Climate, Adaptation, and the Value of Forestland: A National Ricardian Analysis of the United States

Christopher Mihiar *Research Economist, U.S. Department of Agriculture Forest Service Southern Research Station, Forest Economics and Policy, Research Triangle Park, North Carolina; Christopher.Mihiar@usda.gov*

David J. Lewis *Professor, Department of Applied Economics, Oregon State University, Corvallis; lewisda@oregonstate.edu*

ABSTRACT *This study estimates an econometric Ricardian model of the effects of climate on forestry using a novel national data set of county-level net economic returns to forestland. Results show that climate change projections to 2050 will increase forest net returns on the middle latitudes of eastern U.S. timberland. We quantify the value of extensive margin adaptation to climate change by separately estimating climate's effect on 11 distinct forest types. We find that approximately 69% of the positive climate change effect on eastern U.S. forestry arises from the value of extensive margin adaptation. Climate change impacts in the western United States are inconclusive.* (JEL Q23, Q51)

1. Introduction

Climate change can generate multiple costs and benefits on society through its effects on forestland. By inducing range shifts in wildlife habitat (Staudinger et al. 2013), a warming climate is widely expected to generate nonmarket costs to biological diversity (IPBES 2019) that is especially high in forests (Pimm et al. 2014). Climate change can also generate social costs and benefits that operate through the market production of timber. Optimization studies of timber markets find that climate change can generate benefits to the global forestry sector by increasing tree growth productivity (Sohngen and Mendelsohn 1998; Lee and Lyon 2004; Sohngen and Tian 2016), where adaptation by timber management is a key component of the expected benefits on the timber sector (Massetti and Mendelsohn 2018). Because climate change can create an economic value of adaptation by altering the optimal choice of planted tree species (Guo and Costello 2013), the effect of a changing climate on timber market activity and management incentives can alter the flow and resulting nonmarket values associated with ecosystem services that change with forest composition (Hashida and Lewis 2019). Therefore, analyzing climate change effects on the market returns to forestry provide a foundation for understanding management incentives and the many costs and benefits that arise from effects on the market and the nonmarket ecosystem services that flow from forests. Importantly, there are no large-scale empirical economic assessments of climate change effects on the market returns to the forestry sector (Aufhammer 2018).

This article develops the first large-scale Ricardian econometric analysis that estimates the effects of climate on a measure of annualized net economic returns to forestry across the coterminous United States. The Ricardian method has been developed and widely applied to estimate the effects of climate on agricultural land values using cross-sectional data (e.g., Mendelsohn, Nordhaus, and Shaw 1994; Schlenker, Hanemann, and Fisher 2005). By empirically relating a region's climate to the land values that arise from private land-use decisions, the key advantage of Ricardian analyses is that they implicitly account for privately optimal adaptation to climate. The foundation of our analysis is a novel county-level database of annualized net returns to forestry for the coterminous 48 states that we compiled and estimated from numerous data sources. Unlike U.S. agriculture, there is no readily

Land Economics • November 2021 • 97 (4): 911–932
doi:10.3368/le.97.4.011620-0004R1
ISSN 0023-7639; E-ISSN 1543-8325

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 establishment cost estimates developed by Nielsen, Plantinga, and Alig (2014). Finally, we develop and estimate highly localized timber growth equations by exploiting a large data set comprised of 32 million individual tree observations from the U.S. Forest Service's Forest Inventory and Analysis (FIA) data spanning the coterminous United States. Our database includes approximately 42,500 separately estimated timber growth equations that generate timber yields, which vary by county, species group, and forest type group. Forest type groups are defined by the U.S. Forest Service and are combinations of individual tree species groups that typically grow together. The fine-scale variation in estimated timber growth equations embed all localized climatic factors, such as direct productivity effects and landowners' intensive margin adaptation decisions from managing particular tree species. A final average annualized net return to forestry measure is constructed for each county, where net returns are weighted by each county's observed share of timber volume in different forest type groups. Weighting by observed forest type shares in a county builds a net return to forestry measure that implicitly accounts for how landowners have adapted to their current climate through their observed choices of which tree species to plant.[1]

Our application of the Ricardian approach to forestry uses cross-sectional variation to estimate composite Ricardian functions for the 1,624 eastern and 241 western U.S. counties that have private timberland and observable prices. The composite Ricardian functions include average measures of the county-level net returns to forestry as the dependent variable. We regress average county net returns to forestry on multiple downscaled climate variables as well as controls for soil quality on forestland and regional fixed effects. We provide explicit tests for interactions between temperature and precipitation variables, and we explore robustness to alternative specifications of temperature and precipitation as annual or seasonal measures. The estimated composite Ricardian models are used to examine the effects of down-scaled climate change predictions on the spatial distribution of timberland values across eastern and western U.S. counties. Our results find robust positive and statistically significant effects of climate change on 71.4% of eastern forest timberland that lies roughly in the middle latitudes of the eastern United States (approximately 325 million acres of land). Results are either insignificant or inconclusive as to whether climate change would raise or lower net returns to forestry in the northern, western, and far southern United States.

This study presents a large-scale empirical estimation of the effects of climate on net returns to forestry using a national database. Prior economic studies that find beneficial climate change effects on forestry are derived with intertemporal market optimization models based on calibrated tree growth productivity and dieback from climate change, combined with a set of imposed assumptions regarding the demand for timber (e.g., Sohngen and Mendelsohn 1998; Lee and Lyon 2004; Sohngen and Tian 2016; Favero, Mendelsohn, and Sohngen 2018). The optimization is based on an assumed time path of climate change and generates a dynamically consistent time path of optimal management adaptations to a changing climate. There is also a rich set of natural science studies that examine climate-induced shifts in the geographic range of tree species (e.g., Iverson et al. 2008), and empirical studies of forest productivity that find heterogeneous effects of climate change on the biological growth and productivity of alternative species of trees (Latta et al. 2010; Huang et al. 2011; Rehfeldt et al. 2014; Restaino, Peterson, and Littell 2016). Finally, other studies have coupled biophysical simulations of tree species range shifts with numerical calculations of land values, finding net costs from climate

[1] E.g., 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).

change on the European forestry sector (Hanewinkel et al. 2013). In contrast to these prior studies, our empirical approach builds off climate econometrics methods that have been widely applied to sectors outside of forestry (e.g., Schlenker and Robert 2009; Hsiang, Burke, and Miguel 2013; Albouy et al. 2016; Hsiang 2016; Dundas and von Haefen 2020) and is differentiated from numerical economic optimization and simulation analyses of forestry by using statistical theory to test hypotheses about the significance and heterogeneity of climate effects on forestry. Our approach is differentiated from natural science studies by quantifying climate effects on an economic measure of forestland values and accounting for adaptation.

We develop an approach to estimating the share of the composite Ricardian climate change effects that arise from extensive margin adaptation across different forest types. In addition to accounting for productivity effects of climate change on tree growth, climate change effects estimated from the composite Ricardian model implicitly account for adaptation by landowners under an assumption of costless extensive margin adaptation across alternative forest types (e.g., converting an oak-hickory forest to a loblolly pine forest). However, one cost of extensive margin adaptation in the forestry sector is forgoing future growth of existing stands with premature harvest, which implies that adaptation will be slowed by replanting decisions that occur once over multiple-decade harvest rotation cycles (Hashida and Lewis 2019). We explore the extent to which an assumption of costless extensive margin adaptations are likely driving the composite Ricardian model results by separately estimating Ricardian functions for the 11 major forest type groups in the eastern United States, and computing a climate change effect that assumes no extensive margin adaptation across forest types. By using observed growing stock data, each forest type–specific Ricardian function implicitly accounts for adaptation along the intensive margin (e.g., rotation length, site preparation, seeding strategies). By combining separately estimated Ricardian functions across forest types, we can examine whether the projected changes from the composite eastern Ricardian model could be explained by intensive margin changes in each forest type or whether extensive margin changes across forest types are needed to explain the composite model's climate change effects. We find strong evidence of significant adaptation value along the extensive margin, where approximately 69% of the estimated positive and significant effects of climate change on net returns in the eastern United States arise from the value of adaptation on the extensive margin. Much of the value of adaptation likely arises from the potential of commercially valuable southern yellow pine species to move northward and westward through planting. Therefore, the incentives for extensive margin adaptations in forestry are high in the middle latitudes of the eastern United States.

Finally, our analysis contributes to broad inquiries into society's many climate adaptation possibilities. Whereas management decisions and adaptation to climate in the timber industry are driven by landowners' incentive to maximize private economic returns, such decisions have consequences for ecosystem services with public goods characteristics (Hashida et al. 2020). For example, the distribution of tree species directly affects the habitat suitability for numerous wildlife species that are specialized to certain forest types (Wilcove et al. 1998), and our finding of incentives to increase plantations of southern pine species could have strong negative consequences for biodiversity (Haskell, Evans, and Pelkey 2006). In addition, the aggregate stock of land devoted to timber and agriculture is affected by the relative net returns to both substitute land uses, which affects the provision of a number of nonmarket ecosystem services (Lubowski, Plantinga, and Stavins 2006; Lawler et al. 2014). Understanding the linkages between forest management, climate change, and natural systems is vital for understanding the social costs of climate change and designing optimal land conservation policy in response to climate change (Lewis and Polasky 2018).

2. Theoretical Framework

We formalize the concept of adaptation in forestry and develop the intuition behind our empirical strategy that uses a series of cross-sectional regressions of the net economic returns to forestry on measures of climate and land quality. The U.S. Forest Service classifies forests into forest type groups (F), where each group is composed of multiple species groups (s). For example, the loblolly/shortleaf pine forest type group can include pine species from multiple species groups, such as loblolly, shortleaf, Virginia, and more. We adopt the U.S. Forest Service classification system for our analysis.

Net Returns to Forestry

Rotational forestry consists of periodic harvests with subsequent replanting. The landowner only earns profit at harvest, and the landowner's value function can be written in dynamic programming form as follows (Guo and Costello 2013):

$$V_t(a,F,C_t) = \max\begin{cases} P(F,t)\cdot vol^F(a,C_t) - R + \rho V_{t+1}(1,F_1,C_{t+1}) \\ P(F,t)\cdot vol^F(a,C_t) - R + \rho V_{t+1}(1,F_2,C_{t+1}) \\ \quad\quad . \\ \quad\quad . \\ P(F,t)\cdot vol^F(a,C_t) - R + \rho V_{t+1}(1,F_S,C_{t+1}) \\ \quad\quad \rho V_{t+1}(a+1,F,C_{t+1}) \end{cases}, \quad [1]$$

where $P(F,t)$ is the stumpage price of forest type F at time t, $vol^F\,(a,C_t)$ is the forest type F timber volume of age a trees growing in climate conditions C_t, R is a replanting cost, and ρ is a discount factor. Because tree volume is a function of the weather outcomes that have occurred since the tree was planted, the climate variable C_t represents a long-term average of weather conditions that occurred in the years up to t. At each point in time t, the landowner chooses whether to harvest and earn a one-time profit of $P(F,t)\cdot vol^F\,(a,C_t)–R$, with subsequent replanting optimized over the choice of which forest type F_j to plant. If the landowner chooses not to harvest, their trees grow by $vol^F\,(a+1,C_{t+1})–vol^F\,(a,C_t)$ over the next period. Indexing the climate conditions variable by t accounts for the fact that climate may change over time. Guo and Costello (2013) use numerical methods to show how climate change can be introduced into the forestry land value function in equation [1] when the timber volume functions for alternative tree species are a function of climate, so the landowners' optimal replanting choice and harvest time depends on landowners' expectations of climate change.

Land values are commonly written as the present value of the future stream of annualized net returns to land (rents) (e.g., Capozza and Helsely 1989). As such, we write the land value function for forestry as

$$V_t(a,F,C_t) = \sum\nolimits_{t=0}^{\infty} \rho^t NR_t(a,F,C_t), \quad [2]$$

where ρ is a discount factor and $NR_t(a,F,C_t)$ is the annualized net return to land in time t. The term $NR_t(a,F,C_t)$ is equivalent to the concept of cash rents for crops, which is used in agricultural economics (e.g., Ortiz-Bobea 2020). For land that is used for timber, current period (t = 0) annualized net returns to land $NR_0(a,F,C_0)$ reflect prices and timber productivity of the land's forest type from the current period only. In contrast, future annualized net returns to land $NR_t(a,F,C_t)$ for $t > 0$ depend on a set of expectations that the landowner has about future prices, climate change, and the effect that climate change might have on the timber yield functions for each forest type, $vol^F\,(a,C_t)$. In addition, if the landowner expects to convert their land to another use in the future—such as urban development—then future net returns could reflect factors that affect rents to other land uses. Because landowner expectations about the future are unknown to the researcher, we attempt to learn about the link between climate C_t and the value of forestland V_t by examining a measure of current period net returns to bare (a = 0) forest land:

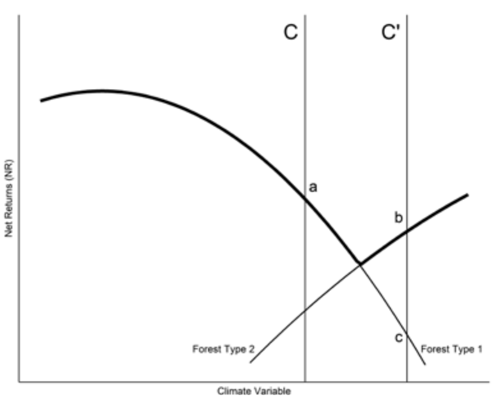
$$NR_0 = g(C_0, x; \boldsymbol{\beta}, \boldsymbol{\gamma}), \quad [3]$$

where x represents a set of nonclimate variables (e.g., soils) affecting forest returns, $g()$ is a function that relates climate and nonclimate variables to NR_0, $\boldsymbol{\beta}$ is a parameter vector that links C_0 to NR_0, and $\boldsymbol{\gamma}$ is a parameter vector that links x to NR_0. We build our empirical approach off estimating the function in equation [3] as a way to use observable information—for example, current timber returns and current climate—and recognize that we do not observe other information needed to estimate $V_t(a,F,C_t)$ (e.g., landowner expectations about future climate change effects on forestry). Our premise is that estimating the functional link between current climate and current forest returns, represented by $\boldsymbol{\beta}$, provides useful information on the link between future climate and forest returns. Thus, our approach is consistent with the findings of Ortiz-Bobea's (2020) agricultural Ricardian analysis, which found that basing estimation on current rental values rather than capitalized land values (asset prices) avoids biases from the presence of numerous unobserved factors (like expectations) that affect land values but not rental values.

Ricardian Theory

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 Figure 1 includes a measure of current net returns (*NR*), and the *x*-axis is a climate variable such as temperature. Since *NR* is defined from the optimized land value function in equation [2], the curve labeled "Forest Type 1" presents net returns reflecting the fact that small changes in climate will induce the landowner to make small decisions continuously to maximize the return to having the land planted in Forest Type 1. We refer to these continuous management decisions as acting on the intensive margin. As indicated

Figure 1
Ricardian Value Function



in equation [1], altering the rotation age is a prominent example of an intensive margin decision in forest management. Other intensive margin actions in forestry include thinning out the parcel to encourage growth, spraying herbicides, or treating to reduce fire risk, all while continuing to keep the land planted in Forest Type 1.

In addition to small continuous adaptations, there is a set of discrete management choices that can be characterized by a threshold that defines the extensive margin. As denoted in the solution to equation [1], an important extensive margin choice in forestry is the decision to switch the type of trees growing from Forest Type 1 to Forest Type 2 in Figure 1 (Guo and Costello 2013). For example, if climate in Figure 1 begins at *C* and changes to *C'*, then the landowner solving equation [1] switches their forest from Forest Type 1 (with an optimal net return at point *a*) to Forest Type 2 (with an optimal net return found at point *b*). If they had remained in Forest Type 1 with new climate *C'*, then their net return would have been found at point *c*. The value of extensive margin adaptation in Figure 1 is the difference between the net returns at point *b* and the net returns at point *c* and is contingent on the level of climate (Guo and Costello 2013). A critical insight from Mendelsohn, Nordhaus, and Shaw (1994) was that regressing cross-sectional observations of net returns to land on climate would implicitly capture all continuous and discrete adaptations landowners have made to their current climate by tracing a function akin to the upper envelope of net return curves in Figure 1. For example, the Ricardian model generates an estimate of $\boldsymbol{\beta}$ that captures the effect of the discrete change in climate from *C* to *C'* in Figure 1 as the difference in net returns from point *a* to point *b*.

A cross-sectional regression of current forestry net returns (*NR*) on climate (*C*) can be used to estimate a variant of equation [3] and obtain parameter vectors $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$:

$$NR_i = \boldsymbol{\beta} f(C_i) + \boldsymbol{\gamma}\mathbf{x}_i + \varepsilon_i, \qquad [4]$$

where $f(C_i)$ is a linear-in-parameters function of climate in county i, $\mathbf{x}_i$ is a vector of nonclimatic independent variables such as soil quality, and ε_i captures unobservable drivers of NR_i. Because most counties' forestland base includes multiple types of forest species, NR_i is a weighted average of forest net returns across all forest types F and in county i: $NR_i = \sum_{F=1}^{F_i} NR_i^F \cdot share_i^F$, where $share_i^F$ is the observed share of county's forestland growing forest type F. Because $share_i^F$ captures all past forest management choices, it necessarily captures past extensive margin adaptations to the region's climate and local timber market conditions. Therefore, estimating $\boldsymbol{\beta}$ from equation [4] captures both intensive margin and extensive margin adaptations to climate.

Extensive margin adaptation in forestry may be sluggish and occur gradually. Our data indicates that forests are infrequently disturbed in a manner that would allow adaptation on the extensive margin. For example, the observed timber rotation time is approximately 15 to 100 years across the United States and varies by region and forest type. In an empirically based simulation of extensive margin adaptation along the U.S. West Coast, Hashida and Lewis (2019) find that the average probability of replanting an already-harvested plot as Douglas fir in Oregon goes from 50% under the current climate to only 25% under the climate change expected by 2090. However, due to the infrequent harvest rotation length (~50 years for Douglas fir) and gradually changing climate, the probability of observing a plot of Douglas fir at any age is a much higher 41% by 2090. Given the temporal barriers to extensive margin adaptation in forestry, interpreting estimates of $\boldsymbol{\beta}$ as an estimate of the effects of climate on net returns to forestry may arguably be too optimistic. We approach this problem by estimating the effects of climate on net returns to forestry in a model where NR_i^F is measured as the net returns to forest type F:

$$NR_i^F = \boldsymbol{\beta}^{\mathbf{F}} f(C_i^F) + \boldsymbol{\gamma}^{\mathbf{F}} \mathbf{x}_{\mathrm{i}} + \epsilon_i^F . \quad [5]$$

By using cross-sectional variation in NR_i^F across counties i for the same forest type F, estimates of $\boldsymbol{\beta}^{\mathbf{F}}$ capture only intensive margin adaptations made in forest type F (e.g., rotation age for F). Combining estimates of $\boldsymbol{\beta}^{\mathbf{F}}$ for all F with the currently observed landscape shares in each forest type ($share_i^F$) provides a lower bound estimate of climate change effects on forestry under an assumption that landowners can adapt on the intensive margin but no extensive margin adaptation occurs. In contrast, estimating $\boldsymbol{\beta}$ from equation [4] provides an upper bound estimate of climate change effects on forestry that assumes landowners can freely undertake extensive margin adaptation with no constraints. For example, in Figure 1, $\boldsymbol{\beta}^{\mathbf{F}} = c - a$ while $\boldsymbol{\beta} = b - a$.

Our approach builds on insights from an existing literature estimating agricultural-climate Ricardian models throughout the world, which is 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 that identify climate change effects from weather deviations (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 (15–100-year rotations) than those in agriculture. The panel solutions advanced in the agricultural-climate literature do not apply to a forestry model because the variation of year-to-year weather shocks on timber growth is averaged out by the broader climate over the multidecade period. Another potential omitted variable correlated with climate is development pressure (Albouy et al. 2016), which would be capitalized in market prices for forestland. Rather than using land prices for timberland, we follow Ortiz-Bobea (2020) and use a "cash rent" concept that is affected by current use productivity rather than anticipated future development values. In particular, we construct net returns measures directly from stumpage price and estimated tree growth equations, and thus our measure of forestland value is not affected by local development pressures.

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 coterminous United States, which constitutes the primary dependent variable in the forestland Ricardian functions estimated below. Classical forest economics argues that forest land values depend on timber growth, stumpage price, replanting costs, a discount rate, and the rotation period with which harvest occurs (Faustmann 1849). Our aim is to construct a measure of the current annual profitability of U.S. timberland at the county level as developed in equation [3]. Our measure combines current stumpage prices, replanting costs, timber-yield functions (estimated from observable data on tree volume and corresponding tree age from private land), and observed state-level timber removal ages for different forest types.

Stumpage Price and Replanting Cost Data

Analysis of forestry returns at the national level has been limited by the lack of a centralized data source for stumpage prices, P. We compile a unique national stumpage price data set for 1997–2014 from numerous sources including state-level departments of natural resources, university extension services, the U.S. Forest Service, and private reporting services (see Appendix Table A1). All stumpage prices are georeferenced to the county level, and the reported species are mapped to species groups defined by the U.S. Forest Service. Missing years for each county-species pair are interpolated linearly using the observed values. We approximate R from equation [1] with forest establishment costs estimated by Nielsen, Plantinga, and Alig (2014) for each county in the coterminous United States based on enrollment data from the USDA's National Conservation Reserve Program.

Yield Functions for Tree Growth

Past natural science literature has shown examples of how climate affects the tree growth functions for selected species and regions (e.g., Latta et al. 2010; Rehfeldt et al. 2014). Given the substantial climate variability across the United States, we require tree growth functions that differ across fine spatial scales to capture fine-scale climate differences. Using data from FIA plots comprising nearly 32 million individual tree observations of growing stock volume along with the average stand age for the plot where each tree is located, we estimate approximately 42,500 county-species specific timber growth equations at the species group level using a permutation of von Bertalanffy's function for organic growth (von Bertalanffy 1938):

$$vol_i^s(a) = \alpha_{is}(1 - e^{-\beta_{is}a})^3, \qquad [6]$$

where $vol_i^s(a)$ is the growing stock volume in cubic feet of an individual tree in county i belonging to forest species group s at average stand age a. We estimate α_{is} and β_{is} using nonlinear least squares with the Broyden-Fletcher-Goldfarb-Shanno (BFGS) quasi-Newton computational method to minimize the sum of squared deviations of equation [6].[2] Equation [6] is estimated using the average stand age in years for the plot where individual trees are located. 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 (2010) use von Bertalanffy functions to estimate growth for measuring carbon characteristics on U.S. forestland. Since equation [6] is estimated from observed data in recent years, $vol_i^s(a)$ implicitly embeds the current climate at location i. Appendix Figure A1 illustrates how two estimated von Bertalanffy growth functions for Douglas fir in two distinct Oregon counties embed differences in temperature and precipitation. Our estimated timber growth data covers 47 forest species groups

[2] We estimate equation [6] only if (1) we have at least 30 observations of s in i, (2) the function converges, and (3) the estimated $\beta_{is} \leq 0.25$ for a reasonable growth path. If any of these criteria fail, we use estimates of equation [6] at the state level rather than the county level.

that combine to form 109 different forest type groups. When averaged across all county-species equations across the United States, we obtained estimated values for α and β of 28.76 and 0.0498, respectively.

An Annualized Net Returns to Forestry Measure for One Rotation

With an available price P_{is}, a per acre replanting cost R_i, and estimated volume functions $vol_i^s(a)$ for each county (i)–species (s) pair, we require a timber removal age (i.e., rotation length) to determine a one-rotation forestry profit. We focus on one rotation to get a good measure of current profitability of timberland, and we use empirical removal ages derived from FIA plots that recorded timber harvesting activities. In particular, we use the state average stand age of all recent timber removals recorded in the FIA's condition table by species group s to proxy for rotation length T_{is}, and then calculate the present value of a one-rotation profit from harvesting $vol_i^s(T_{is})$ in T_{is} years:

$$[\overline{P_{is}} \cdot vol_i^s(T_{is}) \cdot TA_{is} - R_i]\rho^{T_{is}} = PVProfit_{is}, \quad [7]$$

where $\overline{P_{is}}$ is the average stumpage price for forest species group s in county i over the period 1998–2014, $vol_i^s(T_{is})$ is the estimated von Bertalanffy volume of timber for an individual tree of species s evaluated at age $a = T_{is}$, TA_{is} measures trees per acre of species group s in county i, and R_i and ρ are replanting cost and discount factors as defined previously. Our measure of annualized net returns per acre is the annual payment NR_i^s, in which a landowner would be indifferent to receiving $PVProfit_{is}$ today or a series of annual payments NR_i^s for T_{is} years:

$$NR_i^s \sum_{t=1}^{T_{is}} \rho^t = PVProfit_{is}. \quad [8]$$

The final step is to translate per acre net returns for each species group to a forest type (F) average for the county and to a composite average for each county's total forestland base. We construct county average net returns through two species group-weighted averages:

$$NR_i = \sum_{s=1}^{S_i} NR_i^s \cdot share_i^s \quad [9]$$

$$NR_i^F = \sum_{s=1}^{S_i} NR_i^s \cdot share_{i,F}^s, \quad [10]$$

where NR_i is the composite average net return to forestry for county i, $share_i^s$ is the share of county i's growing stock volume of timber in forest species s, and S_i is the total number of observed species groups in county i. In equation [10], we construct a measure of net returns for each forest type group F in county i, which is a weighted average where $share_{i,F}^s$ represents the volume share of county i's land in forest type F that is composed of species group s. Our approach differs from Lubowski, Plantinga, and Stavins's (2006) construction of a similar measure of NR_i in that (1) our volume functions were disaggregated by county i and forest types F, as opposed to aggregated functions over broad regions; and (2) we use observed state-average removal ages T_{is} rather than solving a Faustmann formula. Our final measure of NR_i is comparable across counties and interpreted as the current average annual net return to forestry for an acre of bare forestland as defined in equation [3]. Table 1 presents descriptive measures of the mean of the composite and forest-type-specific net returns. The standard deviation of annual precipitation in the western United States is more than double the standard deviation in the east. Furthermore, eastern U.S. annual precipitation ranges from 450 mm to 1,900 mm, while annual precipitation in the west has a much bigger range, from 298 mm to 3,114 mm.

We contend that the measure of NR_i in equation [9] reflects current period net returns to forestry as developed in equation [3] and is not influenced by unknown future expectations of climate change. Equation [9] assumes that landowners have chosen forest types on their land (reflected in $share_i^s$) to adapt to the current climate rather than future climate change projections. However, if forest landowners are forward-looking and anticipate future climate change forecasts, they may already be growing forest types that would perform better under future climates than the current climate, which means that regressing NR_i on current climate would be biased (Severen, Costello, and Deschenes 2018). If the observed county

Table 1
Ricardian Estimation Data Summary

	Number of Counties	Mean Net Return per Acre ($/acre) (St. Dev.)	Mean Temperature (°C) (St. Dev.)	Range of Temperature (°C)	Annual Precipitation (mm) (St. Dev.)	Range of Precipitation (mm)	Mean Percentage of County Land in Best Soil Quality Class
All forest types	1,865	30.45 (24.27)	12.86 (4.81)	(0.78, 24.33)	1,148.67 (315.80)	(298, 3,114)	59.8
Eastern forest types	1,624	29.90 (23.13)	13.76 (4.36)	(3.30, 24.33)	1,186.52 (222.01)	(452, 1,900)	64.2
Western forest types	241	35.28 (28.08)	6.79 (2.87)	(0.78, 17.54)	893.59 (605.15)	(298, 3,114)	30.4
White-red-jack pine	371	16.76 (25.12)	8.59 (2.94)	(3.30, 15.78)	1,083.57 (230.47)	(587, 1,900)	49.7
Spruce fir	151	22.35 (15.66)	5.97 (1.26)	(3.30, 8.75)	951.29 (209.66)	(603, 1,432)	49.4
Longleaf-slash pine	328	82.11 (35.39)	18.84 (1.71)	(15.20, 24.33)	1,325.81 (145.20)	(1,095, 1,735)	68.3
Loblolly-shortleaf pine	878	113.69 (53.56)	16.38 (2.63)	(6.13, 23.44)	1,295.35 (148.89)	(934, 1,765)	63.2
Oak-pine	1,207	33.62 (23.37)	14.47 (4.34)	(3.30, 23.86)	1,234.59 (194.47)	(556, 1,900)	60.3
Oak-hickory	1,531	14.91 (11.79)	13.85 (4.31)	(3.39, 23.86)	1,201.28 (203.13)	(556, 1,900)	64.0
Oak-gum-cypress	825	16.04 (18.19)	16.92 (2.56)	(7.52, 23.86)	1,303.52 (145.70)	(830, 1,735)	67.8
Elm-ash-cottonwood	1,349	27.58 (24.67)	13.39 (4.46)	(2.83, 23.86)	1,167.72 (249.01)	(327, 2,876)	65.0
Maple-beech-birch	703	11.36 (21.51)	9.93 (2.98)	(3.30, 16.46)	1,060.93 (204.38)	(459, 1,678)	61.1
Aspen-birch	338	16.22 (16.38)	6.43 (2.06)	(1.33, 11.83)	892.42 (232.05)	(384, 1,330)	47.8
Eastern red cedar	235	34.46 (31.90)	6.43 (2.83)	(5.48, 22.79)	1,228.50 (159.09)	(589, 1,556)	60.6
Douglas fir	141	48.51 (32.97)	14.75 (2.67)	(1.61, 14.11)	1,064.84 (701.18)	(298, 3,114)	32.4
Hemlock-Sitka spruce	42	46.06 (40.60)	7.95 (1.93)	(3.92, 11.33)	1,669.93 (758.67)	(528, 3,114)	39.9
Ponderosa pine	139	21.50 (15.84)	7.01 (2.40)	(2.62, 14.21)	701.90 (300.83)	(358, 1,974)	28.5
Lodgepole pine	72	23.12 (22.35)	4.81 (1.97)	(0.78, 9.67)	766.51 (280.93)	(463, 2,566)	27.8
Fir-spruce-mountain hemlock	119	12.93 (23.18)	5.76 (2.20)	(0.78, 10.86)	812.38 (424.80)	(400, 2,876)	29.1
Other western softwoods	26	3.63 (5.54)	5.74 (2.42)	(1.72, 10.60)	647.81 (224.42)	(408, 1,455)	22.4

forest type shares are influenced by climate change forecasts, there should be evidence of significant recent switching of forest types by landowners.

To examine whether there has been recent switching of forest types, we compute the percentage of FIA plots where the landowner has switched the growing forest type between loblolly pine and some other forest type in the eastern United States, and between Douglas fir and some other forest type in the western United States. We focus on loblolly pine and Douglas fir because those are the two most common forest types planted using what the U.S. Forest Service calls "artificial regeneration." If there has already been significant climate change adaptation involving switching forest types, it would most likely occur in these heavily managed species. Using repeated measurements of the same FIA plots after 2001, we find that of the 44,154 loblolly pine plots that were most recently measured in the eastern United States, only 262 (82) transitioned into (out of) loblolly pine from (to) another forest type through artificial regeneration. In the western United States, we find that of the 11,088 Douglas fir plots on private land that were most recently measured, only 8 (52) transitioned into (out of) Douglas fir from (to) another forest type through artificial regeneration. Because well under 1% of the current stock of the most commonly planted trees have recently transitioned between other forest types through planting, we find little evidence that the current landscape is largely affected by landowners preemptively altering their forests in anticipation of future climate change. Thus, regressing NR_i on current climate measures while omitting climate forecasts is appropriate.

Climate Data

Measures of historically observed temperature and precipitation were obtained from Oregon State University's PRISM downscaled climate data (Daly 2006) at an 800 m spatial resolution. Because we are interested in the effect of climate on forestland value, we use the long-term average ("normal") of each location's weather variable to represent a location's climate. Climate is defined as the average annual temperature and precipitation for the period 1981–2010 measured in degrees Celsius and millimeters (mm), respectively.

Predictions of future climate at 4 km spatial resolution are obtained from the University of Idaho, MACA Statistically Downscaled Climate Data for CMIP5 (Abatzoglou 2013). The results and analysis below are based on predictions from the ensemble mean of 20 global climate models under emissions scenario RCP 8.5. Average change in temperature and precipitation is defined as the difference between the baseline period (1975–2005) and the future period (2020–2050). Following Burke et al.'s (2015) suggestion to incorporate uncertainty in climate change model predictions, we estimate changes in U.S. forestland returns across 20 alternative global circulation models under RCP 8.5. We present climate change effect results across all available GCMs (Appendix Figure A3), and show that although the effect distributions vary, the overall result is robust to choice of GCM. Therefore, we settle on the ensemble mean climate change for our main analysis.

We derive county-level climate on forestland by using the forest-weighted average of grid observations within a county. Timberland area weights are recovered from spatially explicit forest cover found in the FIA database (Nelson and Vissage 2007). Climate observations that occur outside of the observed forest cover are dropped, and the remaining observations (those in forested areas) are averaged in a county. All climate data are processed initially at the monthly scale allowing construction of annual and seasonal climate measures. We define four seasons (winter, spring, summer, and fall) where each is composed of the mean (sum) over the relevant three-month period for temperature (precipitation).

4. Econometric Specifications: Composite and Forest-Type Models

Western U.S. forests generally occur at higher elevations and in a drier climate (especially in the growing season) than eastern U.S. forests, which has led to minimal overlap in current forest types across the eastern and western United States. Therefore, we estimate a composite Ricardian model for the eastern United States and a separate one for the western United States.[3] This approach intentionally precludes adapting to climate change in the western United States by planting eastern U.S. forest types (e.g., loblolly pine). We also estimate a single nationally estimated Ricardian for interested readers (see Appendix Table A2), although we find the separate eastern and western models more reasonable for assessing climate effects. The composite Ricardian models are defined by using the county average net returns to forestry for county i, NR_i, as the dependent variable. The econometric function is

$$\text{Composite Ricardian Function:}\\ NR_i = \alpha + \boldsymbol{\beta} f\left(Temp_i, PPT_i\right) + \boldsymbol{\gamma} soil_i + \boldsymbol{\delta}_r + \varepsilon_i, \quad [11]$$

where $f(Temp_i, PPT_i)$ is a polynomial function of 30-year averages of mean annual temperature and precipitation measures, $soil_i$ is the county share of forestland in land capability class 1–4 (i.e., the best soil quality), $\boldsymbol{\delta}_r$ is a vector of regional fixed effects, and ε_i is the model unobservable. The function $f(Temp_i, PPT_i)$ also includes interactions between $Temp_i$ and PPT_i. We estimate parameters $\boldsymbol{\beta}$, $\boldsymbol{\gamma}$, $\boldsymbol{\delta}_r$, and α using ordinary least squares with standard errors clustered by ecoregion. Clustering by ecoregions allows for arbitrary forms of heteroskedasticity and spatial correlation across counties but within each ecoregion. We use a series of F-tests to test for the preferred order for the polynomial function $f()$.We also assess robustness to alternative climate measures by substituting seasonal means of temperature and precipitation in place of $Temp_i$ and PPT_i.

Our identifying assumption is that our climate and soil variables are exogenous. One identification critique concerns our use of state average removal age in computing the dependent variable. If there is significant within-state variation in removal age correlated with climate, this could create some bias in estimating $\boldsymbol{\beta}$ that arises from measurement error. Although our use of forest type–specific removal age helps mitigate this measurement error to some extent, we cannot completely rule it out. The composite Ricardian function is used to generate the following climate change effect:

$$\text{Composite Climate Change Impact} =\\ \Delta NR_i = \hat{\boldsymbol{\beta}} f(Temp_i^C, PPT_i^C) - \hat{\boldsymbol{\beta}} f(Temp_i, PPT_i), \quad [12]$$

where $Temp_i^C$ and PPT_i^C represent projected climate changes in $Temp_i$ and PPT_i, and $\hat{\boldsymbol{\beta}}$ indicates the estimated parameter vector. The composite climate change effect reflects intensive margin adaptation (e.g., changes in rotation length) and extensive margin adaptation (e.g., changes in the forest types replanted).

We also estimate separate forest-type Ricardian functions for the 11 major forest type groups in the eastern United States. A forest type is a mix of individual tree species, such as loblolly-shortleaf pine in the southeast or spruce-fir in the northeast. The forest-type Ricardian functions use the county average net returns to forest type F for county i, NR_i^F as the dependent variable. The econometric function is

$$\text{Forest-Type Ricardian Function:}\\ NR_i^F = \alpha^s + \boldsymbol{\beta}^{\mathbf{F}} f^F(Temp_i, PPT_i) + \boldsymbol{\gamma}^{\mathbf{F}} \mathbf{soil_i} \\ + \boldsymbol{\delta}_r^F + \varepsilon_i^F, \quad [13]$$

where $f^F(Temp_i, PPT_i)$ is specific to forest type F, thereby allowing us to separately test for the appropriate polynomial order for each forest type. We use data specific to each forest type F to separately estimate parameters $\boldsymbol{\beta}^{\mathbf{F}}$, $\boldsymbol{\gamma}^{\mathbf{F}}$, $\boldsymbol{\delta}_r^F$, and α^F. The forest type Ricardian functions are used to generate the following climate change effect for each forest type F:

$$\text{Forest-Type F Climate Change Impact} =\\ \hat{\boldsymbol{\beta}}^{\mathbf{F}} f^F(Temp_i^C, PPT_i^C) - \hat{\boldsymbol{\beta}}^{\mathbf{F}} f^F(Temp_i, PPT_i), \quad [14]$$

where $Temp_i^C$ and PPT_i^C represent climate changes as defined above. As discussed in Section 2, the forest type climate change effect reflects intensive margin adaptation in each forest type (e.g., changes in rotation length), but no extensive margin adaptation

[3]The east is defined using U.S. Forest Service subregions Northeast, North Central, Southeast, and South Central. The west is defined using U.S. Forest Service subregions Rocky Mountain North and South and Pacific Coast North and South.

across forest types. We use the estimated forest type climate change effect to generate an intensive-margin-only climate change effect as follows:

$$\text{Intensive-Margin-Only Climate Change Impact} = \sum_{F=1}^{FT_i} share_i^F[\hat{\boldsymbol{\beta}}^{\mathbf{F}} f^F(Temp_i^C, PPT_i^C) - \hat{\boldsymbol{\beta}}^{\mathbf{F}} f^F(Temp_i, PPT_i)]. \quad [15]$$

The intensive-margin-only climate change effect holds the composition of each county's forest fixed at current levels, where $share_i^F$ is defined as the currently observed share of the county's forestland in forest-type F. Thus, the climate change impact in equation [15] differs from the climate change impact in equation [12] in that extensive margin adaptation across forest types is implicit in equation [12] but not in equation [15]. Since landowners would adapt to climate change on the extensive margin only if it would raise the value of their land, then the composite climate change effect serves as an upper bound climate change effect, while the intensive-margin-only climate change effect serves as a lower bound climate change effect.

We omit explicitly modeling net 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 it 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 effect of fire occurrence on average timber growth that we use in constructing the dependent variable.

5. Results

Composite Forest Ricardian Functions for the Eastern and Western United States

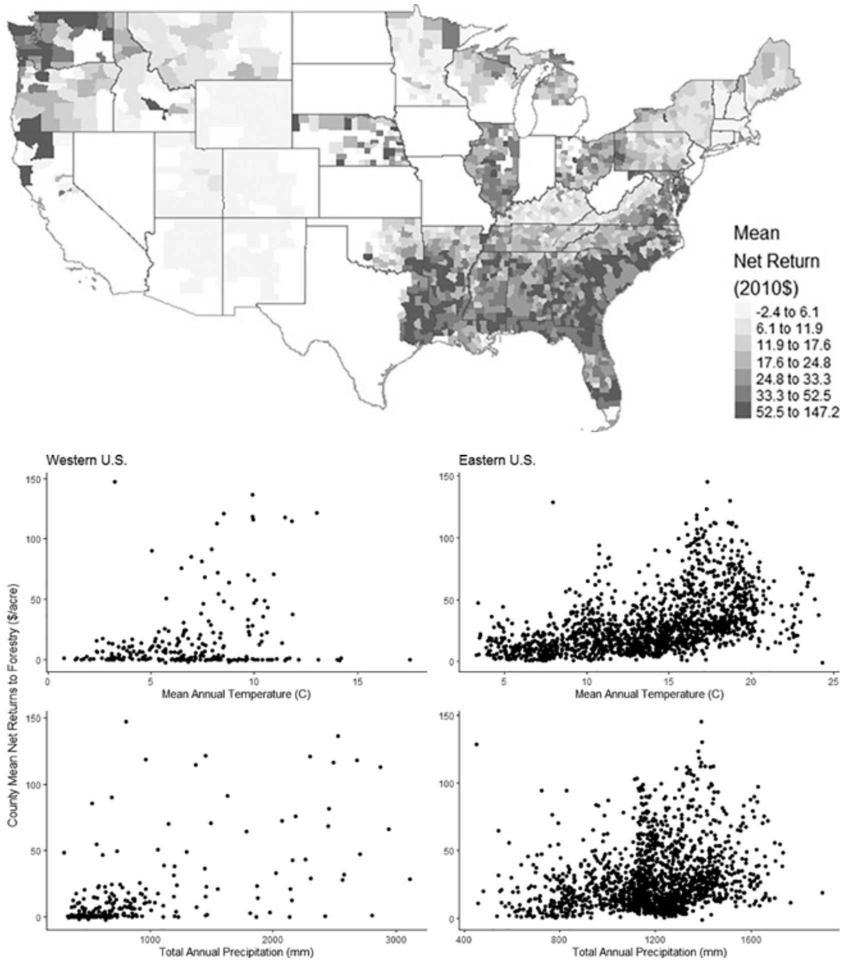
Figure 2 shows the spatial distribution of the dependent variable NR_i and plots its values against $Temp_i$ and PPT_i. This descriptive data indicate that the function *f*() is likely to be nonlinear for both the eastern and western United States. We test alternative polynomial functions of *f*() through a series of *F*-tests and by comparing adjusted *R*-squared across alternative polynomial functions. Results indicate that a fourth-order polynomial for $Temp_i$ and PPT_i is preferred for the eastern United States, while a second-order polynomial for $Temp_i$ and PPT_i is preferred for the western United States.

Parameter estimates from equation [11] are presented in Appendix Table A2. Parameters are estimated by ordinary least squares with regression functions weighted by timberland area in each county. Given the nonlinear polynomial functions estimated in Appendix Table A2, we examine the more intuitive average marginal effect (AME) of $Temp_i$ and PPT_i in the first two columns of Table 2. The AMEs of $Temp_i$ and PPT_i are significantly different from zero (5% level) for the western model, whereas only the AME of $Temp_i$ is significant for the eastern model. The AME for $Temp_i$ is larger in the east than in the western United States, while the AME for PPT_i is much larger (and positive) in the drier western United States.

Figure 3 unpacks the shape of the estimated nonlinear marginal effect (ME) across the range of the data. For the eastern United States, the ME of $Temp_i$ is positive and statistically significant (5% level) for average temperatures between 7°C and 19°C, but turns sharply negative above 21°C. The ME of PPT_i in the east is never statistically significant (5% level). For the western United States, the ME of $Temp_i$ is positive at all temperature levels but not significant (5% level), while the ME of PPT_i is positive and significantly different from zero (5% level) only in the moderate range of current precipitation levels between 760 mm/yr and 1,470 mm/yr.[4] A final way to examine the composite model is to present contour plots of the estimated eastern and western U.S. composite Ricardian models, which indicates that the eastern U.S. Ricardian function is highly nonlinear with a clear optimal range of $Temp_i$ and PPT_i that happens

[4] Approximately one-quarter of western counties are in the range where the ME of precipitation is statistically significant.

Figure 2
Spatial and Numerical Distribution of Composite Net Return to Forestry



to lie over the current climate of the prime loblolly pine–growing region of the southeastern United States (Appendix Figure A2a).

Climate change effects using the composite Ricardian models are calculated using equation [12], where all climate variables are shifted to their projected 2050 levels.[5] We used the Krinsky-Robb method for calculating 95% confidence intervals of the climate change impact for each county.[6] Given our findings about the nonlinear shape of our marginal effect functions, we separate results into counties where there are statistically significant climate change effects (5% level) and counties where there are not statistically significant effects. Table 3 presents mean effects by region from the eastern and western U.S. composite models. For the East, about 71% of the private timberland acreage is projected to see a statistically significant average increase in net returns to forestry of approximately

[5] Although some counties were not included in estimation because of missing price data, we include all counties with forestland in the climate effects analysis given the more complete coverage of climate data.

[6] The Krinsky-Robb method simulates a parameter vector as $\beta_s = \hat{\boldsymbol{\beta}} + C'x_k$, where $\hat{\boldsymbol{\beta}}$ is the estimated parameter vector from the econometric model, C is the K × K Cholesky decomposition of the estimated econometric variance-covariance matrix, and xk is a K-dimensional vector of draws from a standard normal distribution.

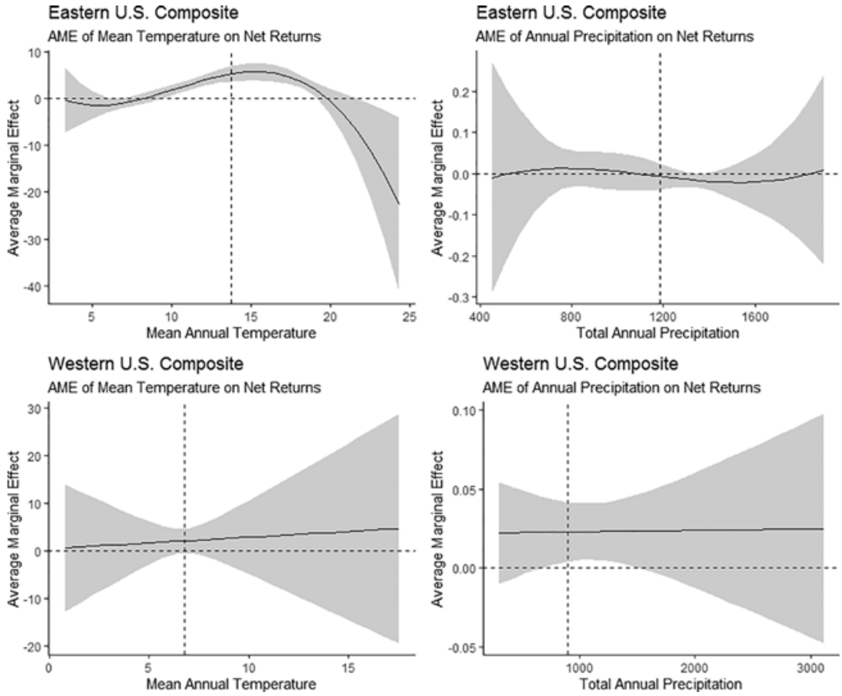
Table 2
Forest Group Type Ricardian Model Result Summary

	Average Marginal Effect of Temp Change (Std. Err.)	Average Marginal Effect of Precip Change (Std. Err.)	Climate Change Impact in $/acre (95% CI)	Percentage of Acres in Significantly Positive Region	Percentage of Acres in Significantly Negative Region	Total Acres (Millions)	Poly-nomial Order (Temp / Precip)	Spatial Fixed Effect
Eastern U.S. Ricardian	3.75*** (0.231)	−0.0007 (0.0049)	5.64 (2.61, 8.66)	71.4	10.6	454.6	4th / 4th	Subregion
Western U.S. Ricardian	2.13* (1.24)	0.023*** (0.0089)	3.53 (−7.45, 14.50)	12.1	0	32.1	2nd / 2nd	None
White-red-jack pine	4.34*** (0.808)	−0.0548*** (0.0112)	5.57 (1.18, 9.96)	70.4	0	7.8	2nd / 2nd	None
Spruce-fir	−2.35** (1.128)	0.0208*** (0.0070)	−7.81 (−21.39, 5.78)	0	42.0	10.0	2nd / 2nd	None
Longleaf-slash pine	16.32*** (1.894)	0.0281 (0.0185)	14.06 (3.76, 24.35)	76.3	4.6	11.7	2nd / 2nd	Subregion
Loblolly-shortleaf pine	4.85*** (1.295)	−0.0610*** (0.0201)	−3.83 (−11.95, 4.29)	20.7	48.3	54.1	2nd / 1st	Region
Oak-pine	2.09*** (0.315)	0.0079* (0.0047)	5.32 (−2.31, 7.63)	46.9	6.0	41.1	4th / 2nd	Region
Oak-hickory	1.18*** (0.139)	0.0052** (0.0021)	2.15 (0.68, 3.61)	82.4	3.2	177.8	4th / 2nd	Region
Oak-gum-cypress	1.01*** (0.315)	−0.011** (0.0046)	1.63 (−0.54, 3.80)	10.5	0	38.1	1st / 1st	None
Elm-ash-cottonwood	2.24*** (0.303)	0.021*** (0.0057)	5.26 (3.29, 7.23)	78.3	0.7	36.3	2nd / 2nd	Subregion
Maple-beech-birch	3.40*** (0.586)	−0.013 (0.0090)	4.03 (0.44, 7.62)	58.2	0	59.0	2nd / 2nd	Subregion
Aspen-birch	−1.29* (0.767)	−0.012 (0.0087)	−3.48 (−12.47, 5.51)	0	13.6	12.4	2nd / 2nd	Region
Eastern red cedar	5.80*** (1.253)	−0.0145 (0.0260)	9.07 (2.28, 15.85)	86.9	0	2.3	2nd / 2nd	Region

*$p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Figure 3

Estimated Marginal Effect of Average Annual Temperature and Total Annual Precipitation



\$9.17/acre, and about 11% of acreage is projected to see a statistically significant decrease in net returns to forestry of approximately \$7.33/acre. The climate change effects for the remaining acreage is not statistically significant. The acreage weighted average of the positive, negative, and zero climate change effects is an approximately \$5.64/acre increase. The land with the positive effects corresponds with where the ME of temperature is positive and significant (mean temperature from 7°C to 19°C), which mostly occurs in the middle latitudes of the eastern United States. The land with the negative effects corresponds to where the ME of temperature is negative and significant (mean temperature above 21°C). For the western United States, the composite Ricardian using annual climate measures projects statistically significant positive increases in net returns to forestry on about 12% of the timberland, with the rest being insignificant.

To examine robustness of climate change effects, we reestimate equation [11] using seasonal climate measures of $Temp_i$ and PPT_i (e.g., summer temp, fall temp) rather than annual measures. Parameter estimates from the seasonal composite Ricardian models are presented in Appendix Table A3, while estimated climate change effects for the eastern U.S. seasonal model is presented in Table 3. Notably, the adjusted R-squared measures indicate that the seasonal representation of climate fits much better than annual climate measures for the western United States but only slightly better for the eastern United States. The seasonal composite model generates positive and statistically significant (5% level) climate change effects for about 78% of eastern U.S. timberland, with the remainder being insignificant. Thus, the finding that the middle latitudes of the eastern United States will see positive climate change effects is strongly robust across specifications using alternative climate specifications, while the negative climate change effects for the far southern United States from the annual climate specification is not robust when using a seasonal model for climate change effects. The climate change effects for the west are never significantly different from zero for the composite Ricardian

Table 3
Climate Change Effects and the Value of Extensive Margin Adaptation

	Eastern Composite (Annual Climate)				Western Composite (Annual Climate)				Eastern Composite (Seasonal Climate)			
	Counties	Acres	% Share of Acres	Mean Impact	Counties	Acres	% Share of Acres	Mean Impact	Counties	Acres	% Share of Acres	Mean Impact
Significant positive impact	1,737	324.5	71.4	9.17	40	3.9	12.1	6.10	1,876	355.4	78.2	17.03
Significant negative impact	154	48.3	10.6	−7.33	0	—	—	—	0	—	—	—
Impact not significantly diff. from zero	290	81.8	18.0	—	222	28.2	87.9	—	305	137.7	30.3	—
Significant positive adaptation value	1,568	307.3	67.6	6.34*	40	2.9	9.0	10.89*	1,616	316.9	69.7	16.21*

Note: Confidence intervals based on 5,000 Krinsky-Robb draws. Acres measured in millions. Mean impact is the acreage weighted climate change effect measured in annualized dollars per acre.
*Mean impact in the last row is mean adaptation value in the counties where adaptation value is positive and significant.

model that specifies seasonal climate measures, and we have little confidence that western forests will experience significant changes in net returns to forestry (5% level). We also find that our climate change effects are robust to including a broader set of soil quality controls, mean elevation on timberland, variables representing nearby timber mill capacity, and latitude; see Appendix Tables A5 and A6. Climate effects from the national model are also presented in Appendix Table A5 to show that our preferred strategy of separately estimating eastern and western Ricardian functions is robust to pooled estimation of a full national model.

Altogether, our results from the composite Ricardian estimations indicate strong robustness in the finding that climate change will have a positive average effect on the net returns to forestry in the middle latitudes of the eastern United States (current mean temperature between approximately 7°C and 19°C), though the magnitude is sensitive to whether climate is represented as a seasonal or annual measure. In contrast, our finding of positive climate change effects for the western United States is not robust when using annual climate measures compared with seasonal measures. A major limitation when doing this analysis in the western United States is that there are only 32 million acres of private timberland compared with 455 million acres of private timberland in the eastern United States, and these acres are distributed over far fewer counties, which define our unit of observation for estimation.

Forest-Type Ricardian Functions for the Eastern United States

As detailed in Section 4, the composite Ricardian climate effects assume full adaptation along the intensive and extensive margins. We evaluate the importance of extensive margin adaptation in the climate change effects by estimating separate forest type Ricardian functions to get a lower bound climate change effect estimate that assumes no adaptation on the extensive margin. Estimating separate Ricardian functions for each forest type in equation [13] requires data from the geographic range where each forest type is currently growing.

Given the restricted geographical ranges for the forest type Ricardian functions, we opt for the simpler climate specifications of using annual measures of $Temp_i$ and PPT_i for the eastern United States only. The lack of robustness and poor fit from the annual climate measures in the western U.S. composite model leads us to lack confidence in accurately representing western U.S. forestry with simple annual climate measures.

Parameter estimates for each of 11 eastern forest type Ricardian models are presented in Appendix Table A4, while estimated average marginal effects (AMEs) for each model are presented in Table 2. The forest type that covers the largest acreage is oak-hickory, and the smallest is eastern red cedar. The most profitable forest type is loblolly-slash pine (Table 1), which is the most commercially valuable of the southern yellow pine species. As in the composite model, we use adjusted R-squared to evaluate alternative polynomial functions to specify f^F ($Temp_i$,PPT_i) in equation [13], where the chosen polynomial order is presented in the seventh column of Table 2. The AME of $Temp_i$ (PPT_i) is positive for 9 (5) of the 11 eastern forest types. Ten of the AMEs of $Temp_i$ are significantly different from zero, and six of the AMEs of PPT_i are significant (5% level).

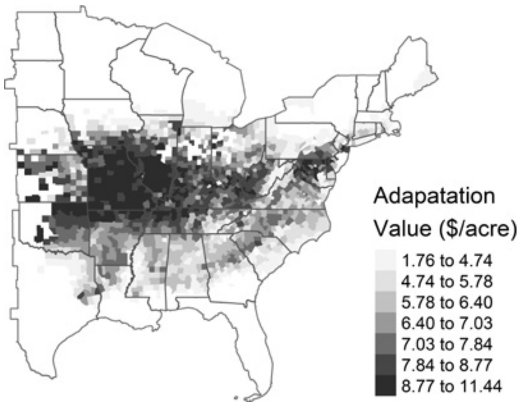
Appendix Figure A2c presents contour plots for the estimated Ricardian function for loblolly-shortleaf pine, the most valuable forest type in the eastern United States. The contour plots indicate a clear range of temperature and precipitation that maximizes the net returns to this forest type, which occurs in the area where loblolly-shortleaf is currently most abundant. Appendix Figure A2c indicates that warming temperatures would generate a sharp increase in net returns to loblolly in areas that are currently below 16°C, and a sharp decrease in net returns in areas that are currently above 19°C. It should be noted that the value of $Temp_i$ that maximizes net returns to loblolly-shortleaf is almost the same as the value of $Temp_i$ that maximizes the composite Ricardian function, highlighting the importance of the loblolly-shortleaf forest type in the composite Ricardian.

Climate change effects for each forest type (equation [14]) are separately presented in Table 2 and account for intensive margin adaptation in each forest type. By holding the amount and location of each forest type fixed, the forest type climate change effects do not account for extensive margin adaptation. Six of 11 forest types are projected to see positive and significant climate change effects on their respective net returns by 2050, while the climate change effects for the remaining five are not significantly different from zero.

Value of Extensive Margin Adaptation

The forest type Ricardian functions can be combined to determine landscape level impacts assuming that the composition of the forest remains fixed, which we refer to as intensive-margin-only climate change effects (equation [15]). The difference between the composite Ricardian climate change effect and the intensive-margin-only climate change effect is the value of adaptation on the extensive margin, presented in Table 3. Using the 95% confidence interval of climate change effects from the composite Ricardian, we test whether the effects from the composite model are equal to the intensive-margin-only climate change effect. Given the robustness checks, we focus on the effects with the most confidence—the eastern timberland with a significant and positive climate change effect in the annual climate model. Table 3 shows value of extensive margin adaptation estimates for counties where those estimates are significantly different from zero (5% level). Results indicate that about 67.6% of eastern timberland has a positive value of adaptation on the extensive margin. The average value of adaptation on the extensive margin is $6.34/acre, which is 69% of the composite Ricardian's positive climate change effect of $9.17/acre. Thus, a sizable proportion of the estimated positive Ricardian climate change effect comes from adaptation on the extensive margin. Figure 4 presents a map of the estimated value of adaptation on the extensive margin that is significantly greater than zero (5% level). Notably, the portion of the United States with positive value of extensive margin adaptation lies just to the north of the prime southern timberlands composed of the commercially valuable yellow pine

Figure 4
Adaptation Value Mapped over Confidence Region



species, particularly loblolly pine. Thus, one interpretation of Figure 4 is that it depicts an area where forest landowners will likely have an economic incentive to plant yellow pine species as an adaptation strategy to climate change. Extensive planting of pine species in the recent past shows that planting is one mechanism through which landowners can alter a forested landscape from hardwoods to pine (Sohngen and Brown 2006). The speed of such planting in response to climate change is an open question that is not addressed here.

6. Discussion

We estimate large-scale Ricardian functions of the link between the net economic returns to forestry and current climate, and we use the estimated functions to quantify the effect of climate change on the economic returns to forestry for the United States. Using alternative climate specifications, results are robust in indicating that climate change will increase forestry returns in the middle latitudes of the eastern United States in areas with current average temperatures between approximately 7°C and 19°C. Approximately 71% of eastern U.S. timberland is projected to see positive effects of climate change on the net returns to timber production. Estimation results for the northern, western, and far southeastern United States are inconclusive and either not significantly different from zero or not robust to alternative representations of climate. It is likely that assessing climate effects in the western states requires a finer-scale than the county, as western counties tend to be large with significant within-county climate variation. Extending prior plot-level analyses of western forest management under climate change (Hashida and Lewis 2019) to evaluate welfare is a method that could better capture within-county data variation. For the portion of the eastern United States that is projected to experience positive and statistically significant climate change effects on net returns to forestry, we find that approximately 69% of the projected gains arise from value of climate change adaptation on the extensive margin. The extensive margin comprises the margin where different types of forests are replanted or regenerated following harvest.

Our article offers three primary contributions. First, by providing the first empirically estimated link between current climate and forestry returns, we fill an important gap in the economics literature that uses empirical analysis to quantify costs and benefits of climate change on various economic sectors. Our finding of robust, positive, and statistically significant climate change effects in the middle portion of the eastern United States is broadly consistent with past literature that uses numerical assessments to examine climate change impacts in forestry (Sohngen 2020). However, we also find strong heterogeneity in climate change effects that is consistent with analyses of physical productivity measures (e.g., Latta et al. 2010), with clear positive effects only in moderate current climates of the middle latitudes of the eastern United States. Our ability to test hypotheses and calculate statistical significance regarding the effects of climate change on forestry returns across space differentiates this analysis from prior numerical studies of climate change and the forestry sector. Second, we develop a method that allows us to disentangle the value of extensive margin adaptation across forest types from our estimate of climate change effects by estimating separate Ricardian functions across individual forest type groups (e.g., maple-beech-birch, loblolly-shortleaf pine) in the eastern United States. By combining our forest type Ricardian functions with the current share of the landscape in each forest type, we construct lower bound climate change effects on forestry that assume no adaptation on the extensive margin. Third, by quantifying the value of extensive margin adaptation differentially across regions, we show that the incentive to adapt by switching forest types is strongest in the middle latitudes of the eastern United States. It is likely that much of the value of extensive margin climate change adaptation arises from converting hardwoods to commercially valuable pine species that would become more productive under a warming climate in the middle latitudes of the eastern United States. Because different forest types provide varying levels of nontimber ecosystem services, and planted pine forests have been shown to have lower biodiversity than natural hardwoods (Haskell, Evans, and Pelkey 2006), our results suggest that regions where land-use changes in forestry (and corresponding ecosystem services) are likely to be largest as a result of climate change adaptation.

The role of extensive margin adaptations in forestry is an important consideration when examining our composite results. The composite Ricardian model assumes no constraints or hysteresis in adaptation, whereas there are reasons to think that extensive margin adaptations in forestry may happen sluggishly. Because forest landowners do not make harvest and replanting choices annually but once over several decades, extensive margin adaptation can involve significant opportunity costs of forgoing future growth of existing stands, and it can take time to radically convert a forested landscape from one dominant tree species to another (Hashida and Lewis 2019). Therefore, we suggest that our composite Ricardian results be treated as an upper bound on the potential gains to U.S. forestry under climate change because the framework assumes that the full set of optimal adaptation can and will happen by 2050. Our results also suggest many new research questions. How quickly can extensive margin adaptation in forestry occur, and what barriers exist? How do current landowners anticipate future climate change and respond? Guo and Costello's (2013) numerical analysis of extensive margin adaptation in forestry assumes that landowners anticipate future climate and preemptively adjust the types of trees they grow. However, a study of family foresters in the northwestern United States found little evidence that landowners are making management decisions in response to climate change forecasts (Grotta et al. 2013). Using repeated plot-level data from the FIA database, we calculate minimal recently observed switching of forest types since 2001 that involve the most commonly planted species of loblolly pine and Douglas fir.

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, Plantinga, and Stavins 2008). Furthermore, in a Ricardian analysis of agriculture in the eastern United States, Schlenker, Hanemann, and Fisher (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 United States, 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 nonmarket ecosystem services, from carbon sequestration to wildlife habitat (Lawler et al. 2014). Optimal conservation policy under climate change compares the dynamics of benefits and costs over time, where benefits and costs of conservation may change in response to climate (Lewis and Polasky 2018). By showing how climate change can influence private returns to U.S. forestry, 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.

Acknowledgments

We acknowledge the insightful comments from Darius Adams that helped shape this work. We acknowledge comments from Jeff Kline, Steve Dundas, Brent Sohngen, and

David Wear that helped clarify our approach. We thank the two anonymous reviewers and seminar participants at the AERE annual meeting (2017) and the AERE sessions in the SEA meetings (2018) as well as the participants in seminars at the University of Wisconsin–Madison and at Oregon State University for feedback. Funding was provided by joint venture agreements with the USDA Forest Service, Southern Research Station (18JV1133015523) and the Pacific Northwest Research Station (14-JV-11261955-059) and a USDA National Institute of Food and Agriculture competitive grant (2017-67023-26275).

References

Abatzoglou, J. T. 2013. "Development of Gridded Surface Meteorological Data for Ecological Applications and Modelling." *International Journal of Climatology* 33 (1): 121–31.

Albouy, D., W. Graf, R. Kellogg, and H. Wolff. 2016. "Climate Amenities, Climate Change, and American Quality of Life." *Journal of the Association of Environmental and Resource Economists* 3 (1): 205–46.

Angrist, J. D., and J. S. Pischke. 2008. *Mostly Harmless Econometrics*. Princeton, NJ: Princeton University Press.

Auffhammer, M. 2018. "Quantifying Economic Damages from Climate Change." *Journal of Economic Perspectives* 32 (4): 33–52.

Blanc, E., and W. Schlenker. 2017. "The Use of Panel Models in Assessments of Climate Impacts on Agriculture." *Review of Environmental Economics and Policy* 11 (2): 258–79.

Burke, M., J. Dykema, D. B. Lobell, E. Miguel, and S. Satyanath. 2015. "Incorporating Climate Uncertainty into Estimates of Climate Change Impacts." *Review of Economics and Statistics* 97 (2): 461–71.

Capozza, D. R., and R. W. Helsley. 1989. "The Fundamentals of Land Prices and Urban Growth." *Journal of Urban Economics* 26 (3): 295–306.

Daly, C. 2006. "Guidelines for Assessing the Suitability of Spatial Climate Data Sets." *International Journal of Climatology* 26 (6): 707–21.

Dundas, S. J., and R. H. von Haefen. 2020. "The Effects of Weather on Recreational Fishing Demand and Adaptation: Implications for a Changing Climate." *Journal of the Association of Environmental and Resource Economists* 7 (2): 209–42.

Faustmann, M. 1849. "On the Determination of the Value which Forest Land and Immature Stands Possess for Forestry." Translated by M. Gane (1968) Commonwealth Forestry Institute Paper 42. Oxford, UK: Commonwealth Forestry Institute.

Favero, A., R. Mendelsohn, and B. Sohngen. 2018. "Can the Global Forest Sector Survive 11°C Warming?" *Agricultural and Resource Economics Review* 47 (2): 388–413.

Grotta, A. T., J. H. Creighton, C. Schnepf, and S. Kantor. 2013. "Family Forest Owners and Climate Change: Understanding, Attitudes, and Educational Needs." *Journal of Forestry* 111 (2): 87–93.

Guo, C., and C. Costello. 2013. "The Value of Adaption: Climate Change and Timberland Management." *Journal of Environmental Economics and Management* 65 (3): 452–68.

Hanewinkel, M., D. A. Cullmann, M. J. Schelhaas, G. J. Nabuurs, and N. E. Zimmermann. 2013. "Climate Change May Cause Severe Loss in the Economic Value of European Forest Land." *Nature Climate Change* 3 (3): 203–7.

Haskell, D. G., J. P. Evans, and N. W. Pelkey. 2006. "Depauperate Avifauna in Plantations Compared to Forests and Exurban Areas." *PLoS One* 1 (1): e63. https://doi.org/10.1371/journal.pone.0000063.

Hashida, Y., and D. J. Lewis. 2019. "The Intersection between Climate Adaptation, Mitigation, and Natural Resources: An Empirical Analysis of Forest Management." *Journal of the Association of Environmental and Resource Economist* 6 (5): 893–926.

Hashida, Y., J. Withey, D. J. Lewis, T. Newman, and J. D. Kline. 2020. "Anticipating Changes in Wildlife Habitat Induced by Private Forest Owners' Adaptation to Climate Change and Carbon Policy." *PLoS One* 15 (4): e0230525. https://doi.org/10.1371/journal.pone.0230525.

Hsiang, S. 2016. "Climate Econometrics." *Annual Review of Resource Economics* 8: 43–75.

Hsiang, S. M., M. Burke, and E. Miguel. 2013. "Quantifying the Influence of Climate on Human Conflict." *Science* 341 (6151): 1235367. https://doi.org/10.1126/science.1235367.

Huang, J., B. Abt, G. Kindermann, and S. Ghosh. 2011. "Empirical Analysis of Climate Change Impact on Loblolly Pine Plantations in the Southern United States." *Natural Resource Modeling* 24 (4): 445–76.

IPBES (Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services). 2019. *Summary for Policymakers of the Global Assessment Report on Biodiversity and Ecosystem Services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services*. Bonn, Germany: IPBES.

Iverson, L. R., A. M. Prasad, S. N. Matthews, and M. Peters. 2008. "Estimating Potential Habitat for 134 Eastern US Tree Species under Six Climate Scenarios." *Forest Ecology and Management* 254 (3): 390–406.

Latta, G., H. Temesgen, D. Adams, and T. Barrett. 2010. "Analysis of Potential Impacts of Climate Change on Forests of the United States Pacific Northwest." *Forest Ecology and Management* 259 (4): 720–29.

Lawler, J. J., D. J. Lewis, E. Nelson, A. J. Plantinga, S. Polasky, J. C. Withey, D. P. Helmers, S. Martinuzzi, D. Pennington, and V. C. Radeloff. 2014. "Projected Land-Use Change Impacts on Ecosystem Services in the United States." *Proceedings of the National Academy of Sciences* 111 (20): 7492–97.

Lee, D. M., and K. S. Lyon. 2004. "A Dynamic Analysis of the Global Timber Market under Global Warming: An Integrated Modeling Approach." *Southern Economic Journal* 11: 467–89.

Lewis, D. J., and S. Polasky. 2018. "An Auction Mechanism for the Optimal Provision of Ecosystem Services under Climate Change." *Journal of Environmental Economics and Management* 92: 20–34.

Lubowski, R. N., A. J. Plantinga, and R. N. Stavins. 2006. "Land-Use Change and Carbon Sinks: Econometric Estimation of the Carbon Sequestration Supply Function." *Journal of Environmental Economics and Management* 51 (2): 135–52.

———. 2008. "What Drives Land-Use Change in the United States? A National Analysis of Landowner Decisions." *Land Economics* 84 (4): 529–50.

Massetti, E., and R. Mendelsohn. 2018. "Measuring Climate Adaptation: Methods and Evidence." *Review of Environmental Economics and Policy* 12 (2): 324–41.

Mendelsohn, R. O., and E. Massetti. 2017. "The Use of Cross-Sectional Analysis to Measure Climate Impacts on Agriculture: Theory and Evidence." *Review of Environmental Economics and Policy* 11 (2): 280–98.

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

Nelson, M. D., and J. Vissage. 2007. "Mapping Forest Inventory and Analysis Forest Land Use: Timberland, Reserved Forest Land, and Other Forest Land." In *Proceedings of the Seventh Annual Forest Inventory and Analysis Symposium*, edited by R. E. McRoberts, G. A. Reams, P. C. Van Deusen, and W. H. McWilliams, 185–91. General Technical Report WO-77. Washington, DC: U.S. Department of Agriculture, Forest Service.

Nielsen, A. S. E., A. J. Plantinga, and R. J. Alig. 2014. "New Cost Estimates for Carbon Sequestration through Afforestation in the United States." General Technical Report PNW-GTR-888. Portland, OR: U.S. Department of Agriculture.

Ortiz-Bobea, A. 2020. "The Role of Nonfarm Influences in Ricardian Estimates of Climate Change Impacts on US Agriculture." *American Journal of Agricultural Economics* 102 (3): 934–59.

Pimm, S. L., C. N. Jenkins, R. Abell, T. M. Brooks, J. L. Gittleman, L. N. Joppa, P. H. Raven, C. M. Roberts, and J. O. Sexton. 2014. "The Biodiversity of Species and Their Rates of Extinction, Distribution, and Protection." *Science* 344 (6187).

Rehfeldt, G. E., B. C. Jaquish, J. López-Upton, C. Sáenz-Romero, J. B. St. Clair, L. P. Leites, and D. G. Joyce. 2014. "Comparative Genetic Responses to Climate for the Varieties of *Pinus ponderosa* and *Pseudotsuga menziesii*: Realized Climate Niches." *Forest Ecology and Management* 324: 126–37.

Restaino, C. M., D. L. Peterson, and J. Littell. 2016. "Increased Water Deficit Decreases Douglas Fir Growth throughout Western US Forests." *Proceedings of the National Academy of Sciences* 113 (34): 557–62.

Schlenker, W., W. M. Hanemann, and A. C. Fisher. 2005. "Will US Agriculture Really Benefit from Global Warming? Accounting for Irrigation in the Hedonic Approach." *American Economic Review* 95 (1): 395–406.

———. 2006. "The Impact of Global Warming on US Agriculture: An Econometric Analysis of Optimal Growing Conditions." *Review of Economics and Statistics* 88 (1): 113–25.

Schlenker, W., and M. J. Roberts. 2009. "Nonlinear Temperature Effects Indicate Severe Damages to US Crop Yields under Climate Change." *Proceedings of the National Academy of Sciences* 106 (37): 15594–98.

Severen, C., C. Costello, and O. Deschenes. 2018. "A Forward-Looking Ricardian Approach: Do Land Markets Capitalize Climate Change Forecasts?" *Journal of Environmental Economics and Management* 89: 235–54.

Sohngen, B. 2020. "Climate Change and Forests." *Annual Review of Resource Economics* 12: 23–43.

Sohngen, B., and S. Brown. 2006. "The Influence of Conversion of Forest Types on Carbon Sequestration and Other Ecosystem Services in the South Central United States." *Ecological Economics* 57 (4): 698–708.

Sohngen, B., and R. Mendelsohn. 1998. "Valuing the Impact of Large-Scale Ecological Change in a Market: The Effect of Climate Change on US Timber." *American Economic Review* 88 (4): 686–710.

Sohngen, B., and Tian, X. 2016. "Global Climate Change Impacts on Forests and Markets." *Forest Policy and Economics* 72: 18–26.

Staudinger, M. D., S. L. Carter, M. S. Cross, N. S. Dubois, J. E. Duffy, C. Enquist, R. Griffis, et al. 2013. "Biodiversity in a Changing Climate: A Synthesis of Current and Projected Trends in the US." *Frontiers in Ecology and the Environment* 11 (9): 465–73.

Van Deusen, P. C., and L. S. Heath. 2010. "Weighted Analysis Methods for Mapped Plot Forest Inventory Data: Tables, Regressions, Maps and Graphs." *Forest Ecology and Management* 260 (9): 1607–12.

Von Bertalanffy, L. 1938. "A Quantitative Theory of Organic Growth (Inquiries on Growth Laws. II)." *Human Biology* 10 (2): 181–213.

Wilcove, D. S., D. Rothstein, J. Dubow, A. Phillips, and E. Losos. 1998. "Quantifying Threats to Imperiled Species in the United States." *BioScience* 48 (8): 607–15.