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Weather Variability Risks Slow Climate Adaptation: An Empirical Analysis of Forestry

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Abstract: The timing of climate adaptation decisions can have substantial consequences for the assessment of climate damages. Since weather variability can create risks for natural resource management that differ across adaptation choices, such variability has the potential to alter the speed of climate adaptation. This paper estimates the effect of weather variability on the timing of adaptation decisions of forest landowners in the Eastern United States. A discrete-choice econometric model of forest management is estimated and used in a bio-economic simulation that shows how variability in cold temperatures can significantly slow the rate of adapting from cold-tolerant natural hardwood forests to cold-sensitive, but highly valuable pine plantations. The range of weather variability in climate projections and across the landscape generates large differences in adaptation timing. Ignoring projected future decreases in weather variability results in a large downward bias in estimating future paths of climate adaptation. Since pine plantations produce fewer non-market ecosystem services than natural hardwood forests, an important source of future conservation uncertainty is the economic response of private forest landowners to changing weather variability.

Keywords: climate adaptation, forestry, weather variability, econometric model, land-use modeling

JEL Codes: Q23, Q54, Q57

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1. Introduction

The continuing pace of climate change is spurring significant interest in adapting the management of natural resources to new environmental conditions. Knowing how and when people make decisions to adapt resource management to climate change is crucial to assessing climate damages as well as designing effective policies. While adaptation is often viewed as a means of mitigating or lessening damages from climate change, private adaptation decisions, particularly in the realm of natural resource management, can generate social costs. Social costs arise because many adaptive resource management decisions can alter the ability of resource stocks to provide ecosystem services, thereby generating externalities (Hashida et al. 2020). For example, altering water applications in agriculture can affect both the supply and quality of water (Narita and Quaas, 2014; Fezzi et al., 2015); allocating land to investments in renewable energy like wind and solar can alter natural landscapes (Aycrigg et al., 2023) and induce local wildlife mortality (Smallwood, 2013; Schöll and Nopp-Mayr, 2021). Social costs, along with uncertainty about the dynamics of adaptation decisions present significant challenges to policymakers who may wish to incentivize socially optimal adaptation behavior. By studying the factors that affect adaptation timing, we can better understand how to design effective policies to mitigate or reduce the social costs of private adaptation.

Weather variability is a key component of climate that can potentially alter the rate of adaptation by creating risks for certain land uses and management choices through non-linear responses to small changes in weather (Schlenker and Roberts, 2009). Weather variability is a particularly salient element of adapting forests to climate change for several reasons. First, in countries with significant private ownership of forests like the United States, any private adaptation to climate change that occurs through harvest and planting decisions will alter the composition of forests and the many market and non-market ecosystem services they provide (Hashida et al., 2020). Therefore, adapting private forests to climate change will likely entail a range of social costs. Second, previous research finds that climate change may positively affect the global forestry sector through productivity improvements (Sohngen, 2020), though a significant portion of the benefits are expected to arise through adaptation by altering the types of forests that are planted (Massetti and Mendelsohn, 2018). However, variability in weather can affect the speed of adaptation in forestry because different tree species, such as various species of commercially valuable conifers, vary in their sensitivity to weather variability. For example, Douglas-fir in the western U.S. is sensitive to heat events and drought (Marias et al., 2017; Jarecke et al., 2023; Still et al., 2023), whereas most species of yellow pine in the southeastern U.S. are sensitive to cold events (South et al., 2002; Nedlo et al., 2009; Pickens and Crate, 2018; Lu et al., 2021). In contrast, many common species of hardwood trees are relatively more climate resilient with wider natural ranges (Thompson et al., 2009). Therefore, when weather variability creates more risk for one forest type than another, changes in weather variability from climate change have the potential to alter adaptation incentives between those two types of forests, thereby impacting the speed of adaptation and its social costs. No previous study has explored the effect of weather variability on the timing of adaptation decisions within forestry, and therefore, it is unclear how important it is to account for weather variability when trying to project and anticipate future climate adaptation decisions that might generate social costs.

The purpose of this paper is to develop an empirical framework for identifying and estimating the impact of weather variability on the timing of adaptation decisions through an application to the forestry sector in the eastern United States. By combining the work of Reed (1984), Guo and Costello (2013), and Hashida and Lewis (2019), we outline a theoretical framework for identifying the effect of weather-induced risks on climate adaptation decisions in forestry, develop a discrete-choice econometric model to empirically estimate the effect of weather variability on the probability of harvest and planting choices, and develop a bio-economic simulation that allows us to isolate the role of weather variability on the time-path of adapting eastern U.S. hardwood forests to pine plantations in response to climate change. Previous work estimates future private benefits to forestry from adapting eastern U.S. hardwood forests to pine plantations (Mihiar and Lewis, 2021), though that study does not examine adaptation timing and ignores how weather variability may alter the rate of adaptation. Our empirical framework tests whether weather variability slows adaptation from hardwoods to pine forests, and also examines the sensitivity of adaptation paths to the range of weather variability in future climate projections.

To estimate our empirical model, we use observed plot-level management decisions and land characteristics from the U.S. Forest Service's Forest Inventory and Analysis (FIA) Database, downscaled climate data from the Parameter-elevation Regressions on Independent Slopes

Model (PRISM)[1], and a newly developed database of net returns to forestry (Mihiar and Lewis, 2021). A key part of our empirical approach is the use of historical daily variation in wintertime low temperatures to construct a measure of weather variability relevant to the adaptive planting decision. Using a measure of cold temperature weather variability that measures the average number of days with temperatures below freezing (0°C), our results show that more days below freezing has a significant and empirically large negative effect on the probability of planting pines, even while controlling for winter temperature means. Using a bio-economic simulation of the time-path of adaptation based on our parameter estimates, we illustrate that more cold weather variability slows adaptation from hardwood forests to pine plantations and that ignoring weather variability leads to a large downward bias in estimating future paths of climate adaptation. We also find that the range of projected future weather variability from global circulation models generates a wide range of adaptation paths. Further, we provide evidence regarding the mechanism of weather variability effects on adaptation: freezing temperatures reduce timber yields and increase risks of natural disturbance, and these effects are larger for pines than for hardwoods. This empirical example provides the first evidence of how weather variability can affect the temporal path of forest landscape change through management actions, with a key focus on the highly policy-relevant conversion of natural hardwood forests to pine plantations in the eastern U.S. Any research focused on modeling climate adaptation behavior in a setting where weather variability creates differential risks across adaptation choices should consider these incentives to alter adaptation timing.

This paper contributes to the broader empirical economics literature covering climate change impacts on agriculture and natural resource management. Significant prior attention has focused on estimating long-run equilibrium effects on agricultural land values using Ricardian cross-sectional econometrics (Massetti and Mendelsohn, 2018). Weather variability is a key part of panel approaches to estimating short-run effects on agriculture, where identification of climate impacts is from within-region weather variation in linear econometric models (Blanc and Schlenker, 2017). Daily weather data has also been shown to be useful in identifying key thresholds that can create non-linear responses in an economic outcome from climate (Schlenker

[1] PRISM Climate Group, Oregon State University, https://prism.oregonstate.edu, data created 6 Mar 2018, accessed 14 July 2023.

and Roberts, 2006, 2009), or in developing various climate measures through binning, and other methods, to use as independent variables (Hsiang, 2016). Empirical forest-climate work consists of Ricardian studies of climate impacts on U.S. forest rents (Mihiar and Lewis, 2021), estimation of past carbon fertilization on U.S. wood volume (Davis et al. 2022), and an analysis of the effect of climate means on forest management decisions and the future forest landscape in the Pacific states of the western U.S. (Hashida and Lewis, 2019). In addition, there is evidence that changes in wildfire risks – which partially emerge from weather variability extremes – have altered risk expectations and lowered western U.S. timberland prices (Wang and Lewis, 2024). We contribute to this literature by showing how risk from weather variability can impact adaptation timing for long-lived forest resources, by using daily weather data to create measures of risk that vary across adaptation choices, and then estimating how weather variability affects discrete adaptation choices from empirical data. Further, by showing how uncertain future weather variability generates a range of future adaptation paths for forests, we contribute to the literature on adjustment costs in climate change, which focuses on how landowners may imperfectly learn about and adapt to climate change (Kelly et al. 2005; Wright and Erickson 2004; Narita and Quaas 2014).

This paper also contributes to the forest economics literature focused on analyzing climate change impacts on state, U.S., and global timber markets, as well as societal welfare (Sohngen and Mendelsohn, 1998; Sohngen et al., 2001; Lee and Lyon, 2004; Sohngen and Tian, 2016). These studies primarily use dynamic optimization methods and partial equilibrium frameworks and show that there are positive productivity and supply effects of climate change in the forestry sector which are heavily influenced by adaptation (Sohngen, 2020). However, these approaches rely heavily on assumptions of optimal decision-making and perfect foresight and lack empirical evidence on the link between weather variability and forest management decisions. By taking an empirical approach to analyzing adaptation decisions in forestry, we can explicitly test whether weather variability influences forest management, and the degree to which projected weather variability influences the path of adaptation.

Finally, since the forest sciences literature finds that natural forests produce more non-market ecosystem services and biodiversity than plantation forests (Hua et al., 2022), our findings also provide a broad empirical contribution for conservation science by showing how weather variability will affect the timing of landowner adaptation from natural to plantation forests, a key piece of information for optimal conservation planning (Costello and Polasky, 2004). By showing how weather variability will slow adaptation and therefore slow the loss of ecosystem services across the eastern U.S., these findings can inform the prioritization of conservation actions. For example, conservation becomes more urgent in regions with less cold weather variability where the conversion of natural hardwoods to plantation pines is likely to occur at a faster rate.

The remainder of the paper is organized as follows: Section 2 provides context for the forest adaptation decision in the eastern United States. Section 3 presents a theoretical model to identify the intuition of risk from weather variability in this decision. Section 4 outlines our empirical methods. Section 5 presents our data. Section 6 and 7 present the results of our empirical estimation and our simulation exercise. We conclude with a discussion of our results, their implications, and avenues for future research.

2. Study context

2.1 Pines vs Hardwoods: distribution, ecosystem services

The study area, which comprises 10 states in the southeast and mid-Atlantic U.S. has four key characteristics that make it an ideal location to study the effects of weather variability on climate adaptation. First, over 86% of the forestland in the southeastern United States is privately owned, which means that changes in forest composition will primarily be the result of economically motivated management decisions (harvest and planting). Second, the forest types in this region can be broadly categorized into two groups, planted pines and hardwoods, which we use to define our choice set in the empirical model. The "planted" distinction here refers to the fact that post-harvest, southern pine species are primarily replanted by hand. In fact, 92% of the planted forests in this region are comprised of the forest groups in our planted pine choice group (Oswalt et al., 2014). Planting differs from natural regeneration methods where, upon harvest, seed trees are left standing in order to allow a stand to naturally regrow. While 100% of observed pine forests in our sample are not planted, the majority of them are[2]. Third, the most

[2] See Table A1 in the supplementary material for detailed data on artificial regeneration by forest type group.

commercially valuable trees, pines, are grown in warmer locations in the south while the cooler regions in the inland mid-Atlantic, Kentucky and Tennessee in particular, are dominated by less commercially valuable hardwood forests (Fig. 1). Planted pine forests make up 43% of our sample, while natural hardwood forests make up the other 57%. Fourth, planted pines and hardwoods have different sensitivities to cold weather, and so variability in minimum temperatures is likely to influence landowner choices in this region.

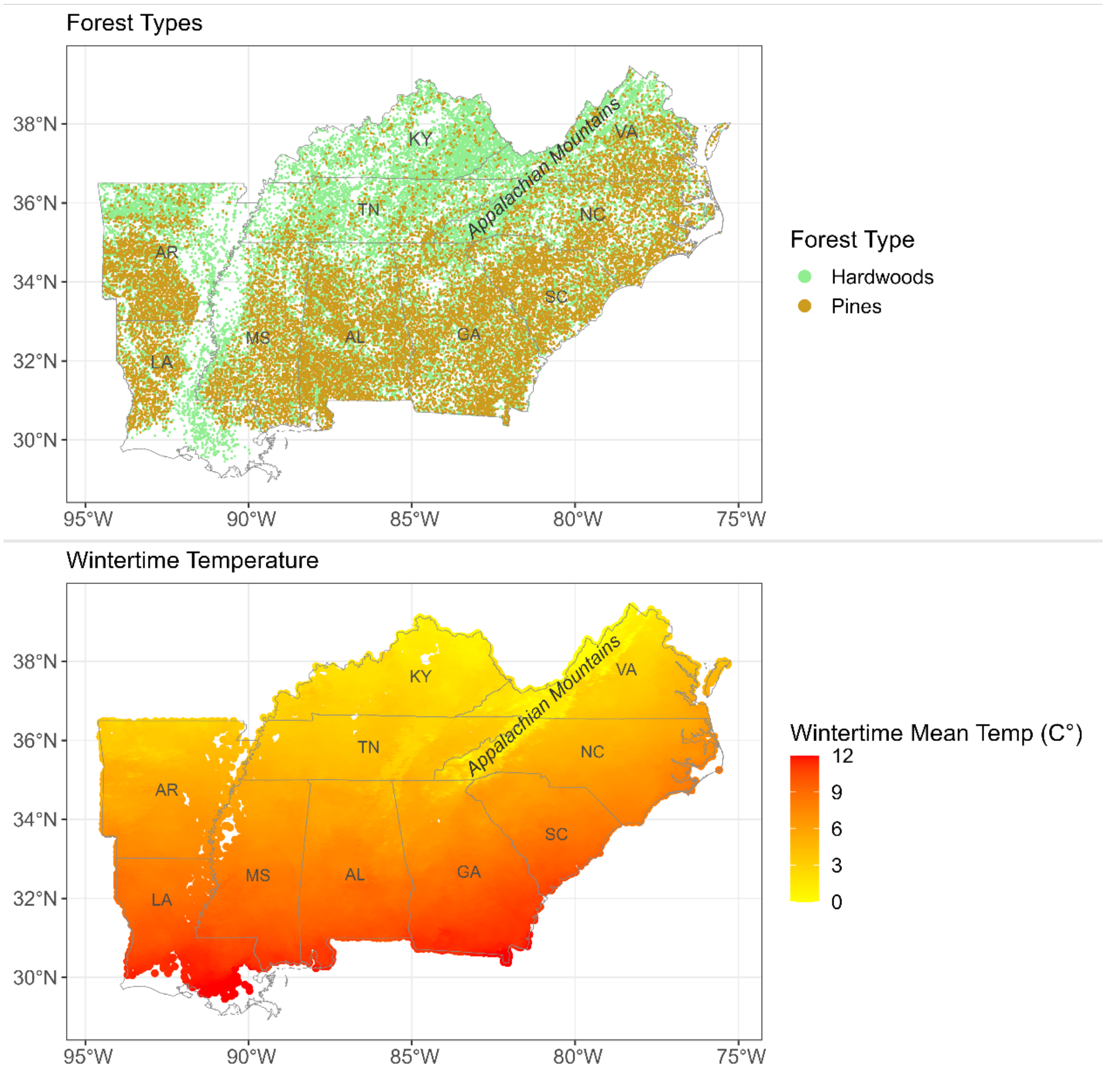

Figure 1: Average wintertime temperature and forest group distribution. **Top Panel:** current distribution of hardwood and pine forests. See Table A1 for the categorization of forest types into these choice groups. **Bottom panel:** current long-term (30 year) average non-growing season temperatures. **Data source:** PRISM Climate Group, Oregon State University, https://prism.oregonstate.ed

The distinction between the two replanting decisions (hardwoods or pines) is important in the context of ecosystem service provision. Pine forests are heavily managed and commonly occur as plantations to the detriment of ecosystem functions (Gilliam, 2016), whereas hardwood forests tend to be naturally regenerated, managed less intensively, and have notably high biodiversity. For example, researchers have found that outside of the tropics, the hardwood forests of the Appalachian region have some of the highest levels of tree diversity (Keyser and Brown, 2016). Differential rates of carbon sequestration across forest types (Schiffman and Johnson, 1989; Brown and Schroeder, 1999; Goodale et al., 2002; Novick et al., 2015) means adaptation between forest types will have additional climate consequences. As such, landowners' decisions to convert hardwood forests to pine plantations in response to a changing climate is a land-use change that may negatively affect biodiversity and alter the level of other forest ecosystem services (Carnus et al., 2006; Haskell et al., 2006; Paillet et al., 2010; Hua et al., 2022).

2.2 Incentives for adaptation in the mid-Atlantic United States

Since climate can alter the relative returns to different forest types, climate change has the potential to alter the management decisions of forest landowners, and consequently the forest landscape, as landowners adapt to a new climate. Areas in the mid-Atlantic are expected to reach temperatures similar to the region directly south, increasing the relative returns of pine forests and incentivizing landowners to plant pine forests in favor of hardwood forests. To illustrate the incentives that landowners in the eastern U.S. will have to switch to pine forests under climate change, Figure 2 presents a graph of two estimated Ricardian functions for a common hardwood forest type (elm-ash-cottonwood) and a pine forest type (loblolly-shortleaf). While meant for illustrative purposes, this figure highlights the large economic premium that the planted pine species have over hardwoods at the higher temperatures of the southeastern U.S., while also illustrating the sharp decline in that premium at lower temperatures.

In a world without adaptation costs, a landowner with recently harvested land at a location with a mean temperature around 12°C would be indifferent between planting the two forest types, according to this figure. At locations below this temperature, elm-ash-cottonwood forests have higher returns and would be preferred by the landowner, whereas above 12°C, loblolly-shortleaf forests would be preferred. We refer to locations like this as the adaptive margin. While we are most interested in adaptation decisions at this margin, including the states furthest south gives us the range of climate data needed to estimate the relationship between observed landowner behavior and warmer temperatures that have not yet been seen in the mid-Atlantic.

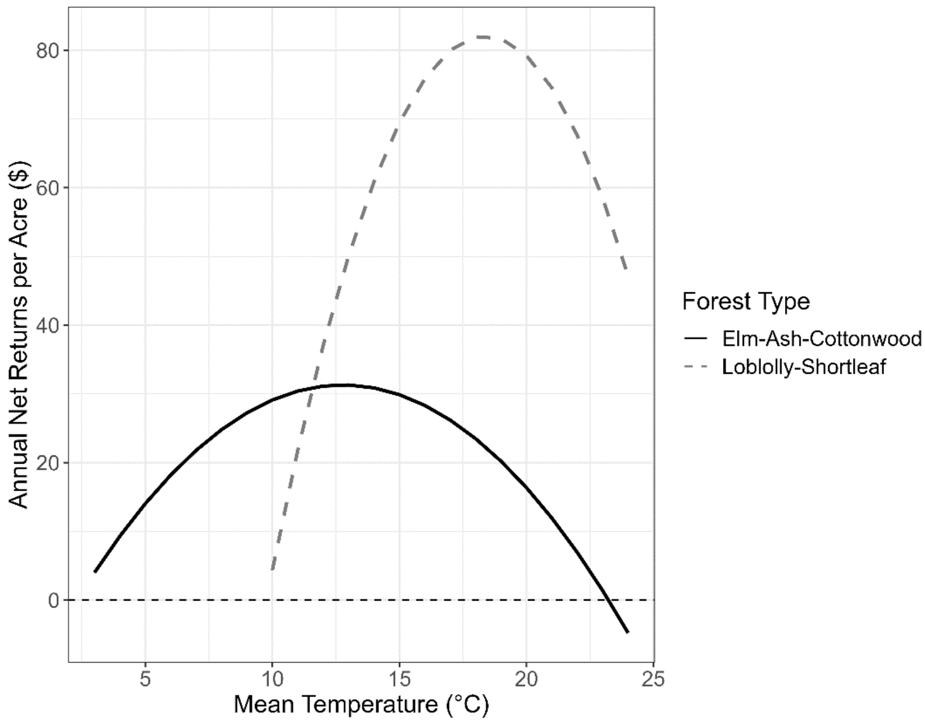

Figure 2: Ricardian functions of a pine and hardwood forest type: Elm-Ash-Cottonwood (solid line) and Loblolly-Shortleaf (dashed line). These functions were estimated with county-level data from Mihiar and Lewis (2021), using simple Ricardian functions with annual net returns to forestry regressed on a quadratic function of mean annual temperature. One way to look at this graph is to consider that moving left to right along the x axis is like moving from north to south in the eastern U.S.

To put these data into context, take the state of Kentucky for example, where the average temperature of FIA forest plots is 13.2°C (slightly above the adaptive margin), and where 94% of FIA forest plots are hardwood types. In 2050, the average temperature in Kentucky is projected to increase to 15.9°C [3]. With such temperature increases, Figure 2 suggests that loblolly-shortleaf pines will become increasingly more profitable for the landowner than the elm-ash-cottonwood hardwood forests.

[3] According to aggregated MACA climate projections assuming the RCP 8.5 warming scenario.

3. Climate adaptation under weather variability risk: Theoretical foundations

This section integrates the work of Reed (1984), Guo and Costello (2013), and Hashida and Lewis (2019), and illustrates how weather variability can impact the timing of forest management choices through changes in risk that vary across management choices.

3.1 Weather variability affects the value of forestland through its effect on risk and timber yields

Consider the risk-neutral owner of a forest parcel with type *F* trees of age a in year *t* who discounts future values with a constant factor δ. The landowner faces a set of climate conditions (c_t) described by measures of central tendency such as seasonal means of temperature and precipitation that directly affect the productivity of growing trees. In addition, the landowner faces weather variability (wv_t) such as variation in seasonal temperature extremes. The landowner's plot of timber is influenced by a yield function Y_F for their forest type *F*, which governs how the trees grow over time. Yields are a function of stand age, climate means, and weather variability: $Y_F(a, c_t, wv_t)$. If the owner harvests their stand, they gain net harvest revenues of $V^h(F, a)$ and then must choose the forest type to plant on their bare land (*a*=0) post-harvest (*ph*). If the owner decides not to harvest, the stand continues to grow until t+1.

The landowner also faces the risk of a catastrophic event that eliminates their growing stock, where the event occurs with a known annual probability of λ_F that follows an independent Poisson process and is a function of climate means (c_t) and weather variability (wv_t). The post-harvest land value function is therefore an expected value conditional on $\lambda_F(c_t, wv_t)$: $V^{ph|h}(F, Y_F(a, c_t, wv_t), \lambda_F(c_t, wv_t))$, as is the value of not harvesting (*nh*): $\delta V^{ph|nh}(F, Y_F(A + 1, c_{t+1}, wv_{t+1}), \lambda_F(c_{t+1}, wv_{t+1}))$.

The landowner's value function in time *t* is the solution to the problem of picking the maximum of i) harvesting the stand today and planting the optimal forest type *F* to maximize the expected post-harvest land value function, or ii) letting the stand grow in age to *a*+1 and revisiting the harvest decision:

$$V(F, Y_F(a, c_t, wv_t), \lambda_F(c_t, wv_t)) = max\begin{cases} V^h(F, a) + \max_F[\delta V^{ph|h}(F, Y_F(0, c_{t+1}, wv_{t+1}), \lambda_F(c_{t+1}, wv_{t+1}))]_{F=1}^{F\prime} \\ \delta V^{ph|nh}(F, Y_F(A + 1, c_{t+1}, wv_{t+1}), \lambda_F(c_{t+1}, wv_{t+1})) \end{cases} \quad (1)$$

The climate adaptation decision on the extensive margin occurs when the landowner harvests their stand and chooses type *F* trees to replant from a choice set of *F'* different types of trees that can physically grow on their land (Guo and Costello, 2013). A landowner that chooses not to harvest in t=1 postpones the adaptation decision.

3.2 When weather variability affects the value of alternate land uses differentially, adaptation speed is affected.

The representation of the value function in Eq. (1) assumes that weather variability affects land value through incremental effects on timber yields (Y_F) and through the risk of discrete catastrophic loss die-back events (λ_F). Prior literature on forest management establishes that the presence of a catastrophic risk raises the rate used to discount future timber rents from the land by an amount equal to λ_F, such that $\partial V/\partial \lambda_F < 0$ and $\partial V^{ph|h}/\partial \lambda_F < 0$ (Reed, 1984). In addition, higher yields indicate a more productive stand that raises the value function: $\partial V/\partial Y_F > 0$. Further, assume that the relationship between stand value and weather variability arises because the effect of weather variability on yields has the opposite sign from the effect of weather variability on risk,

Assumption: If $\partial Y_F/\partial wv_t > 0 \Rightarrow \partial \lambda_F/\partial wv_t < 0$, and if $\partial Y_F/\partial wv_t < 0 \Rightarrow \partial \lambda_F/\partial wv_t > 0$

Intuitively, an increase in weather variability that lowers yields will also increase catastrophic risks, and vice versa. For example, increasingly large changes in extreme temperatures that lower timber yields will make a die-back event more likely for the whole stand of trees.

To consider the mechanisms for how an exogenous change in weather variability affects adaptation in forestry, consider the common situation where a landowner is currently growing type F_1 forests, and is considering whether to harvest their land and either replant with the same type F_1 trees or convert to type F_2 trees. Now consider two simple cases. In case 1, suppose that weather variability only affects the yields and risks of growing type F_2 trees while having no effect on the currently growing type F_1 trees. Therefore, any exogenous change in weather variability that increases yields and reduces risk for type F_2 land – i.e. Y_{F_2} increases and λ_{F_2} falls – will accelerate adaptation to type F_2 land by increasing the value of the adapting use and, therefore, increasing the opportunity cost of waiting to harvest. In contrast, any exogenous change in weather variability that lowers yields and increases risk for type F_2 land – i.e. Y_{F_2}

decreases and λ_{F_2} rises – will slow adaptation to type F_2 land by decreasing the value of the adapting use and, therefore, decreasing the opportunity cost of waiting to harvest. Case 1 would apply to owners of hardwood forests in the Mid-Atlantic U.S. where the adapting use (type F_2) are cold-sensitive pine trees.

Now consider a second case (case 2) where weather variability only affects the yields and risks of growing the current stock of type F_1 trees, while having no effect on the other type F_2 trees to which the landowner is considering adapting. Therefore, any exogenous change in weather variability that raises yields and reduces risk for type F_1 land – i.e. Y_{F_1} increases and λ_{F_1} falls – will slow adaptation to type F_2 land by increasing the value of the current use and thus increasing the opportunity cost of harvesting the F_1 stand today. In contrast, any exogenous change in weather variability that lowers yields and increases risk for type F_1 land – i.e. Y_{F_1} decreases and λ_{F_1} rises – will accelerate adaptation to type F_2 land by decreasing the value of the current use and thus decreasing the opportunity cost of harvesting the F_1 stand today. This mechanism arises because changes in weather variability affect the post-harvest value function from continuing to grow type F_1 trees along with the value function from letting the current type F_1 trees grow, while having no impact on the value function for F_2 forests. Case 2 could apply to owners of Douglas-fir conifer trees in the western U.S. that are sensitive to extreme heat while other alternatives such as hardwoods or ponderosa pines are less sensitive.

A key feature of Eq. (1) is that weather variability affects yields and catastrophic risk in the opposite direction, and those effects differ across adaptation choices. In contrast, risks that affect all adaptation choices (e.g. wildfire) are less likely to impact adaptation choices since those risks create less of a difference between the value function of each choice. The empirical application in this paper most closely fits case 1, whereby owners of hardwood forests face minimal yield impacts and risk of cold damage to their existing forests but considerable yield impacts and risk of cold damage if they adapt to a pine plantation. Thus, the theoretical framework leads to a testable hypothesis that any increase in cold weather variability that lowers productivity and/or raises risks to planted pines will slow adaptation from hardwoods to pine forests, ceteris paribus. Testing this hypothesis also requires controlling for the key climate means (c_t) that can affect tree growth and risk, along with devising empirical measurements of cold weather variability that impact yields and risk to pine forests.

4. Empirical methods

We test the hypotheses that 1) weather variability with regard to wintertime temperatures slows adaptation to pine forests, and it does so through 2) increasing the risk associated with planting pines, and/or 3) decreasing yields. We use a nested discrete choice model of forest management decisions that explicitly accounts for the effect of weather variability on the decision to plant pines and on the probability of a loss-generating discrete disturbance event. To test the second mechanism through which weather variability affects adaptation speed, we estimate the effects of short-term weather variability on short-term annual timber yields. Additionally, we test the extent to which ignoring weather variability leads to biased projections of adaptation speed. To accomplish this, we estimate a version of the model presented below where our measure of weather variability, *days<0*, is excluded from planting and disturbance nests.

The key empirical contribution comes from our use of long-term and short-term daily weather variation to create measures of variability that represent the differential risk across economic adaptation choices. Since replanting choices on any given plot only occur once every few decades when the plot is harvested, and since we observe replanting choices at several points in time for different plots in a pooled cross section, our identification of the effects of climate and weather variability on management decisions relies on both spatial and temporal variation in the climate variables, including our measure of weather variability (e.g. Fig. 4). We first describe our measures of variability, followed by our estimation methods.

4.1 Measures for weather variability that affect adaptation in forestry

Climate is the distribution of weather, including its variability. In our study region of the southeastern U.S., studies have identified that winter temperatures are a key environmental variable determining risk to the survival of southern pines (Schmidtling, 2001; Lu et al., 2021). Furthermore, unseasonably warm wintertime temperatures can increase the risk of cold damage to southern pine seedlings, especially when followed by very cold temperatures (Pickens and Crate, 2018). In contrast, cold temperatures create minimal risks to the survival of the hardier hardwood forest types that thrive in cooler parts of the eastern U.S. Thus, an owner of a southeastern U.S. hardwood forest is likely to be well described by case 1 in Section 3.1, where weather variability creates risk for the adapting forest type (pines) but not the existing forest type (hardwoods).

Perhaps the simplest way to empirically measure cold weather variability is by counting the number of days in a year that a minimum temperature is expected to be below a threshold temperature (T^*), where temperatures less than T^* harm the growth of pine trees. For southeastern U.S. pines that are sensitive to freezing temperatures, T^*could be set to 0°C and the number of days in a year with a minimum temperature below T^*would be a pertinent measure of weather variability. We construct both a short- and long-term variability measure which we compute as the average annual number of days below 0°C in the 5 years and 20 years preceding the plot's observation in year *t*.

Figure 3 illustrates the impact of cold weather variability on the feasibility of planting southeastern U.S. pines. Both panels represent the distributions of daily minimum non-growing season temperatures of two plots with the same mean non-growing season temperature ($\overline{temp}$) but different levels of weather variability. Therefore, more days below T^* can lower yields ($\partial Y_F/\partial wv_t < 0$) and can increase the probability of catastrophic loss ($\partial \lambda_F/\partial wv_t > 0$).

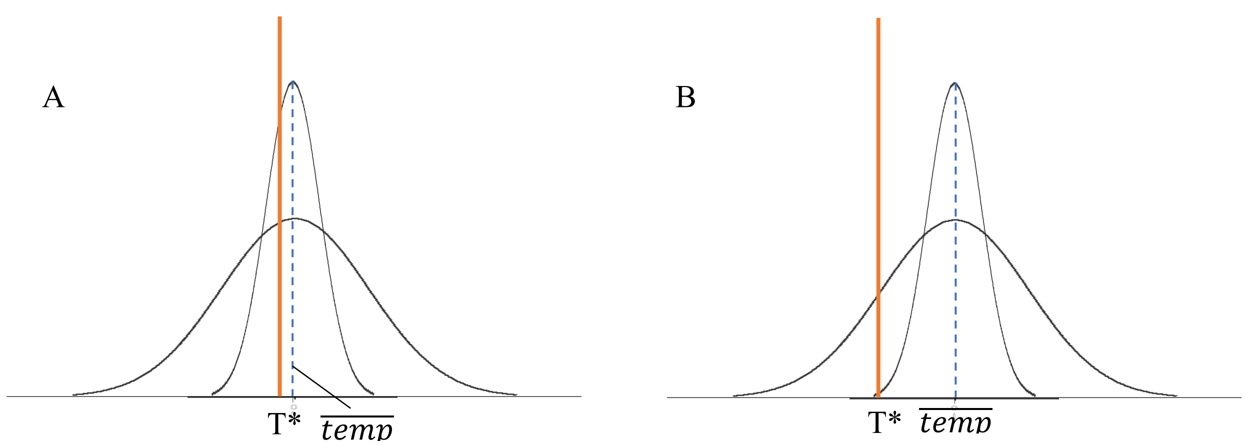

Figure 3: Illustration of the effect of weather variability on planting pines. Catastrophic risks to pine survival occur at temperatures below T^* and the probability of catastrophic loss is $\lambda = Prob(t \leq T^*)$.

Panel A in Figure 3 shows temperature distributions of two plots that have $\overline{temp}$ just above T* (orange vertical line). In this case, even though both plots have different levels of variability, they have similar *days<0* and therefore face similar yield effects and catastrophic loss risks from cold temperatures. The difference in weather variability across both plots would have minimal impacts on either plots' yields or risks of catastrophic loss. On the other hand, panel B depicts the same two plots but with higher $\overline{temp}$. In this case, the landowner with lower variability faces fewer days below T* and thus a smaller negative yield impact and lower risk of catastrophic loss from adapting to pines than their counterpart. As such, the landowner with lower weather variability is more likely to plant pines. A key point from Figure 3 is that the yield effects and probability of catastrophic loss depends on measures of weather variability which are distinctly different from climate/mean temperature. The two plots in Panel A indicate an example of two plots with a similar climate mean ($\overline{temp}$) and a similar value of the relevant weather variability measure (days below T*). On the other hand, Panel B indicates an example where the two plots have a similar, but higher climate mean ($\overline{temp}$) and very different values of the days below T* measure of weather variability. Thus, empirically controlling for climate means ($\overline{temp}$) is not sufficient for measuring weather variability impacts on forestland values and, therefore, adaptation decisions.

Figure 4 highlights the spatial and temporal heterogeneity of *days<0* which is notably lower east of the Appalachian Mountains and much higher north and west of that range. Temporal changes in days<0 are slight, but we do see an increase over time in days<0.

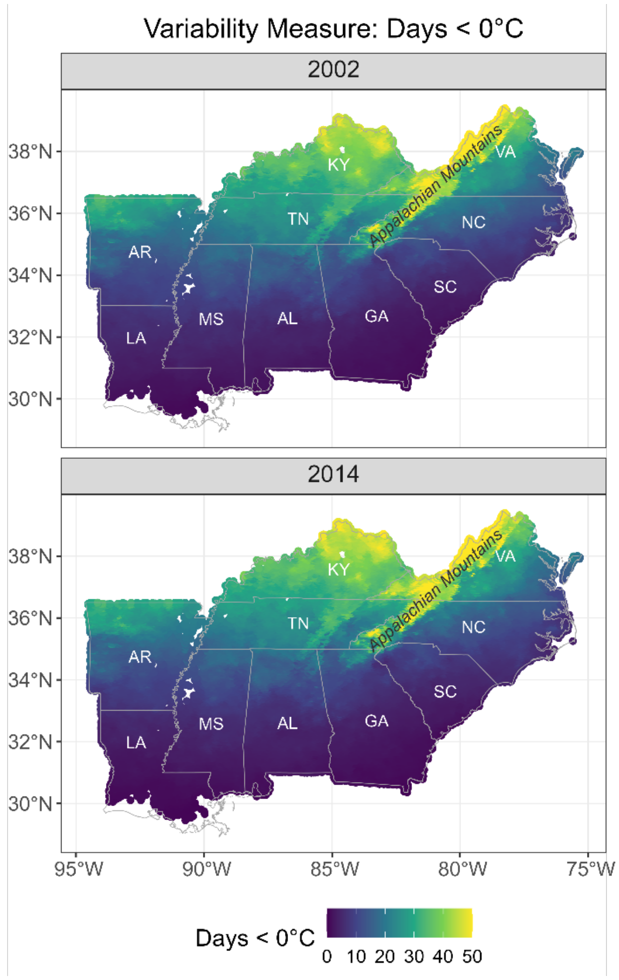

Figure 4: Weather variability in 2002 (top) and 2014 (bottom) as measured by the 20-year average annual number of days < 0°C . **Data source:** PRISM Climate Group, Oregon State University, https://prism.oregonstate.edu

4.2 Empirical specification

We model the climate adaptation decision using a nested discrete-choice, random utility framework, building off the work of Hashida and Lewis (2019). The nested nature of the forest management problem is illustrated in Figure 5. An owner of a timber stand faces the decision to harvest their stand or not. Conditional on harvesting, they face the decision to plant pines or regenerate hardwoods. Conditional on not harvesting, the stand continues to grow and the landowner bears some risk of natural disturbance. Climate and weather variability enter into both the planting and natural disturbance models (in the lower nest) which are separately estimated, while also affecting the harvest decision due to the inclusive value from the nested logit structure (Train 2009), which is consistent with the theoretical foundation in Eq. (1).

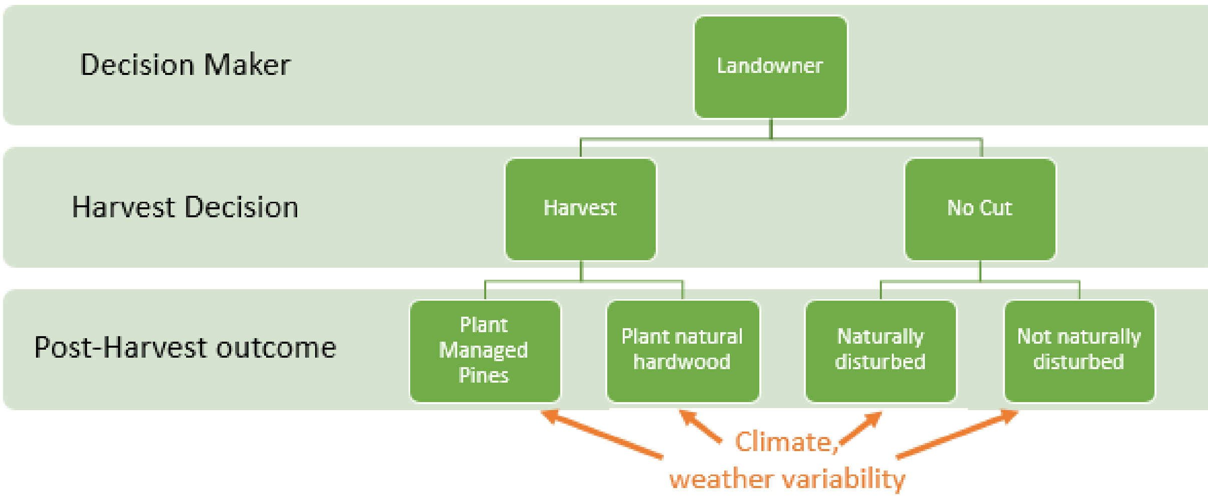

Figure 5: The nested structure of forest management decisions. Climate enters the lower nest planting and disturbance models.

4.2.1 Disturbance and growth model

If a landowner chooses not to harvest their forest, it will continue to grow, but also face the possibility of being naturally disturbed by weather, fire, pests, animals, or disease. We define a plot as naturally disturbed if two conditions are met: 1) it is observed to have been naturally disturbed, and 2) it has experienced negative growth, which indicates that the disturbance caused substantial damage to the stand. The probability of disturbance, conditional on a plot not being harvested, is a function of climate, weather variability, ownership, elevation, and location. Since we know that observed disturbance events occurred between inventory years *t-d* and *t*, we construct our weather variability and climate measures over that same time period in order to capture the weather events and climate near the time of the disturbance. In our application, *d*=5 years to capture the measurement period of the FIA data.

Disturbance is estimated with the following latent value binary outcome specification:

$$V_{nt}^{ph|nh} = \alpha_0 + \alpha_1 \overline{tmean}_{nt} + \alpha_2 \overline{wprecip}_{nt} + \alpha_3 stwv_{nt} + \alpha_4 pine_n + \alpha_5 elevation_n + \alpha_6 private_n + \alpha_7 pine_n * stwv_{nt} + \vartheta_{s(n)} + \varepsilon_{njt} \quad (2)$$

For $ph|nh = natural\ disturbance\ event \mid no\ harvest$

Where $V_{nt}^{ph|nh}$ is a latent variable depicting the value of stand *n* in year *t* that has not been harvested (*nh*). Since the unharvested stand is subject to natural disturbance events that affect its value, we estimate parameters in Eq. (2) with a binary dependent variable equal to 1 if plot *n* has been naturally disturbed and 0 if not; $\overline{tmean_{nt}}$ is the 5-year mean annual temperature, $\overline{wprecip_{nt}}$ is the 5-year mean wintertime precipitation, and $stwv_{nt}$ is the short-term (5-year) weather variability; $pine_n$ indicates whether the stand is a pine stand ($pine_n = 1$) or a hardwood stand ($pine_n = 0$); $private_n$ is a binary variable indicating whether the plot is privately owned or otherwise; and $\vartheta_{s(n)}$ are state-level fixed effects. The disturbance model is estimated using the 58,466 plot-time observations that were not harvested. As a robustness check, we also estimate this model with a long-term measure of weather variability where *d = 20*.

In order to test if weather variability negatively affects pine yields more than hardwood yields consistent with Sec. 3, we estimate short-term (5-year) timber growth using a two-part Tobit model with similar specifications to the disturbance model. The first part is a binary probit model which estimates the probability that a stand experiences zero growth. This model is estimated using the sample of plots that experienced non-negative growth:

$$\begin{aligned} Prob(nogrowth_{nt} = 1) \\ = \Phi(\tau_0 + \tau_1 age_{nt} + \tau_2 age_{nt}{}^2 + \tau_3 elevation_n + \tau_4 private_n + \tau_5 \overline{tmean_{nt}} \\ + \tau_6 \overline{ngprecip_{nt}} + \tau_7 stwv_{nt} + \tau_8 pine_n + \tau_9 pine_n * stwv_{nt} + \phi_{s(n)}) \end{aligned} \quad (3)$$

Where $nogrowth_{nt}$ is a binary variability indicating whether a plot experienced zero growth (=1) or positive growth (=0) between years *t-5* and *t*, and Φ indicates the standard normal CDF. The second part of the Tobit estimates stand growth on the sample of plots that are actively growing (positive growth):

$$\begin{aligned} \log(\Delta vol_{nt}) = \gamma_0 + \gamma_1 age_{nt} + \gamma_2 age_{nt}{}^2 + \gamma_3 elevation_n + \gamma_4 private_n + \gamma_5 \overline{tmean_{nt}} + \\ \gamma_6 \overline{ngprecip_{nt}} + \gamma_7 stwv_{nt} + \gamma_8 pine_n + \gamma_9 pine_n * stwv_{nt} + \gamma_{s(n)} + \omega_{njt} \end{aligned} \quad (4)$$

Where the dependent variable, (log(Δvol_{tn}), is the log of stand growth observed on plot n between years *t-5* and *t*. Stand growth is the annual change in merchantable timber volume, measured in metric board feet (mbf)/acre/year. Stand age in time t (age_{nt}) is also included as a quadratic, to approximate standard non-linear tree growth functions.

Both the disturbance and growth models include an interaction term: $pine_n * stwv_{nt}$ which allows us to directly estimate how cold temperatures differentially affect the yields and disturbance risks of pine and hardwood forests, providing a single parameter test on the interaction parameter of the mechanisms through which weather variability can affect adaptation speed between these forest types as presented in Sec. 3.

4.2.2 Planting Model

Conditional on harvesting[4], a landowner of plot *n* can choose to either plant a managed pine stand or regenerate natural hardwoods. We assume that the plot of land must remain in forest, eliminating the option of converting the land to other uses. Post-harvest, the landowner chooses the forest type *j* in time *t* that maximizes the net present value of their land. We choose spatially and temporally varying climate variables to test the relationship between climate and the planting decision and include other explanatory variables that we expect to affect the post-harvest land value $V_{njt}^{ph|h}$. We specify the post-harvest land value $V_{njt}^{ph|h}$ from Eq. (1) in random utility form as follows:

$$V_{njt}^{ph|h} = \beta_0 + \beta_{1j}\overline{wtmax}_{nt} + \beta_{2j}\overline{precip}_{nt} + \beta_{3j}land_n + \beta_4 NR_{r(n)jt} + \beta_5 NR_{r(n)jt} * \overline{wtmax}_{nt} + \beta_{6j}wv_{nt} + \varphi_{njt} \tag{5}$$

For $ph|h = plant|clear - cut$

Where $\overline{wtmax}_{nt}$ represents the average wintertime maximum temperature from the 20 years prior to *t*, $\overline{precip}_{nt}$ represents average annual precipitation from the 20 years prior to *t.* The choice of these two variables was determined by the primary climatic factors affecting pine growth and survival, which are wintertime temperatures and precipitation. We represent long-term weather variability (wv_{nt}) with $days < 0_{nt}$ to capture exposure to freezing temperatures.

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[4] Given our focus on how weather variability affects the decision to plant pines over hardwoods, and that pines are predominantly established through planting on cleared land, we define harvest events as clear-cuts only. Partial-cut harvests imply that the landowner will not change the forest type on their plot and are embedded in the “no-harvest” nest. We do not separately estimate drivers of partial cut harvests.

The weather variability measure $days < 0_{nt}$ is computed as a long-term measure of average number of days below 0°C during the 20 years preceding plot measurement.

Other control variables include land quality ($land_n$) measured with the FIA's site class codes[5], and a regional level measure of the net returns to forestry $NR_{r(n)jt}$which varies across time *t,* forest group *j,* and region *r*[6]. Due to the long timeframe between planting and harvest, forest owners do not know their profits from planting a given forest type with certainty. As such, we construct an expected annualized net returns variable for forest group *j* by taking an average of the region *r* average net returns from the five years preceding time *t* to approximate how a landowner may assess the economic tradeoffs of different replanting choices. The interaction $NR_{r(n)jt} * \overline{wtmax}_{nt}$ scales the regional average net return based on plot-level variation in $\overline{wtmax}_{nt}$. Notably, the net returns variable $NR_{r(n)jt}$ captures observed stumpage prices that vary across region *r*, forest type *j*, and time *t*. Finally, there are unobservable factors that drive management choice *j* (e.g. landowner capability) that are captured in ε_{njt}. The choice *j* specific parameters must be normalized to zero for one choice for identification.

We exploit the within-region climate variation to identify the relationship between climate and a landowner's replanting decision. While the climate variables – including *wv* – vary across plots of land n, they do not vary over the choice of forest group *j*. As such, in the econometric specification, the coefficients on each of the three climate variables are indexed by choice in order to estimate differences in land value. Intuitively, we would also expect the relationship between climate and land value to be different across different forest groups. For example, if U.S. southern pine species are more suited to warmer temperatures, we would expect a positive relationship between temperature and land values for plots with those species planted.

Because the planting model is estimated with a pooled cross-sectional of harvested plots, it is more susceptible to omitted variable bias compared to estimating the model with panel data and plot fixed-effects. While we expect some omitted variables in φ_{njt} such as management

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[5] The site class code takes on discrete values from 1 to 7 where 1 indicates the highest land quality. A site class code of 1 indicates that the plot of land can potentially grow timber at a rate of 225+ cubic feet/acre/year, whereas a site class code of 7 indicates a growth rate of 0-19 cubic feet/acre per year.

[6] Regions are defined by the FIA survey units and are comprised of 18 counties on average. Each state has on average 5 regions. There are 50 regions in our study area.

experience, risk preferences, and reasons for owning land to affect the planting decision, it is unlikely that these characteristics are correlated with climate or weather variability. As such, their exclusion from the model would not bias our estimates of the coefficients on our variables of interest ($wv_{nt}, \overline{wtmax}_{nt}$, and $\overline{precip}_{nt}$). As a robustness check, we estimate this model using spatial fixed effects at the ecological subregion level to control for spatially-varying but time-invariant climatic and geological unobserved variables likely to influence the planting decision. The results of this specification are presented in the supplementary index (SI) (Table A6, column 3). Additionally, to ensure that the planting model is robust to alternative ways of measuring climate, we also estimate the model with a double-selection Lasso logit method, which takes a machine learning approach to selecting the climate covariates from a set of 20 different variables representing climate means from the growing and non-growing seasons. Key results from this estimation are presented in the SI (Figure A1).

4.2.3 Harvest Model

The harvest decision is estimated as the upper nest of the forest management decision, which embeds the solutions from the lower nest planting and disturbance models. Given a plot of forestland, the landowner can choose to harvest (*h*=clear-cut) or let their stand grow for another period (*h*=no clear cut). If the owner of plot *n* harvests the land, they receive the estimated volume-weighted revenue from harvesting all tree species that are currently growing on plot *n* in time *t* and represented as Rev_{nt}. If the owner chooses not to clear cut harvest the land, the owner lets the stand grow another period and gains additional revenue from tree volume growth which is represented as ΔRev_{nt}. Eq. (6) indicates these payoffs.

$$V_{nt}^{h} = \begin{cases} \delta_0 + \delta_1 Rev_{nt} & if\ h = clear\ cut \\ \delta_2 \Delta Rev_{nt} & if\ h = no\ clear\ cut \end{cases} \tag{6}$$

The intercept parameter δ_0 implicitly captures harvest costs. As shown in Eq. (1), the harvest decision is dependent on both V_{nt}^{h} and on the optimized post-harvest value function of the land, represented in the nested logit model by the inclusive values formed from the planting and natural disturbance nests [$I_{nt}^{h} = ln \sum_{j=1}^{J} exp\left(V_{njt}^{ph|h}/\lambda_h\right)$]. The inclusive value is the optimized value of the respective lower nest model. The nested logit model embeds I_{nt}^{h} into the harvest model as a set of independent variables for each harvest decision *h*. If a generalized extreme value captures unobservable drivers of harvest decisions, then the probability of the full set of management actions is defined with a nested logit representation (Train, 2009):

$$Prob_{njt} = Prob_{nt}^{h} \cdot Prob_{njt|h}^{ph|h} = \frac{\exp(V_{nt}^{h}+\lambda_h I_{nt}^{h})}{\sum_{h=1}^{2}\exp(V_{nt}^{h}+\lambda_h I_{nt}^{h})} \cdot \frac{\exp(V_{njt}^{ph|h}/\lambda_h)}{\sum_{j=1}^{J}\exp(V_{njt}^{ph|h}/\lambda_h)} \tag{7}$$

The advantage of the nested logit model is that its structure reflects the theoretical nesting structure from Eq. (1) – the optimized post-harvest decision affects the harvest decision directly. We estimate the parameters of these models sequentially as described in Train (2009). While the sequential estimation is consistent, a consequence of it is that the standard errors of the upper nest model have a downward bias (Train, 2009). To deal with that we use a bootstrapping procedure to estimate the upper nest standard errors[7].

5. Data

For a full list of data and sources, see Table A2 in the SI. We use plot-level panel data with 61,599 observations of forest management decisions across 30,962 plots measured by the USFS FIA from 2002 to 2014. The FIA conducts annual inventories of about 20% of all plots in each state in the southern U.S. so each plot in this region is measured approximately once every five years. Approximately 16% of plots are only observed once in the data, while the remaining 84% of plots are observed at least twice. The FIA inventory measures various tree and land characteristics through both on-the-ground field crews and remote measurement techniques. For each observation, the FIA indicates the forest type, ownership, management decisions, disturbance events, site quality, tree volume and growth[8], and other plot characteristics. We

[7] We repeat the following procedure 1000 times to obtain standard error estimates for the harvest model parameters: 1) Create a dataset by sampling with replacement from the original dataset. 2) Estimate the planting and disturbance models using the subset of harvested and non-harvested observations respectively. 3) Calculate inclusive values for the planting and disturbance models. 4) Estimate the harvest model using the inclusive values from (3).

[8] Volume is measured for a handful of site trees on a plot. To calculate the total volume on a plot, we multiply each recorded tree's volume by its trees-per-acre (TPA) expansion factor and aggregate the volumes within each species group within each plot. This gets us the volume per acre for each species group within each condition. To calculate volume growth, we use net annual merchantable cubic-foot growth variable from the FIA and aggregate it in the

combine these data with downscaled daily weather data from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) to construct our variability measures (Sec. 4.1) and 5-year and 30-year means for the other climate variables in our econometric model. Annualized net returns to forestry come from a novel dataset developed by Mihiar and Lewis (2021)[9]. Table 1 presents summary statistics for our key variables of interest.

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Stand age (years)	42	27	0	184
Elevation (feet)	639	669	-10	5620
Proportion privately owned	0.88	0.33	0	1
Proportion pines	0.42	0.49	0	1
Proportion disturbed	0.0084	0.091	0	1
Annual net return premium of pines ($/acre)	14	8.1	2.7	68
Stand growth (mbf/acre/year)	0.5	0.86	-18	22
Stand volume (mbf/acre)	16	15	0	191
Annual mean temp. (°C) *(30-year)*	16	2.2	7	21
Mean wintertime max temp. (°C) *(30-year)*	12	3.2	2.1	20
Mean annual precip. (mm) *(30-year)*	1297	148	873	2503
Mean wintertime precip. (mm) *(30-year)*	326	63	176	727
Days<0 (20-year)	14	12	0.2	92
Days<0 (5-year)	15	13	0	93

Table 1: Summary statistics for key variables.

Of the 61,599 observations of management decisions, 3,133 (5.1%) of those are clear-cut harvests and are used to estimate our planting model, Eq. (5). Due to the timespan of our sample, we only observe the planting decision once for any given harvested plot, leaving us with a pooled cross-sectional dataset to estimate Eq. (5). The remaining 58,466 observations are non-harvests and are used to estimate the disturbance model (Eq. 2). All observations are used to estimate the upper nest harvest model (Eq. 6). Both the disturbance model and harvest model are estimated with unbalanced panel datasets as about 16% of the total observations have only been measured once.

same fashion to get the cubic foot annual growth for each species group on a given plot. These volume and growth measurements are then converted to thousand board feet (mbf).

[9] See Table A2 in the SI for a description of these data.

6. Econometric Estimation Results

Parameter estimates for the full nested forest management model (disturbance, planting, and harvest nests) are presented in SI Table A3. We estimate two distinct models: the full model as presented in Section 4 (Table A3, column 1), and a model that excludes weather variability (Table A3, column 2). Given the non-linearity and interactions in the econometric model, we present estimated partial effects of climate and weather variability on natural disturbance along with the planting and harvest decisions. Using the average climate of the study area as a baseline, we estimate the partial effects of the average projected climate changes between 2020 and 2050 for the region. These projections include a 2 °C increase in wintertime maximum temperatures, a 3°C increase in mean annual temperatures, a 60 mm increase in annual precipitation, a 40 mm increase in wintertime precipitation, a 7-day decrease in short-term *days<0,* and a 12-day decrease in long-term *days<0.*

We first present the results of the disturbance and growth models, which provide evidence for the two mechanisms through which weather variability affects the speed of adapting to pines. The key statistical test of the difference in the effect of *days<0* on pines vs hardwoods is the interaction parameters of the two respective models, both of which are significantly different from zero (p<0.01). Section 6.2 presents the results of the two management decisions: planting and harvest.

6.1 Partial effects of weather variability on disturbance and stand growth

We highlight two key findings illustrated in Fig. 6 that confirm two key points from the theory in Sec. 3. First, a reduction in cold weather variability lowers the probability of natural disturbance for both pine and hardwood stands (p<0.01). A 7-day decrease in short-term *days<0* lowers the probability of disturbance for pines (hardwoods) by 0.3 percentage points (0.28 percentage points), which equates to the 55% (26%) reduction in the mean disturbance rate for pines (hardwoods) that is depicted in Fig. 6. Based on the estimate of the interaction parameter α_7 from Eq. (2), a reduction in cold weather variability has a larger magnitude effect on disturbance for pines than for hardwoods (p<0.01). We present the full disturbance model coefficient estimates alongside those of our alternative model which uses the long-term measure of weather variability in the SI (Table A5) and we confirm that the short-term *days<0* fits the disturbance model best as indicated by McFadden's pseudo R^2.

Second, we find that a reduction in cold weather variability increases the growth of actively growing pine and hardwood stands but has a much larger effect on pines than hardwoods. We estimate that a projected 7-day decrease in short-term *days<0* increases the growth of actively growing pine stands by 21.94% ($p<0.01$), while it only increases the growth of actively growing hardwoods by about 7.39% ($p<0.01$). Thus, consistent with the theory in Sec. 3, reductions in cold weather variability both raise timber yields and lower the probability of natural disturbance, with larger magnitude effects for pines than hardwood forests. The full set of parameter estimates for the growth model is presented in SI Table A4.

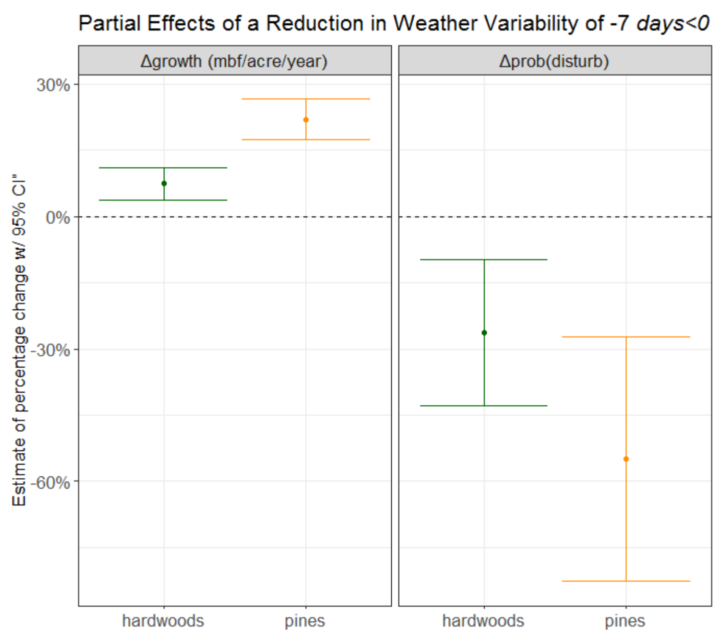

Figure 6: Estimated partial effects of a reduction in weather variability, which is represented here as the effect of a 7-day decrease in days<0 on the percentage change in stand growth (panel A) and on the percentage change in the probability of disturbance (panel B) for both hardwoods (green) and pines (orange). Note that the plotted change in the probability of disturbance is expressed as a proportion of each forest type's mean probability of disturbance.

6.2 Partial effects of climate and weather variability on management decisions

Examining the partial effects of weather variability on the planting and harvest decisions (Table 2), we find clear empirical evidence that lower weather variability, measured as fewer *days<0,* raises the probability of planting pines and the probability of harvesting ($p<0.01$). The projected 12-day decrease in long-term *days<0* increases the probability of planting pines by 19% on average, while increasing the probability of harvesting by about 4% on average. Additionally, we find that the projected increase in $\overline{wtmax}$ lowers the probability of planting pines by about 4% and lowers the probability of harvest by about 0.4%. The projected increase in $\overline{precip}$ increases the probability of planting pine by about 2% and the probability of harvest by about 0.3%. Comparing the partial effects of the projected change in *days<0* to those of the projected changes in the climate means ($\overline{wtmax}$, $\overline{precip}$), we see that the effects of projected future changes in weather variability on the forest management decisions are much larger than the effects of future changes in mean climate. We can also compute the combined effects of these projected climate changes on forest management where all three elements (*days*<0, $\overline{wtmax}$, and $\overline{precip}$) change together as expected in climate change projections (Table 2, rows 4 and 8). We estimate that the combined effect of the climate changes leads to an increase in the probability of planting pines by 17.4% and in the probability of harvest by 3.6%.

We also estimate the partial effects of the projected changes in temperature and precipitation using the empirical model that omits weather variability (bottom half of Table 2). When weather variability is omitted, the sign of the partial effect for $\overline{wtmax}$ turns from negative to positive, as the mean temperature variable picks up some of the omitted weather variability effects. However, the combined effects of projected climate change (Table 2, bottom row) best illustrates the significant bias that arises when ignoring weather variability. When weather variability is omitted, we estimate that the projected combined change in climate only leads to a 6.4% increase in the probability of planting pine and a 1.1% increase in the probability of harvesting. The magnitude of climate change effects on harvest and planting probabilities is much smaller when weather variability is omitted.

Full Model that includes weather variability		
	Δ prob(plant pine)	**Δ prob(harvest)**
Days < 0°C -12 days	0.194*** (0.045)	0.044** (0.017)
$\overline{wtmax}$ **+2°C**	-0.042* (0.020)	-0.004* (0.002)
$\overline{precip}$ **+60mm**	0.023*** (0.004)	0.003*** (0.001)
Combined climate impacts	0.174*** (0.028)	0.036*** (0.008)
Model that ignores weather variability		
	Δ prob(plant pine)	**Δ prob(harvest)**
$\overline{wtmax}$ **+2°C**	0.044*** (0.0085)	0.007*** (0.001)
$\overline{precip}$ **+60mm**	0.020*** (0.004)	0.003*** (0.001)
Combined climate impacts	0.064*** (0.008)	0.011*** (0.002)

Significance level: ***0.10%, **1%, *5%

Table 2: Estimated mean partial effects of projected climate changes between 2020 and 2070 on the probability of planting pines (column 1) and the probability of harvest (column 2). This table presents partial effects for individual elements of weather variability (Days<0), mean seasonal temperature ($\overline{wtmax}$), and total annual precipitation ($\overline{precip}$), holding other measures fixed. We also present the combined climate impacts where we change all individual elements together.

6.3 Alternative planting model specifications.

The SI presents results of three alternative planting model specifications: a planting model estimated with spatial fixed effects (Table A6, column 3), one estimated with the short-term weather variability measure instead of the long-term measures (Table A6, column 2), and a planting model estimated using a double-selection Lasso logit method (Figure A1). Results are consistent across the three specifications confirming that the preferred planting model (presented here) is robust to regional-level omitted variable bias and alternative climate measures. However, as expected, in the spatial fixed-effects planting model, there is less climate variation within regions, highlighted by the fact that the coefficient estimate on *days<0* is only significant at the

10% level. Furthermore, we confirm that the long-term weather variability measure fits the planting model best (indicated by McFadden's pseudo R^2).

7. Future climate bio-economic simulation

The marginal effects from the econometric model provide insight into how climate and weather variability affect the probabilities of harvesting and planting pine forests, but they do not elucidate how weather variability affects the timing of those decisions. The fact that harvests and subsequent plantings happen infrequently does not get captured in the econometric results. However, because we have explicitly included weather variability in our econometric model, we are able to simulate how changes in weather variability alter the time path of adaptation under future climate change. The bio-economic simulation allows us to model the dynamics of forest growth and the timing of harvest and planting decisions while accounting for the stochastic nature of the econometric model.

7.1 Simulation methodology

The simulation starts with a given plot *n* in time *t=0* with the following characteristics: a standing hardwood forest,[10] an observed climate (c_0) including means and weather variability, and an observed growing stock volume that generates either i) an expected revenue upon harvest (rev_{njt}), or ii) an expected revenue growth if not harvested (Δrev_{njt}). We estimate the nested probabilities of harvest choice *k* ($\widehat{Prob}^{h}_{nkt}$), disturbance *i* ($\widehat{Prob}^{ph|nh}_{nit}$) and post-harvest management choice *j* ($\widehat{Prob}^{ph|h}_{njt}$) using the parameters from econometric models. Since these estimated timber management probabilities are functions of climate, we use climate projections to determine how they evolve over time. The simulation follows the nested structure of the econometric model (Fig. 5) and begins by drawing a uniformly distributed random number *r* between 0 and 1. One of two possible outcomes follows:

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[10] Specifically, we choose plots with standing oak-hickory forests as this is the most abundant and widespread hardwood forest type across the eastern US.

1. $r \geq \widehat{Prob}^{h}_{nkt}$: the plot is not harvested. The stand now faces the probability of disturbance. We draw a different random number r^d from which there are two possible outcomes:
   i. $r^d < \widehat{Prob}^{ph|h}_{nit}$: the stand is naturally disturbed and the revenue from harvesting for all subsequent periods is reduced by an amount equal to the average revenue loss of all disturbed plots in our sample.
   ii. $r^d \geq \widehat{Prob}^{ph|h}_{njt}$ the stand continues to grow according to timber yield functions from Mihiar and Lewis (2021) until the next period when the harvest decision is considered again under a new climate (c_{t+1}).
2. $r < \widehat{Prob}^{h}_{nkt}$: the plot is harvested, and the simulation moves to the planting decision. We draw a different random number r^{ph} from which there are two possible outcomes:
   i. $r^{ph} < \widehat{Prob}^{ph|h}_{njt}$: pines are planted. In this case, we assume that the plot will remain in pine and the simulation stops[11].
   ii. $r^{ph} \geq \widehat{Prob}^{ph|h}_{njt}$: hardwoods are regenerated. Again, we use the timber yield functions to determine how the stand grows until the next period when the harvesting decision is revisited under a new climate (c_{t+1}).

Repeating this process over multiple time periods and with many different random draws generates a simulated distribution of outcomes. For each sample plot, we simulate future scenarios with and without climate change in 5-year time steps starting in 2020 and ending in 2100. Our Monte Carlo simulation is repeated 1000 times, generating 1000 different adaptation paths. We then calculate the proportion of times that the plot switches to pine within a given number of years (from 10 to 80) relative to the no climate change scenario and graph the results (Fig. 7, 8).

[11] By stopping the simulation when the plot converts to pines (step 2.i), we are implicitly examining the time until first adaptation from hardwoods to pines. In principle, land could convert from pines back to hardwoods at some point, but we ignore this possibility to better isolate the timing of the first adaptation.

7.2 Sample Plots

We simulate the forest management decisions for three sample plots in three states reflecting the average climate of their state: Kentucky, Tennessee, and Virginia. Kentucky and Tennessee are states currently dominated by hardwoods and on the adaptive margin where forest transitions are most likely to occur. The plots in Virginia were chosen as a point of comparison – it is the northernmost state in our sample, and a region where we expect many areas to have temperatures too cool for landowners to plant pines even under climate change. Simulation results for six additional sample plots are found in SI Sec. A2. Key climate measures and projections for all nine plots are in Table A7.

7.3 Future Climate Projections:

We use downscaled Multivariate Adaptive Constructed Analogs (MACA) future climate projections assuming the RCP 8.5 scenario to create the future yearly climate measures for our sample plots. All plots are expected to become warmer and wetter. The top row of Figure 7 shows how the *days<0* metric evolves over time for the three climate models we use: the Canadian Fourth Generation Global Climate Model (CESM), the Community Climate System Model version 4 (CCSM), and the Hadley Centre Global Environment Model version 2 (Hadley). There is a clear downward trend across all climate models, among which, the Hadley model exhibits the most warming and consistently fewer *days<0*.

7.4 Results

All results represent the probability of planting pines under a climate change scenario minus the probability of planting pines under the no climate change scenario. Key findings are summarized below:

7.4.1 All else equal, increased weather variability slows adaptation.

The first goal of the bio-economic simulations is to isolate the effects of weather variability on the time-path of adaptation from hardwoods to pine forests, where we would expect that a greater number of *days<0* (higher variability) would slow adaptation. This is the first hypothesis we test with our simulation. To do so, we simulate the adaptation path of each of our sample plots using the climate variables projected by the Hadley model. Because the other two climate models (CCSM and CESM) consistently project more *days<0*, we then simulate the adaptation path of each of these plots using the Hadley temperature and precipitation projections while substituting the *days<0* projected by the other two models (Fig. 7, bottom row).

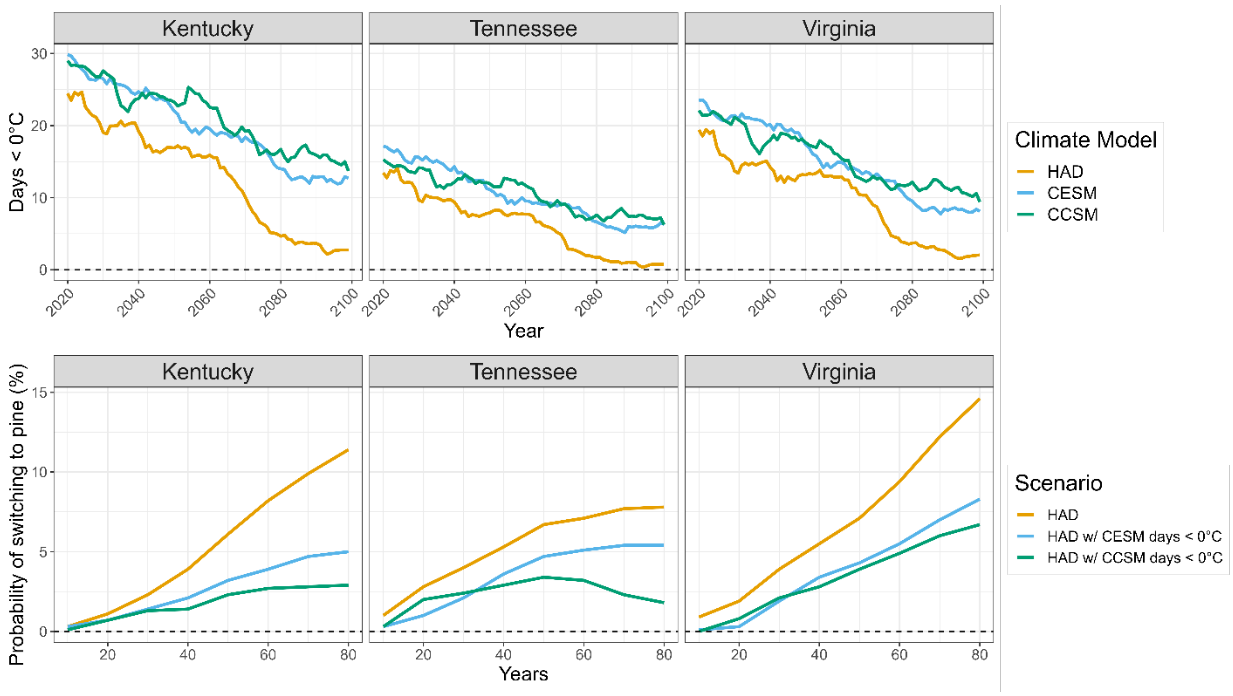

Figure 7: The simulation results highlight that higher levels of weather variability slow the time path of adaptation **Top row:** projected *days<0* for each of our three sample plots using the three different climate models. **Bottom row:** Simulation results from Section 7.4.1. The orange line is the simulated adaptation path using the Hadley (HAD) climate model. The blue (green) line is the simulated path of the Hadley model, but with the *days<0* projected by the CESM (CCSM) model.

The main finding from this simulation is that all else equal, increased weather variability slows climate adaptation. These results are consistent across the three sample plots (as well as the six plots in SI Sec. A2). When more *days<0* are substituted (Fig. 7, bottom row, blue and green lines), the speed of adaptation diminishes relative to the Hadley scenario (orange line). Under the Hadley projections, the probability of climate adaptation to pine forests by 2100 is 11.4%, 7.8% and 14.6% for the Kentucky, Tennessee, and Virginia sample plots respectively. When the *days<0* projected by the CESM model are substituted into the Hadley projections, the probability of climate adaptation to pine decreases for all three sample plots to 5.0%, 5.4%, and 8.3% respectively. And when the *days<0* projected by the CCSM model (the model which projects the most *days<0* by 2100) are substituted, the probability of climate adaptation to pine is even lower at 2.9%, 1.8%, and 6.7% respectively. Given the fact that non-market ecosystem services and biodiversity are significantly lower in pine plantations relative to natural forests (Haskell et al., 2006; Hua et al., 2022), our results imply uncertain conservation outcomes that are driven by economic uncertainties in adaptation behavior of forest landowners that critically depend on how weather variability evolves with climate change.

7.4.2 Ignoring weather variability leads to a smaller range of adaptation paths and underestimates adaptation speed.

A second goal of this simulation is to illustrate how ignoring weather variability may bias predictions of adaptation behavior. While the empirical results in Section 6.2 highlight how ignoring weather variability can greatly alter estimations of the impact on climate changes on forest management behavior at a particular point in time, the simulation illustrates the key dynamics involved in infrequent forest management decisions. To do this, we estimate a forest management model that excludes weather variability[12] from the planting and disturbance nests (Table A3, column 2), and then simulate adaptation paths using projections from each of the climate models. We plot these results (Fig. 8 blue band) next to the range of adaptation paths that result from the simulation that uses the model presented in Section 4 (Fig. 8 orange band).

[12] Note that excluding weather variability is not the same as setting *days<0* = 0.

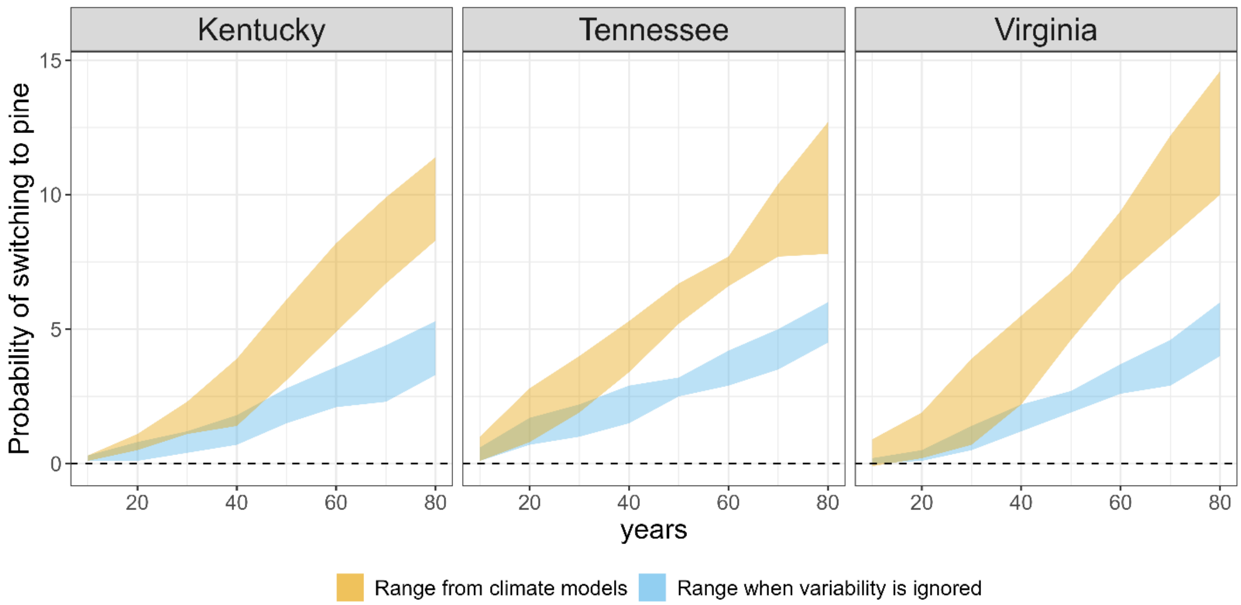

Figure 8: Simulation Results. The orange (blue) band shows the range of adaptation paths generated by the range of projected future climate across three climate models for the bio-economic simulation that includes weather variability (ignores weather variability).

The key takeaway from this approach is that adaptation paths i) are sensitive to the range of climate in the MACA projections, and ii) are significantly underestimated when weather variability is omitted from the econometric model and therefore ignored in the bio-economic simulation. These results are consistent across the three sample plots and four of the six additional sample plots in the SI (see Sec. A2 for details). Using the empirical model that includes weather variability, we find that the range in projected future climate generates a range in the probability of switching to pines by 2100 of 3.1 (8.3% to 11.4%), 4.9 (7.8% to 12.7%), and 4.6 (10.0% to 14.6%) percentage points for the Kentucky, Tennessee, and Virginia sample plots respectively. When weather variability is ignored, the estimated range of future adaptation probabilities are consistently biased downward. In this case, the range in probability of switching to pines by 2100 is 3.3% to 5.3% for Kentucky, 4.5% to 6.0% for Tennessee, and 4.0% to 6.0% for Virginia. Ignoring weather variability results in a downward bias on the adaptation probability. The fact that ignoring weather variability leads to an underestimate of the magnitude of adaptation behavior highlights the importance of considering weather variability in understanding adaptation in forest management. Given that the adaptation behavior of converting natural hardwood forests to pine plantations may reduce biodiversity (Hua et al. 2022; Haskell et al. 2006), underestimating how quickly landowners adapt to pine could have serious consequences for conservation planners who may make conservation decisions based on risk of conversion (Costello and Polasky 2004).

8. Discussion

In an application to forest management in the southeastern U.S., we study how weather variability affects the timing of adapting natural resources to climate change. In the forestry setting where tree species have different sensitivities to climate extremes, weather variability is a key component of climate that can alter the rate of adaptation from one forest type to another through its differential effects on the risks associated with growing each type of forest. Focusing on the decision to adapt natural hardwood forests to planted pine forests, we empirically test and confirm the hypothesis that increased weather variability in cold temperatures reduces tree yields and creates more risk in the adapting land use (pines) than in the current land use (hardwoods). We then test and confirm the hypothesis that increased weather variability in cold temperatures slows the rate of adaptation to pines by 1) estimating an econometric model of forest management decisions as a function of weather variability and climate means, and 2) examining how changes in projected weather variability alter adaptation timing with a bioeconomic simulation of forest growth and management under future climate scenarios.

The simulation highlights the large differences in projected adaptation that arise from differences in projected future weather variability across climate models. Thus, uncertain future weather variability in cold temperatures creates significant uncertainty in the future composition of eastern U.S. forestland. Such uncertainty in projections of future weather variability could also induce a second mechanism that would reinforce weather variability's effect on slowing adaptation from hardwoods to pines – an option value from climate uncertainty. Since harvesting and replanting trees are costly to reverse (Plantinga, 1998), and since there is significant uncertainty in future weather variability (Fig. 7) that we have shown can greatly alter the incentives to plant pines, then landowners may also hold an option value of waiting for information on how future weather variability will evolve before adapting hardwood forests to pines. Option values from price uncertainty have been shown to explain friction in other land-use decisions (Schatzki, 2003), and our results suggest that uncertainty in future weather variability may also create frictions that slow climate adaptation of eastern U.S. hardwoods to plantation pines. Our empirical evidence supports prior theoretical literature which indicates how uncertain future environmental conditions can delay adaptation in water management and agriculture due to an option value (Fisher and Rubio, 1997; Wright and Erickson, 2004; Narita and Quaas, 2014), and that adaptation delays in agriculture can arise from the potential for maladaptation (Sims et al., 2021).

The simulation also illustrates how ignoring weather variability creates a large downward bias in estimating future adaptation paths in forestry. We find that adaptation probabilities that do not account for weather variability are roughly one-half the size of adaptation probabilities that do account for weather variability. Whereas previous studies on climate adaptation in forestry have identified the effects of climate means on land-use decisions and the economic benefits of adaptation, none have addressed how weather variability affects the timing of, or any potential barriers to, adaptation. Considering the large bias that arises when weather variability is ignored, it is imperative that the design and implementation of climate and conservation policy accounts for how natural resource managers react to this component of climate.

Understanding the dynamics of how climate adaptation in forestry occurs is crucial for assessing the non-market damages arising from private adaptation to climate change, and for informing conservation priorities in the face of potentially large-scale conversion of natural forests to plantation stands. From the perspective of a conservation planner, knowing the timing of land-use change – such as the conversion of hardwood forests to pine forests – greatly impacts the timing of optimal conservation decisions (Costello and Polasky, 2004). In particular, conservation actions that conserve natural hardwood forests increase in urgency with an increased speed of private management decisions that adapt land use to pine plantations. Our results show that the speed of adaptive conversion between hardwoods and pine forests is highly sensitive to how variation in wintertime low temperatures actually evolve, highlighting the importance of accounting for such weather variability when assessing the urgency of conservation actions. Furthermore, given the wide range of outcomes in the time-path of forest composition between pines and hardwoods that our simulation illustrates and the difference in non-market ecosystem service provision between natural and plantation forests (Haskell et al., 2006; Hua et al., 2022), our results suggest that an important source of future conservation uncertainty arises from the economic response of private forest landowners to weather variability in making adaptation decisions.

The literature has made clear that adaptation must be accounted for in climate change impact studies because while adaptation induced by private incentives can reduce climate damages (Guo and Costello, 2013; Auffhammer, 2018; Kolstad and Moore, 2020), adaptation decisions, have significant consequences for the provision of ecosystem services and produce social costs (Fezzi et al., 2015). In the context of forestry, privately optimal adaptation decisions generate externalities due to the wide range of public benefits that forests provide and that are not internalized by private landowners (Hashida et al., 2020). While this is beyond the scope of our paper to quantify, our results indicate that while weather variability affects the private benefits from adaptation, there are potentially many social costs arising from these adaptive behaviors.

There are numerous other climate adaptations where we would expect weather variability to affect the speed of adaptation. These decisions can include managed retreat in coastal and freshwater floodplains, forestry adaptation in other regions, and agricultural decisions that require land-use or systems changes, to name a few. These are all adaptation decisions where weather variability may have varying impacts on different decisions, e.g. higher weather variability may create more costly flood risks to houses than natural wetlands, or more costly risks to drought-sensitive crops and trees. Our paper shows how to include weather variability in models of private landowner adaptation decisions.

There are several limitations to our analysis that are worth mentioning. First, our simulation does not account for any future changes in timber prices that may arise from supply shifts in the timber market. While this does not negate the fact that we are able to isolate and illustrate the effect of changes in future weather variability, which is the goal of this paper, future work could include simulations of future timber prices and provide a clearer picture of other important drivers of these adaptation decisions. Second, the assumptions underlying the definition of our planting choice groups could be reconsidered in future work. We frame our planting choice as a binary decision between one of two broad forest groups (pines vs hardwoods) rather than the decision to plant a plantation forest. Anyone interested in examining the latter decision using this framework may define their choice groups accordingly. Additionally, our planting decision excludes the choice to convert land to other uses and should be considered in future work but is outside the scope of this paper. To accomplish this, an understanding of the effects of climate on returns to other land uses is needed. The assumption that landowners cannot convert their land to other uses may mean that our results do not show how the area of forestland changes as relative profits of various land uses change, but even without this aspect, our results still provide valuable insights into the tradeoffs between forest types and how climate affects those tradeoffs. Finally, our model assumes that landowners make management decisions in response to the current climate they face rather than the future climate they expect, and thus our simulation should be viewed as representing how landowners react to climate change that occurs rather than anticipating how it will evolve. While one recent study has attempted to test whether farmland prices anticipate future climate change (Severen et al., 2018), there is no evidence yet on how timberland owners use forecasts of climate change in their management decisions. Future work that tests how climate forecasts affect timber management would be a fruitful extension of this work.

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