Climate, adaptation, and the value of forestland: A national Ricardian analysis of the United States

Christopher Mihiar[1]

David J. Lewis

Department of Applied Economics, Oregon State University

Job Market Paper

October 30, 2017

Abstract

This study develops a national dataset of county-level net economic returns to forestland, and uses the data to estimate an econometric Ricardian model of the effects of climate on forest returns. The model implicitly accounts for direct biophysical effects of climate on forestry as well as belief effects that influence landowner adaptation through forest management. We find that climate change projections to 2050 will increase annual returns to forestry, though results indicate significant spatial variation in impact with some regions experiencing declines and others experiencing gains. We explore the extent to which assumptions about extensive margin adaptations affect the national estimates by analyzing separately estimated Ricardian functions across alternative commercially valuable forest species in the western U.S. and in the southeastern U.S. Results suggest significant economic incentives for adaptation out of currently dominant loblolly pine in southern latitudes of the southeast, but less incentive for adaptation away from currently dominant softwood species in the western U.S.

JEL classification: Q23, Q51, Q54, Q57
Keywords: Climate change, Adaptation, Forestry, Econometrics

[1] Mihiar (mihiarc@oregonstate.edu) is senior author and corresponding author, Ph.D. candidate. Lewis (lewisda@oregonstate.edu) is professor, Department of Applied Economics, Oregon State University. We acknowledge numerous insightful comments from Darius Adams that helped shape this work. We acknowledge comments from Jeff Kline, Steve Dundas, and David Wear that helped clarify this paper's approach. We thank seminar participants at the Association of Environmental and Resource Economists annual meeting (2017) and at Oregon State University for useful feedback. Funding was provided by a joint venture agreement with the USDA Forest Service, Pacific Northwest Research Station (14-JV-11261955-059) and a USDA National Institute of Food and Agriculture competitive grant (# 2017-67023-26275).

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 (Schlenker et al. 2005; Roberts and Schlenker 2009), labor allocation (Graff Zivin and Neidell 2014), war (Hsiang et al. 2013), and electricity demand (Aufhammer et al. 2017). Within the recent strand of empirical studies on human-climate linkages is the Ricardian method that estimates the effects of climate on agricultural land values using cross-sectional data on agricultural net returns and climate (e.g. Mendelsohn et al. 1994; Schlenker et al. 2005). As reviewed recently by Mendelsohn and Massetti (2017), 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. By empirically relating a region's climate to the agricultural land values that arise from private land-use decisions under that climate, the key advantage of agricultural Ricardian analyses is that they implicitly account for privately optimal adaptation to climate.

Climate has been shown to affect the forestry sector of the economy through its effects on the biological growth and productivity of trees (Latta et al. 2010; Huang et al. 2011; Rehfeldt et al. 2014). Recent numerical analyses have highlighted the potential economic value of extensive margin adaptation in forestry, particularly through replanting choices (Hannah et al. 2011; Guo and Costello 2013). 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. In a review of climate econometrics methods, Hsiang (2016) asserts that climate affects economic outcomes in two ways. 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 landowner’s trees by extending the growing season. Second, climate has a belief effect on economic outcomes by influencing people’s decisions through adaptive measures. For example a forestland owner located in the intermountain western United States plants ponderosa pine trees because the landowner believes ponderosa will be more profitable than Douglas-fir trees given the region’s dry climate and cold winters. Both direct and belief effects are important when analyzing the effects of climate on economic outcomes.

This paper develops a new Ricardian analysis that estimates the effects of climate on annualized net economic returns to forestry across the conterminous United States. The Ricardian method allows us to analyze climate impacts on forests in a manner that accounts for both direct and belief effects of climate. The foundation of our analysis is a novel county-level database of net returns to forestry for the lower 48 states that we 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. We bring together three primary data products to develop the full database. First, we compile stumpage price data for numerous tree species across dozens of public and private data sources across the country from 1998 to 2014. Second, we incorporate recent county-level timber management cost estimates developed by Nielsen et al. (2014). And finally, we develop and estimate highly localized timber growth equations by exploiting a big dataset comprised of 32 million observations of growing stock volume and stand age from the U.S. Forest Service’s Forest Inventory and Analysis (FIA) data across the lower 48 states. Our database includes approximately 41,000 separately estimated timber growth equations that generate timber yields which vary by county and by tree species group. The fine-scale variation in the estimated timber growth equations embed all localized climatic factors such as direct productivity impacts and belief effects arising from landowner's intensive margin adaptation decisions from managing particular tree species. A final average annualized net return to forestry measure is then constructed for each county, where net returns are weighted by each county's observed share in different tree species. Weighting by observed tree species shares in a county builds a net return to forestry measure that implicitly accounts for belief effects embedded in landowner adaptation to climate that operates through their *observed* choices of which tree species to plant.[2]

Our application of the Ricardian approach to forestry uses cross sectional variation across the approximately 2,400 U.S. counties that have timberland. We regress average county net returns to forestry over 1998 to 2014 on regional fixed effects and multiple climate variables derived from the Parameter-Elevation Relationships on Independent Slopes (PRISM) model at Oregon State University. Our national model includes explicit tests for interactions between temperature and precipitation variables, and we explore robustness to alternative specifications of temperature and precipitation, as well as alternative controls for soil quality. The estimated Ricardian model is then used to examine the effects of down-scaled climate change predictions on the spatial distribution of timberland values across U.S. counties. Following Burke et al.'s (2015) suggestion to incorporate uncertainty in climate model predictions, we 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.

[2] For example, the southern U.S. net return measures are heavily influenced by the large share of softwoods in the current forest base, and past research has shown that current southern softwood abundance has been driven by landowner plantings (Sohngen and Brown 2006).

Our 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 model's 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 the multiple decade harvest rotation cycle. We 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 could 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 analysis in this paper provides multiple contributions to the literature on the economic costs and benefits of climate change. First and foremost, this paper fills a gap in the literature by conducting the first large-scale Ricardian analysis of climate on forestland net returns. A recent review article of empirical climate-human linkages did not include any analysis of the forestry sector of the economy (Hsiang et al. 2017). However, about one-third of the United States' land base is comprised of forests, and 68% of U.S. forest area is timberland (U.S. Forest Service 2014). The majority of the current forestry literature that uses empirical analysis primarily focuses on climate's biophysical effects, where results suggest that climate change projections will increase biophysical productivity of particular tree species in the U.S. southeast (Huang et al. 2011) and the Pacific Northwest (Latta et al. 2010). Second, our Ricardian analysis uses empirical methods on 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 (1998) 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. Perez-Garcia et al.'s (2002) 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 (Sohngen and Tian 2016; Tian et al. 2016). In a parcel-level approach, Guo and Costello (2013) use numerical dynamic programming techniques to examine the value of adaptation in 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.

Our analysis further contributes to broad inquiries into society's many adaptation possibilities. While management decisions and adaptation to climate in the timber industry are driven by land owner's incentive to maximize their private economic returns, decisions based on private economic returns have consequences for ecosystem services that have public goods characteristics. For example the distribution of tree species directly affects the habitat suitability for numerous wildlife species which are specialized to certain forest types. 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 (Lubowski et al. 2006). Understanding the linkages between forest management, climate change, and natural systems is vital for understanding the economic costs of climate change and for evaluating climate and land conservation policy.

2. The Ricardian Climate Model

This section formalizes the concept of adaptation and develops the intuition behind our empirical strategy. Consider an alteration of the classic figure (figure 1) of the agricultural Ricardian climate model from the seminal work of Mendelsohn, Nordhaus, and Shaw (1994). The y-axis of fig. 1 includes a measure of the net economic return to forestry, while the x-axis is a climate variable such as temperature. 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 acting on the intensive margin. Intensive margin decisions include actions like altering the rotation age, thinning out the parcel to encourage growth, or treating the parcel to reduce fire risk, all while continuing to keep the land planted in “Species 1”.

[Figure 1]

In addition to small continuous adaptations, there is a set of discrete management choices that can be made 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 fig. 1. Mendelsohn et al.’s (1994) main insight was that regressing net returns to land on climate would implicitly capture all continuous and discrete land owner adaptations by tracing out a function akin to the upper envelope of net return curves in fig. 1. Guo and Costello (2013) extend Mendelsohn et al.’s setup and develop an analytical framework for valuing climate change adaptation on the extensive margin. Consider figure 2, where climate begins at *C* and changes to *C’*. At *C*, the landowner optimally plants “Species 1” and their net return is found at point *a*. At *C’*, the landowner optimally plants “Species 2” and their net return is found at point *b*. If they had remained in “Species 1” with new climate *C’*, then their net return would have been found at point *c*. The impact of the discrete change in climate from *C* to *C’* in figure 2 is the difference in net returns from point *a* to point *b* and implicitly includes the value of adaptation on the extensive margin. The value of adaptation in figure 2 is the difference between the net returns at point *b* and the net returns at point *c*, and figure 2 also makes clear that the value of adaptation is contingent on the level of climate (Guo and Costello 2013).

[Figure 2]

The flexibility of the Ricardian model to capture extensive margin adaptation increases as the net return measure encompasses more potential land uses. For example, if we define net return as that accruing 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 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 besides "Species 1" or "Species 2" or leaving forestry altogether.

Hsiang (2016) 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 the land in forestry (e.g. warmer temperatures increase tree growth rate). Further, climate affects decisions by landowners, which is driven by their expectation of how climate and weather impacts their production, known as the belief effect. Let NR^k be the net return to forest land of species group *k*, and $\mathbf{C}$ be a vector containing temperature and precipitation.

$$NR^k(\mathbf{C}) = NR^k(\mathbf{c}(\mathbf{C}), \mathbf{b}(\mathbf{C})) \tag{1}$$

The net returns to forestry 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 forest management 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.

$$\begin{aligned} \frac{dNR^k(C)}{dC} &= \nabla_c NR(C) \cdot \frac{dc}{dC} + \nabla_b NR(C) \cdot \frac{db}{dC} \\ &= \sum_{k=1}^{K} \frac{\partial NR(C)}{\partial c_k} \frac{dc_k}{dC} + \sum_{n=1}^{N} \frac{\partial NR(C)}{\partial b_n} \frac{db_n}{dC} \end{aligned} \tag{2}$$

Equation (2) provides an expression where the total marginal effects of climate are equal to the sum of the direct effects and the belief effects. Our aim is to identify the total effect of climate on net returns in an econometric estimation of adaptation.

Our empirical problem is to estimate the average treatment effect β for a change in climate $\Delta C_{i\tau}$ on the net returns to forestry.

$$\beta \quad = E[NR_{i\tau} \mid C_{i\tau} + \Delta C_{i\tau}, x_{i\tau}] - E[NR_{i\tau} \mid C_{i\tau}, x_{i\tau}] \tag{3}$$

That is, the difference in expected outcomes given all non-climactic factors under two different climates. We cannot directly observe β because county i can never be in both climate states at the same time, which is known as the fundamental problem of causal inference (Holland 1986). If two counties i and j were identical in every way except for their climate then the unit homogeneity assumption holds. This assumption is represented by the equality

$$E[NR_{i\tau} \mid C, x_{i\tau}] = E[NR_{j\tau} \mid C, x_{j\tau}]. \tag{4}$$

Unit homogeneity is the identifying assumption for the cross-sectional approach and assumes that no unobserved drivers of NR 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

$$\begin{aligned} \hat{\beta} \quad &= E[NR_{j\tau} \mid C_{i\tau} + \Delta C_{i\tau}, x_{j\tau}] - E[NR_{i\tau} \mid C_{i\tau}, x_{i\tau}] \\ &= E[NR_{i\tau} \mid C_{i\tau} + \Delta C_{i\tau}, x_{i\tau}] - E[NR_{i\tau} \mid C_{i\tau}, x_{i\tau}] \\ &= \beta. \end{aligned} \tag{5}$$

We rely on the extensive revealed preference literature to estimate a variant of the following equation to recover the marginal effect of climate on the net returns to forestry.

$$NR_i^k = \alpha^k + \beta^k \mathbf{C}_n^k + \gamma^k \mathbf{x}_n + \epsilon_n^k \tag{6}$$

Where $\mathbf{C}$ is a vector of climate variables specific to county n and species group k, and $\mathbf{x}_n$ is a vector of non-climactic variables that also affect net returns.

Net returns in county *i* for species group *k* can be weighted by the observable shares of a county's timberland in species group *k* to obtain an estimable function explaining weighted average net returns to timberland,

$$NR_i = \alpha + \beta f(T_i, P_i) + \mathbf{x}_i + \delta_r + \epsilon_i \tag{7}$$

Where $f(T_i, P_i)$ is a quadratic function of temperature and precipitation that includes an interaction, T_i is an annual measure of temperature on forested land in county i, P_i is the total annual precipitation on forested land in county i, $\mathbf{x}_i$ is a set of county control variables such as soil quality, and δ_r is a set of region *r* fixed effects.

The cross-sectional operationalization we employ to estimate climate's effect on land value builds on the framework popularized by Mendelsohn et al. (1994). Many follow-up articles have examined agricultural-climate Ricardian models throughout the world and are reviewed by Mendelsohn and Massetti (2017). We 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 (e.g. see the review by Blanc and Schlenker 2017). 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 our data, observed harvest and replanting decisions are made over 15-100 year horizons on average. The panel solutions advanced in the agricultural-climate literature 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.

We omit explicitly modeling net forestry returns as a function of drought or fire risk indices because of what Angrist and Pischke (2009) call a bad control problem. 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 that we use in constructing the dependent variable.

3. Constructing Net Returns to Forestry Measures

This analysis features a unique construction of current county-level annualized net economic returns to forestland for the contiguous U.S., which comprises the primary dependent variable in the forestland Ricardian function. Classical forest economics argues that forestry land values depend on timber growth, stumpage prices, a discount rate, and the rotation period with which harvests occur (Faustmann 1849). In contrast to agriculture, forestry rotations happen across decades rather than on an annual basis. Our aim is to construct a measure of current annual profitability of U.S. timberland at the county-level. We build off the strategy of Lubowski et al. (2006) in constructing annualized county-level net returns to forestry. Relative to

Lubowski, our approach presents far greater spatial 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 the Faustmann formula.

3.1 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 landowner's value function can be written in dynamic programming form as follows (Guo and Costello 2013):

$$V_t(a,s) = max \begin{cases} P(s,t) \cdot vol(a,t,s) - C + \rho V_{t+1}(1,s_1) \\ P(s,t) \cdot vol(a,t,s) - C + \rho V_{t+1}(1,s_2) \\ \vdots \\ P(s,t) \cdot vol(a,t,s) - C + \rho V_{t+1}(1,s_S) \\ \rho V_{t+1}(a+1,s) \end{cases} \tag{8}$$

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 a afforestation cost, and ρ is a discount factor. At each point in time *t*, the landowner chooses whether to harvest and earn a one-time profit of $P(s,t) \cdot vol(a,t,s) - C$, with subsequent replanting optimized over the choice of which tree species s_j to plant. If the landowner chooses not to harvest, then their trees grow by $vol(a+1,t+1,s) - vol(a,t,s)$ 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 (8) and emerges when landowners have static expectations and expect no future changes in price, the timber volume function, and afforestation costs.

Guo and Costello (2013) show how climate change can be introduced into the forestry land value function in (8) when the timber volume functions for alternative tree species are a function of climate, and so the landowners' optimal replanting choice and harvest time depends 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. (2006) 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 solving for a fixed rotation time T by solving the maximization problem in (8) for each county under a static expectations Faustmann assumption. Guo and Costello (2013) and Lubowski et al. (2006) 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. imposes a belief that nothing changes in the future, and so the same rotation length T occurs in perpetuity. Our goal is to construct county-level net returns measures that impose as little as possible about landowners' belief effects with respect to climate change. We therefore try to use observed data to *infer* as much as possible about belief effects and impose as little as possible.

3.2 Stumpage price and afforestation cost data

Analysis of forestry returns at the national level has been limited by the lack of a centralized data source for stumpage prices. We 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 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 as defined by the U.S. Forest Service. Missing years for each county-species pair are interpolated linearly using the observed values. The reported stumpage prices are used to spatially extrapolate to counties that did not have a reported stumpage price.[3] The extrapolation is done whenever the observed species was present in large enough volumes to estimate growth in that county. Figure 3 shows the price trends for the period of our data, 1997-2014. These regions correspond to the level of regional fixed effects that will be used below in the Ricardian function. The trends are relatively stable with the exception of the Pacific Coast Region. Further, each region was affected by the U.S. housing crisis of 2007/2008. Forest establishment costs were estimated by Nielsen et al. (2014) for each county in the contiguous United States based on enrollment data from the USDA's national Conservation Reserve Program.

[Fig. 3]

3.3 Growth functions for tree growth

Past natural science literature has shown examples of how climate affects the tree growth functions for selected species and regions, $vol(a, t, s)$ (e.g. Latta et al. 2010; Rehfeldt et al. 2014). Given the substantial climate variability across the conterminous U.S., we want tree

[3] Stumpage prices are reported for 10,280 species-county pairs and we derive an additional 17,609 pairs to match our estimated growth functions. Our spatial algorithm first looks at neighboring counties for the missing price. If multiple prices are found, then the average is used. This is repeated for 2nd and 3rd degree neighbors. When county-neighbor price is unavailable, the state or regional average is used.

growth functions that differ across fine spatial scales to capture fine-scale climate differences. We estimate approximately 59,000 county-species specific timber growth equations[4] at the forest type and species group level using a permutation of von Bertalanffy's function for organic growth (von Bertalanffy 1938).

$$vol(a)_{is} = \alpha_{is}(1 - e^{-\beta_{is}a})^3 \tag{9}$$

Where a is stand age as defined above, and α_{is} and β_{is} are parameters to be estimated which vary across county *i* and forest species *s*. von Bertalanffy growth functions have been used extensively in natural resource sciences and apply generally to any organic life. For example, Van Deusen and Heath (2016) use von Bertalanffy functions to estimate growth for the measurement of carbon characteristics 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). Figure 4 presents an example of the plot-level FIA observations for Douglas-fir trees in Benton County in western Oregon, along with an estimated von Bertalanffy growth function (figure 5). Figure 6 contrasts two estimated von Bertalanffy growth functions for Douglas-fir for two different Oregon counties – Deschutes county ($\alpha = 124.4$, $\beta = 0.023$) in the dry central portion of Oregon, and Benton county ($\alpha = 753.6$, $\beta = 0.021$) 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 fine spatial scales.

---

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

[Fig 4] [Fig 5] [Fig 6]

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 across the United States, we obtained estimated values for α and β of 39.9 and 0.068, respectively.

3.4 An annualized net returns to forestry measure for one rotation

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

$$[\overline{P_{is}} \cdot vol(T_{is},s) - C_i]\rho^{T_{is}} = PVProfit_{is} \tag{10}$$

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

$$NR_{is}(\rho^1 + \rho^2 + \cdots + \rho^{T_{is}}) = PVProfit_{is} \tag{11}$$

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

$$NR_i = \sum_{s=1}^{S_i} NR_{is} \cdot Share_{is} \qquad (12)$$

Where $Share_{is}$ is the share of county *i*'s private timberland in forest species s, and S_i is the total number of observed forest species in county i. Average net returns from equation (12) are presented in Table 1, and the spatial distribution of our composite net return is presented in figure 7. For robustness, we also estimate the Faustmann T_{is} by solving (8) for each county as done in Lubowski et al. (2006), with the corresponding assumption that landowners have static expectations, don't expect climate change, and are pure profit maximizers. The Faustmann optimized net return exhibits a comparable numerical (figure 8) and spatial distribution (figure 9) as the net returns derived from the observed rotation periods.

[Table 1] [Fig. 7] [Fig. 8] [Fig. 9]

4. Climate Data

Historically observed weather and climate data are obtained from Oregon State University's PRISM Climate Group (PRISM 2017). PRISM data provides estimates 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 forestland value, we use the long term average ("normal") of each location's 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.

[Fig 10] [Fig 11]

Predictions of future climate are obtained from the University of Idaho, MACA Statistically Downscaled Climate Data for CMIP5 (Abatzoglou 2011). MACAv2-METDATA is used with precipitation measured in inches/month (converted to mm) and temperature measured in degrees Celsius. Temperature and precipitation are reported at a 4km (1/24-deg) resolution. Spatial weighting with respect to each land use type is used to scale the climate data to the county level.

Our main result uses the multi-model mean from 20 Global Climate Models under emissions scenario RCP 8.5. A summary of the average change in temperature and precipitation between the baseline period (1950-2005) and the future period (2020-2050) are presented in table 6. Predictions are calculated for 2,390 U.S. counties. Warming is predicted to occur across the entire U.S. with greater increases as you move south to north (figure 12). Most areas of the U.S. are expected to see increased precipitation. The multi-model mean predicts the eastern U.S. getting wetter relative to the west, with the exception of the northern Pacific coast (figure 13).

[Fig 12] [Fig 13]

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. Timberland area weights are recovered from spatially referenced timberland data sourced from the FIA data. Nelson and Vissage (2007) combine satellite land cover data with FIA observations of timberland to generate a map of timberland in the United States. 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 important particularly in the western U.S., where forests tend to be found in mountainous regions which have different climates than the valleys where agriculture tends to be found.

5. Results

5.1 National Forest Ricardian

We begin our analysis by estimating a forest system Ricardian for the conterminous U.S. to estimate the total impact of climate on the economic net returns to forestry. Predictions made using the national Ricardian model approximate the outer envelope from figure 1 and implicitly account for the total impact (direct plus belief effects) of climate change on annualized net returns to U.S. forestland. That is, the Ricardian model's 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 from 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 2020-2050 versus the baseline period 1981-2010.

The annualized net returns to an acre of private forestland in county *i* 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 (Weiskittel et. al. 2012; Rehfeldt et. al. 2014). Annual precipitation and its square are also included. Finally, we have included an interaction between precipitation and temperature extremes. Sub-regional fixed effects as defined by the FIA 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. We control for land quality using county shares of forestland in alternative categories of the land capability class (LCC) measure. We use LCC to approximate soil quality effects on each county's forests, where LCC is derived from the USDA's 2012 National Resource Inventory (NRI) observed LCC data on each county's forestland.

Our base estimates include maximum temperatures, minimum temperatures, and annual precipitation specified as a quadratic, temperature and precipitation interactions, and separate variables indicating shares of each county's forests in the eight alternative LCC soil quality classes (table 2), and sub-regional spatial fixed effects. Given the quadratic specifications, we focus on the estimated average marginal effects of the key climate variables in table 3. 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.

[Table 2] [Table 3]

There are numerous 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 (Latta et. al. 2010; Huang et. al. 2011; Weiskittel et. al. 2012). Therefore, we estimate twenty-seven alternative specifications of the national Ricardian model which differ 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 presents average marginal effects of the principal climate measures across all twenty-six alternative specifications. We find clear robustness in the estimated marginal effects of annual precipitation, mean temperature, and maximum temperature, with very little variation across the alternative specifications. We do find some sensitivity to our estimated marginal effects of minimum temperature. Our base model in Table 2 is model number 17 in Table 4. Comparison of model 17 with models 8 and 14 in Table 4 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 appendices), 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 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 projections vary significantly over space, where some counties will experience a loss in forest net returns, and others experience a gain (figure 14). 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 (table 8).

[Table 8] [Fig 14]

By using the 20 down-scaled climate models available from MACA to predict net returns to forestry, we also check the robustness of the results to different climate change projections, which Burke et al. (2015) refer to as climate model uncertainty. We evaluate the national Ricardian function for 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 15).

[Fig 15]

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

The national Ricardian model from section 5.1 presents 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 our national model approximates the outer envelope of forestry returns from figure 1, we explore what drives some of the projected changes in net returns. 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. 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. Our theoretical example in figures 1 and 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 we estimate Ricardian net return functions separately 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, we can examine whether extensive margin adaptations likely explain some of the predictions of the national Ricardian estimates.

5.2.1 Loblolly & Shortleaf Pine

We estimate separate Ricardian net return functions for two of the primary timber species in the southern U.S., loblolly and shortleaf pine. We analyze 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 1. 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 5). Estimated marginal effects of both mean temperature and precipitation for shortleaf pine are approximately double the effects for loblolly (table 6). Using the multi-model mean climate change projections we predict that the 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 (table 8). 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 (figures 16 and 17). 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 model's positive projected gains in net returns in this region illustrate incentives for extensive margin adaptation away from loblolly/shortleaf to an alternative forest type.

[Table 5] [Fig 16] [Fig 17]

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, which we call the loblolly premium. For the 651 counties currently home to loblolly forests, nearly all of them (647) have a positive loblolly premium. By 2050, we predict that the premium will 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, we find that climate change lowers the loblolly premium by $37/acre. As with each of our results, there is significantly 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. We predict that under future climate change, the shortleaf premium will be reduced by $9.15/acre. Over the range of shortleaf, we predict that 131 counties will 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 our forest type Ricardian and our aggregated Ricardian that includes all potential forest types, we 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 we currently observe both loblolly and shortleaf forest types. 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.

5.2.2 Douglas-fir & ponderosa pine

We separately estimate Ricardian functions for Douglas-fir and ponderosa pine, two of the most commercially important forest species in the American west which overlap for most of their observed range. However, by restricting our sample to these specific forest types we lose much of the climate variation within LCC classes that the full national model relied on. This requires us to model 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 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 1. 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 that we include here are generally colder, dryer, and have less productive soil relative than the national average.[5]

Parameter estimates for the western Ricardian models are presented in table 5 and marginal effects are shown in table 6. Although many of the individual climate parameter estimates are insignificant in table 5, 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 6). 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, we predict that the net returns to Douglas fir production will increase by approximately $10.93/acre (44%) on average, and the net returns for ponderosa pine will increase by about $23.28/acre (101%) (table 8). The spatial distribution of projected climate impacts are presented in figures 18 and 19, and indicate the largest positive effects for Douglas-fir (in level form) are found in the northern Rocky Mountain

---

[5] The coastal region of the Pacific Northwest is a notable exception, with a warm and wet climate and net returns to Douglas-fir that are much higher than the national average.

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.

[Fig 18] [Fig 19]

Consider the difference between the currently observed net returns to Douglas-fir and the average net returns to all forest types, which we label 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 among the most profitable species. By 2050, we predict that the share of counties with a positive Douglas-fir premium will remain almost 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.

6. Discussion

The purpose of this paper is to empirically quantify the effects of climate change on the annualized net economic return to timberland in the United States. We develop a new national database of county-level net returns to forestry by i) compiling stumpage price data from dozens of public and private sources, ii) incorporating recent county-level afforestation cost estimates (Nielsen et al. 2014), and iii) estimating approximately 59,000 tree growth equations that vary by county and tree species group and capture localized climatic effects on tree growth. The net returns measures represent the current annualized profitability of forests and are developed using observable average rotation times that vary across states and tree species. An average annual net return to forestry measure for each county is constructed by weighting species-specific net returns by the currently observable stock of privately owned forests in different tree species. Our unique net returns data facilitates an econometric analysis that is the first large-scale forestry application of the Ricardian framework which has been widely used to study the effects of climate on agricultural returns (e.g. Mendelsohn and Massetti 2017). The Ricardian framework implicitly accounts for adaptation in forest management along the intensive margin and the extensive margin. A primary finding from the national Ricardian analysis is that average U.S. forest returns 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, we 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.

Our projected gains in forestry returns 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. We explore the possible extent to which extensive margin adaptation is incentivized 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 intermountain west. However, 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 the two dominant commercial pine species of loblolly and shortleaf, while the national model projects increases in overall forest net returns for these same lower latitudes of the southeastern U.S. Our 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, and so suggest significant incentives for extensive margin adaptation away from loblolly and shortleaf. However, 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 (e.g. Fei et al. 2017), but their projections have never included human management in response to profit.

The role of extensive margin adaptations in forestry is an important consideration when examining our 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 (2017) 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, we suggest that our national results 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. Our 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 Costello's (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).

Our projected increases to forestry returns from climate change also raise questions about extensive margin adaptations across agricultural and forest land uses. For example, 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. Lubowski et al. 2006; Lewis and Plantinga 2007). Further, in a Ricardian analysis of agriculture in the eastern U.S., Schlenker et al. (2006) 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., then 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 (Lawler et al. 2014). The Ricardian model in this study provides a foundation to explore numerous questions regarding the interaction between climate change, land use, ecosystem services, and conservation policy.

References

Abatzoglou J. T. " Development of gridded surface meteorological data for ecological applications and modelling " International Journal of Climatology. (2011)

Alig, Ralph J, Darius M Adams, and Bruce A McCarl. 2002. “Projecting Impacts of Global Climate Change on the Us Forest and Agriculture Sectors and Carbon Budgets.” *Forest Ecology and Management* 169 (1). Elsevier: 3–14.

Angrist, Joshua, and Jörn-Steffen Pischke. "Mostly Harmless Econometrics: An Empiricists Guide." (2009).

Antle, John M, and Susan M Capalbo. 2010. “Adaptation of Agricultural and Food Systems to Climate Change: An Economic and Policy Perspective.” *Applied Economic Perspectives and Policy*. Oxford University Press, ppq015.

Auffhammer, Maximilian, Patrick Baylis, and Catherine H. Hausman. "Climate change is projected to have severe impacts on the frequency and intensity of peak electricity demand across the United States." *Proceedings of the National Academy of Sciences* (2017): 201613193.

Blanc, Elodie, and Wolfram Schlenker. "The use of panel models in assessments of climate impacts on agriculture." *Review of Environmental Economics and Policy* 11, no. 2 (2017): 258-279.

Burke, Marshall, and Kyle Emerick. 2012. “Adaptation to Climate Change: Evidence from Us Agriculture.” *Available at SSRN 2144928*.

Burke, Marshall, John Dykema, David B. Lobell, Edward Miguel, and Shanker Satyanath. "Incorporating climate uncertainty into estimates of climate change impacts." *Review of Economics and Statistics* 97, no. 2 (2015): 461-471.

Burke, Marshall, and Kyle Emerick.. 2016. “Adaptation to Climate Change: Evidence from US Agriculture.” *American Economic Journal: Economic Policy* 8 (3): 106–40. doi:10.1257/pol.20130025.

Carleton, Tamma A, and Solomon M Hsiang. 2016. “Social and Economic Impacts of Climate.” *Science* 353 (6304). American Association for the Advancement of Science: aad9837.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. 2013. “What Do We Learn from the Weather? The New Climate-Economy Literature.” National Bureau of Economic Research. http://www.nber.org/papers/w19578.

Deschênes, Olivier, and Michael Greenstone. 2012. "The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather: Reply." *The American Economic Review* 102 (7): 3761–73. http://www.ingentaconnect.com/content/aea/aer/2012/00000102/00000007/art00026.

Fei, Songlin, Johanna M. Desprez, Kevin M. Potter, Insu Jo, Jonathan A. Knott, and Christopher M. Oswalt. "Divergence of species responses to climate change." *Science Advances* 3, no. 5 (2017): e1603055.

Graff Zivin, Joshua, and Matthew Neidell. "Temperature and the allocation of time: Implications for climate change." *Journal of Labor Economics* 32, no. 1 (2014): 1-26.

Grotta, Amy T., Janean H. Creighton, Christopher Schnepf, and Sylvia Kantor. "Family forest owners and climate change: Understanding, attitudes, and educational needs." *Journal of Forestry* 111, no. 2 (2013): 87-93.

Guo, Christopher, and Christopher Costello. "The value of adaption: Climate change and timberland management." *Journal of Environmental Economics and Management* 65, no. 3 (2013): 452-468.

Hashida, Y., and D.J. Lewis. 2017. "The intersection between climate adaptation, mitigation, and natural resources: An empirical analysis of forest management." Working Paper. Department of Applied Economics, Oregon State University. Accessed 10/25/17 at http://www.science.oregonstate.edu/~lewisda/Hashida_Lewis.pdf

Holland P. 1986. "Statistics and causal inference." *J. Am. Stat. Assoc.* 81:945-60

Hsiang, Solomon M., Marshall Burke, and Edward Miguel. "Quantifying the influence of climate on human conflict." *Science* 341, no. 6151 (2013): 1235367.

Hsiang, Solomon. "Climate econometrics." *Annual Review of Resource Economics* 8 (2016): 43-75.

Hsiang, Solomon, Robert Kopp, Amir Jina, James Rising, Michael Delgado, Shashank Mohan, D. J. Rasmussen et al. "Estimating economic damage from climate change in the United States." *Science* 356, no. 6345 (2017): 1362-1369.

Huang, Jin, Bob Abt, Georg Kindermann, and Sujit Ghosh. 2011. "Empirical Analysis of Climate Change Impact on Loblolly Pine Plantations in the Southern United States." *Natural Resource Modeling* 24 (4). Wiley Online Library: 445–76.

Kirilenko, Andrei P, and Roger A Sedjo. 2007. "Climate Change Impacts on Forestry." *Proceedings of the National Academy of Sciences* 104 (50). National Acad Sciences: 19697–19702.

Latta, Gregory, Hailemariam Temesgen, Darius Adams, and Tara Barrett. 2010. "Analysis of Potential Impacts of Climate Change on Forests of the United States Pacific Northwest." *Forest Ecology and Management* 259 (4). Elsevier: 720–29.

Lawler, Joshua J., David J. Lewis, Erik Nelson, Andrew J. Plantinga, Stephen Polasky, John C. Withey, David P. Helmers, Sebastián Martinuzzi, Derric Pennington, and Volker C. Radeloff. "Projected land-use change impacts on ecosystem services in the United States." *Proceedings of the National Academy of Sciences*111, no. 20 (2014): 7492-7497.

Lewis, David J., and Andrew J. Plantinga. "Policies for habitat fragmentation: combining econometrics with GIS-based landscape simulations." *Land Economics* 83, no. 2 (2007): 109-127.

Lubowski, Ruben N., Andrew J. Plantinga, and Robert N. Stavins. "Land-use change and carbon sinks: econometric estimation of the carbon sequestration supply function." *Journal of Environmental Economics and Management* 51, no. 2 (2006): 135-152.

Mendelsohn, Robert, William D. Nordhaus, and Daigee Shaw. 1994. "The Impact of Global Warming on Agriculture: A Ricardian Analysis." *The American Economic Review* 84 (4): 753–71.

Mendelsohn, Robert O., and Emanuele Massetti. "The use of cross-sectional analysis to measure climate impacts on agriculture: theory and evidence." *Review of Environmental Economics and Policy* 11, no. 2 (2017): 280-298.

Nelson, Mark D., and John Vissage. 2007. “Mapping Forest Inventory and Analysis Forest Land Use: Timberland, Reserved Forest Land, and Other Forest Land.” http://www.treesearch.fs.fed.us/pubs/17041.

Nielsen, A.J. Plantinga, and R.J. Alig. 2014. “New Cost Estimates for Carbon Sequestration Through Afforestation in the United States.” US Forest Service, Pacific Northwest Research Station. Gen. Tech. Rep. PNW-GTR-888.

Nordhaus, William D. 2017. “Revisiting the Social Cost of Carbon.” *Proceedings of the National Academy of Sciences*, 201609244. http://www.pnas.org/content/early/2017/01/30/1609244114.short.

Perez-Garcia, John, Linda A Joyce, A David McGuire, and Xiangming Xiao. 2002. “Impacts of Climate Change on the Global Forest Sector.” *Climatic Change* 54 (4). Springer: 439–61.

PRISM Climate Group, Oregon State University, http://prism.oregonstate.edu, created July 2017.

Rehfeldt, Gerald E., Barry C. Jaquish, Javier López-Upton, Cuauhtémoc Sáenz-Romero, J. Bradley St Clair, Laura P. Leites, and Dennis G. Joyce. "Comparative genetic responses to climate for the varieties of Pinus ponderosa and Pseudotsuga menziesii: Realized climate niches." *Forest Ecology and Management* 324 (2014): 126-137.

Schlenker, Wolfram, W. Michael Hanemann, and Anthony C. Fisher. "Will US agriculture really benefit from global warming? Accounting for irrigation in the hedonic approach." *The American Economic Review* 95, no. 1 (2005): 395-406.

Schlenker, Wolfram, W. Michael Hanemann, and Anthony C. Fisher. "The impact of global warming on US agriculture: an econometric analysis of optimal growing conditions." *The Review of Economics and Statistics* 88, no. 1 (2006): 113-125.

Schlenker, Wolfram, and Michael J. Roberts. "Nonlinear temperature effects indicate severe damages to US crop yields under climate change." *Proceedings of the National Academy of sciences* 106, no. 37 (2009): 15594-15598.

Sohngen, Brent, and Robert Mendelsohn. "Valuing the impact of large-scale ecological change in a market: The effect of climate change on US timber." *American Economic Review* (1998): 686-710.

Sohngen, Brent, and Xiaohui Tian. “Global climate change impacts on forests and markets.” Forest Policy and Economics, 72 (2016): 18-26.

Sohngen, Brent, and Sandra Brown. "The influence of conversion of forest types on carbon sequestration and other ecosystem services in the South Central United States." *Ecological Economics* 57.4 (2006): 698-708.

Tian, Xiaohui, Brent Sohngen, John B. Kim, Sara Ohrel, and Jefferson Cole. “Global climate change impacts on forests and markets.” Environmental Research Letters, 11 (2016): 0355011.

Van Deusen, Paul C., and Linda S. Heath. "Weighted analysis methods for mapped plot forest inventory data: tables, regressions, maps and graphs." *Forest ecology and management*260, no. 9 (2010): 1607-1612.

Von Bertalanffy, Ludwig. "A quantitative theory of organic growth (inquiries on growth laws. II)." *Human biology* 10, no. 2 (1938): 181-213.

Weiskittel, Aaron R., Nicholas L. Crookston, and Gerald E. Rehfeldt. "Projected future suitable habitat and productivity of Douglas-fir in western North America." *Schweizerische Zeitschrift fur Forstwesen* 163, no. 3 (2012): 70-78.

Zhang, Daowei, and Peter H. Pearse. *Forest economics*. UBC Press, 2011.

Figures

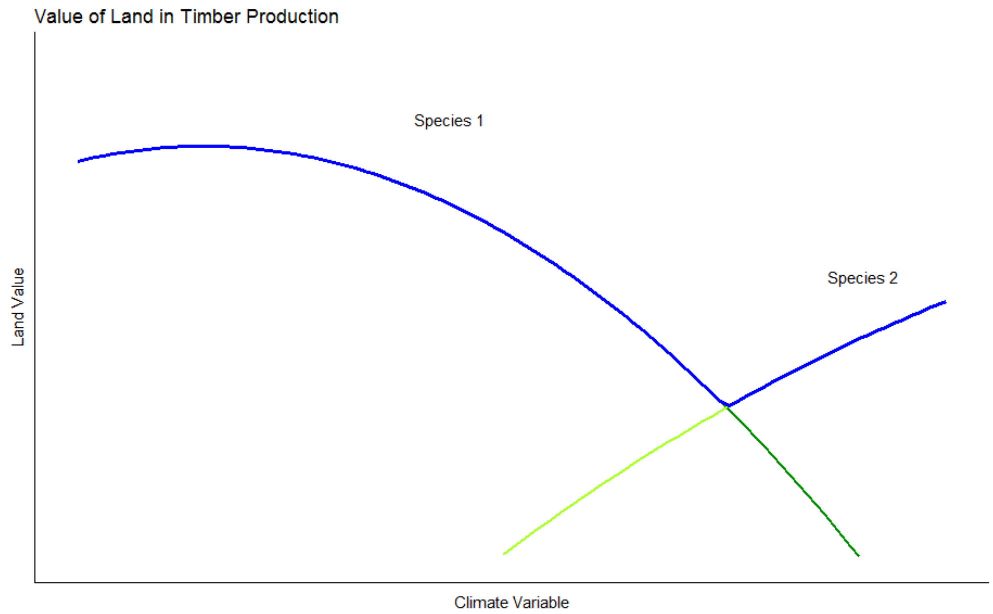

Figure 1: Ricardian Value Function

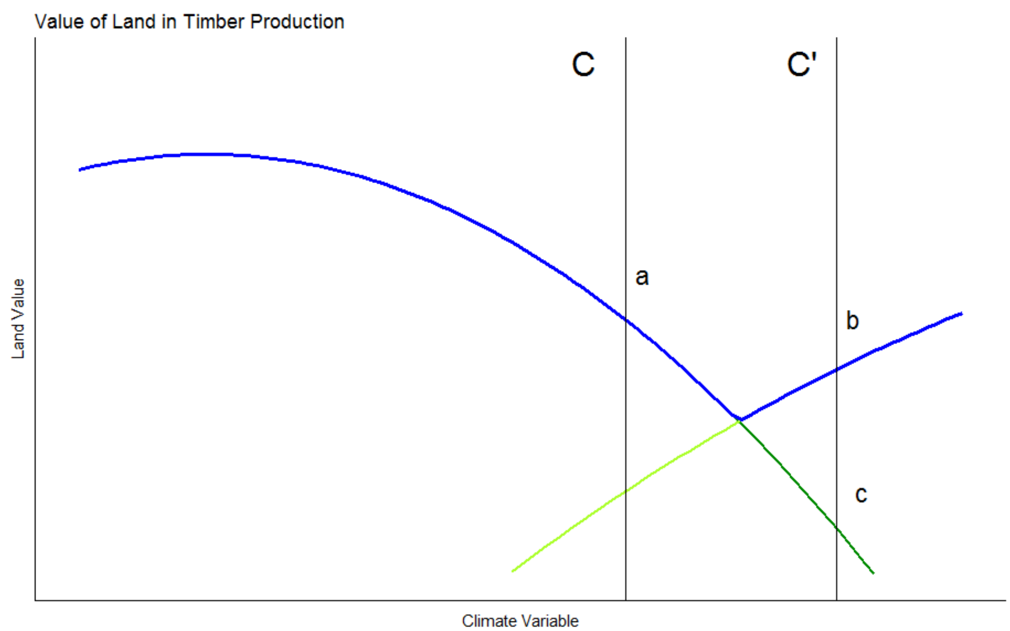

Figure 2: Climate Change Adaptation

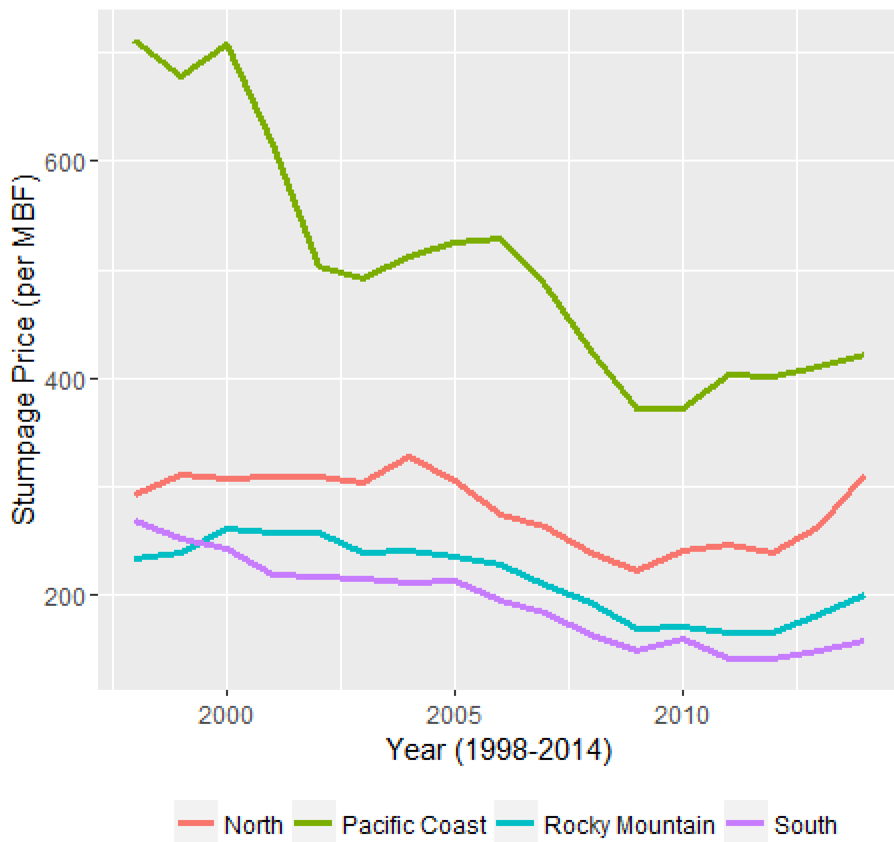

Figure 3: Temporal Stumpage Price Trend

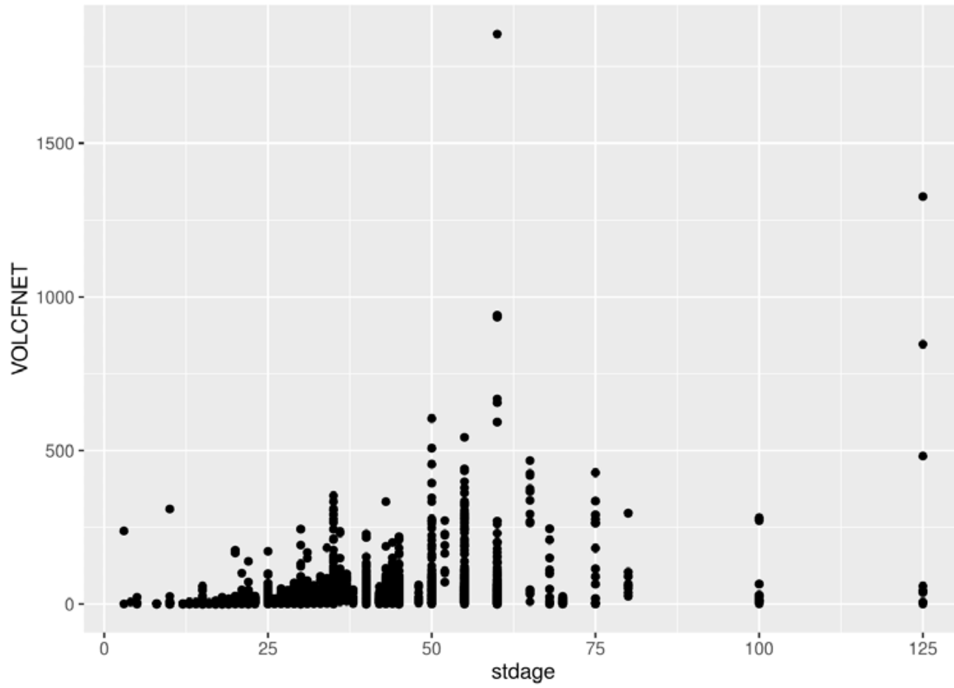

Figure 4: FIA Observations of Douglas fir

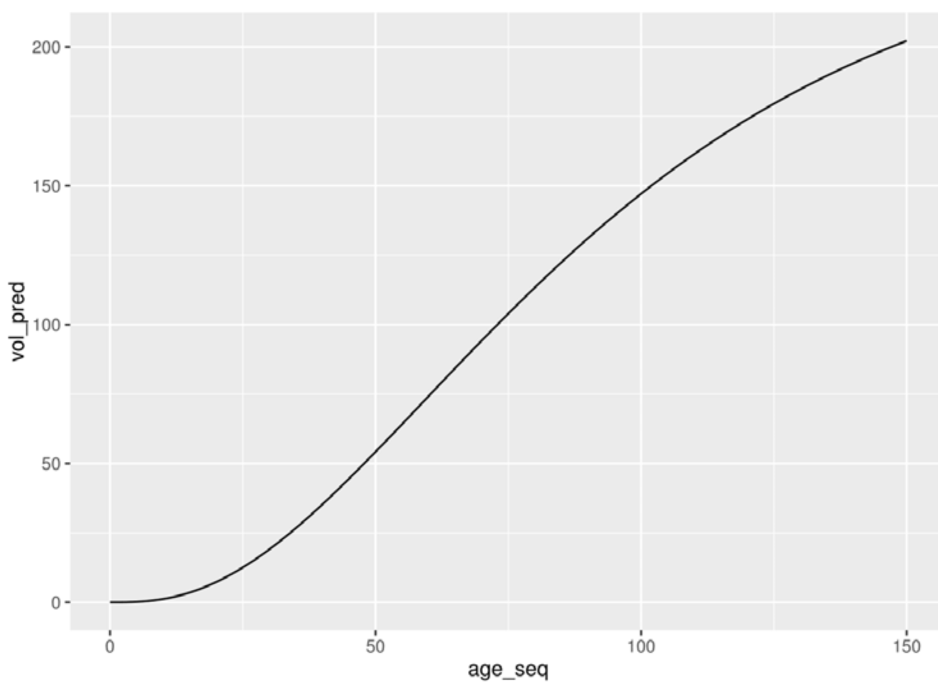

Figure 5: Estimated Growth for Douglas fir

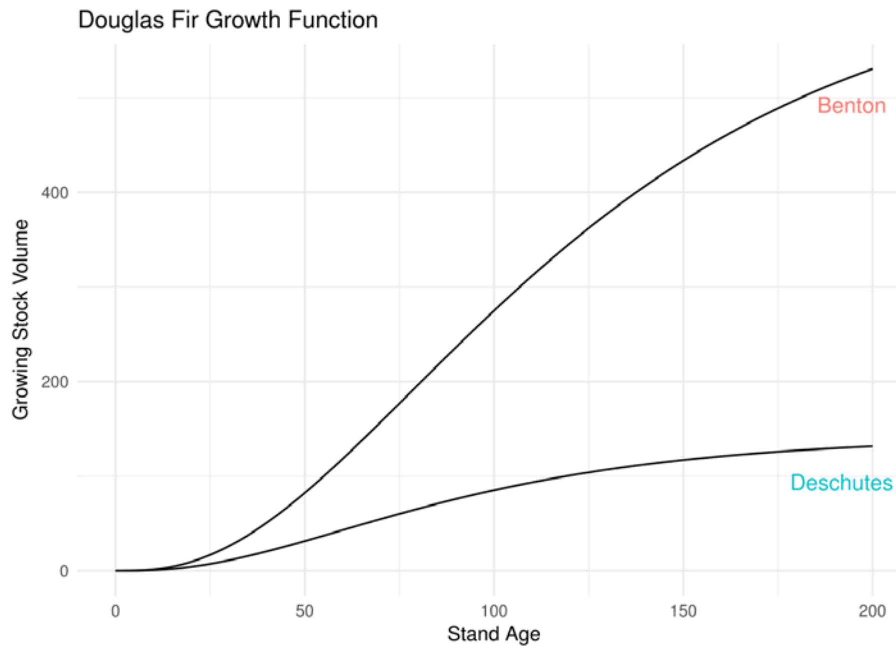

Figure 6: Cross-Sectional Variation in Growth

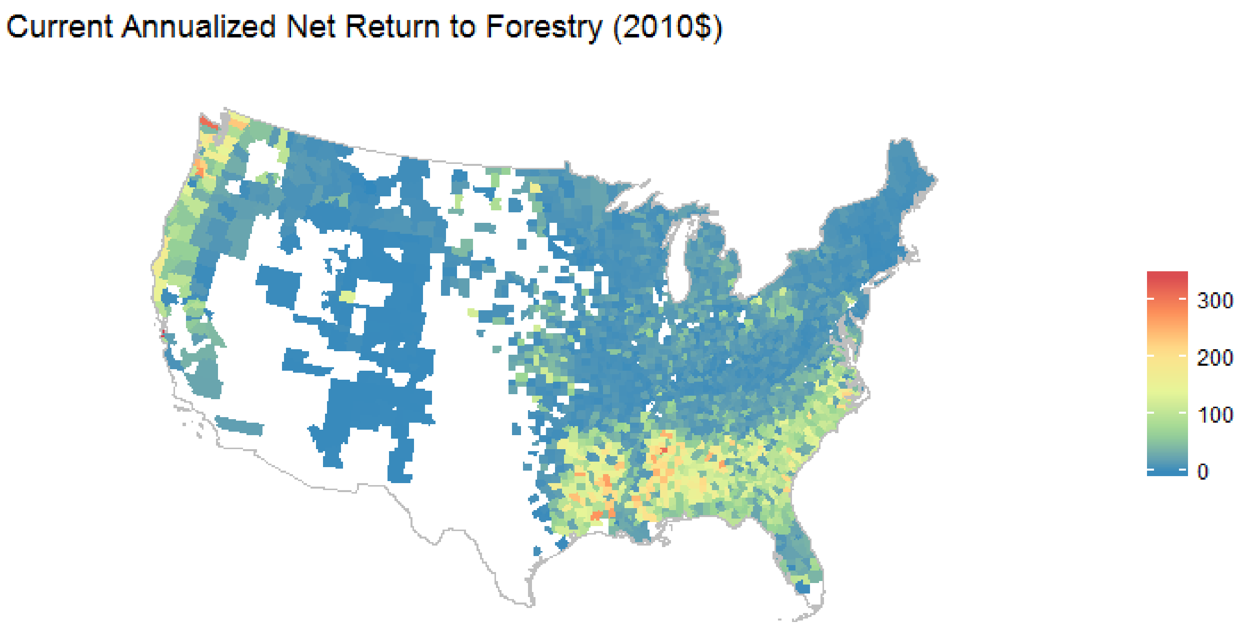

Figure 7

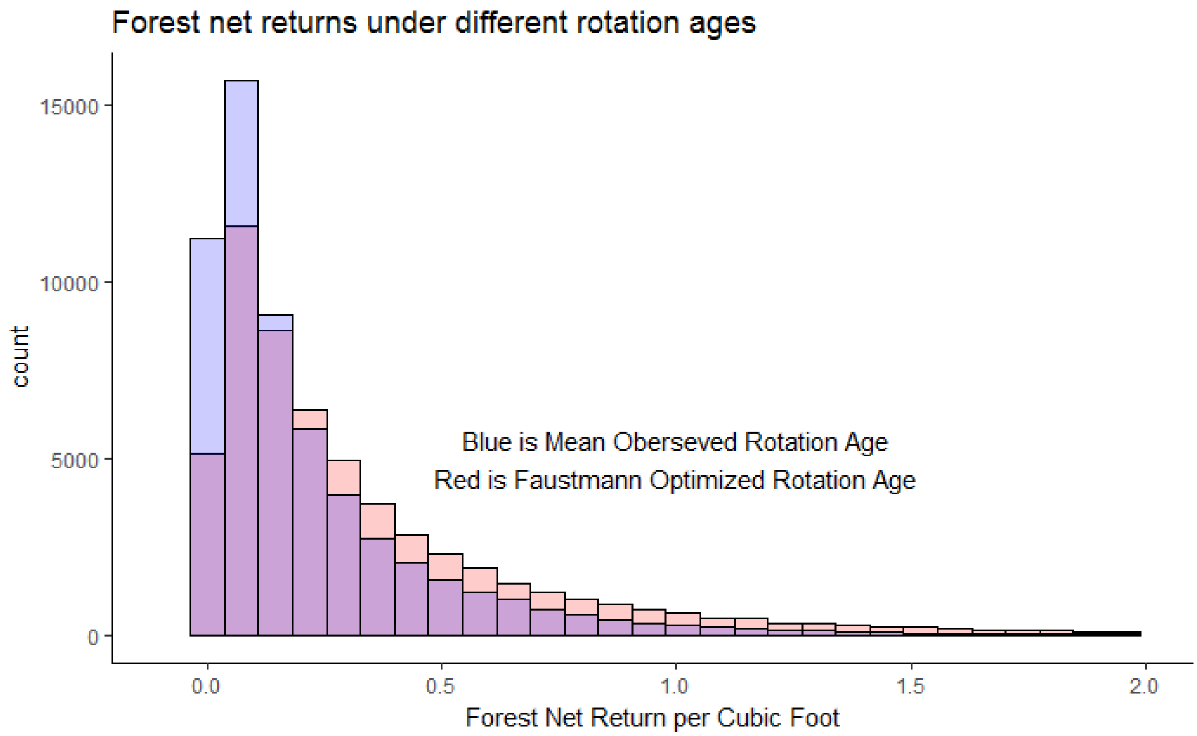

Figure 8

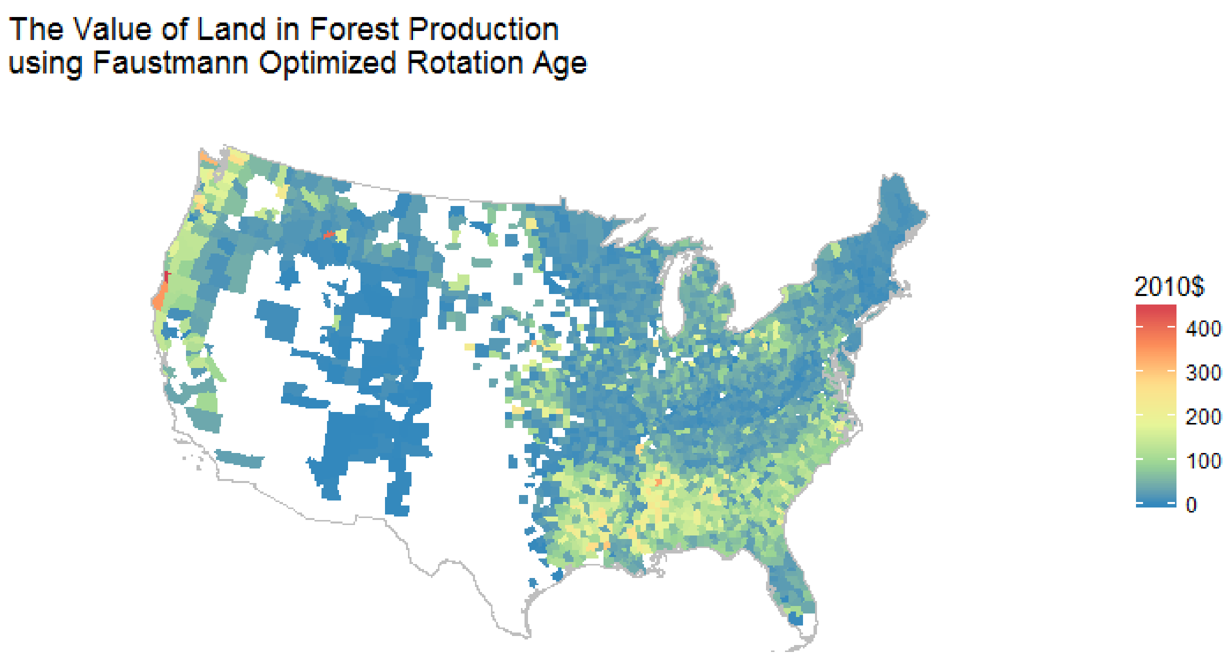

Figure 9

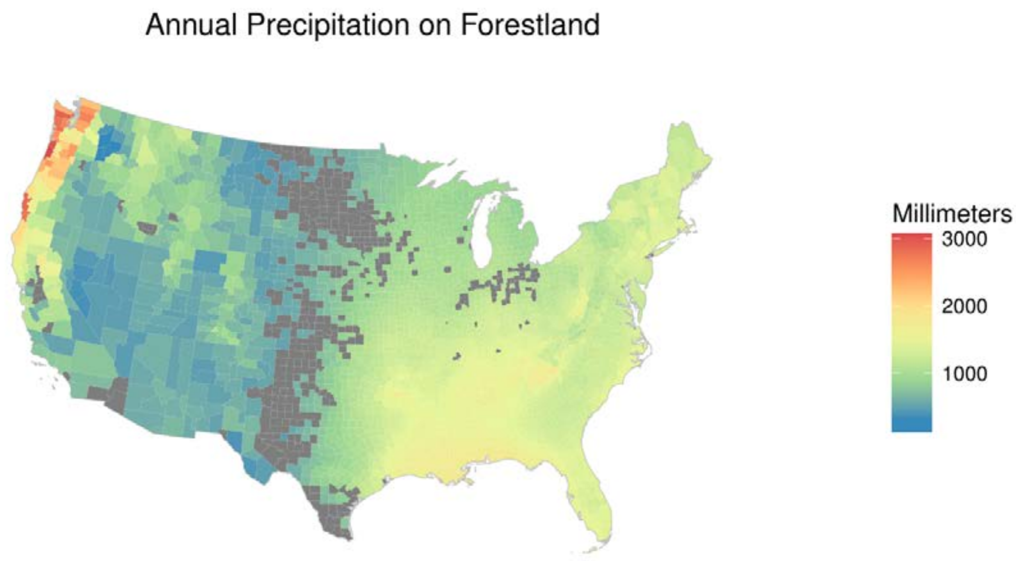

Figure 10: PRISM 30-year normal precipitation

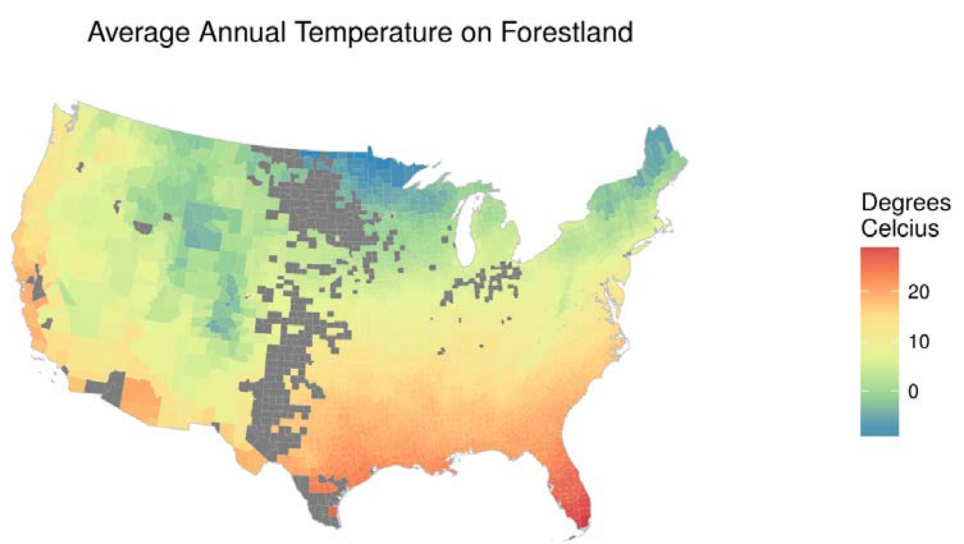

Figure 11: PRISM 30-year normal temperature mean

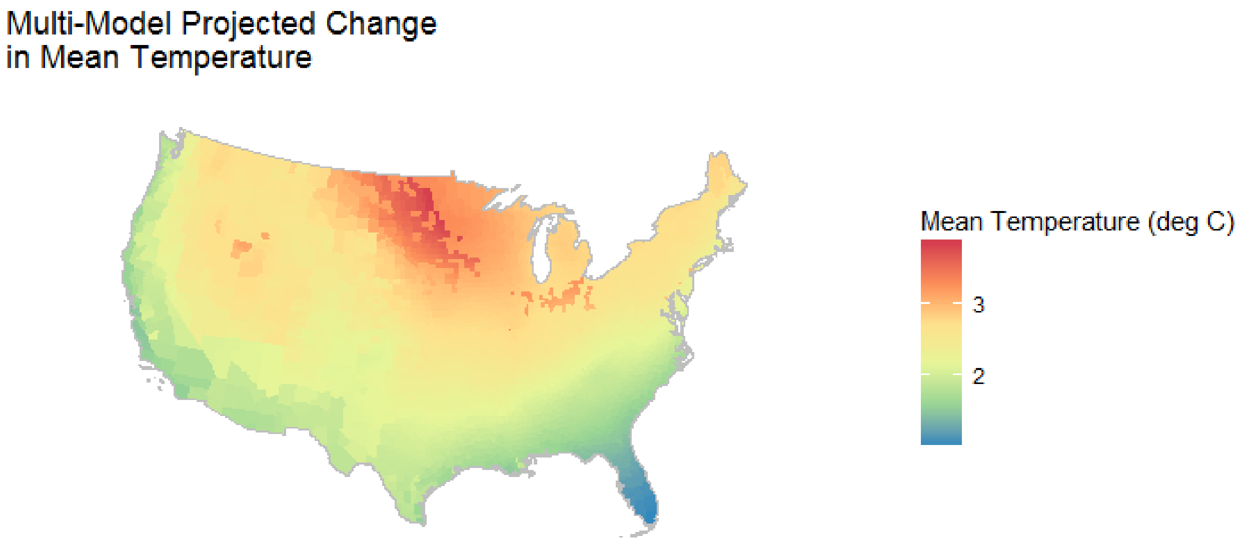

Figure 12: Multi-Model Change in Mean Temperature

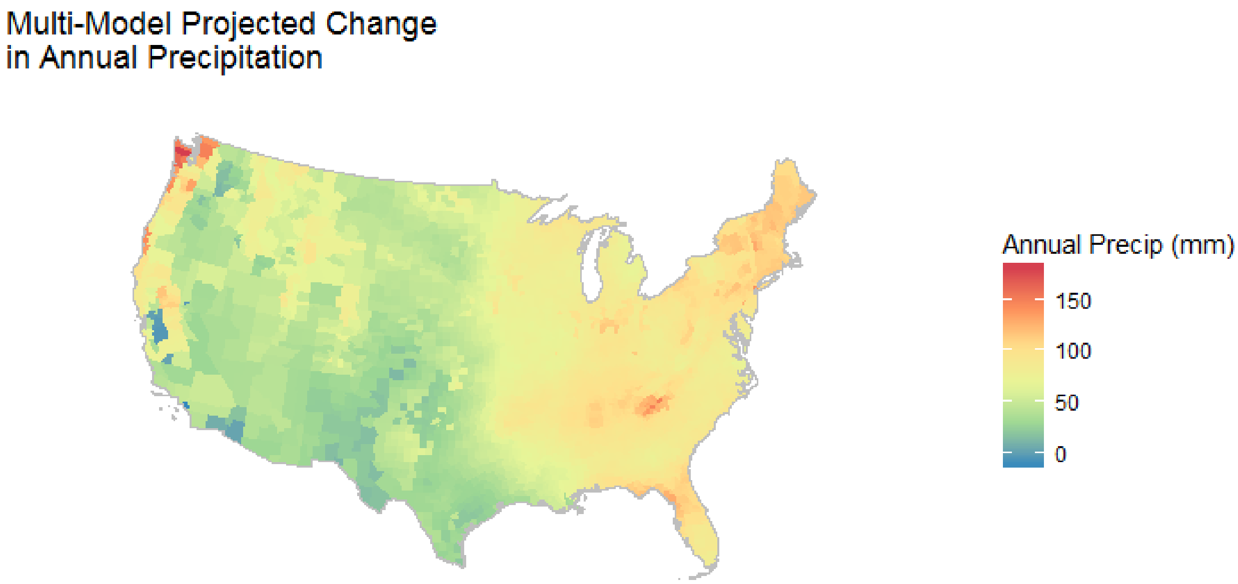

Figure 13: Multi-Model Change in Annual Precipitation

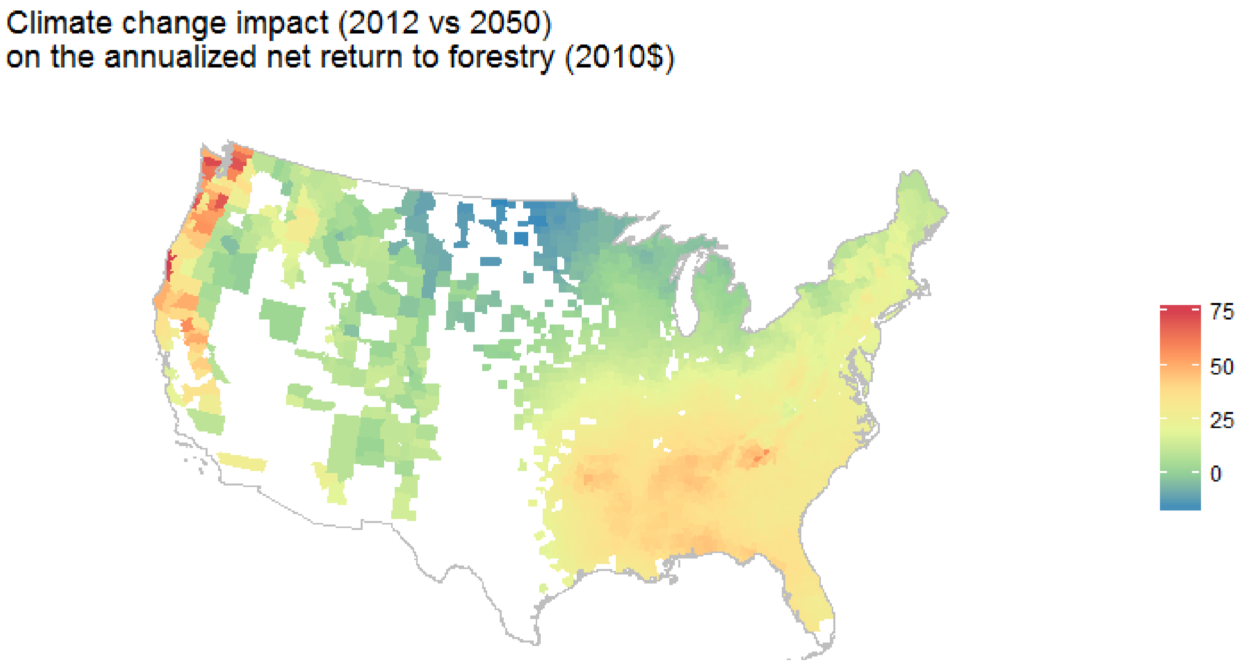

Figure 14

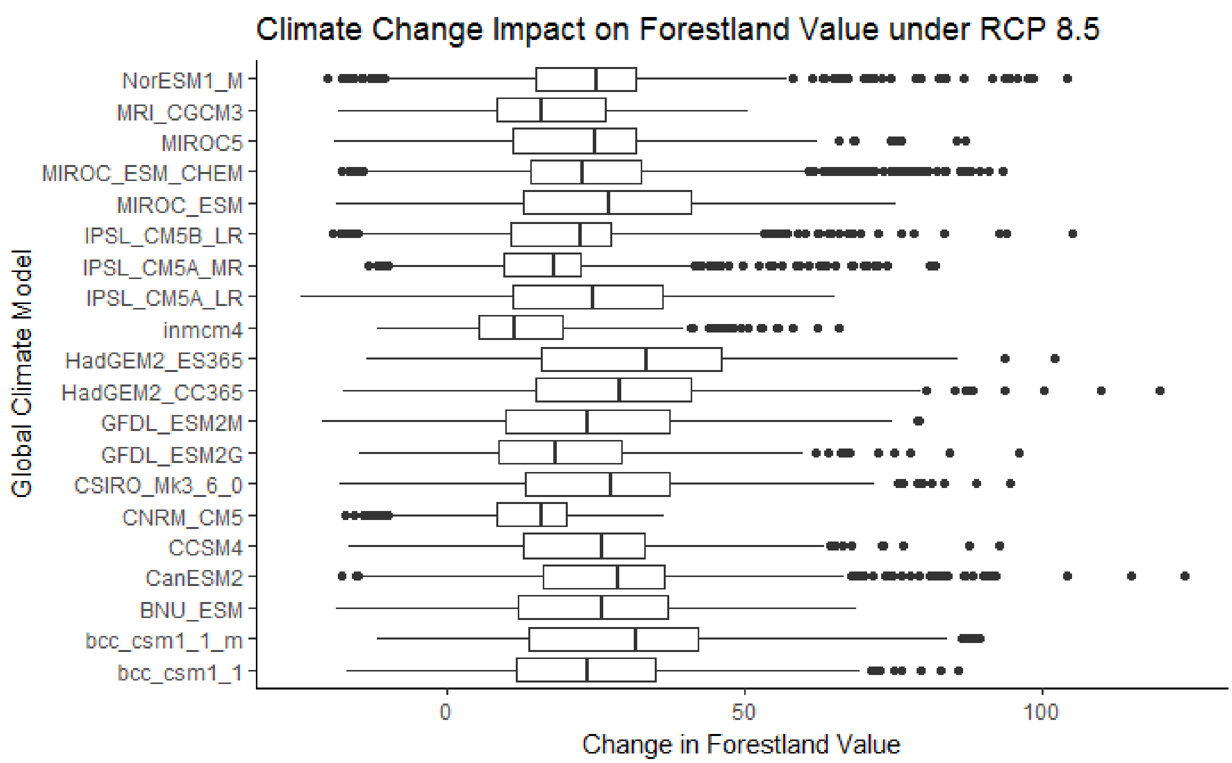

Figure 15

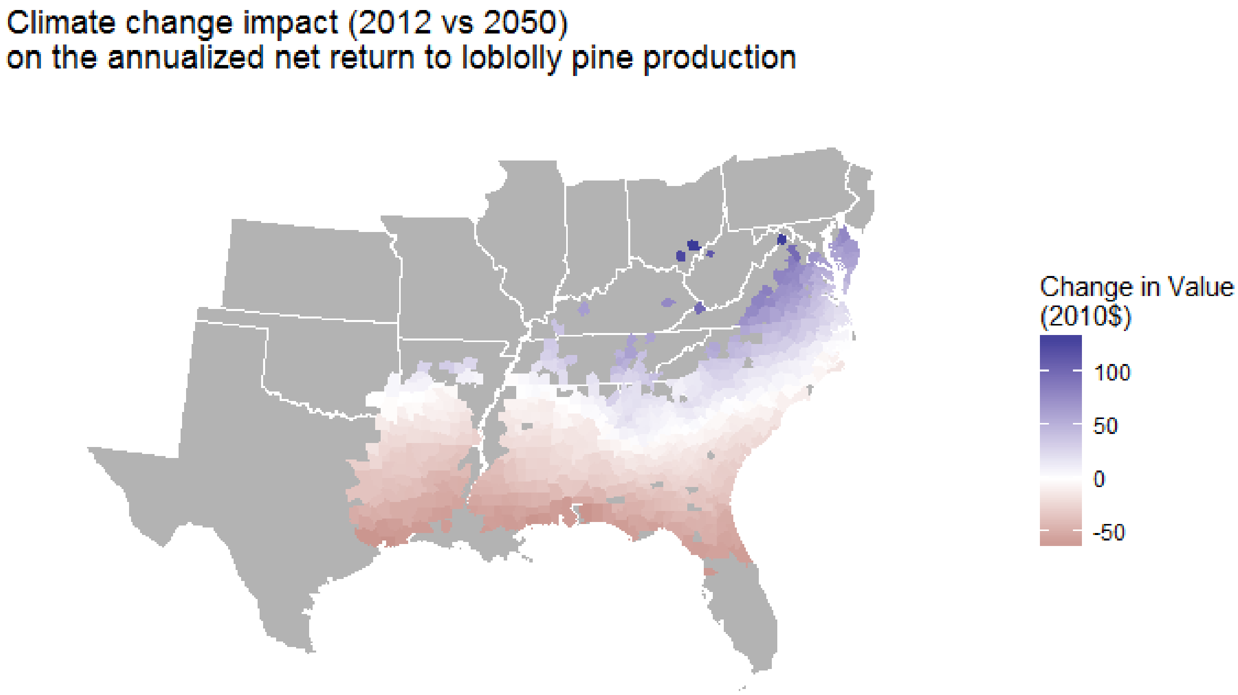

Figure 16

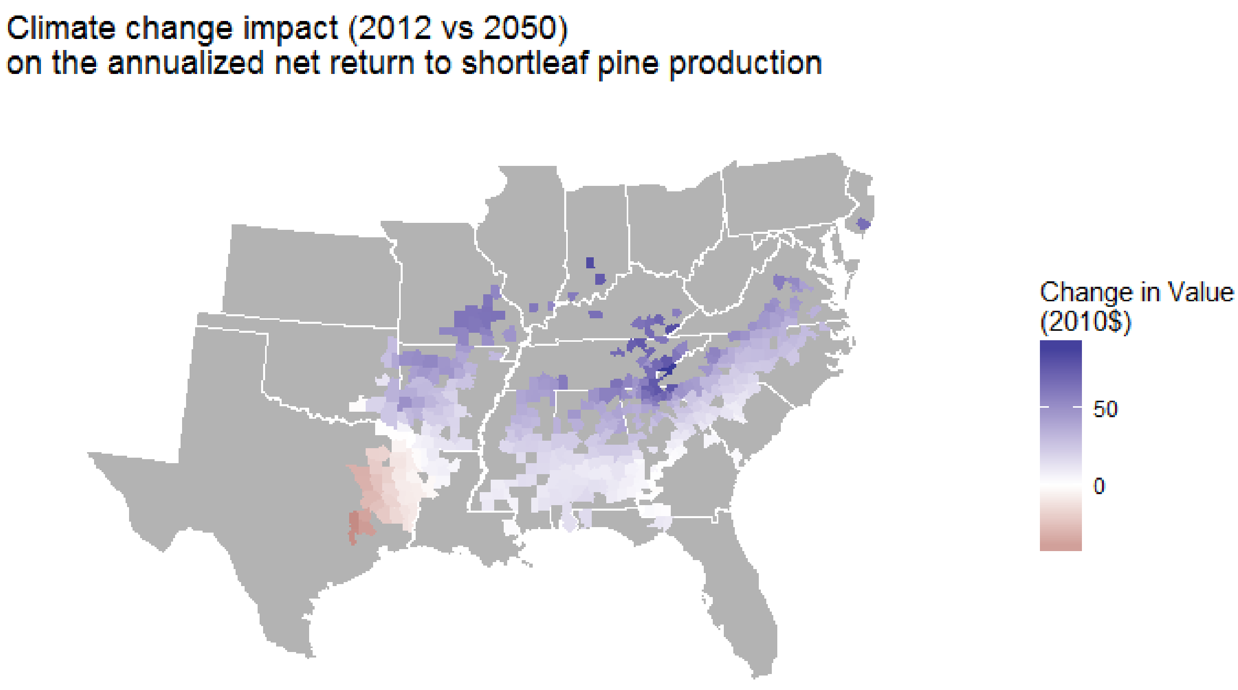

Figure 17

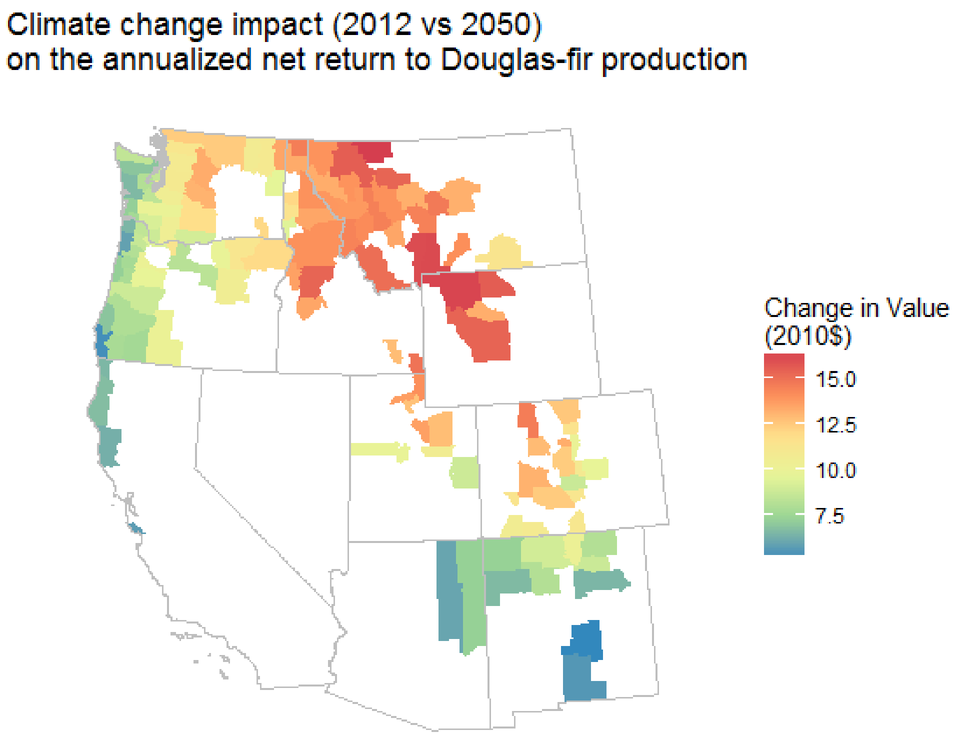

Figure 18

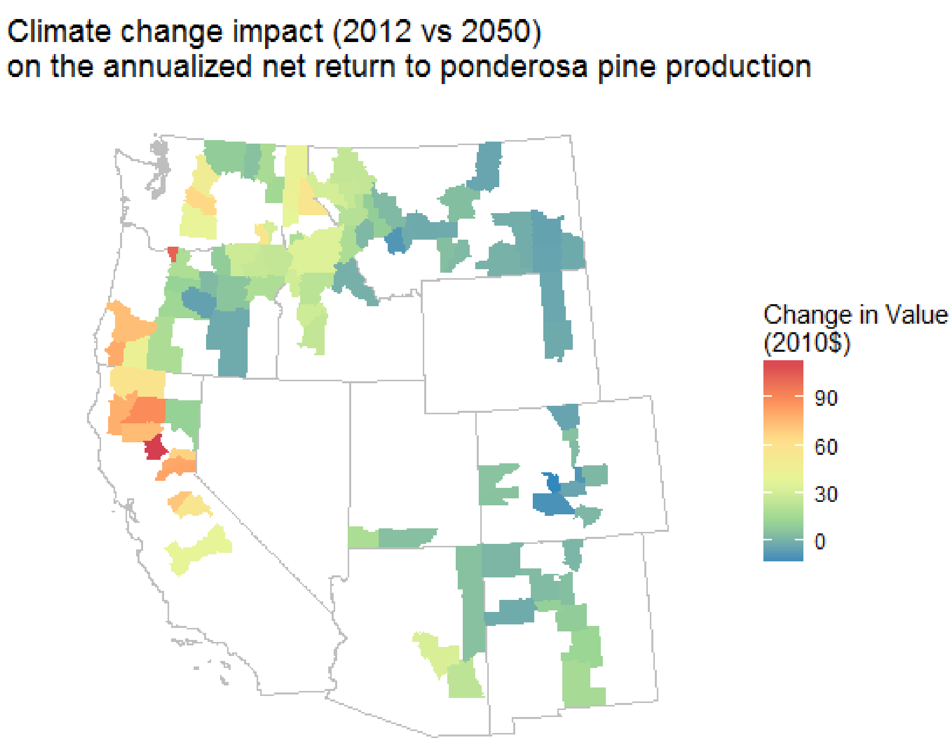

Figure 19

Tables

Table 1: Ricardian Estimation Data Summary

	National				Douglas-fir / Ponderosa				Loblolly / Shortleaf			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Net return per acre	38.91	50.24	-2.00	351.35	23.56	56.13	0.001	373.91	131.62	107.11	0.105	481.89
County forest acres (1000s)	211	193	1.561	3,752	76	105	0.948	827	46	55	0.671	334
Max temp	19.418	4.224	9.150	31.330	17.751	2.929	11.400	29.350	23.570	1.855	18.060	28.460
Min temp	5.241	5.051	-9.52	17.230	-3.421	3.312	-9.520	6.570	9.649	2.174	2.810	15.240
Mean temp	12.371	4.464	1.406	23.724	6.918	2.632	1.406	14.631	16.717	1.940	11.208	21.803
Precip	1111	293	315	3,039	956	595	359	3,039	1,305	137	982	1,769
Share of forest in LCC 1	0.008	0.031	0.000	0.741	0.0003	0.002	0.000	0.030	0.008	0.022	0.000	0.374
Share of forest in LCC 2	0.162	0.174	0.000	1.000	0.009	0.021	0.000	0.118	0.190	0.133	0.000	0.643
Share of forest in LCC 3	0.182	0.155	0.000	1.000	0.051	0.089	0.000	0.733	0.227	0.133	0.000	0.801
Share of forest in LCC 4	0.148	0.130	0.000	1.000	0.106	0.131	0.000	0.577	0.176	0.110	0.000	0.792
Share of forest in LCC 5	0.050	0.100	0.000	0.909	0.007	0.028	0.000	0.250	0.066	0.092	0.000	0.597
Share of forest in LCC 6	0.193	0.182	0.000	1.000	0.325	0.257	0.000	0.999	0.151	0.130	0.000	0.643
Share of forest in LCC 7	0.242	0.243	0.000	1.000	0.471	0.264	0.000	1.000	0.176	0.191	0.000	0.976
Share of forest in LCC 8	0.016	0.060	0.000	0.803	0.031	0.060	0.000	0.313	0.006	0.028	0.000	0.436

Table 2: Ricardian Value Function: Composite of all Species

	Forest Net Returns per Acre
Max temp	-17.401*** (2.740)
Max temp squared	0.283*** (0.072)
Min temp	2.988* (1.629)
Min temp squared	-0.182*** (0.055)
Precip	-0.209*** (0.037)
Precip squared	0.00002** (0.00001)
Max temp : precip	0.010*** (0.002)
Min temp : precip	-0.002 (0.002)
Constant	171.861*** (33.685)
Soil Control	Yes
Sub-region Fixed Effect	Yes
F Statistic	49.236*** (df = 23; 2389)
Adjusted R^2	0.358
Residual Std. Error	40.250 (df = 2374)
Note:	**p<0.1; **p<0.05;* ***p<0.01

Table 1: U.S. Forest Ricardian parameter estimates with robust standard errors. Includes separate repressor for the share of forestland in each of the eight Land Capability Classes (LCC). LCC is a measure of the soil's capability to produce commonly cultivated crops and pasture. 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.

Table 3: Average Marginal Effects: Composite of all Species

	AME	SE	z-score	p-value
Max Temp	5.2520	0.7350	7.1457	0.0000
Min Temp	-0.7851	0.6439	-1.2192	0.2228
Precip	0.0311	0.0058	5.3585	0.0000

Table 2: US Forest Ricardian Average Marginal Effects

Table 4: Functional Form Sensitivity Analysis

Model Number	Model Specification	Precip	Mean Temp	Max Temp	Min Temp
1	Linear precip and mean temp	0.0396*** (0.0038)	3.8121*** (0.2473)		
2	Linear climate with interaction	0.0599*** (0.0041)	3.3156*** (0.2457)		
3	Quadratic climate	0.0269*** (0.0042)	4.6863*** (0.2662)		
4	Quadratic climate with interaction (**preferred forest type model)**	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 with 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 with interaction	0.0289*** (0.0051)		5.3611*** (0.5238)	-0.3313 (0.4719)
9	Quadratic with interaction and sub-region fixed effects	0.0331*** (0.0054)	4.5513*** (0.3890)		
10	Quadratic with interaction and region fixed effects	0.0397*** (0.0054)	4.2271*** (0.3385)		
11	Quadratic with interaction and soil controls (lcc share)	0.0436*** (0.0048)	3.9232*** (0.2936)		
12	Quadratic with interaction, sub-region fixed effects, and soil controls (lcc share)	0.0367*** (0.0054)	3.7961*** (0.4170)		
13	Quadratic with interaction, region fixed effects, and soil controls (lcc share)	0.0491*** (0.0054)	3.0716*** (0.3702)		
14	Quadratic with interaction and sub-region fixed effects	0.0247*** (0.0058)		4.0090*** (0.7300)	1.0805* (0.5970)

15	Quadratic with interaction and region fixed effects	0.0397*** (0.0059)		2.4924*** (0.6554)	1.5229*** (0.5224)
16	Quadratic with interaction and soil controls (lcc share)	0.0387*** (0.0052)		6.5177*** (0.5332)	-2.0695*** (0.5209)
17	Quadratic with interaction, sub-region fixed effects, and soil controls (lcc share) **(preferred national model)**	0.0311*** (0.0058)		5.2520*** (0.7350)	-0.7851 (0.6439)
18	Quadratic with interaction, region fixed effects, and soil controls (lcc share)	0.0497*** (0.0059)		3.5149*** (0.6534)	-0.3056 (0.5677)
19	Quadratic with interaction, sub-region fixed effects, and 2 lcc groups	0.0280*** (0.0057)		5.1056*** (0.7347)	-0.5741 (0.6267)
20	Quadratic with interaction, region fixed effects, and 2 lcc groups	0.0488*** (0.0059)		3.3114*** (0.6527)	-0.0548 (0.5466)
21	Quadratic climate with interaction, east/west fixed effect, and 8 lcc groups	0.0471*** (0.0053)		4.9051*** (0.5853)	-0.4274 (0.5763)
22	Quadratic climate with interaction, east/west fixed effect, and 2 lcc groups	0.0434*** (0.5832)		4.7166*** (0.5832)	-0.1509 (0.5600)
23	Quadratic climate with interaction and 4 lcc groups	0.0451*** (0.0048)	3.7737*** (0.2798)		
24	Quadratic climate with interaction and 2 lcc groups	0.0420*** (0.0047)	3.8583*** (0.2787)		
25	Quadratic climate with interaction and 4 lcc groups	0.0391*** (0.0051)		6.4421*** (0.5296)	-2.0172*** (0.5002)
26	Quadratic climate with interaction and 2 lcc groups	0.0353*** (0.0051)		6.3141*** (0.5298)	-1.8018*** (0.4993)

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

Table 5: Forest Type Ricardian Estimates

	Net return per acre				
	All Species	Douglas-fir	Ponderosa	Loblolly	Shortleaf
Mean temp	-4.407*** (1.066)	5.185 (7.625)	-27.097*** (6.186)	169.755*** (32.651)	80.559*** (37.142)
Mean temp squared	0.119** (0.051)	-0.165 (0.650)	0.650 (0.401)	-4.221*** (0.953)	-3.802*** (1.080)
Precip	-0.105*** (0.105)	0.060 (0.045)	-0.136** (0.054)	0.903* (0.501)	-0.093 (0.571)
Precip squared	0.00004*** (0.00000)	-0.00002 (0.00001)	-0.00003 (0.00002)	-0.0002 (0.0002)	-0.0002 (0.0002)
Mean temp : precip	0.005*** (0.001)	0.001 (0.005)	0.031*** (0.004)	-0.016 (0.016)	0.042*** (0.015)
Constant	66.298*** (9.762)	-52.243 (35.737)	128.808*** (37.657)	-1931.375*** (357.323)	-713.614 (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 (df = 2384)	53.074 (df = 129)	31.049 (df = 101)	99.309 (df = 645)	75.163 (df = 365)
F Statistic	221.450*** (df = 5; 2384)	6.218*** (df = 5; 129)	43.616*** (df = 5; 101)	12.280*** (df = 5; 645)	19.410*** (df = 5; 365)
Note:					**p<0.1; ***__*p<0.05;*__ ***p<0.01

Table 6: Average Marginal Effects for Forest Type Models

	All Species			Douglas-fir			Ponderosa			Loblolly			Shortleaf		
	AME	SE	p-value	AME	SE	p-value	AME	SE	p-value	AME	SE	p-value	AME	SE	p-value
Precip	0.039	0.005	0.000	0.034	0.013	0.009	0.037	0.014	0.009	0.071	0.033	0.030	0.167	0.033	0.000
Mean Temp	4.342	0.273	0.000	4.290	2.216	0.053	5.759	1.424	0.000	5.034	2.189	0.023	11.63	2.223	0.000

Table 7: Summary of Climate Change Predictions

	All Forest Land				Douglas-fir / Ponderosa pine				Loblolly / Shortleaf pine			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Change in precip	76.030	62.572	-370.8	388.84	64.708	76.884	-370.8	388.84	85.478	68.501	-225.5	337.59
Change in max temp	3.145	0.863	0.634	6.571	3.090	0.701	0.768	5.315	2.802	0.761	0.675	6.571
Change in mean temp	2.382	0.796	0.238	5.202	2.381	0.654	0.714	4.318	1.974	0.577	0.256	4.608
Change in min temp	1.620	0.939	-0.622	5.406	1.672	0.862	-0.358	5.038	1.146	0.605	-0.339	3.892

Note: 56,012 obs. across 20 GCMs for RCP 8.5

Table 8: Climate Change Impact

	All Species			Douglas-fir			Ponderosa			Loblolly			Shortleaf		
	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Base value	38.908	-30.963	219.308	24.747	-11.250	74.551	23.057	-14.028	271.217	166.132	-45.392	194.046	71.050	-76.218	173.265
Value Change	22.308	-17.064	75.474	10.928	5.130	16.320	23.275	-12.536	113.513	-2.961	-67.566	137.000	26.668	-49.453	94.083

Appendix

Table A1: National Ricardian models 1-4

	Forest Net Return			
Mean temp	3.812*** (0.247)	-5.716*** (0.905)	-2.599** (1.012)	-4.407*** (1.066)
Mean temp squared			0.294*** (0.038)	0.119** (0.051)
Precip	0.040*** (0.004)	-0.041*** (0.008)	-0.060*** (0.013)	-0.105*** (0.015)
Mean temp : precip		0.008*** (0.001)		0.005*** (0.001)
Precip squared			0.00004*** (0.00000)	0.00004*** (0.00000)
Constant	-52.296*** (3.499)	36.700*** (8.833)	34.960*** (7.686)	66.298*** (9.762)
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 A2: National Ricardian models 5-8

	Forest Net Return			
Max temp	3.542^{***} (0.357)	-8.196^{***} (1.105)	-13.356^{***} (2.114)	-14.065^{***} (2.089)
Max temp squared			0.447^{***} (0.060)	0.219^{***} (0.066)
Min temp	0.546^{*} (0.302)	2.552^{***} (0.875)	1.404^{***} (0.348)	3.822^{***} (0.926)
Min temp squared			-0.065 (0.042)	-0.070 (0.047)
Precip	0.041^{***} (0.004)	-0.170^{***} (0.020)	-0.051^{***} (0.013)	-0.229^{***} (0.027)
Max temp : precip		0.012^{***} (0.001)		0.010^{***} (0.001)
Min temp : precip		-0.003^{***} (0.001)		-0.003^{***} (0.001)
Precip squared			0.00004^{***} (0.00000)	0.00004^{***} (0.00000)
Constant	-78.420^{***} (6.184)	128.202^{***} (19.322)	126.033^{***} (19.545)	216.117^{***} (22.518)
Adjusted R^2	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 A3: National Ricardian models 9-13

	Forest Net Return				
Mean temp	-4.746*** (1.268)	-4.844*** (1.062)	-6.245*** (1.070)	-5.977*** (1.252)	-6.825*** (1.054)
Mean temp squared	0.040 (0.055)	0.089* (0.050)	0.127** (0.052)	0.045 (0.056)	0.084* (0.051)
Precip	-0.107*** (0.018)	-0.071*** (0.017)	-0.122*** (0.015)	-0.109*** (0.018)	-0.064*** (0.017)
Precip squared	0.00002*** (0.00001)	0.00002*** (0.00001)	0.00004*** (0.00000)	0.00002*** (0.00001)	0.00001** (0.00001)
NLS sub-region	3.895 (4.052)			-0.214 (4.064)	
NPS sub-region	-3.727 (3.114)			-5.736* (3.090)	
PNW sub-region	49.316*** (6.876)			52.372*** (6.835)	
PSW sub-region	28.932*** (7.526)			41.242*** (7.548)	
RMN sub-region	-0.342 (6.729)			7.163 (6.676)	
RMS sub-region	-12.129* (6.369)			0.895 (6.423)	
SC sub-region	-0.341 (3.745)			4.591 (3.744)	
SE sub-region	4.897 (3.803)			6.385* (3.788)	
PC region		43.957*** (5.148)			54.231*** (5.165)
RM region		8.107** (3.495)			17.782*** (3.612)
SO region		4.964* (2.905)			11.179*** (2.920)
Share of forest in LCC 1			99.907*** (30.483)	109.589*** (30.058)	103.375*** (29.773)
Share of forest in LCC 2			94.997*** (14.921)	103.204*** (14.799)	102.936*** (14.589)
Share of forest in LCC 3			88.626*** (15.128)	93.629*** (14.968)	97.929*** (14.796)

Share of forest in LCC 4			73.584*** (15.330)	72.827*** (15.252)	75.514*** (14.975)
Share of forest in LCC 5			72.733*** (16.619)	80.561*** (16.420)	78.515*** (16.237)
Share of forest in LCC 6			77.051*** (14.770)	74.631*** (14.570)	70.020*** (14.453)
Share of forest in LCC 7			63.907*** (14.846)	65.279*** (14.651)	62.543*** (14.558)
Mean temp : precip	0.007*** (0.001)	0.006*** (0.001)	0.006*** (0.001)	0.008*** (0.001)	0.007*** (0.001)
Constant	71.110*** (13.865)	47.298*** (11.673)	8.819 (15.438)	0.903 (18.169)	-26.038 (16.339)
Adjusted R^2	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 A4: National Ricardian models 14-18

	Forest Net Return				
Max temp	-19.776*** (2.902)	-17.296*** (2.208)	-11.358*** (2.118)	-17.401*** (2.883)	-15.517*** (2.229)
Max temp squared	0.292*** (0.078)	0.310*** (0.069)	0.192*** (0.066)	0.283*** (0.077)	0.311*** (0.069)
Min temp	5.905*** (1.270)	3.182*** (0.926)	0.671 (0.979)	2.988** (1.291)	0.207 (0.972)
Min temp squared	-0.171*** (0.053)	-0.107** (0.048)	-0.088* (0.047)	-0.182*** (0.053)	-0.136*** (0.048)
Precip	-0.221*** (0.030)	-0.124*** (0.030)	-0.216*** (0.026)	-0.209*** (0.029)	-0.104*** (0.030)
Precip squared	0.00002*** (0.00001)	0.00001** (0.00001)	0.00004*** (0.00000)	0.00002*** (0.00001)	0.00001** (0.00001)
NLS sub-region	-5.931 (4.389)			-6.400 (4.348)	
NPS sub-region	-5.764* (3.198)			-6.361** (3.180)	
PNW sub-region	58.452*** (7.597)			54.492*** (7.566)	
PSW sub-region	18.906* (9.725)			16.123* (9.615)	
RMN sub-region	14.856** (7.523)			15.395** (7.388)	
RMS sub-region	25.934*** (9.436)			22.350** (9.269)	
SC sub-region	-0.064 (3.848)			3.312 (3.807)	
SE sub-region	2.189 (4.002)			1.629 (3.967)	
PC region		49.469*** (6.352)			49.212*** (6.324)
RM region		20.971*** (4.213)			23.646*** (4.223)
SO region		8.936*** (3.076)			11.298*** (3.031)
Share of forest in LCC 1			95.384*** (30.121)	97.086*** (29.882)	89.909*** (29.762)

Share of forest in LCC 2			92.995^{***} (14.831)	92.462^{***} (14.753)	92.184^{***} (14.653)
Share of forest in LCC 3			87.277^{***} (14.973)	85.381^{***} (14.882)	90.831^{***} (14.779)
Share of forest in LCC 4			64.388^{***} (15.238)	60.952^{***} (15.211)	63.211^{***} (15.039)
Share of forest in LCC 5			69.931^{***} (16.427)	69.112^{***} (16.312)	68.401^{***} (16.238)
Share of forest in LCC 6			63.336^{***} (14.602)	60.747^{***} (14.537)	57.886^{***} (14.449)
Share of forest in LCC 7			52.450^{***} (14.674)	52.795^{***} (14.618)	54.553^{***} (14.536)
Max temp : precip	0.011^{***} (0.001)	0.007^{***} (0.001)	0.009^{***} (0.001)	0.010^{***} (0.001)	0.006^{***} (0.001)
Min temp : precip	-0.003^{**} (0.001)	-0.0005 (0.001)	-0.002^{*} (0.001)	-0.002 (0.001)	0.001 (0.001)
Constant	273.207^{***} (31.040)	200.642^{***} (22.333)	109.142^{***} (26.697)	171.861^{***} (33.800)	98.699^{***} (26.379)
Adjusted R^2	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 A5: National Ricardian models 19-22

	Forest Net Return			
Max temp	-18.051*** (2.875)	-15.455*** (2.186)	-16.693*** (2.258)	-16.666*** (2.227)
Max temp squared	0.293*** (0.077)	0.307*** (0.068)	0.302*** (0.068)	0.298*** (0.067)
Min temp	3.883*** (1.281)	0.885 (0.951)	2.834*** (1.027)	3.666*** (1.010)
Min temp squared	-0.188*** (0.053)	-0.138*** (0.047)	-0.177*** (0.048)	-0.173*** (0.048)
Precip	-0.209*** (0.029)	-0.097*** (0.030)	-0.157*** (0.028)	-0.157*** (0.028)
Precip squared	0.00002*** (0.00001)	0.00001* (0.00001)	0.00002*** (0.00001)	0.00002*** (0.00001)
NLS sub-region	-7.681* (4.341)			
NPS sub-region	-5.916* (3.158)			
PNW sub-region	54.232*** (7.523)			
PSW sub-region	14.707 (9.620)			
RMN sub-region	15.889** (7.431)			
RMS sub-region	23.496** (9.325)			
SC sub-region	3.199 (3.823)			
SE sub-region	0.888 (3.956)			
PC region		48.494*** (6.259)		
RM region		25.476*** (4.183)		
SO region		10.959*** (3.039)		
Share of forest in LCC 1-4	29.124*** (3.739)	31.343*** (3.658)		30.389*** (3.635)
West of the 100th			34.814*** (5.416)	34.329*** (5.436)

Meridian				
Share of forest in LCC 1			102.576*** (29.890)	
Share of forest in LCC 2			95.741*** (14.713)	
Share of forest in LCC 3			89.059*** (14.850)	
Share of forest in LCC 4			67.396*** (15.118)	
Share of forest in LCC 5			74.122*** (16.303)	
Share of forest in LCC 6			63.854*** (14.480)	
Share of forest in LCC 7			55.015*** (14.556)	
Max temp : precip	0.011*** (0.001)	0.006*** (0.001)	0.009*** (0.001)	0.009*** (0.001)
Min temp : precip	-0.002** (0.001)	0.0005 (0.001)	-0.001 (0.001)	-0.002* (0.001)
Constant	232.757*** (31.093)	148.352*** (22.831)	125.309*** (26.592)	183.080*** (23.050)
Adjusted R^2	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 A6: National Ricardian models 23-24

	Forest Net Return	
Mean temp	-5.738*** (1.067)	-5.357*** (1.064)
Mean temp squared	0.113** (0.051)	0.124** (0.050)
Precip	-0.111*** (0.015)	-0.111*** (0.015)
Precip squared	0.00004*** (0.00000)	0.00004*** (0.00000)
Share of forest in LCC 1-2	36.244*** (5.060)	
Share of forest in LCC 3-4	22.622*** (4.571)	
Share of forest in LCC 5-6	16.985*** (5.037)	
Share of forest in LCC 1-4		23.122*** (3.253)
Mean temp : precip	0.006*** (0.001)	0.006*** (0.001)
Constant	59.872*** (9.745)	64.693*** (9.665)
Adjusted R^2	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)
Note:		*p<0.1;* ***p<0.05;*** p<0.01

Ricardian Value Function: Composite of all Species

	Forest Net Return	
Max temp	-10.686*** (2.113)	-11.456*** (2.086)
Max temp squared	0.174*** (0.066)	0.191*** (0.065)
Min temp	0.860 (0.969)	1.492 (0.957)
Min temp squared	-0.086* (0.046)	-0.088* (0.046)
Precip	-0.209*** (0.026)	-0.214*** (0.026)
Precip squared	0.00003*** (0.00000)	0.00004*** (0.00000)
Share of forest in LCC 1-2	46.284*** (5.512)	
Share of forest in LCC 3-4	28.834*** (4.878)	
Share of forest in LCC 5-6	16.393*** (5.050)	
Share of forest in LCC 1-4		29.839*** (3.663)
Max temp : precip	0.009*** (0.001)	0.009*** (0.001)
Min temp : precip	-0.002* (0.001)	-0.002** (0.001)
Constant	147.570*** (23.692)	165.498*** (23.068)
Adjusted R^2	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)
Note:		*p<0.1;* ***p<0.05;*** p<0.01

State	Source
Alabama	Timber Mart-South (Website)
Arizona	U.S. Forest Service Southwestern Region (Website)
Arkansas	Timber Mart-South (Website)
California	California State Board of Equalization (Website)
Colorado	U.S. Forest Service Rocky Mountain Region (Website)
Connecticut	University of Massachusetts Extension (Website)
Delaware	University of Maryland Extension (Website)
Florida	Timber Mart-South (Website)
Georgia	Timber Mart-South (Website)
Idaho	Idaho Department of Lands (Website)
Illinois	University of Illinois Extension (Website)
Indiana	Purdue Extension (Website)
Iowa	No Data
Kansas	No Data
Kentucky	Kentucky Division of Forestry (Website)
Louisiana	Louisiana Department of Agriculture & Forestry (Website)
Maine	Maine Forest Service (Website)
Maryland	University of Maryland Extension (Website)
Massachusetts	University of Massachusetts Extension (Website)
Michigan	Michigan Department of Natural Resources (Website)
Minnesota	Minnesota Department of Natural Resources (Website)
Mississippi	Mississippi State University Extension (Website)
Missouri	Missouri Department of Conservation (Website
Montana	U.S. Forest Service Northern Region (Website)
Nebraska	Nebraska Forest Service (Website)
Nevada	No Data
New Hampshire	New Hampshire Department of Revenue (Website)
New Jersey	No Data
New Mexico	U.S. Forest Service Southwestern Region (Website)
New York	New York Department of Environmental Conservation (Website)
North Carolina	Timber Mart-South (Website)
North Dakota	No Data
Ohio	Ohio State University Extension (Website)
Oklahoma	Data extrapolated from Texas price data
Oregon	Oregon Department of Forestry (Website)
Pennsylvania	Penn State Extension (Website)
Rhode Island	University of Massachusetts Extension (Website)
South Carolina	Timber Mart-South (Website)
South Dakota	U.S. Forest Service Rocky Mountain Region (Website)
Tennessee	Timber Mart-South (Website)

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