.918
Share of land in LCC 8	0.011	0.039	0.000	0.705
Share of land w/o LCC	0.097	0.117	0.003	0.915

Table 4.20: Summary of Estimation Data for Pasture Ricardian: Eastern U.S.

Statistic	Mean	St. Dev.	Min	Max
Net return per acre	284.626	598.599	−278.804	13,369.660
Winter Temp	1.514	6.335	−13.783	19.891
Winter Precip	220.688	111.088	30.196	480.895
Spring Temp	12.619	4.505	2.725	24.104
Spring Precip	287.369	64.669	105.307	436.401
Summer Temp	23.752	2.843	16.298	30.266
Summer Precip	313.563	64.469	148.956	709.614
Fall Temp	13.864	4.135	4.216	25.587
Fall Precip	262.029	58.806	90.907	451.851
Share of land in LCC 1	0.025	0.051	0.000	0.563
Share of land in LCC 2	0.258	0.189	0.000	0.904
Share of land in LCC 3	0.212	0.129	0.000	0.900
Share of land in LCC 4	0.124	0.093	0.000	0.654
Share of land in LCC 5	0.028	0.049	0.000	0.415
Share of land in LCC 6	0.116	0.114	0.000	0.774
Share of land in LCC 7	0.122	0.163	0.000	0.918
Share of land in LCC 8	0.008	0.037	0.000	0.705
Share of land w/o LCC	0.106	0.121	0.005	0.915

Table 4.21: Summary of Estimation Data for Pasture Ricardian: Northeastern U.S.

Statistic	Mean	St. Dev.	Min	Max
Net return per acre	292.684	529.276	−278.804	7,301.914
Winter Temp	−3.396	3.531	−13.515	3.632
Winter Precip	167.429	69.632	44.739	312.941
Spring Temp	9.024	2.621	2.725	15.270
Spring Precip	268.585	51.972	120.945	392.332
Summer Temp	21.489	1.944	16.298	26.280
Summer Precip	306.625	32.142	221.015	425.589
Fall Temp	10.697	2.248	4.732	15.920
Fall Precip	249.029	42.816	128.823	368.677
Share of land in LCC 1	0.032	0.058	0.000	0.343
Share of land in LCC 2	0.297	0.213	0.000	0.904
Share of land in LCC 3	0.208	0.130	0.000	0.705
Share of land in LCC 4	0.109	0.092	0.000	0.501
Share of land in LCC 5	0.015	0.030	0.000	0.227
Share of land in LCC 6	0.108	0.115	0.000	0.601
Share of land in LCC 7	0.108	0.151	0.000	0.896
Share of land in LCC 8	0.006	0.015	0.000	0.187
Share of land w/o LCC	0.116	0.134	0.008	0.914

Table 4.22: Summary of Estimation Data for Pasture Ricardian: Southeastern U.S.

Statistic	Mean	St. Dev.	Min	Max
Net return per acre	220.334	627.724	−273.185	13,369.660
Winter Temp	6.720	3.731	−1.386	19.891
Winter Precip	293.968	92.083	56.269	480.895
Spring Temp	16.259	2.763	8.419	24.104
Spring Precip	316.080	59.082	110.553	436.401
Summer Temp	25.857	1.852	18.919	30.266
Summer Precip	325.695	82.510	148.956	709.614
Fall Temp	17.160	2.736	9.952	25.587
Fall Precip	290.397	48.633	127.113	451.851
Share of land in LCC 1	0.015	0.032	0.000	0.346
Share of land in LCC 2	0.204	0.143	0.000	0.810
Share of land in LCC 3	0.213	0.129	0.000	0.900
Share of land in LCC 4	0.138	0.094	0.000	0.654
Share of land in LCC 5	0.041	0.061	0.000	0.415
Share of land in LCC 6	0.121	0.112	0.000	0.774
Share of land in LCC 7	0.149	0.179	0.000	0.918
Share of land in LCC 8	0.011	0.051	0.000	0.705
Share of land w/o LCC	0.108	0.114	0.005	0.915

Table 4.23: Parameter estimates for pasture Ricardian function

	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 4.24: Average marginal effects of climate on pasture net returns

Variable	Conterminous U.S.	Eastern U.S.	Northeast	Southeast
Spring Temperature	−464.895*** (48.204)	−275.360*** (60.050)	−424.300*** (89.500)	257.015* (151.351)
Spring Precipitation	−3.642*** (0.707)	−1.479** (0.756)	4.2573*** (1.403)	−4.284*** (1.263)
Summer Temperature	402.333*** (44.833)	377.416*** (55.665)	−0.276 (1.1425)	−121.372 (118.000)
Summer Precipitation	2.700*** (0.328)	2.857*** (0.562)	−0.276 (1.000)	60128*** (0.823)
Fall Temperature	−139.136** (64.585)	−435.903*** (77.446)	−31.341 (126.878)	−33.672 (153.355)
Fall Precipitation	−0.705 (0.642)	0.691 (0.583)	−1.058 (1.112)	3.142*** (0.875)
Winter Temperature	243.828*** (34.885)	303.510*** (36.230)	130.545** (56.500)	−189.381* (99.549)
Winter Precipitation	2.088*** (0.485)	0.1579 (0.492)	−1.308** (1.143)	−1.232* (0.737)

Table 4.25: Summary of Estimation Data for Urban Ricardian: Conterminous U.S.

Statistic	Mean	St. Dev.	Min	Max
Net return per acre	34,661	36,825	3,455	409,492
Heating degree days	2,755	1,211	150	6,393
Cooling degree days	714	446	0	2,344
Mean Temp	12	4	0	23
Precip	992	349	84	2,941
Population Density	237	1,392	0	49,412
Medium income	29,603	5,632	15,223	69,076

Table 4.26: Summary of Estimation Data for Urban Ricardian: Eastern U.S.

Statistic	Mean	St. Dev.	Min	Max
Net return per acre	25,113	17,206	3,455	158,383
Heating degree days	2,613	1,159	150	5,668
Cooling degree days	781	427	70	2,234
Mean Temp	13	4	3	23
Precip	1,086	247	449	1,815
Population Density	266	1,502	0	49,412
Medium income	29,660	5,577	15,223	69,076

Table 4.27: Summary of Estimation Data for Urban Ricardian: Northeastern U.S.

Statistic	Mean	St. Dev.	Min	Max
Net return per acre	26,260	16,814	3,455	134,437
Heating degree days	3,526	738	2,028	5,667
Cooling degree days	452	198	70	1,067
Mean Temp	10	3	3	15
Precip	1,001	158	556	1,436
Population Density	398	2,245	2	49,412
Medium income	31,271	5,856	17,031	61,023

Table 4.28: Summary of Estimation Data for Urban Ricardian: Southeastern U.S.

Statistic	Mean	St. Dev.	Min	Max
Net return per acre	24,731	18,687	4,200	158,383
Heating degree days	1,672	607	150	3,451
Cooling degree days	1,090	365	154	2,234
Mean Temp	16	3	9	23
Precip	1,225	213	529	1,815
Population Density	197	556	0	9,002
Medium income	28,611	5,276	15,502	69,076

Table 4.29: Parameter estimates for urban Ricardian function

	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 4.30: Average marginal effects of climate on urban net returns

Variable	Conterminous U.S.	Eastern U.S.	Northeast	Southeast
HDD	-37.882^{***} (1.549)	-3.896^{***} (1.379)	-6.917^{***} (2.477)	-4.734^{**} (2.8322)
CDD	-113.950^{***} (3.580)	-5.964^{*} (3.300)	1.658 (6.341)	-2.223 (4.760)
Precip	-15.096^{***} (2.278)	-5.855^{***} (2.150)	-8.046 (6.841)	-8.957^{***} (3.016)

Chapter 5: Climate and Land-use Change

This chapter 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 representing the current distribution of a particular land-use within a defined spatial region. The observed land area in each broad land-use type and transitions between land-uses for the recent historical past are presented in tables 5.1 - 5.6. Each model presented below is separately estimated for land starting in a particular use within either the eastern, northeastern, southeastern, or conterminous U.S. 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.

5.1 Logit Model Specification & Estimation Results

Combining the climate driven net return predictions from chapter 4 with the plot-level land quality data from the NRI, I specify the alternative specific utility that enters into equation 2.6 as

$$U_{inkt} = \alpha_k + \beta_k LCC_i + \gamma_k NR_{nkt} + \epsilon_{inkt}. \tag{5.1}$$

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 equation 5.1 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 5.8 - 5.12 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. The alternative specifications are used to test two important assumptions; the influence of option value, and the presence of unobserved heterogeneity that may be correlated with net returns.

5.1.1 Specification Issues

The specifications that include the change in net returns impose different assumptions about how land owners form expectations about the future. The land-use decision is driven by the relative net returns to each use, and expectations about how those rents will change in the future help to determine the optimal choice. Uncertainty in how future rents will evolve, combined with costly conversion, leads to option value. The greater the uncertainty, the higher the option value (i.e. the option to reverse the land-use decision in the future). The presence of conversion costs and option value leads to the negative sign on α_k in the results, because it is often optimal to simply delay the cost of conversion by doing nothing. Conversion occurs when the benefit of the new use, including the option value, exceeds the conversion cost (see section 2.1).

Assuming the landscape is in equilibrium and option value is negligible, then only changes in net returns matter in the land-use conversion decision [46]. In the presence of option values, the levels of net return drive the relative threshold that induces conversion. Because the Ricardian climate models developed in chapter 4 yield predictions of net returns levels, the main analysis presented in section 5.2 assumes that the conversion threshold (i.e. net return levels) dominates land-use decisions.

In order to shed light on the potential impact of option value on land-use, I estimate the following alternative specification of the discrete choice model.

$$U_{inkt} = \alpha_k + \beta_k LCC_i + \gamma_k^1 \Delta NR_{nkt} + \epsilon_{inkt} \tag{5.2}$$

Where ΔNR_{nkt} is the change in net returns to use k over the transition period. Parameter estimates for equation 5.2 are presented in table 5.10. A third specification includes both levels and changes in net returns. Comparisons between models 5.2 and 5.3 may reveal evidence of the presence of option value in explaining land-use conversion.

$$U_{inkt} = \alpha_k + \beta_k LCC_i + \gamma_k^0 NR_{nkt} + \gamma_k^1 \Delta NR_{nkt} + \epsilon_{inkt} \tag{5.3}$$

Likelihood ratio tests between the model estimates in tables 5.10 and 5.11 result in rejection of the hypothesis that γ_k^0 is zero in each of the twelve model iterations. The test results suggest that the assumption of no option value does not hold for these transition types and study areas.

In the presence of correlation between individual effects and net returns, the Mundlak approach [38] to the random effects model provides a means of testing whether a model that includes the mean of net returns is preferred to the model with levels only. In the standard random effects model it is assumed that individual effects are uncorrelated with the other regressors such that unobserved random effect may lead to inconsistent estimates. The Mundlak device uses the group means to correct for possible violations of the random effects assumption that unobservable characteristics are uncorrelated with the independent variables [18]. The Mundlak approach is applied to my estimation of land-use choice and serves as a form of fixed effect in equation 5.4. First, I estimate a model that includes only the mean level of net returns over the two-year period preceding the starting year. Secondly, a model is specific that also includes the group means of net returns.

The model of net return levels only is specified in 5.1 and the Mundlak specification is

$$U_{inkt} = \alpha_k + \beta_k LCC_i + \gamma_k^1 NR_{nkt} + \gamma_k^2 \overline{NR}_{nkt} + \epsilon_{inkt}. \tag{5.4}$$

A likelihood ratio test is performed to test the null hypothesis that γ_k^2 is equal to zero by comparing the estimated models in tables 5.8 and 5.9. In all twelve models estimated, I reject the hypothesis that γ_k^2 equals zero. This suggests that the mean net return level does impact the estimates, however in many cases the variation between the level and its group mean is too low to provide significant estimates for the parameters of interest due to the correlation between net return levels and their respective means. Since I am most interested in recovering the parameters on net returns levels (because these are the variables for which climate has been parameterized), I settle on the net returns only model estimates for climate impact analysis.

5.1.2 Estimation Results

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 in this chapter. 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.

Nine models are estimated using the levels only specification (equation 5.1): three starting uses by three spatial scales. 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 levels-changes models found in table 5.11.

5.2 Climate Change Impact on Conversion Probability and the Future Landscape in the U.S. Southeast

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 5.13. 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 100^{th} 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 5.7). 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).

5.2.1 The Partial and Total Effects of Climate Change

Using the framework developed in section 2.3, I analyze the impact of climate change on the probability of conversion between broad land-use systems. The partial climate effect with respect to land-use k is found by calculating the increment in probability (equation 2.16) resulting from shifting net returns to a single land-use while holding fixed climate's impact on the alternative land-use rents. Because each net return measure is optimized over climate, holding net return fixed implies failure to re-optimize for the new climate. The counter-factual underlying the partial effect is that intensive margin adaptation occurs only within the k^{th} land-use system. The total effect (equation 2.15) is calculated by simultaneously shifting all four net returns levels by a discrete change in climate from today's baseline to the climate of 2050 under scenario NorESM1-M RCP 8.5. The total effect allows for intensive adaptation within all four land-use types.

The box-plots in figures 5.1 - 5.3 summarize the partial and total effect of climate change on the probability of land conversion. Each distribution is over parcels in the study area. The box represents the 1st and 3rd quartile and the median change in probability. The point inside the box is the mean probability change for an acre of land and this is labeled in each box-plot. Because this model is highly non-linear, the partial climate effects do not necessarily sum to the total impact. Recall that partial effects will sum to zero across all four probabilites for each starting use by construction.

Consider climate's effect on the probability that land starting in crop use will remain in crop use (figure 5.1). The model predicts that climate change will lower the probability of remaining in crop use. This result is largely driven by climate's partial effect on pasture rents. As pasture becomes relatively more profitable, more crop land can be expected to convert to pasture land. The probability of crop land remaining in crop use is lower regardless of the partial effect considered.

Looking at climate's effect on crop net returns alone may lead to the false conclusion that crop land is more likely to convert to pasture, but when the total increment is calculated the effect is clearly negative. The negative total effect of climate on the probability of converting from crop to pasture is driven by climate's effect on pasture net returns. Partial and total effects of climate's impact on the probability of converting from crop to forest are near zero suggesting little climate effect on this transition type. Under climate change the likelihood of converting from crop to urban use is higher under all partial effects. The total climate effect indicates that crop land is 10.4% more likely to convert to urban land under this scenario.

Consider forest land remaining in forest use (figure 5.3). The model for land starting in forest use predicts that forest land is less likely to convert to crop use under each partial effect and under the total effect of climate change. Crop, urban, and forest partial effects on the probability of forest converting to pasture indicate lower likelihood, but the pasture partial effect and the total effect are positive. When climate impacts occur within crop and urban systems, forest land is less likely to leave forest use, but the total effect suggests the opposite result. That is, the total effect of climate reduces the probability that forest land will remain in forest use.

Climate change impacts increase the probability of converting from forest to urban. The own partial effect dominates climate's total effect. The own partial effect is the relationship between starting use impact and that uses' partial effect (e.g. the own partial effect for land starting in forest is the partial effect associated with forest net returns). The positive sign on forest partial effects here suggests there are incentives within forest systems to adapt to climate change by converting from forestry to urban use. On average, conversion to crop use is less likely under climate change, as is the probability of remaining in forestry, and conversions to pasture and urban systems are more likely.

The spatial distribution of total climate effects are mapped in figures 5.4 - 5.6. Looking at land currently in crop and pasture, there will be less land in these uses, with conversion to forest and urban increasingly likely. The results suggest that there is an incentive to move into forest and urban uses from pasture use. The results also imply that there will be an incentive for current forest land to move into urban and pasture uses, with land that would otherwise have gone into urban use instead moving into pasture or remaining in forestry (figure 5.6).

5.2.2 The Future Southeastern Landscape under Climate Change

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 5.13 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.

Recall from section 2.4 that 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 5.7 - 5.10. To explore the changes underlying these figures I 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 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 5.7). 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 5.9). Notice that the counties experiencing the greatest decline in baseline acres have the highest level of climate impact. These results are consistent with the analysis of loblolly and shortleaf pine detailed in section 4.1.3. 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.

Table 5.1: Observed Land-use Transitions in the eastern U.S. (2000-2012)

	End in Crop	End in Pasture	End in Forest	End in Urban	End in Other	Total in 2000
Start in Crop	255,265	13,698	1,501	2,038	4,297	277,099
	92.23%	4.94%	0.542%	0.735%	1.55%	100%
Start in Pasture	8,384	84,886	5,749	1,584	2,364	102,968
	8.14%	82.44%	5.58%	1.54%	2.30%	100%
Start in Forest	447	1,969	334,207	4,596	1,859	343,078
	0.130%	0.083%	99.43%	0.289%	0.542%	100%
Start in Urban	92	54	188	64,653	35	65,022
	0.141%	0.083%	0.289%	99.43%	0.054%	100%
Total in 2012	269,583	103,225	344,089	74,020		
	(−7,516)	(+257)	(+1,011)	(+8,998)		

Note: Four major land-uses are included as rows and again as columns where each cell reports the area of land (in thousands of acres) converted from the row use to the column use between the starting and ending period. Other land-use includes CRP, federal land, minor land, rural transportation, small water areas, and larger water areas. The last row is the total land area in each land-use in the ending period and the net change in over the transition period.

Table 5.2: Observed Land-use Transitions in the southeastern U.S. (2000-2012)

	End in Crop	End in Pasture	End in Forest	End in Urban	End in Other	Total in 2000
Start in Crop	62,125	6,941	1,096	846	1,372	72,380
	85.83%	9.59%	1.51%	1.17%	1.90%	100%
Start in Pasture	3,501	51,350	3,361	1,083	1,412	60,706
	5.77%	84.59%	5.54%	1.78%	2.33%	100%
Start in Forest	226	1,341	179,790	2,992	1,211	185,561
	0.12%	0.72%	96.89%	1.61%	0.65%	100%
Start in Urban	38	33	101	30,747	25	30,944
	0.12%	0.11%	0.33%	99.36%	0.08%	100%
Total in 2012	66,471	60,810	185,980	36,543		
	(−5,909)	(+104)	(+419)	(+5,599)		

Note: Four major land-uses are included as rows and again as columns where each cell reports the area of land (in thousands of acres) converted from the row use to the column use between the starting and ending period. Other land-use includes CRP, federal land, minor land, rural transportation, small water areas, and larger water areas. The last row is the total land area in each land-use in the ending period and the net change in over the transition period.

Table 5.3: Observed Land-use Transitions in the northeastern U.S. (2000-2012)

	End in Crop	End in Pasture	End in Forest	End in Urban	End in Other	Total in 2000
Start in Crop	135,414	5,466	385	1,102	1,863	144,229
	93.89%	3.79%	0.270%	0.764%	1.29%	100%
Start in Pasture	4,100	29,065	2,335	481	592	36,573
	11.21%	79.47%	6.38%	1.32%	1.62%	100%
Start in Forest	192	601	151,864	1,581	617	154,855
	0.124%	0.388%	98.07%	1.02%	0.398%	100%
Start in Urban	51	21	87	32,221	8	32,387
	0.157%	0.065%	0.269%	97.97%	0.025%	100%
Total in 2012	142,220	36,056	155,339	35,612		
	(−2,009)	(−517)	(+484)	(+3,225)		

Note: Four major land-uses are included as rows and again as columns where each cell reports the area of land (in thousands of acres) converted from the row use to the column use between the starting and ending period. Other land-use includes CRP, federal land, minor land, rural transportation, small water areas, and larger water areas. The last row is the total land area in each land-use in the ending period and the net change in over the transition period.

Table 5.4: Observed Land-use Transitions in the eastern U.S. (2010-2012)

	End in Crop	End in Pasture	End in Forest	End in Urban	End in Other	Total in 2010
Start in Crop	266,531	1,421	54	131	462	268,599
	99.23%	0.53%	0.02%	0.05%	0.14%	100%
Start in Pasture	1,634	101,008	558	125	217	103,542
	1.58%	97.55%	0.54%	0.12%	0.21%	100%
Start in Forest	110	168	343,169	341	203	343,991
	0.03%	0.05%	99.76%	0.10%	0.06%	100%
Start in Urban	23	13	53	73,314	7	73,410
	0.03%	0.02%	0.07%	99.87%	0.001%	100%
Total in 2012	269,583	103,225	344,089	74,020		
	(+684)	(−317)	(+98)	(+610)		

Note: Four major land-uses are included as rows and again as columns where each cell reports the area of land (in thousands of acres) converted from the row use to the column use between the starting and ending period. Other land-use includes CRP, federal land, minor land, rural transportation, small water areas, and larger water areas. The last row is the total land area in each land-use in the ending period and the net change in over the transition period.

Table 5.5: Observed Land-use Transitions in the southeastern U.S. (2010-2012)

	End in Crop	End in Pasture	End in Forest	End in Urban	End in Other	Total in 2010
Start in Crop	65,605	698	51	54	79	66,487
	98.67%	1.05%	0.08%	0.08%	0.12%	100%
Start in Pasture	628	59,721	331	85	132	60,897
	1.03%	98.07%	0.54%	0.14%	0.22%	100%
Start in Forest	38	137	185,420	219	140	185,954
	0.02%	0.07%	99.71%	0.12%	0.08%	100%
Start in Urban	7	8	28	36,104	6	36,153
	0.02%	0.02%	0.08%	99.86%	0.02%	100%
Total in 2012	66,471	60,810	185,980	36,543		
	(−16)	(−87)	(+26)	(+390)		

Note: Four major land-uses are included as rows and again as columns where each cell reports the area of land (in thousands of acres) converted from the row use to the column use between the starting and ending period. Other land-use includes CRP, federal land, minor land, rural transportation, small water areas, and larger water areas. The last row is the total land area in each land-use in the ending period and the net change in over the transition period.

Table 5.6: Observed Land-use Transitions in the northeastern U.S. (2010-2012)

	End in Crop	End in Pasture	End in Forest	End in Urban	End in Other	Total in 2010
Start in Crop	140,770	431	2	70	241	141,514
	99.47%	0.30%	0.00001%	0.05%	0.170%	100%
Start in Pasture	822	354,443	227	39	10,268	365,799
	0.22%	96.90%	0.06%	0.01%	2.81%	100%
Start in Forest	58	31	155,025	120	58	155,192
	0.04%	0.02%	99.83%	0.08%	0.037%	100%
Start in Urban	15	5	25	35,360	3	35,408
	0.04%	0.01%	0.07%	99.86%	0.00008%	100%
Total in 2012	142,220	360,557	155,339	35,612		
	(−706)	(−5,242)	(+47)	(+204)		

Note: Four major land-uses are included as rows and again as columns where each cell reports the area of land (in thousands of acres) converted from the row use to the column use between the starting and ending period. Other land-use includes CRP, federal land, minor land, rural transportation, small water areas, and larger water areas. The last row is the total land area in each land-use in the ending period and the net change in over the transition period.

Table 5.7: Observed Land-use Transitions in Selected Southeastern U.S. Counties (2010-2012)

	End in Crop	End in Pasture	End in Forest	End in Urban	End in Other	Total in 2010
Start in Crop	42,269	398	38	38	38	42,781
	98.80%	0.93%	0.089%	0.089%	0.089%	100%
Start in Pasture	553	44,576	304	61	66	45,560
	1.21%	97.84%	0.667%	0.134%	0.145%	100%
Start in Forest	25	126	148,932	175	102	149,360
	0.0167%	0.0844%	99.71%	0.117%	0.0682%	100%
Start in Urban	7	7	25	26,628	1	26,668
	0.0262%	0.0262%	0.0937%	99.85%	0.00004%	100%
Total in 2012	42,993	45,173	149,397	26,936		
	(+212)	(−387)	(+37)	(+268)		

Note: Four major land-uses are included as rows and again as columns where each cell reports the area of land (in thousands of acres) converted from the row use to the column use between the starting and ending period. Other land-use includes CRP, federal land, minor land, rural transportation, small water areas, and larger water areas. The last row is the total land area in each land-use in the ending period and the net change in over the transition period.

Table 5.8: Logit Model Set 1: Net Return Levels

	Land Starting in Crop			Land Starting in Pasture			Land Starting in Forest		
	(East)	(South)	(North)	(East)	(South)	(North)	(East)	(South)	(North)
fr:(intercept)	−8.098***	−6.406***	−11.179***	−2.455***	−2.421***	−2.678***	6.522***	6.622***	6.092***
	(0.286)	(0.395)	(0.621)	(0.108)	(0.152)	(0.163)	(0.245)	(0.386)	(0.315)
ps:(intercept)	−5.135***	−4.613***	−5.699***	3.380***	3.716***	2.890***	0.215	0.840**	−1.671***
	(0.069)	(0.093)	(0.110)	(0.060)	(0.088)	(0.084)	(0.284)	(0.415)	(0.500)
ur:(intercept)	−7.460***	−7.341***	−7.297***	−3.351***	−2.788***	−4.306***	−0.282	0.286	−1.237***
	(0.228)	(0.367)	(0.301)	(0.217)	(0.273)	(0.355)	(0.273)	(0.412)	(0.385)
fr:lcc	0.054	−0.403***	0.749***	0.386***	0.360***	0.421***	0.521***	0.609***	0.519***
	(0.099)	(0.152)	(0.131)	(0.026)	(0.037)	(0.039)	(0.065)	(0.111)	(0.081)
ps:lcc	0.181***	0.102***	0.252***	0.248***	0.235***	0.273***	0.238***	0.335***	0.343***
	(0.020)	(0.029)	(0.030)	(0.017)	(0.026)	(0.023)	(0.074)	(0.118)	(0.113)
ur:lcc	−0.031	−0.092	−0.041	0.163***	0.146**	0.204**	0.399***	0.448***	0.466***
	(0.073)	(0.120)	(0.096)	(0.052)	(0.067)	(0.082)	(0.069)	(0.115)	(0.089)
cr:nr	0.004***	0.003***	0.006***	0.002***	0.002***	0.002***	0.004***	0.005***	0.003**
	(0.0004)	(0.0004)	(0.001)	(0.0002)	(0.0003)	(0.0005)	(0.001)	(0.001)	(0.001)
fr:nr	0.0005***	0.001***	−0.0001	0.001***	0.001***	0.0002***	−0.0001**	0.0001	−0.0002***
	(0.0001)	(0.0002)	(0.001)	(0.00003)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
ps:nr	−0.001***	−0.001***	−0.0005***	−0.0002***	−0.0003**	0.0002**	0.001***	0.0005**	0.001**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0004)
ur:nr	0.00002***	0.00002***	0.00001***	0.00002***	0.00001***	0.00003***	0.00002***	0.00002***	0.00002***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Observations	273,825	82,461	191,364	126,364	75,296	51,068	427,707	236,980	190,727
R^2	0.362	0.291	0.473	0.090	0.205	−0.086	0.757	0.739	0.788
Log Likelihood	−12,010.400	−5,645.650	−5,643.502	−16,646.860	−8,618.243	−8,030.537	−7,112.908	−4,783.248	−2,301.467
LR Test (df = 10)	13,654.130***	4,625.179***	10,144.970***	3,304.957***	4,432.779***	−1,267.182	44,327.870***	27,065.520***	17,121.980***

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

Table 5.9: Logit Model Set 2: Net Return Levels with Mundlak

	Land Starting in Crop			Land Starting in Pasture			Land Starting in Forest		
	(East)	(South)	(North)	(East)	(South)	(North)	(East)	(South)	(North)
fr:(intercept)	−8.062***	−6.282***	−10.932***	−2.507***	−2.414***	−2.722***	6.514***	6.954***	5.970***
	(0.288)	(0.397)	(0.649)	(0.108)	(0.153)	(0.165)	(0.251)	(0.411)	(0.328)
ps:(intercept)	−5.130***	−4.520***	−5.547***	3.302***	3.677***	2.899***	0.206	1.217***	−1.831***
	(0.073)	(0.099)	(0.117)	(0.061)	(0.092)	(0.086)	(0.292)	(0.440)	(0.511)
ur:(intercept)	−7.537***	−7.348***	−7.193***	−3.430***	−2.884***	−4.257***	−0.380	0.546	−1.492***
	(0.239)	(0.379)	(0.328)	(0.229)	(0.286)	(0.376)	(0.280)	(0.437)	(0.395)
fr:lcc	0.057	−0.404***	0.756***	0.386***	0.360***	0.422***	0.523***	0.611***	0.525***
	(0.099)	(0.153)	(0.132)	(0.026)	(0.037)	(0.039)	(0.065)	(0.112)	(0.082)
ps:lcc	0.180***	0.103***	0.246***	0.249***	0.237***	0.272***	0.238***	0.335***	0.345***
	(0.020)	(0.029)	(0.030)	(0.017)	(0.026)	(0.023)	(0.074)	(0.118)	(0.114)
ur:lcc	−0.031	−0.079	−0.049	0.165***	0.154**	0.203**	0.400***	0.449***	0.473***
	(0.073)	(0.121)	(0.096)	(0.052)	(0.067)	(0.082)	(0.069)	(0.116)	(0.090)
cr:nr	0.005***	−0.002**	0.005***	0.004***	0.001	0.002	0.003	−0.005	0.009**
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.004)
fr:nr	0.006***	0.004***	0.010**	0.00003	0.001***	−0.002***	−0.001***	−0.001**	−0.001
	(0.001)	(0.001)	(0.005)	(0.0003)	(0.0003)	(0.001)	(0.0003)	(0.0004)	(0.001)
ps:nr	−0.001**	−0.001***	0.002***	−0.001***	−0.001***	0.0004	0.0001	0.001	−0.001
	(0.0003)	(0.0004)	(0.0004)	(0.0002)	(0.0003)	(0.0003)	(0.001)	(0.001)	(0.001)
ur:nr	0.00000	0.00000	0.00002	0.00001	−0.00001	0.00003**	−0.00001*	−0.00001	−0.00001
	(0.00001)	(0.00002)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
cr:nrmean	−0.001	0.005***	0.002	−0.003***	0.0005	−0.0001	0.001	0.012***	−0.008
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.004)	(0.005)
fr:nrmean	−0.005***	−0.003**	−0.010**	0.001**	−0.0002	0.002***	0.001***	0.001**	0.0005
	(0.001)	(0.001)	(0.005)	(0.0003)	(0.0003)	(0.0005)	(0.0003)	(0.0003)	(0.001)
ps:nrmean	−0.0003	0.0003	−0.002***	0.001***	0.001***	−0.0003	0.001	−0.0003	0.002
	(0.0003)	(0.0003)	(0.0005)	(0.0002)	(0.0003)	(0.0004)	(0.001)	(0.001)	(0.001)
ur:nrmean	0.00002	0.00002	−0.00000	0.00001	0.00002	−0.00001	0.00004***	0.00004***	0.00004***
	(0.00001)	(0.00002)	(0.00002)	(0.00001)	(0.00002)	(0.00002)	(0.00001)	(0.00001)	(0.00001)
Observations	273,825	82,461	191,364	126,364	75,296	51,068	427,707	236,980	190,727
R^2	0.363	0.292	0.475	0.091	0.205	−0.085	0.758	0.740	0.789
Log Likelihood	−12,002.200	−5,632.734	−5,624.929	−16,632.410	−8,613.269	−8,024.448	−7,099.039	−4,768.808	−2,295.922
LR Test (df = 14)	13,670.540***	4,651.012***	10,182.110***	3,333.855***	4,442.728***	−1,255.003	44,355.600***	27,094.400***	17,133.070***

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

Table 5.10: Logit Model Set 3: Net Return Changes

	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 5.11: Logit Model Set 4: Net Return Levels & Changes

	Land Starting in Crop			Land Starting in Pasture			Land Starting in Forest		
	(East)	(South)	(North)	(East)	(South)	(North)	(East)	(South)	(North)
fr:(intercept)	-8.044^{***}	-6.379^{***}	-11.067^{***}	-2.457^{***}	-2.462^{***}	-2.673^{***}	6.505^{***}	6.538^{***}	6.105^{***}
	(0.285)	(0.394)	(0.643)	(0.108)	(0.153)	(0.163)	(0.246)	(0.387)	(0.317)
ps:(intercept)	-5.137^{***}	-4.637^{***}	-5.702^{***}	3.374^{***}	3.722^{***}	2.891^{***}	0.220	0.856^{**}	-1.665^{***}
	(0.069)	(0.092)	(0.110)	(0.060)	(0.088)	(0.084)	(0.285)	(0.415)	(0.502)
ur:(intercept)	-7.435^{***}	-7.375^{***}	-7.302^{***}	-3.347^{***}	-2.784^{***}	-4.287^{***}	-0.290	0.277	-1.222^{***}
	(0.228)	(0.365)	(0.301)	(0.218)	(0.273)	(0.355)	(0.274)	(0.413)	(0.387)
fr:lcc	0.048	-0.387^{**}	0.741^{***}	0.386^{***}	0.359^{***}	0.419^{***}	0.523^{***}	0.611^{***}	0.517^{***}
	(0.098)	(0.151)	(0.131)	(0.026)	(0.037)	(0.039)	(0.065)	(0.111)	(0.081)
ps:lcc	0.178^{***}	0.100^{***}	0.253^{***}	0.248^{***}	0.235^{***}	0.272^{***}	0.239^{***}	0.334^{***}	0.344^{***}
	(0.020)	(0.029)	(0.030)	(0.017)	(0.026)	(0.023)	(0.074)	(0.118)	(0.113)
ur:lcc	-0.035	-0.092	-0.039	0.163^{***}	0.145^{**}	0.203^{**}	0.401^{***}	0.450^{***}	0.464^{***}
	(0.073)	(0.119)	(0.096)	(0.052)	(0.067)	(0.082)	(0.070)	(0.115)	(0.090)
cr:nr	0.004^{***}	0.003^{***}	0.006^{***}	0.002^{***}	0.002^{***}	0.002^{***}	0.004^{***}	0.005^{***}	0.003^{**}
	(0.0004)	(0.0004)	(0.001)	(0.0002)	(0.0003)	(0.0005)	(0.001)	(0.001)	(0.001)
fr:nr	0.00003	0.0001	-0.001	0.001^{***}	0.001^{***}	0.0002^{**}	-0.00004	0.0004^{***}	-0.0002^{***}
	(0.0002)	(0.0004)	(0.001)	(0.00003)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
ps:nr	-0.001^{***}	-0.001^{***}	-0.0005^{***}	-0.0002^{***}	-0.0003^{**}	0.0002^{**}	0.001^{***}	0.0004^{*}	0.001^{*}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0004)
ur:nr	0.00002^{***}	0.00002^{***}	0.00001^{***}	0.00002^{***}	0.00001^{***}	0.00003^{***}	0.00002^{***}	0.00002^{***}	0.00002^{***}
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
cr:nrchange	0.003^{***}	0.003^{***}	-0.00002	0.0004	-0.0004	0.0002	0.002	0.001	0.002
	(0.0004)	(0.0005)	(0.001)	(0.0004)	(0.0005)	(0.001)	(0.001)	(0.002)	(0.002)
fr:nrchange	-0.002^{***}	-0.003^{*}	-0.004^{**}	-0.0003^{*}	0.001^{***}	-0.0004	0.0005^{*}	0.001^{***}	-0.0001
	(0.001)	(0.002)	(0.002)	(0.0001)	(0.0003)	(0.0003)	(0.0002)	(0.0004)	(0.0003)
ps:nrchange	0.001^{***}	0.0004^{**}	0.0004^{*}	-0.0002	-0.00001	-0.0003	0.001^{***}	0.001^{***}	0.001
	(0.0002)	(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	0.00000	0.00000	0.00000
	(0.00000)	(0.00001)	(0.00001)	(0.00000)	(0.00001)	(0.00001)	(0.00000)	(0.00000)	(0.00000)
Observations	273,825	82,461	191,364	126,364	75,296	51,068	427,707	236,980	190,727
R^2	0.364	0.293	0.474	0.090	0.205	-0.085	0.757	0.739	0.788
Log Likelihood	$-11,986.170$	$-5,629.809$	$-5,639.707$	$-16,643.560$	$-8,613.155$	$-8,028.202$	$-7,105.976$	$-4,771.372$	$-2,299.650$
LR Test (df = 14)	$13,702.600^{***}$	$4,656.861^{***}$	$10,152.560^{***}$	$3,311.554^{***}$	$4,442.956^{***}$	$-1,262.513$	$44,341.730^{***}$	$27,089.280^{***}$	$17,125.610^{***}$

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

Table 5.12: Logit Model Set 5: Net Return Changes with Mundlak

	Land Starting in Crop			Land Starting in Pasture			Land Starting in Forest		
	(East)	(South)	(North)	(East)	(South)	(North)	(East)	(South)	(North)
fr:(intercept)	−8.353***	−6.479***	−11.825***	−2.276***	−1.977***	−2.745***	6.192***	6.287***	5.903***
	(0.280)	(0.383)	(0.584)	(0.105)	(0.145)	(0.156)	(0.227)	(0.357)	(0.302)
ps:(intercept)	−5.690***	−4.905***	−6.448***	3.278***	3.642***	2.818***	0.030	0.381	−1.705***
	(0.062)	(0.088)	(0.093)	(0.057)	(0.086)	(0.077)	(0.267)	(0.389)	(0.490)
ur:(intercept)	−7.368***	−7.288***	−7.530***	−3.214***	−2.854***	−3.650***	−0.369	−0.075	−1.027***
	(0.207)	(0.355)	(0.259)	(0.205)	(0.267)	(0.328)	(0.255)	(0.386)	(0.365)
fr:lcc	0.069	−0.393***	0.793***	0.377***	0.348***	0.427***	0.538***	0.612***	0.529***
	(0.097)	(0.150)	(0.129)	(0.026)	(0.037)	(0.039)	(0.065)	(0.111)	(0.081)
ps:lcc	0.230***	0.112***	0.332***	0.251***	0.232***	0.279***	0.238***	0.329***	0.349***
	(0.020)	(0.029)	(0.029)	(0.017)	(0.025)	(0.023)	(0.074)	(0.118)	(0.114)
ur:lcc	−0.052	−0.080	−0.010	0.168***	0.156**	0.183**	0.405***	0.463***	0.441***
	(0.075)	(0.120)	(0.095)	(0.052)	(0.067)	(0.085)	(0.069)	(0.115)	(0.090)
cr:nrchange	0.003***	0.003***	0.001	0.001	−0.0001	0.0005	0.002*	0.002	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**	0.0004*	0.0001
	(0.0004)	(0.001)	(0.001)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0004)
ps:nrchange	0.001***	0.0005**	0.0005**	−0.0001	−0.00002	−0.0001	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	−0.00001	−0.00001	−0.00001	−0.00001	−0.00000	−0.00001	0.00001	0.00001	0.00000
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00000)	(0.00001)	(0.00000)
cr:nrchangemean	0.012***	0.002	0.003	0.001	−0.005**	−0.006**	0.002	−0.008	0.007
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.006)	(0.009)	(0.009)
fr:nrchangemean	−0.008	−0.017	−0.011	0.003	−0.0002	0.005	0.135***	0.090***	0.171***
	(0.029)	(0.034)	(0.068)	(0.013)	(0.031)	(0.014)	(0.025)	(0.010)	(0.027)
ps:nrchangemean	−0.001**	−0.002**	−0.001	−0.002***	−0.001	−0.002**	−0.009***	−0.009***	0.004
	(0.001)	(0.001)	(0.001)	(0.0005)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
ur:nrchangemean	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***	0.0002***
	(0.00002)	(0.00003)	(0.00003)	(0.00002)	(0.00002)	(0.00003)	(0.00001)	(0.00001)	(0.00002)
Observations	273,825	82,461	191,364	126,364	75,296	51,068	427,707	236,980	190,727
R^2	0.357	0.288	0.468	0.086	0.196	−0.087	0.758	0.740	0.789
Log Likelihood	−12,113.320	−5,669.851	−5,703.304	−16,721.480	−8,712.880	−8,043.627	−7,079.349	−4,765.011	−2,296.674
LR Test (df = 14)	13,448.300***	4,576.777***	10,025.370***	3,155.718***	4,243.505***	−1,293.362	44,394.980***	27,102.000***	17,131.570***

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

Table 5.13: Logit Estimates: Net Returns in the Southeastern U.S.

	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

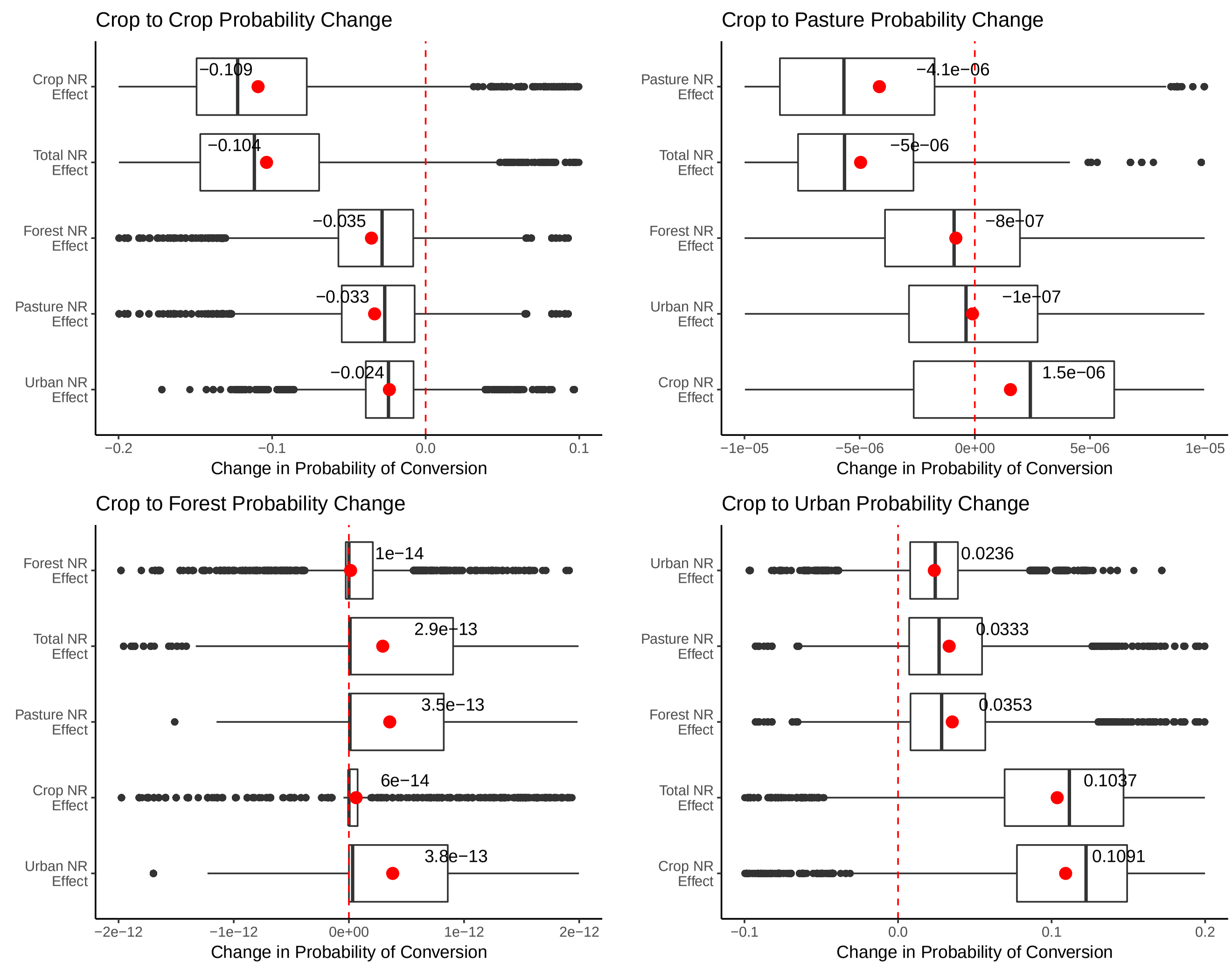

Figure 5.1: Climate Change Effects on the Probability of Crop Land Conversion

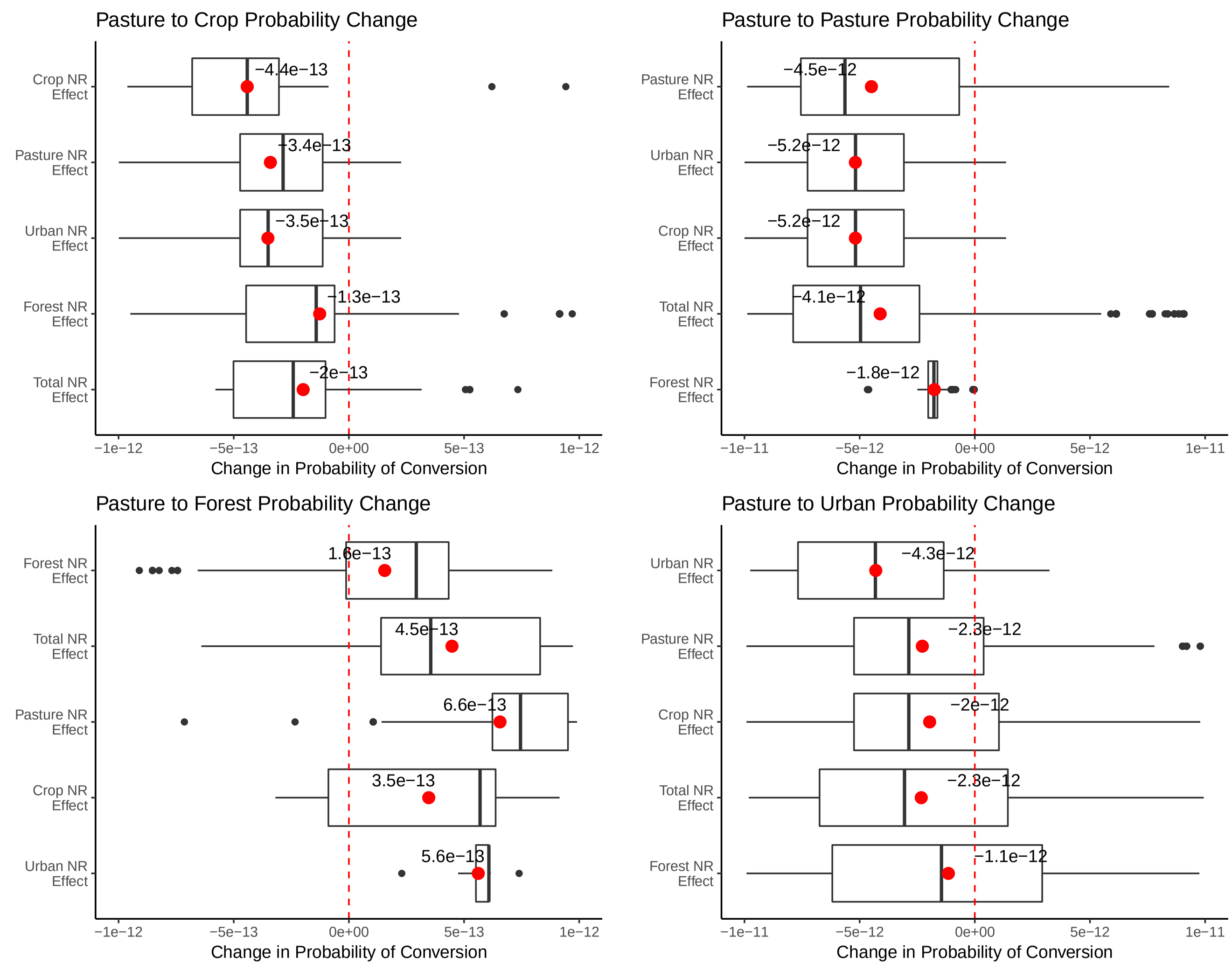

Figure 5.2: Climate Change Effects on the Probability of Pasture Land Conversion

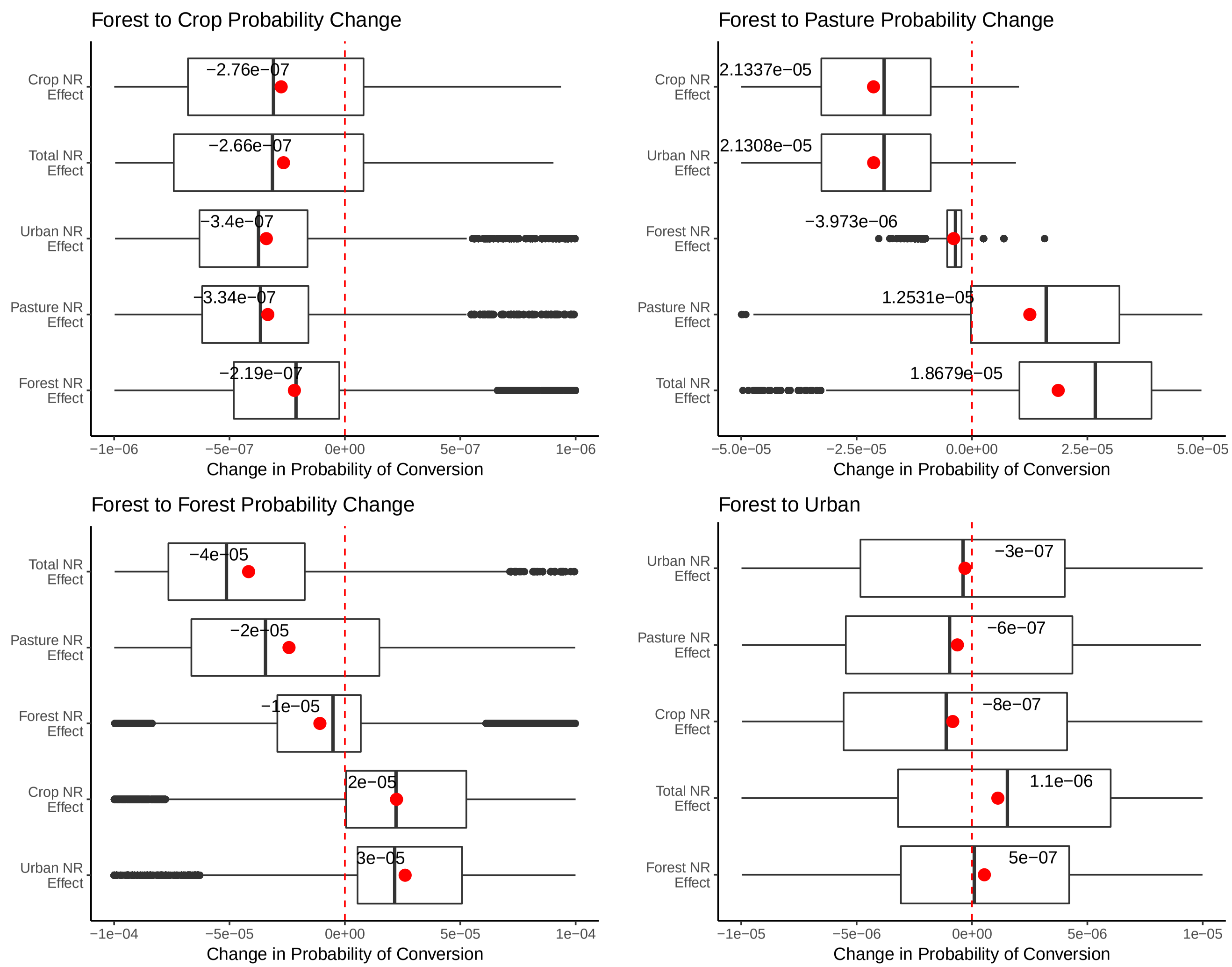

Figure 5.3: Climate Change Effects on the Probability of Forest Land Conversion

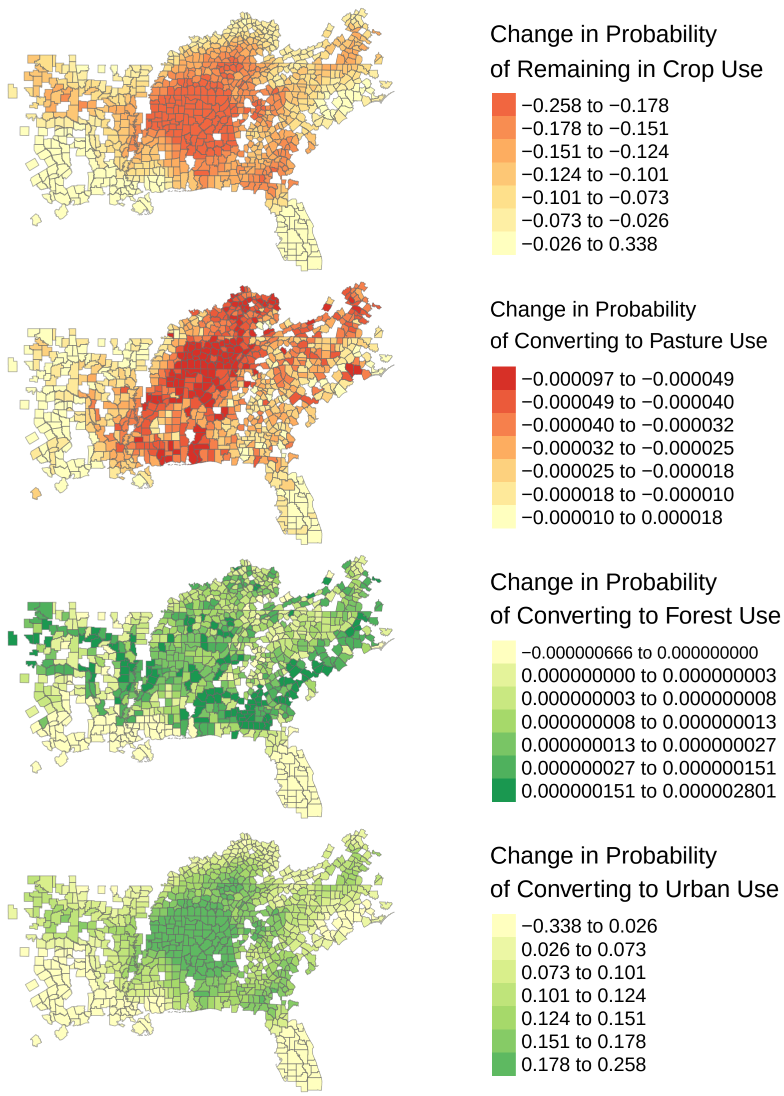

Figure 5.4: Land Starting in Crop Use: Maps of Conversion Probability Change

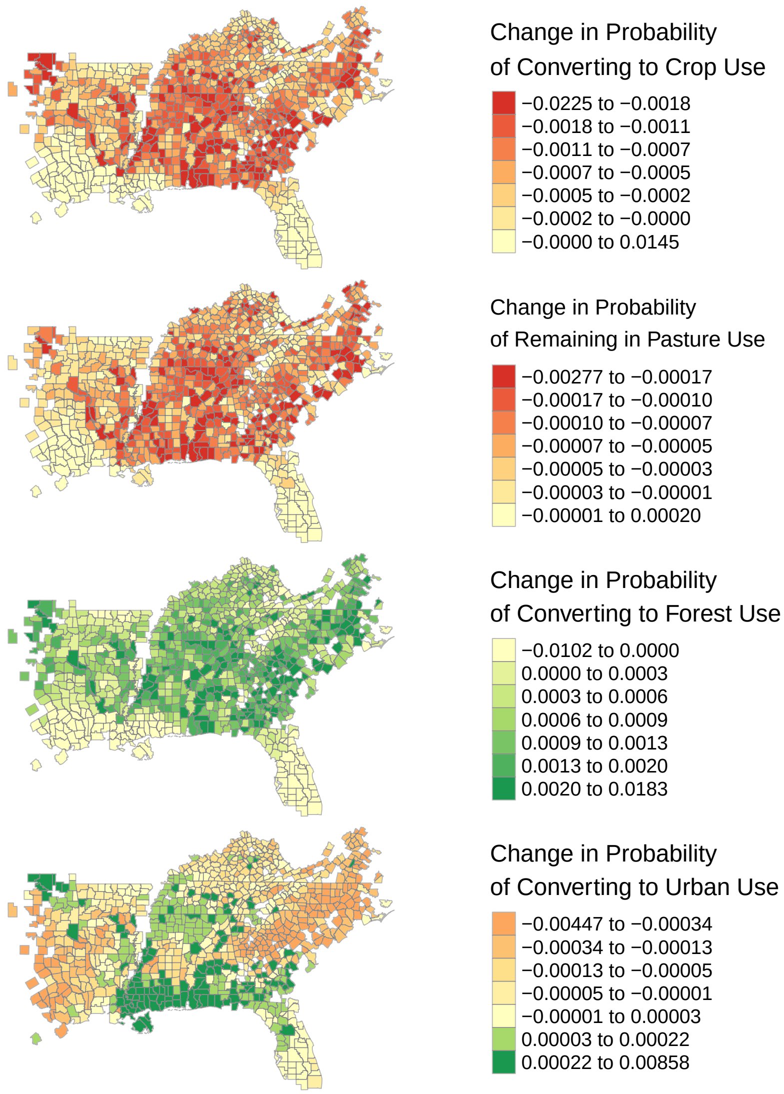

Figure 5.5: Land Starting in Pasture Use: Maps of Conversion Probability Change

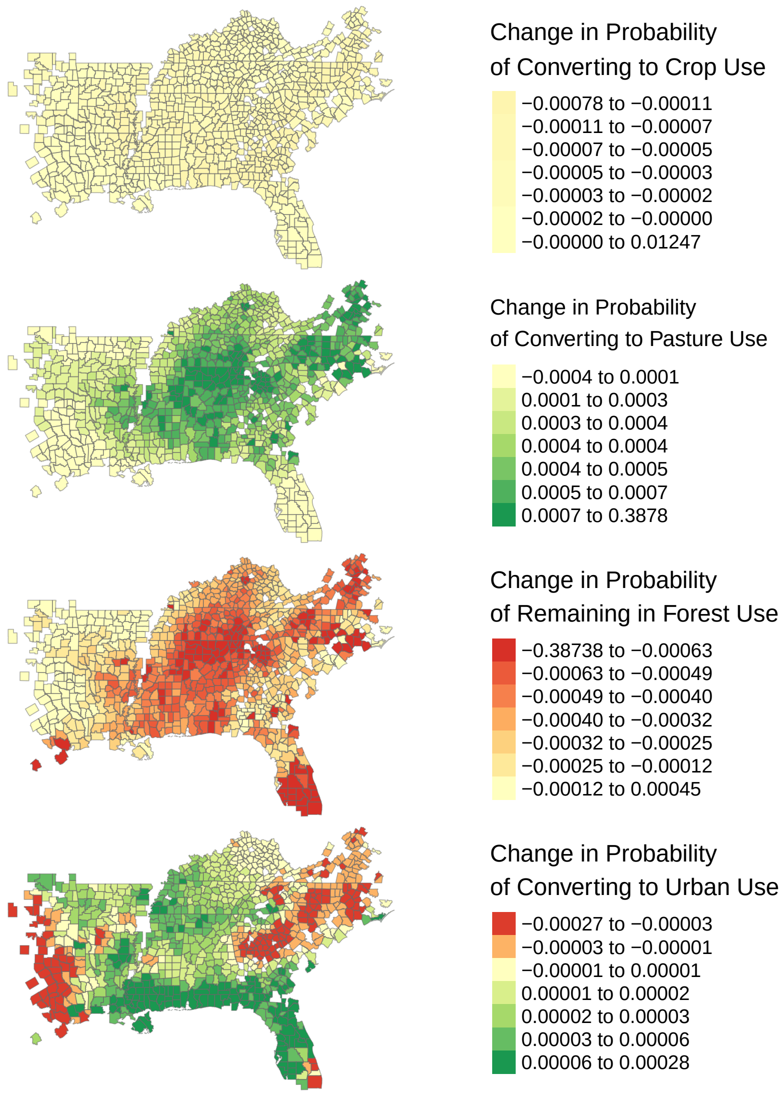

Figure 5.6: Land Starting in Forest Use: Maps of Conversion Probability Change

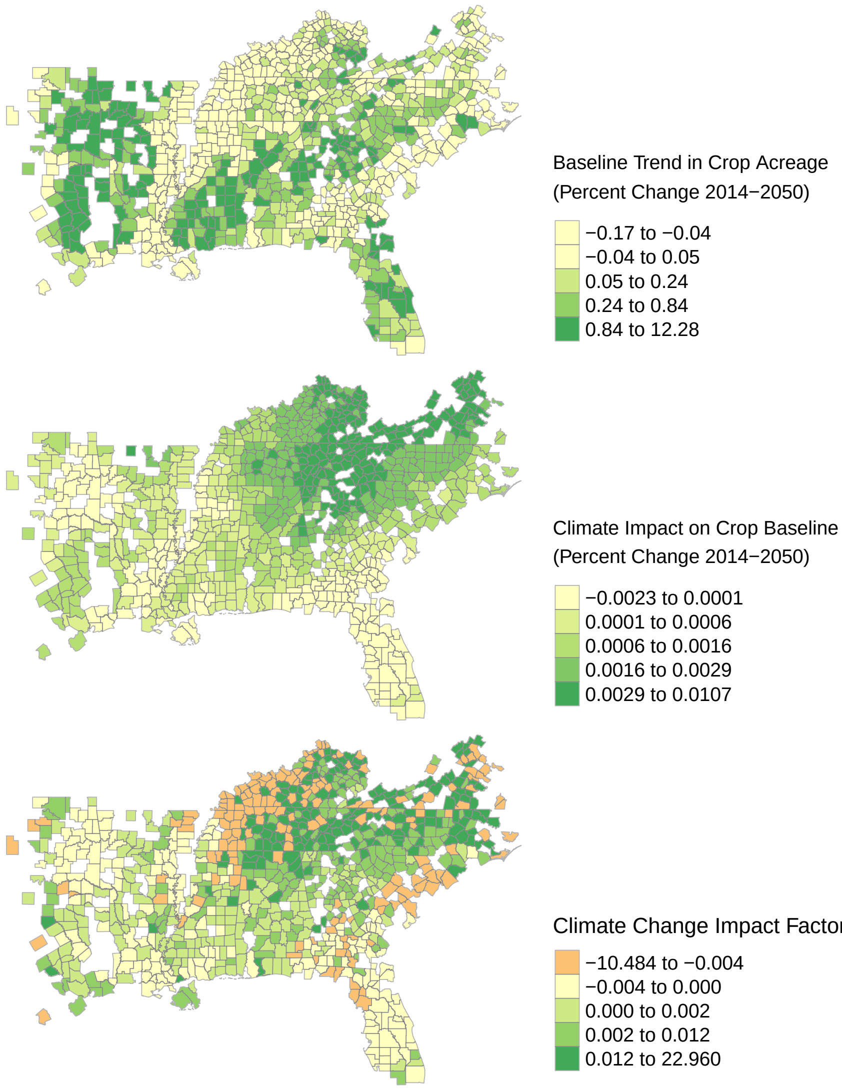

Figure 5.7: Climate Change Impact on Future Crop Acreage

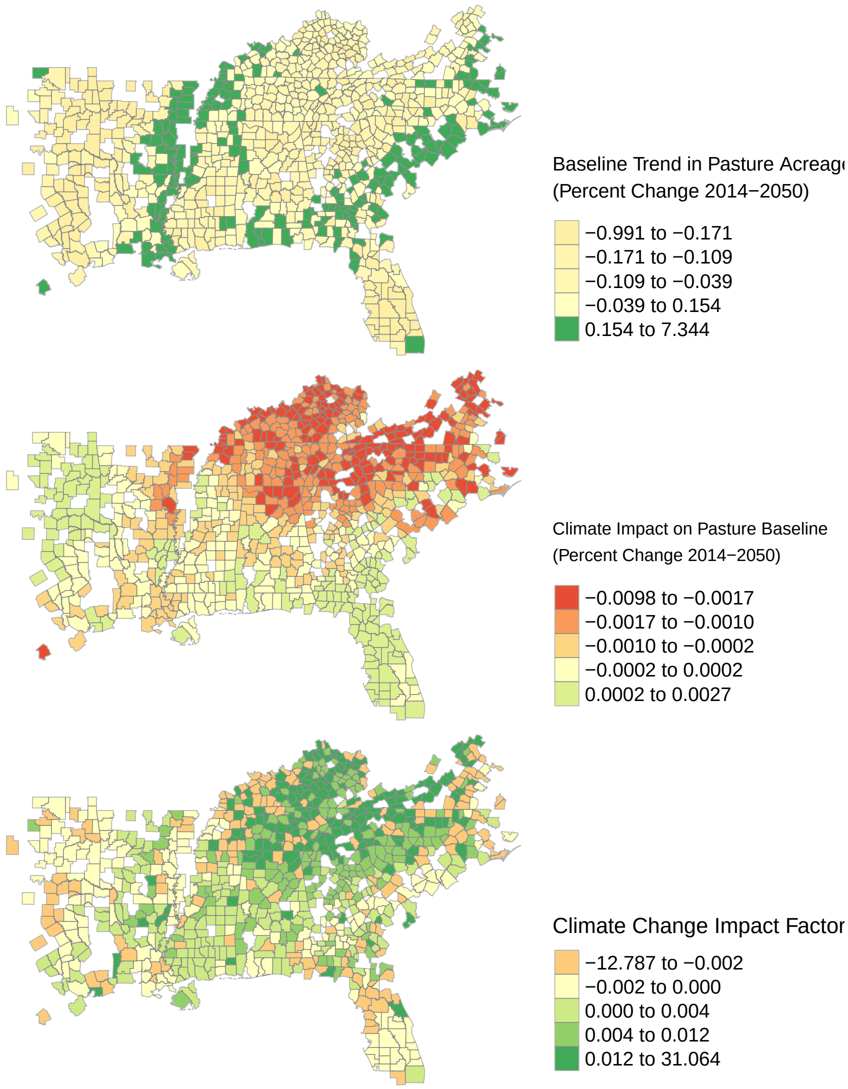

Figure 5.8: Climate Change Impact on Future Pasture Acreage

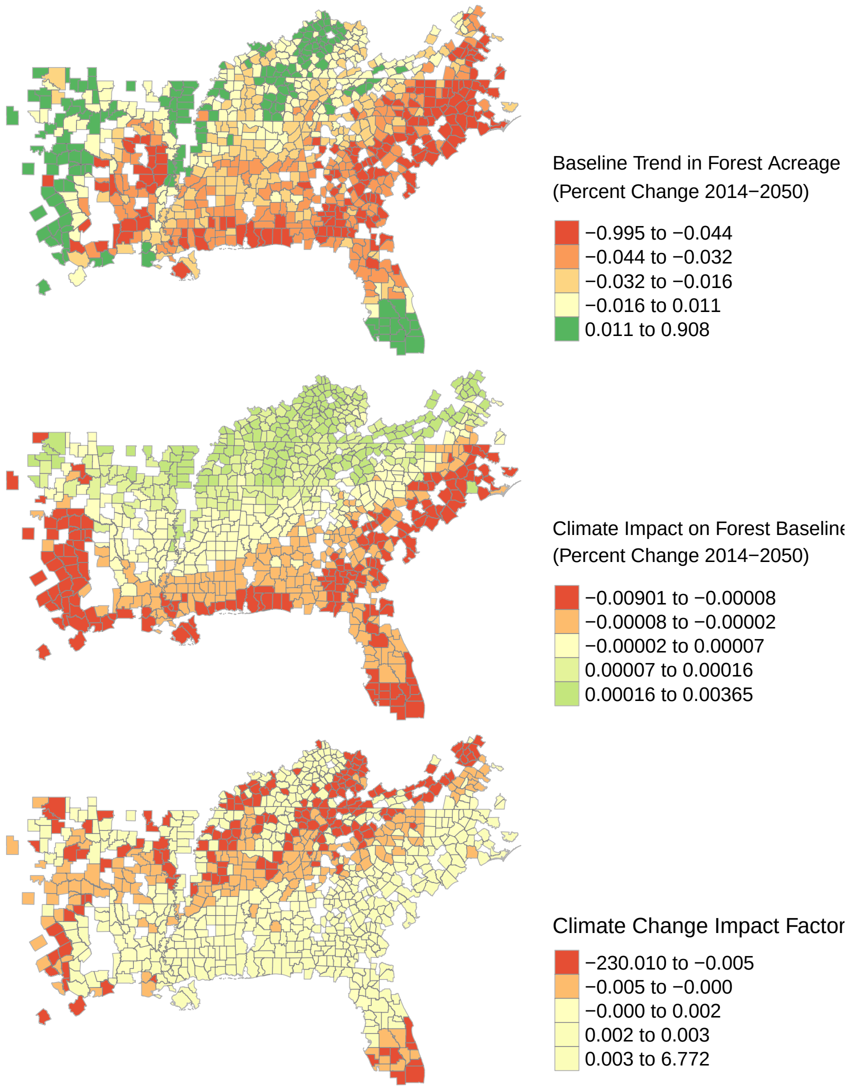

Figure 5.9: Climate Change Impact on Future Forest Acreage

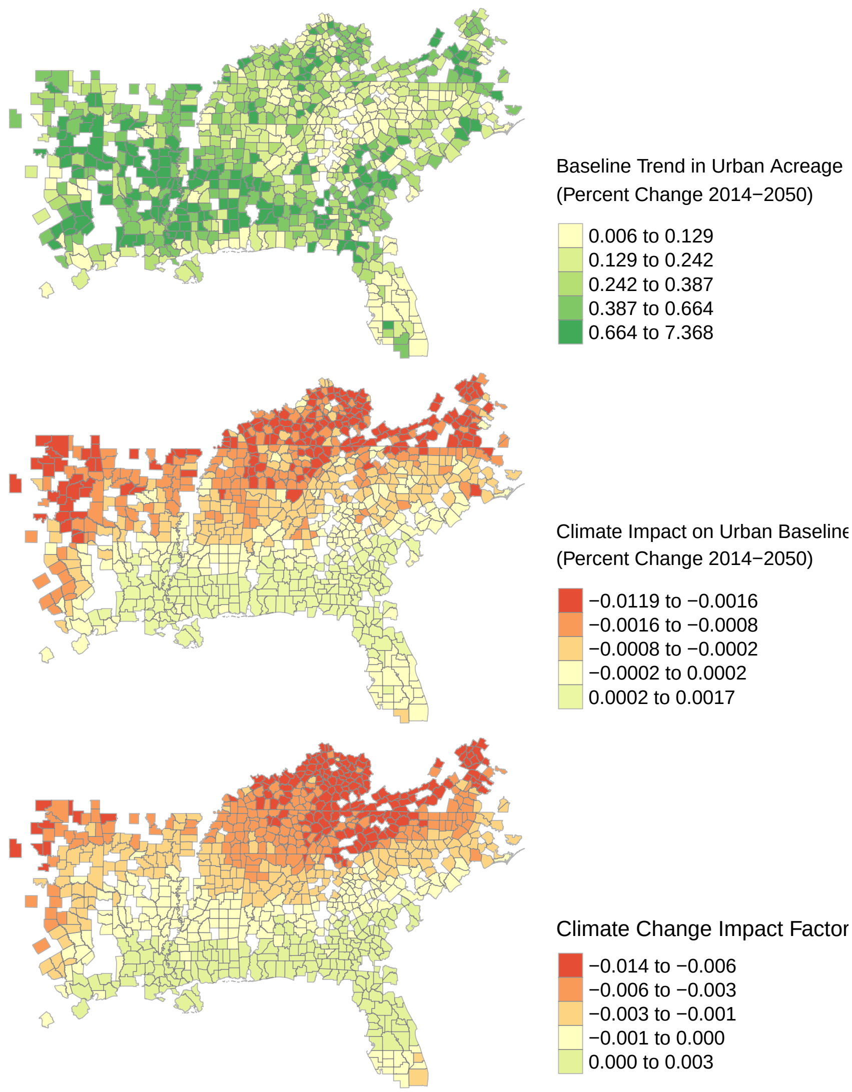

Figure 5.10: Climate Change Impact on Future Urban Acreage

Table 5.14: Regional Aggregate Climate Impact on Landscape

	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

Note:

Chapter 6: Conclusion

The analyses in this dissertation provide multiple contributions to the literature on the economic costs and benefits of climate change. First, this paper fills a gap in the literature by conducting the first large-scale Ricardian analysis of climate on forestland value. A recent review article of empirical climate-human linkages did not include any analysis of the forestry sector of the United States economy [24]. However, about one-third of the U.S. land base is comprised of forests, and 68% of U.S. forest area is timberland. The majority of the current forestry literature that uses empirical analysis primarily focuses on climates biophysical effects, where results suggest that climate change projections will increase biophysical productivity of particular tree species in the U.S. southeast [27] and the Pacific Northwest [31]. The strength of the Ricardian approach is its flexibility in capturing the optimized response of land rents to differences in climate. This advantage is extended to estimate functional relationships between local climate and four alternative land-uses; crop, pasture, forest, and urban. The Ricardian functions implicitly account for human driven management decisions central to the land-use change process.

Secondly, I 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. My dissertation 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 my 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 possible extent to which extensive margin adaptation incentives exist is explored by separately estimating Ricardian functions for four major timber species in the western and southeastern U.S. Results indicate that both major timber species in the western U.S. (Douglas-fir and ponderosa pine) are projected to see increases in net returns from climate, though ponderosa pine returns are projected to go up faster than Douglas-fir for large portions of the inter-mountain west. Evidence suggests that total gains in forestry are driven by intensive margin adaptations such as growth in existing stock. In contrast, results indicate that lower latitude portions of the southeastern U.S. are projected to see declines in net returns to two of the dominant commercial pine species: loblolly and shortleaf. The national model projects increases in overall forest net returns for these same lower latitudes of the southeastern U.S. Projected overall increases in net returns to forestry in the southeastern U.S. cannot be explained by increases in growth of the currently dominant loblolly/shortleaf system, suggesting significant incentives for extensive margin adaptation away from loblolly and shortleaf. The upper latitude portions of the southeastern U.S. are projected to see increases in net returns to loblolly and shortleaf, suggesting potential northward range shifts of these species for profitability reasons. Past natural science research has similarly found potential climate-induced range shifts in tree species [14], but their projections have never included human management in response to profit.

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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APPENDICES

Appendix A: Climate Data

A.1 Climate Data

Historical Climate Historically observed weather and climate data are obtained from Oregon State Universitys PRISM Climate Group [19]. PRISM data is 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 the annual average temperature and precipitation for the period 1981-2010 measured in degrees Celsius and millimeters (mm), respectively. A DEM (digital elevation model) is used by PRISM to interpolate climate variables at an 800m spatial resolution.

The PRISM climate data is aggregated to the level of U.S. counties for each variable using the weighting scheme described below. The current distribution of 30-year normal temperature and precipitation on forest land is shown in figures 10 and 11, respectively. Corresponding to the spatial variation in forest growth, we observe considerable east-west variation in temperature in the western US, and north-south variation in the eastern US.

Predicted Climate 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 [1]. Climate variables are reported at a 4km (1/24-deg) resolution, and include mean daily maximum temperature (C°), mean daily minimum temperature, daily total precipitation (mm). The raw data from MACA includes 20 GCMs, each GCM run under scenarios RCP 4.5 and RCP 8.5, creating 40 total climate scenarios. These RCPs (Representative Concentration Pathways) were specified to create an upper and lower bound of the path of future greenhouse emissions.

In the forest Ricardian estimation, temperature and precipitation enter the function as the annual mean and sum of temperature and precipitation, respectively. Aggregating to an annual measure allows execution of all 40 available climate change scenarios when analyzing potential climate driven shifts in future forest rents (see chapter 4). However, climate enters the urban and agricultural Ricardian estimations as a function of daily climate measures. Processing climate variables at the daily scale comes at a significant computational expense. Therefore, a single climate change scenario is chosen for climate change impact analysis of future urban and agricultural rents. The chosen scenario is carried through to the land-use change modeling and analysis in chapter 5.

As part of the upcoming 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.). Models were evaluated on the bases of their strength at predicting the historically observed climate. Of the five scenarios they identify, the Norwegian Climate Center model NorESM1-M captures a middle of the road scenario between hot and warm, and wet and dry. NorESM1-M is used here for climate impact analysis of urban and agricultural rents, and for climate impact on land-use conversion.

Climate change impacts for the national forest Ricardian (section 4.1 rely on projections from a multi-model mean. The climate variables are weighted by forest land area within a county. Warming occurs across the entire U.S. with greater increases as you move south to north. Changes in precipitation vary spatially across the U.S. with most regions getting wetter, but large sections of the southern U.S. experiencing dryer conditions relative to historical levels.

Forest Weighted Climate Data I develop a custom ArcGIS and python algorithms are used to geo-reference the climate variables from the grid level to the county level. County temperature and precipitation are the spatially weighted average of grid observations that occur within a county. Climate variables used in the forest analysis are the spatially weighted values (i.e. climate measured only on forest land). Timberland area weights are recovered from spatially referenced timberland data sourced from the FIA data. Nelson and Vissage [39] combine satellite land cover data with FIA observations of timberland to generate a map of timberland in the U.S. The timberland area map is overlaid with observed and projected climate data to aggregate climate variables to the county level. Climate observations that occur outside of the observed forest cover are dropped, and the remaining observations (those within forested areas) are averaged within a county. Weighting climate measures by timberland is particularly important in the western U.S., where forests tend to be found in mountainous regions whose climates differ significantly from the valleys where agriculture is common.

Appendix B: Stumpage Price Data Sources

Table B.1: Timber stumpage price data sources

Alabama	Timber Mart-South
Arizona	U.S. Forest Service Southwestern Region
Arkansas	Timber Mart-South
California	California State Board of Equalization
Colorado	U.S. Forest Service Rocky Mountain Region
Connecticut	University of Massachusetts Extension
Delaware	University of Maryland Extension
Florida	Timber Mart-South
Georgia	Timber Mart-South
Idaho	Idaho Department of Lands
Illinois	University of Illinois Extension
Indiana	Purdue Extension
Iowa	No Data
Kansas	No Data
Kentucky	Kentucky Division of Forestry
Louisiana	Louisiana Department of Agriculture & Forestry
Maine	Maine Forest Service

Maryland	University of Maryland Extension
Massachusetts	University of Massachusetts Extension
Michigan	Michigan Department of Natural Resources
Minnesota	Minnesota Department of Natural Resources
Mississippi	Mississippi State University Extension
Missouri	Missouri Department of Conservation
Montana	U.S. Forest Service Northern Region
Nebraska	Nebraska Forest Service
Nevada	No Data
New Hampshire	New Hampshire Department of Revenue
New Jersey	No Data
New Mexico	U.S. Forest Service Southwestern Region
New York	New York Department of Environmental Conservation
North Carolina	Timber Mart-South
North Dakota	No Data
Ohio	Ohio State University Extension
Oklahoma	Data extrapolated from Texas price data
Oregon	Oregon Department of Forestry
Pennsylvania	Penn State Extension
Rhode Island	University of Massachusetts Extension
South Carolina	Timber Mart-South
South Dakota	U.S. Forest Service Rocky Mountain Region
Tennessee	Timber Mart-South

Texas	Timber Mart-South
Utah	U.S. Forest Service Intermountain Region
Vermont	Vermont Department of Forests
Virginia	Timber Mart-South
Washington	Washington State Department of Revenue
West Virginia	West Virginia
Wisconsin	Wisconsin Department of Natural Resources
Wyoming	U.S. Forest Service Intermountain Region

Appendix C: Alternative Specifications for Forest Ricardian Estimation

Table C.1: Forest Ricardian Alternative Specifications 1

	Model 1	Model 2	Model 3	Model 4
Mean Temp	3.812***	-5.716***	-2.599**	-4.407***
	(0.247)	(0.905)	(1.012)	(1.066)
Mean Temp Squared			0.294***	0.119**
			(0.038)	(0.051)
Precip	0.040***	-0.041***	-0.060***	-0.105***
	(0.004)	(0.008)	(0.013)	(0.015)
Mean Temp:Precip		0.008***		0.005***
		(0.001)		(0.001)
Precip squared			0.00004***	0.00004***
			(0.00000)	(0.00000)
Constant	-52.296***	36.700***	34.960***	66.298***
	(3.499)	(8.833)	(7.686)	(9.762)
Soil Control (LCC)	No	No	No	No
Regional Fixed Effect	No	No	No	No
Sub-Regional Fixed Effects	No	No	No	No
Adjusted R^2	0.262	0.297	0.308	0.316
Residual Std. Error	43.162 (df = 2387)	42.130 (df = 2386)	41.786 (df = 2385)	41.563 (df = 2384)
F Statistic	425.150*** (df = 2; 2387)	337.274*** (df = 3; 2386)	267.278*** (df = 4; 2385)	221.450*** (df = 5; 2384)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table C.2: Forest Ricardian Alternative Specifications 2

	Model 5	Model 6	Model 7	Model 8
Max Temp	3.542***	-8.196***	-13.356***	-14.065***
	(0.357)	(1.105)	(2.114)	(2.089)
Max Temp Squared			0.447***	0.219***
			(0.060)	(0.066)
Min Temp	0.546*	2.552***	1.404***	3.822***
	(0.302)	(0.875)	(0.348)	(0.926)
Min Temp Squared			-0.065	-0.070
			(0.042)	(0.047)
Precip	0.041***	-0.170***	-0.051***	-0.229***
	(0.004)	(0.020)	(0.013)	(0.027)
Max Temp:Precip			0.012***	0.010***
			(0.001)	(0.001)
Min Temp:Precip			-0.003***	-0.003***
			(0.001)	(0.001)
Precip Squared			0.00004***	0.00004***
			(0.00000)	(0.00000)
Constant	-78.420***	128.202***	126.033***	216.117***
	(6.184)	(19.322)	(19.545)	(22.518)
Soil Control (LCC)	No	No	No	No
Regional Fixed Effect	No	No	No	No
Sub-Regional Fixed Effects	No	No	No	No
Adjusted R2	0.268	0.309	0.314	0.332
Residual Std. Error	42.977 (df = 2386)	41.752 (df = 2384)	41.605 (df = 2383)	41.075 (df = 2381)
F Statistic	293.107*** (df = 3; 2386)	215.132*** (df = 5; 2384)	183.539*** (df = 6; 2383)	149.215*** (df = 8; 2381)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table C.3: Forest Ricardian Alternative Specifications 3

	Model 9	Model 10	Model 11	Model 12	Model 13
Mean Temp	-4.746***	-4.844***	-6.245***	-5.977***	-6.825***
	(1.268)	(1.062)	(1.070)	(1.252)	(1.054)
Mean Temp Squared	0.040	0.089*	0.127**	0.045	0.084*
	(0.055)	(0.050)	(0.052)	(0.056)	(0.051)
Precip	-0.107***	-0.071***	-0.122***	-0.109***	-0.064***
	(0.018)	(0.017)	(0.015)	(0.018)	(0.017)
Precip Squared	0.00002***	0.00002***	0.00004***	0.00002***	0.00001**
	(0.00001)	(0.00001)	(0.00000)	(0.00001)	(0.00001)
Mean Temp:Precip	0.007***	0.006***	0.006***	0.008***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	71.110***	47.298***	8.819	0.903	-26.038
	(13.865)	(11.673)	(15.438)	(18.169)	(16.339)
Soil Control (LCC)	No	No	Yes	Yes	Yes
Regional Fixed Effect	No	Yes	No	No	Yes
Sub-Regional Fixed Effects	Yes	No	No	Yes	No
Adjusted R2	0.338	0.336	0.338	0.364	0.370
Residual Std. Error	40.884 (df = 2376)	40.955 (df = 2381)	40.871 (df = 2377)	40.061 (df = 2369)	39.878 (df = 2374)
F Statistic	94.781*** (df = 13; 2376)	151.833*** (df = 8; 2381)	102.784*** (df = 12; 2377)	69.444*** (df = 20; 2369)	94.563*** (df = 15; 2374)
Note:					*p<0.1; **p<0.05; ***p<0.01

Table C.4: Forest Ricardian Alternative Specifications 4

	Model 14	Model 15	Model 16	Model 17	Model 18
Max Temp	-19.776***	-17.296***	-11.358***	-17.401***	-15.517***
	(2.902)	(2.208)	(2.118)	(2.883)	(2.229)
Max Temp Squared	0.292***	0.310***	0.192***	0.283***	0.311***
	(0.078)	(0.069)	(0.066)	(0.077)	(0.069)
Min Temp	5.905***	3.182***	0.671	2.988**	0.207
	(1.270)	(0.926)	(0.979)	(1.291)	(0.972)
Min Temp Squared	-0.171***	-0.107**	-0.088*	-0.182***	-0.136***
	(0.053)	(0.048)	(0.047)	(0.053)	(0.048)
Precip	-0.221***	-0.124***	-0.216***	-0.209***	-0.104***
	(0.030)	(0.030)	(0.026)	(0.029)	(0.030)
Precip Squared	0.00002***	0.00001**	0.00004***	0.00002***	0.00001**
	(0.00001)	(0.00001)	(0.00000)	(0.00001)	(0.00001)
Max Temp:Precip	0.011***	0.007***	0.009***	0.010***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Min Temp:Precip	-0.003**	-0.0005	-0.002*	-0.002	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	273.207***	200.642***	109.142***	171.861***	98.699***
	(31.040)	(22.333)	(26.697)	(33.800)	(26.379)
Soil Control (LCC)	No	No	Yes	Yes	Yes
Regional Fixed Effect	No	Yes	No	No	Yes
Sub-Regional Fixed Effects	Yes	No	No	Yes	No
Adjusted R2	0.349	0.349	0.358	0.374	0.376
Residual Std. Error	40.545 (df = 2373)	40.546 (df = 2378)	40.250 (df = 2374)	39.762 (df = 2366)	39.695 (df = 2371)
F Statistic	80.981*** (df = 16; 2373)	117.316*** (df = 11; 2378)	89.919*** (df = 15; 2374)	62.983*** (df = 23; 2366)	80.919*** (df = 18; 2371)
Note:					*p<0.1; **p<0.05; ***p<0.01

Table C.5: Forest Ricardian Alternative Specifications 5

	Model 19	Model 20	Model 21	Model 22
Max Temp	-18.051***	-15.455***	-16.693***	-16.666***
	(2.875)	(2.186)	(2.258)	(2.227)
Max Temp Squared	0.293***	0.307***	0.302***	0.298***
	(0.077)	(0.068)	(0.068)	(0.067)
Min Temp	3.883***	0.885	2.834***	3.666***
	(1.281)	(0.951)	(1.027)	(1.010)
Min Temp Squared	-0.188***	-0.138***	-0.177***	-0.173***
	(0.053)	(0.047)	(0.048)	(0.048)
Precip	-0.209***	-0.097***	-0.157***	-0.157***
	(0.029)	(0.030)	(0.028)	(0.028)
Precip Squared	0.00002***	0.00001*	0.00002***	0.00002***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Max Temp:Precip	0.011***	0.006***	0.009***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)
Min Temp:Precip	-0.002**	0.0005	-0.001	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	232.757***	148.352***	125.309***	183.080***
	(31.093)	(22.831)	(26.592)	(23.050)
Soil Control (LCC)	No	No	Yes	No
Soil Control (2 LCC Groups)	Yes	Yes	No	Yes
Regional Fixed Effect	No	Yes	No	No
Sub-Regional Fixed Effect	Yes	No	No	No
East-West Fixed Effect	No	No	Yes	Yes
Adjusted R2	0.365	0.368	0.369	0.360
Residual Std. Error	40.045 (df = 2372)	39.943 (df = 2377)	39.912 (df = 2373)	40.195 (df = 2379)
F Statistic	81.703*** (df = 17; 2372)	116.931*** (df = 12; 2377)	88.313*** (df = 16; 2373)	135.386*** (df = 10; 2379)

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

Table C.6: Forest Ricardian Alternative Specifications 6

	Model 23	Model 24
Mean Temp	-5.738***	-5.357***
	(1.067)	(1.064)
Mean Temp Squared	0.113**	0.124**
	(0.051)	(0.050)
Precip	-0.111***	-0.111***
	(0.015)	(0.015)
Precip Squared	0.00004***	0.00004***
	(0.00000)	(0.00000)
Mean Temp:Precip	0.006***	0.006***
	(0.001)	(0.001)
Constant	59.872***	64.693***
	(9.745)	(9.665)
Soil Control (2 LCC Groups)	No	Yes
Soil Control (4 LCC Groups)	Yes	No
Regional Fixed Effect	No	No
Sub-Regional Fixed Effect	No	No
East-West Fixed Effect	No	No
Adjusted R2	0.334	0.330
Residual Std. Error	41.019 (df = 2381)	41.138 (df = 2383)
F Statistic	150.438*** (df = 8; 2381)	196.794*** (df = 6; 2383)

Table C.7: Forest Ricardian Alternative Specifications 7

	Model 25	Model 26
Max Temp	-10.686***	-11.456***
	(2.113)	(2.086)
Max Temp Squared	0.174***	0.191***
	(0.066)	(0.065)
Min Temp	0.860 (0.969)	1.492 (0.957)
	(0.065)	(0.065)
Min Temp Squared	-0.086*	-0.088*
	(0.046)	(0.046)
Precip	-0.209***	-0.214***
	(0.026)	(0.026)
Precip Squared	0.00003***	0.00004***
	(0.00000)	(0.00000)
Max Temp:Precip	0.009***	0.009***
	(0.001)	(0.001)
Min Temp:Precip	-0.002*	-0.002**
	(0.001)	(0.001)
Constant	147.570***	165.498***
	(23.692)	(23.068)
Soil Control (2 LCC Groups)	No	Yes
Soil Control (4 LCC Groups)	Yes	No
Regional Fixed Effect	No	No
Sub-Regional Fixed Effect	No	No
East-West Fixed Effect	No	No
Adjusted R2	0.354	0.350
Residual Std. Error	40.387 (df = 2378)	40.522 (df = 2380)
F Statistic	119.960*** (df = 11; 2378)	143.649*** (df = 9; 2380)