Climate uncertainty slows adaptation: an empirical analysis of option values in forestry

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Date of Draft: November 1, 2021

Abstract:

The timing of climate adaptation decisions can have substantial consequences for the assessment of climate damages, and there is a notable lack of research exploring the timing of, and barriers to, climate adaptation. Because many climate adaptation decisions are costly to reverse, and because decision makers face climate uncertainty, real options theory suggests that there may be incentives to delay adaptive decisions. This paper develops a discrete-choice method to identify and empirically estimate the effect of climate uncertainty on the timing of climate adaptation decisions of forest landowners in the Eastern United States where landowners have incentives to adapt to climate change by planting southern pine species in favor of hardwood forests. A fundamental part of our approach is the use of historical variation in daily wintertime low temperatures to create a measure of climate uncertainty that is relevant for the adaptive planting decision in this study. Our results show that climate uncertainty can significantly slow the rate of adaptation and that adaptation paths are highly sensitive to the level of uncertainty. The range of projected variation in wintertime low temperatures generates large differences in the projected probabilities of converting natural hardwood forests to planted pines of between 24% and 59% in regions close to the adaptation threshold. Since natural hardwood forests have more biodiversity than pine plantations, our results suggest that an important source of future conservation uncertainty arises from the economic response of private forest landowners to climate uncertainty in making adaptation decisions.

Keywords: climate adaptation, forestry, uncertainty, option value, econometric model, land-use modeling

JEL Codes: Q23, Q54, Q57

Acknowledgments: We thank the National Institute of Food and Agriculture (# 2017-67023-26275) for funding support. Lewis also acknowledges funding support from the U.S.D.A. Forest Service Southern Research Station (#18JV1133015523). Any errors remain our own.

1. Introduction

The continuing pace of climate change presents a significant challenge to many areas of society and has spurred numerous attempts to mitigate damages and continually assess how humans may adapt to a warming world. Knowing how and *when* people make decisions to adapt to climate change is crucial to both assessing climate damages and designing effective policies. While there has been a considerable amount of empirical work done to understand how humans adapt to climate change, less work has been done to understand the timing of, and barriers to, climate adaptation (Massetti and Mendelsohn 2018). An important barrier that might slow adaptation is the presence of uncertain climate outcomes combined with adaptation decisions that are costly to reverse. For example, an important margin to adapt to climate change is through altering the use and management of land (Guo and Costello 2013), which is widely regarded as being costly to reverse. Converting agricultural lands to forestry (Schatzki 2003), converting undeveloped land to housing (Mills 1981), armoring coastal property against erosion (Beasley and Dundas 2021), effecting managed retreat from sea-level rise (Hino et al. 2017), and harvesting timber (Plantinga 1998) have all been acknowledged to be land-use decisions that have elements of irreversibility. Since climate affects the economic value of many types of land-use decisions (Mendelsohn et al. 1994), and since there is uncertainty in both short-term weather events and long-term climate outcomes (Burke et al. 2015), real options theory would suggest that the timing of adaptation to climate change through land-use decisions will be affected by the magnitude of climate uncertainty (Mezey and Conrad 2010). However, there is a notable lack of economics research assessing and estimating how the combination of climate uncertainty and irreversibility will affect the timing of adaptation decisions made by private individuals with respect to using natural resources.

Understanding the interplay of climate uncertainty and irreversibility has important climate policy implications for at least two reasons. First, past research finds that irreversible decisions are optimally delayed with larger amounts of uncertainty (Arrow and Fisher 1974), and so adaptation decisions subject to greater amounts of climate uncertainty may occur at a slower rate than decisions with less uncertainty. Second, it is important for policy design that assessments of climate damages account for private adaptation decisions, including the timing of those decisions (Auffhammer 2018).

The role of climate uncertainty and irreversibility is a particularly salient element of adaptation in forestry and the resulting landscape composition for several reasons. First, in the United States, approximately 60% of forestland is privately owned, and so any private adaptation to climate change that occurs through harvest and planting decisions will greatly impact the composition of a large portion of the country's forests and the many market and non-market ecosystem services they provide (Hashida et al. 2020). 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). In a Ricardian analysis of climate impacts on U.S. forestry, Mihiar and Lewis (2021) find that positive impacts from climate change are concentrated in the middle latitudes of the eastern U.S. and that 69% of the benefits arise from adaptation away from the dominant hardwood forests towards pine forests. However, the commercially valuable southern pine species that could be planted in the middle latitudes of the eastern U.S. are sensitive to cold temperatures (Nedlo et al. 2009; South et al. 2002; Pickens and Crate 2018; Lu et al. 2021), and thus uncertainty regarding winter temperatures makes adapting to pines risky in regions where they are not yet prevalent. Finally, because harvest and planting decisions are effectively irreversible – or not reversible without large costs – we would expect that climate uncertainty may generate an incentive to delay adaptation decisions and the resulting changes in the composition of landscapes and the ecosystem services they provide. No previous study has explored the effect of climate uncertainty on adaptation decisions within forestry.

The purpose of this paper is to develop an empirical framework for identifying and estimating the impact of climate uncertainty on the timing of adaptive decisions through an application to the forestry sector in the Eastern United States. Building off the work of Guo and Costello (2013) and the natural resource management literature on option values (Mezey and Conrad 2010), we outline a theoretical framework for identifying the option value associated with climate adaptation decisions in forestry, develop a discrete-choice econometric model to be estimated with plot-level data, and empirically estimate the effect of climate uncertainty on the probability of harvest and planting choices. 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, and a newly developed database of net returns to forestry

(Mihiar and Lewis 2021). We also develop a simulation that allows us to isolate the role of climate uncertainty on the time-path of adapting by converting eastern U.S. hardwood forests to pine plantations in response to climate change. The empirical framework is used to test two hypotheses: 1) that climate uncertainty slows adaptation from hardwoods to pine forests, and 2) that the effect of uncertainty is dependent on a location's proximity to the adaptive margin.

The primary contribution of this manuscript is an empirical analysis of climate uncertainty on the time path of land-use change to adapt to climate change. Our empirical example provides the first evidence of how climate uncertainty can affect the temporal path of forest landscape change, with a key focus on the highly policy-relevant conversion of natural hardwood forests to pine plantations in the eastern U.S. Our use of historical weather variation relevant to the adaptive tree planting decision is a key part of our approach to creating a measure of climate uncertainty. Further, we develop a simple theoretical setup along with a two-period example to highlight the intuition for how climate uncertainty can affect adaptation speed.

Our results show that larger variance in wintertime cold temperatures – our measure of climate uncertainty – has a significant negative effect on the probability of planting pines. Using a simulation of the time-path of adaptation based on our parameter estimates, we illustrate that climate uncertainty slows adaptation and that the magnitude of this effect is larger in areas that are closer in proximity to the adaptive margin. Any research focused on modeling climate adaptation behavior in a setting that includes uncertainty and an irreversible adaptation choice should not overlook these incentives to delay adaptation. Our results suggest that research be undertaken to examine if and to what extent this barrier to adaptation exists in other adaptation situations.

2. Literature Review

This paper builds off of a small but growing literature of climate adaptation in forestry, option value literature as it relates to natural resources, and an extensive forestry economics literature. An overall theme is that there has been very little work to date that explores the effects of option values on climate adaptation decisions, especially in forestry.

2.1. Climate adaptation in forestry

There is a small, but growing literature providing empirical evidence of a link between climate and forest management decisions. Guo and Costello (2013) provide the analytical foundation for estimating the economic value of adaptation and for later empirical work to study adaptation in forestry. An important aspect of their work is distinguishing between adaptation on the intensive margin – e.g. rotation length, seed selection, etc. – and on the extensive margin – e.g. changing the types of trees that are replanted.

The empirical work related to climate adaptation in forestry has shown that adaptation incentives exist for forest owners in the eastern U.S. and estimates that 69% of the increase in net returns from climate change comes from extensive margin adaptation (Mihiar and Lewis 2021). This Ricardian analysis assumes that adaptation is costless/frictionless which is generally not the case (Auffhammer 2018). Adaptation in forestry can be sluggish for two reasons. The first is that rotation lengths span decades, and so trees are planted infrequently on any given plot of land. Premature harvest in order to switch to a more profitable species entails a sizable opportunity cost of forgoing growth of the current species. The second reason, and the focus of our study, is that there may be an option value associated with this adaptation decision since harvesting and planting decisions are difficult to reverse (Plantinga 1998), and the landowner may face uncertainty with respect to the future climate on their land. So, while Mihiar and Lewis (2021) find that climate change will lead to incentives for landowners to adapt through their planting decisions, their study does not address the timing and barriers to adaptation, which is a gap our paper seeks to fill.

Hashida and Lewis (2019) apply the framework developed by Guo and Costello (2013) to empirically estimate the effects of climate on forest management decisions and simulate forest landscape changes under climate change and carbon pricing policies. In an application to the Pacific states of the western U.S., they find that a warming climate incentivizes a shift away from the most profitable tree in the region (Douglas-Fir). In contrast, Mihiar and Lewis' (2021) analysis suggests the opposite for the eastern U.S.: a warming climate incentivizes an expansion of the most profitable forest types: southern pines. Furthermore, given that the eastern U.S. has considerably more private forestland than the west coast[1], we would expect these adaptive behaviors to have more severe consequences for the provision of forest ES in this region. Empirical studies estimating how forest owners on the east coast will adapt to climate change are imperative to gaining an understanding of the consequences of climate change for the forest

[1] 81 percent of forestland in the East is privately owned compared to only 30 percent in the West (Butler 2014).

resource and its ecosystem services. Our paper extends this prior work by explicitly modeling and isolating the effect of climate uncertainty on extensive margin adaptation outcomes within forestry.

2.2 Climate impacts on timber markets

Earlier papers also have used dynamic optimization methods and partial equilibrium frameworks to analyze climate change impacts on state, U.S. and global timber markets as well as estimate the welfare effects of that adaptation (Sohngen and Mendelsohn 1998; Sohngen et al. 2001; Lee and Lyon 2004; Sohngen and Tian 2016). Global timber market models use numerical methods and show that there are positive productivity and supply effects of climate change in the forest sector which are heavily influenced by adaptation (Sohngen 2020). Though these papers provide valuable insights into adaptive behavior and the mechanisms through which forest landscapes and production may be altered under climate change, these numerical models rely heavily on assumptions of optimal decision making on the part of the landowners and that landowners have perfect information about the future and can therefore anticipate any future climate changes that might favor one type of tree over another. Importantly, these numerical models assume no option values that might slow adaptation, and thus the benefits to the forestry sector would likely be larger than under a framework that explicitly models the role of climate uncertainty and irreversible adaptation choices. The advantage of an empirical framework for analyzing adaptation decisions in forestry is that we can explicitly test whether climate uncertainty influences forest management, and thus we can test the applicability of the numerical literatures' assumption of no option values. A recent review article highlights the need for economic studies of climate uncertainty on adaptation in forestry (Sohngen 2020).

2.3 Option value in natural resource management

While option values have been studied in many natural resource management cases under uncertainty, including forestry, the focus is primarily on harvest and rotation decisions (Mezey and Conrad 2010). In an empirical application to land-use change between agriculture and forestry, Schatzki (2003) shows that option values arising from uncertain commodity prices induce hysteresis in land-use conversions and reduce the rate of landscape change. We extend these past studies by introducing climate uncertainty to an irreversible adaptive resource management decision. The effect of uncertain climate variables on adaptation in forestry has not been studied. Two economic studies that do apply option value theory to climate adaptation settings for land-use are worth a mention. One application of option value theory is the conservation auction mechanism of Lewis and Polasky (2018), developed as a tool for socially-optimal adaptation to climate change. A second application of option value logic finds empirical evidence of large land market premiums for a policy option to armor shoreline against erosion from sea-level rise (Dundas and Lewis 2020). However, no prior studies analyze how climate uncertainty generates option values that affect private adaptation decisions regarding the use of natural resources.

The source of uncertainty in most prior option value studies is primarily prices or land values (Mezey and Conrad 2010). Also, none of these papers address the timing of these adaptation decisions. Many papers estimate the effect of uncertainty on decision thresholds rather than the actual decision but come to similar findings that risk/uncertainty increases the option value and delays irreversible decisions (Insley 2002, Regan et al. 2015, Mezey and Conrad 2010). Schatzki (2003) is one of the only papers that estimates the effect of uncertainty on a land-use decision rather than the effect of uncertainty on decision thresholds or the option value.

While option value has been used to explain friction in land-use decisions (Schatzki 2003) and in other natural resource contexts including the decision to harvest a stand of trees or harvest old growth forests (Mezey and Conrad 2010; Clarke and Reed 1989; Reed and Clarke 1990; Insley 2002; Reed 1993; Conrad 1997), there has been no work that has used option value to model the forest planting decision or more specifically, the decision to switch forest types.

2.4 Empirical work on adaptation in general

There are a handful of recent empirical analyses and simulation models of human adaptation to climate change across a range of sectors including forestry, agriculture, energy, extreme events, and coastal protection, reviewed in Massetti and Mendelsohn (2018). Notably, there is no discussion of the presence/effect of option value in these scenarios. Many of the adaptation decisions involved in these scenarios (forestry management decision, investment in coastal protection, managed retreat from sea-level rise, land-use changes) involve irreversible decisions. All of these are scenarios could potentially include the existence of an option value and thus, uncertainty can affect the conclusions about when and how these various climate adaptations will take place. Yet we are aware of no explicit test of climate uncertainty on adaptation.

2.5 Road map

Section 3 provides context for the forest adaptation decision in the eastern United States. Section 4 presents a theoretical model to identify the intuition of option value in this decision. Section 5 outlines our empirical Methods. Section 6 presents our data. Section 7 and 8 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.

3. Incentives for adaptation in the Mid-Atlantic United States

To illustrate the incentives that landowners in the eastern U.S. will have to switch to pine forests under climate change, Figure 1 presents a graph of two estimated Ricardian functions for a hardwood forest type (Elm-Ash-Cottonwood) and a pine forest type (Loblolly-Shortleaf). The graph in Fig. 1 is constructed by regressing a U.S. county-average for two different measures of annualized net returns per acre to forestry for these two forest types on quadratic functions of mean temperature using data from Mihiar and Lewis (2021). Fig. 1 highlights the large economic premium that the mostly planted pine species, like loblolly pine, hold over natural hardwood forests like elm-ash-cottonwood at the higher temperatures that occur in the southeastern U.S., while also highlighting how that premium sharply disappears at lower temperatures. In a world of frictionless adaptation, a landowner with recently harvested land at locations with a mean temperature of about 12 degrees C would be indifferent between planting the two forest types, according to Fig. 1. At locations below this temperature, Elm-Ash-Cottonwood forests have higher returns and would be preferred by the landowner, whereas above 12 degrees, Loblolly-Shortleaf forests have higher returns and would be preferred. We refer to locations like this as the adaptive margin.

Figure 1: Ricardian Functions of Selected Pine and Hardwood Forest Types

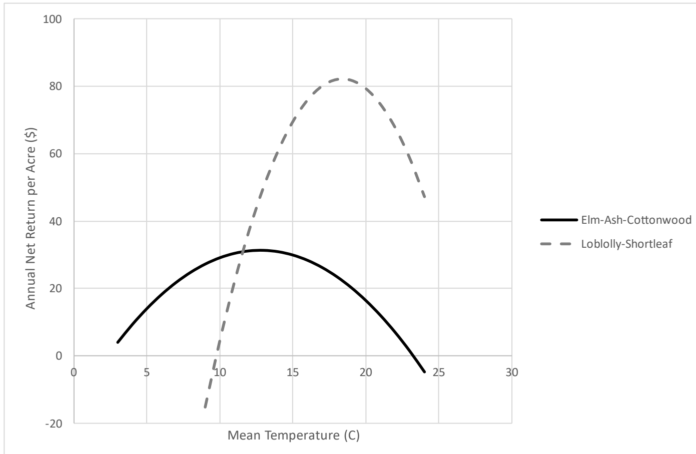


Figure 1: this graph depicts the Ricardian functions of two forest types: Elm-Ash-Cottonwood (solid line) and Loblolly-Shortleaf (dashed line). The y axis is a per-acre measure of annual net returns to forestry. The x axis is mean temperature in degrees C. One way to look at this graph is to consider 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 the context of our paper, take the state of Kentucky for example, where the average temperature of FIA forest plots is 13.2 degrees C (slightly above the adaptive margin). At the same time 94% of FIA forest plots in Kentucky are hardwood forests. In 2050, the average temperature in Kentucky is projected to increase to 15.9[2] degrees C. With such temperature increases, Fig. 1 suggests that Loblolly-Shortleaf pines will become increasingly more profitable for the landowner than the Elm-Ash-Cottonwood hardwood forests.

Fig. 1 is a simple example to illustrate the how climate change will create incentives for landowners in the mid-Atlantic region of the United States to adapt by planting pine forests. However, climate adaptation is not frictionless, and there is an economic reason why landowners may not switch the types of trees they are planting as soon as the returns to pines rise above the returns to hardwoods. Southern pines can be susceptible to cold temperatures, especially young stands (Lu et al. 2021; Nedlo et al. 2009; Pickens and Crate 2018; Schmidtling 2001) – so variation in wintertime cold temperatures creates uncertainty about the viability of planting pines. The combination of this climate uncertainty and the irreversibility of the planting decision generates our hypothesis that there is an option value associated with delaying the adaptation decision to plant pines.

[2] This uses aggregated MACA climate projections and assumes the RCP 8.5 warming scenario

4. A Theoretical Model of Climate Adaptation Under Uncertainty

We extend the work of Guo and Costello (2013) and Hashida and Lewis (2019) to illustrate the role of uncertainty on the timing of forest management decisions. Consider the risk-neutral owner of a forest parcel with type *F* trees of age *a* in year *t*. If the owner harvests their stand they gain net harvest revenues of $V_t^h(F, a)$ and then must choose the forest type to plant on their bare land post-harvest (*ph*). The post-harvest land value function from type *F* trees is a function of the state (*s*) of the future climate (c_{t+1}^s) on their land and is denoted $V_{t+1}^{ph|h}(F, a, c_{t+1}^s)$. The future climate state c_{t+1}^s is uncertain to the landowner and thus a random variable. As such, the post-harvest value function is a random variable and depends on the expectation over future climate states (written as E_s):

$$E_s[V_{t+1}^{ph|h}(F, 0, c_{t+1}^s)]$$

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:

$$V_t(F, a, c_t) = max \begin{cases} V_t^h(F, a) + \delta \cdot \max_F E_s[V_{t+1}^{ph|h}(F, 0, c_{t+1}^s)]_{F=1}^{F\prime} \\ \delta E_s[V_{t+1}(F, a+1, c_{t+1}^s)] \end{cases} \tag{1}$$

Where δ is the discount factor. If the landowner lets the stand grow in age to a+1, then Eq. (1) may also reflect management options besides commercial harvest, such as thinning or controlled burns.

The climate adaptation decision on the extensive margin occurs when the landowner 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 harvests in time *t* must make this choice with the climate information that is available in *t*, which is represented in the term $\max_F E_s[V_{t+1}^{ph|h}(F, 0, c_{t+1}^s)]$ in Eq. (1). A landowner that chooses not to harvest in *t*=1 postpones the adaptation decision of *F* at least until *t*=2. Therefore, the expected value of not cutting $E_s[V_{t+1}(F, a+1, c_{t+1}^s)]$ reflects the fact that the landowner will have gained new information about the set of future climate states occurring between time *t* and *t*+1 before making any future/subsequent adaptation decisions of *F*.

Since the harvest decision is irreversible, the problem in Eq. (1) belongs to a class of stochastic dynamic programming problems whereby the optimal choice depends on the existence of an option value of waiting to gain information on the uncertain variable – the future climate state c_{t+1}^{s} in this case. Eq. (1) extends past studies (Mezzey and Conrad 2010) by bringing climate uncertainty into an irreversible resource management case that is viewed as an adaptation choice.

A Two-Period, Two-State, Two-Forest Type Example

Consider a simple example to set intuition for the factors that influence option values relevant for forestry climate adaptation. This example is motivated by our empirical context, whereby owners of hardwood forests in the eastern U.S. face the possibility of adapting to warmer temperatures by converting their forests to one of a group of more commercially valuable pine species that grow in the hotter portions of the southeastern U.S., commonly called yellow pines.[3] As discussed above, young pines are susceptible to wintertime low temperatures, and future climate change will increase wintertime low temperatures in many areas to the north of the pines' current range, thereby lowering the climatic barrier to planting pines. However, a key source of uncertainty is the possibility of significant wintertime cold spells that can damage young pine stands. If those cold spells don't occur, pines are more likely to thrive and the landowner who plants pines will likely be better off than if they regenerated hardwoods. On the other hand, if wintertime cold spells do occur then there is a risk that the pines will be damaged for those owners that plant them, and they may have instead been better off regenerating hardwoods.

To formalize this logic, consider a landowner that owns a hardwood stand ($F=hw$). Now assume a two-period setting where the current climate in t is known while future climate in t+1 can take one of two states: a high state (c_{t+1}^{H}) or a low state (c_{t+1}^{L}). Once the climate state in t+1 is revealed, there is no further uncertainty. Further, suppose that the post-harvest value function of hardwoods is unaffected by the future climate state, while the post-harvest value function of pines is higher in the high climate state than the lower climate state. Additionally, pines are more valuable than hardwoods in the high climate state while hardwoods are more valuable than pines in the low climate state. Eq. (2) summarizes the assumptions about the post-harvest value functions:

[3] Yellow pines in the U.S. southeast include loblolly, shortleaf, longleaf, and slash pines.

$$V_{t+1}^{ph|h}(pines, a, c_t^H) > V_{t+1}^{ph|h}(hw, a, c_t^H) = V_{t+1}^{ph|h}(hw, a, c_t^L) = V_{t+1}^{ph|h}(hw, a) > V_{t+1}^{ph|h}(pines, a, c_t^L) \tag{2}$$

Finally, the landowner in time *t* has expectations of future climate states in time *t+1*. Let *p* be the landowner's perceived probability that the high climate state occurs in *t*+1, and therefore (1-*p*) is their probability that the low climate state occurs. Though this is a stylized example, it fits the key feature of a forest landowners' replanting problem – a landowner who plants trees today is subject to a random future climate state that determines how well their stand grows into the future. Under this simple two-period setup, harvest and replanting occurs in either *t*=1 or *t*=2, but the termination value of a *t*=2 choice is measured in *t*=3. Given the setup of this problem, the land value functions for the different management choices are presented in Table 1.

Table 1: Land value function resulting from management choice in t=1

Management Choice	**Land value function**
Harvest in *t*=1, plant hw	$V_1^h(hw, a) + \delta V_2^{ph\|h}(hw, 1)$
Harvest in *t*=1, plant pines	$V_1^h(hw, a) + \delta[p \cdot V_2^{ph\|h}(pines, 1, c_2^H) + (1-p) \cdot V_2^{ph\|h}(pines, 1, c_2^L)]$
Wait and harvest in *t*=2	$\delta V_2^h(hw, a+1) + \delta^2[p \cdot V_3^{ph\|h}(pines, 1, c_2^H) + (1-p) \cdot V_3^{ph\|h}(hw, 1, c_2^L)]$

The land value function resulting from management choices in *t*=1 can be used to define the option value of waiting along with some simple comparative statics. If it is optimal to wait until *t*=2 to make the management choice, the option value of waiting is the difference in the land value function from waiting and the optimal value function from harvesting in *t*=1:[4]

[4] If it is not optimal to wait, the option value is zero.

$$[\delta V_2^h(hw, age+1) - V_1^h(hw, age)] +$$

$$[\underbrace{\delta^2 E_S \max_{\{F\in hw,pines\}} V_3^{ph|h}(F,1,c_2^S)}_{\text{Optimal choice once climate has been revealed}} - \underbrace{\delta \max_{\{F\in hw,pines\}} E_S V_2^{ph|h}(F,1,c_2^S)]}_{\text{Optimal choice \textbf{\textit{before}} climate has been revealed}} \tag{3}$$

From Eq. (3), the option value of waiting is an increasing function of i) the growth in harvest value from waiting (first square bracket), and ii) the future value premium arising from making the optimal choice once the climate state *S* has been revealed rather than before it has been revealed (second square bracket). A key feature of Eq. (3) is that the expectation operator is outside the maximization operator when the optimal choice is made in *t*=2 once the climate state is realized, and the expectation operator is inside the maximization operator when the optimal choice is made in *t*=1 before the climate state is realized. One feature revealed by Eq. (3) is the classic tradeoff from waiting to harvest a forest stand – waiting delays the planting date for the new stand but allows the existing stand to grow in value.

Now consider how the option value is affected by uncertainty by supposing that the variance of the post-harvest value function for *pines* increases while the mean stays fixed. If the variance of $V_2^{ph|h}(pines, 1, c_2^S)$ increases while the mean stays fixed, then pine values in the high climate state $V_2^{ph|h}(pines, 1, c_2^H)$ must increase while pine values in the low climate state $V_2^{ph|h}(pines, 1, c_2^L)$ must decrease by the same amount. A fixed mean of the post-harvest pine value function means the expected value of harvesting and planting pines in *t*=1 remains unchanged. However, the one term in Eq. (3) that does change is $E_S \max_{\{F\in hw,pines\}} V_3^{ph|h}(F, 0, c_2^S)$, which must increase since the reward from being able to flexibly plant pines only when the high climate state occurs has increased. Therefore, higher climate uncertainty <u>increases</u> the landowner's incentive to delay the climate adaptation decision – which occurs at the post-harvest, planting stage. Further, an increase in the value of pines in the high climate state - $V_2^{ph|h}(pines, 1, c_2^H)$ - increases the value from harvesting and planting pines in *t*=1 more than delaying the decision because planting in *t*=1 starts the stand growing sooner than delaying until *t*=2 (assuming positive discounting).

5. Empirical methods

Given our theoretical framework and what we know about the incentives for landowners to adapt from Sec. 3, there are two hypotheses we want to test: 1) that uncertainty slows adaptation by lowering the incentive to plant pine, and 2) that the effect of uncertainty is dependent on a location's proximity to the adaptive margin. We test these hypotheses by developing an empirical framework of forest management decisions that explicitly accounts for the effect of climate uncertainty. The key empirical contribution comes from our use of long-term weather variation to represent climate uncertainty. Climate uncertainty creates uncertainty in the value function of different management decisions like is found in Schatzki (2003) but integrated into the discrete-choice model of forest management under climate adaptation found in Hashida and Lewis (2019). We first describe our measure of uncertainty and then get into the estimation methods.

5.1. Measuring uncertainty

We construct a plot-level measure of climate uncertainty defined as the 20-year variance in minimum daily non-growing season temperatures[5]. We will refer to this variable as *var(wtmin)* for the remainder of the paper. Previous research using real-options theory to model forest harvest and land-use decisions generally use future prices or returns as the source of uncertainty (Mezey and Conrad 2010; Schatzki 2003; Regan et al. 2015) rather than climate uncertainty. Our climate uncertainty measure varies at the plot-level giving us more variation to work with than prior empirical studies that measure uncertainty in returns at a courser scale (Schatzki 2003). Further, we do not impose a specific underlying stochastic process to develop our climate uncertainty measure, which has been a source of contention in previous options value literature (Insley 2002). Rather, we exploit historically observed variations in weather.

The choice of climate variable to use in this uncertainty measure is driven by the specific planting decision considered in this study: the fact that pine forests are limited in their expansion northward by wintertime low temperatures. Natural science studies have identified that average minimum winter temperatures are a key environmental variable determining the growth and

[5] We tested the performance of a few different measures of uncertainty, including var(wtmin) calculated over the previous 5 years as well as the number of days below freezing. We found that 1) the variance measure performed better than the number of days below freezing and 2) the long-term 20-year measure performed better in our model. Additionally, we tested a model that included both a short-term 5-year measure and a long-term measure of variance from 20 to 5 years prior to determine if there was any evidence supporting whether landowners update their expectations of climate.

survival of southern pines (Lu et al. 2021; Schmidtling 2001). Furthermore, unseasonably warm temperatures during wintertime can increase the risk of cold damage to southern pine seedlings, especially when followed by very cold temperatures (Pickens and Crate 2018). Because of these relationships between southern pine and cold temperatures, the variance of wintertime low temperatures captures uncertainty over the chance of survival and healthy growth of pine plantations. Specifically, conditional on a given average wintertime low temperature, a higher var(*wtmin*) would signify a greater uncertainty about whether or not a pine species, such as loblolly could grow in those regions whereas a lower var(*wtmin*) would represent greater certainty about the survival/profitability of these forests.

Figures 2A-B illustrate the idea that the impact of uncertainty on planting pines will vary depending on proximity to the adaptive margin. Figures 2A-2B represent the distributions of daily minimum non-growing season temperatures of two plots with the same mean non-growing season temperature ($\overline{temp}$). The vertical line depicts the boundary between the high climate state (c_{t+1}^{H}) and low climate state (c_{t+1}^{L}) discussed in Sec. 4. Fig. 2A shows temperature distributions of two plots that are well below the adaptive margin and could represent northern plots of forest land. While the plot with the wider distribution of daily low temperatures is more uncertain about what the future winters will look like, landowners on both plots would still be highly certain that their land is too cold for a planted pine forest to be more profitable than a hardwood forest. In this case, var(*wtmin*) does not have an impact on the decision to plant pines.

Figure 2A

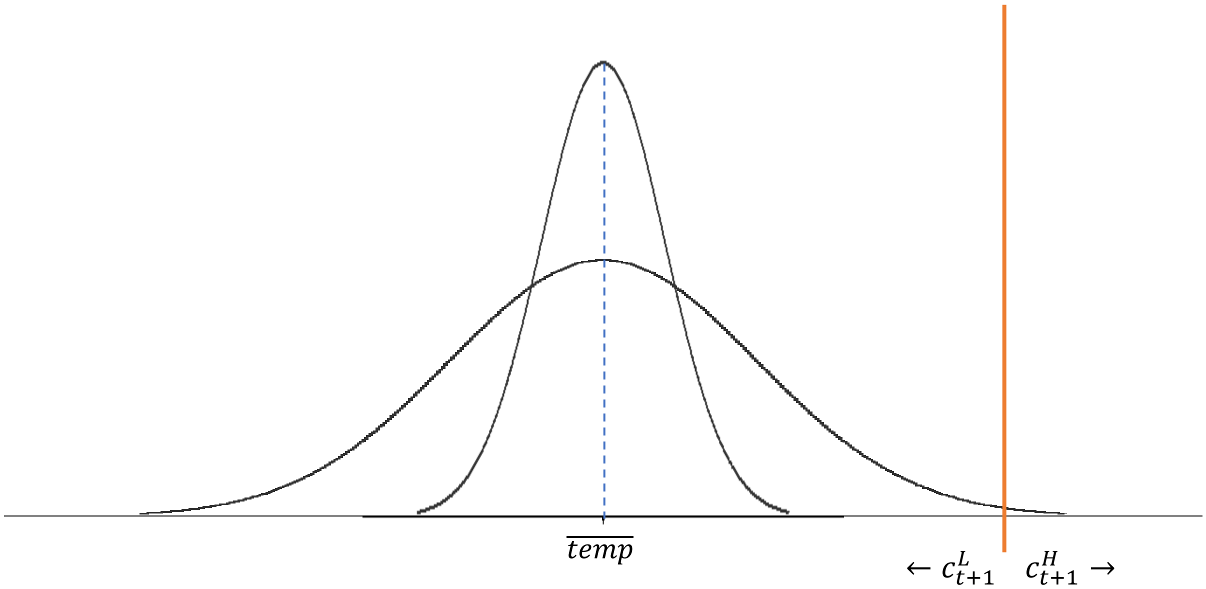
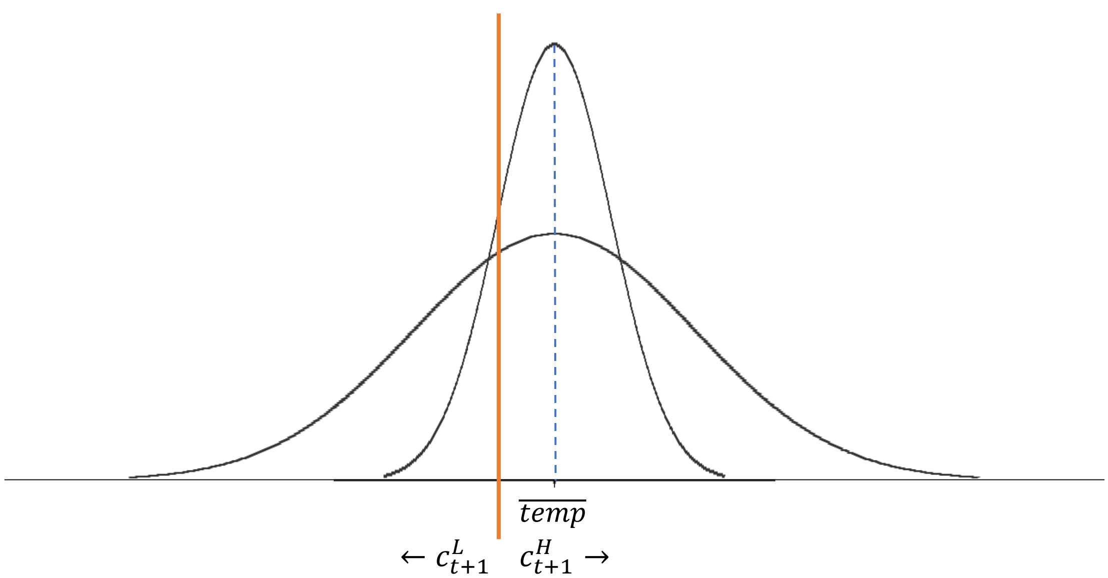


Figure 2B



On the other hand, Figure 2B depicts two theoretical plots closer to the adaptive margin. These plots also have the same average winter temperature ($\overline{temp}$), much closer to the adaptive margin but with two different levels of var(*wtmin*). We would expect to find plots like these from Fig. 2B in areas such as Tennessee and Kentucky. In this case the landowner in the location with less variation in wintertime temperatures is more certain about the high climate state occurring in the future compared to the location that has experienced much greater variation in wintertime temperatures. In locations close to the adaptive margin such as those depicted in Fig. 2B, we would expect the effect of var(*wtmin*) to have a greater impact on harvest and planting decisions.

5.2. Empirical specification

We use a discrete-choice, random utility framework with a nested structure to estimate the management decisions, building off the discrete-choice framework of Hashida and Lewis (2019). An owner of a timber stand faces the decision of whether to harvest their stand or not. Conditional on harvesting, they face the decision of whether to plant pines or regenerate hardwoods. Conditional on not harvesting, the stand grows, and the landowner bears some risk of natural disturbance. The planting decision and the disturbance model are estimated separately as the two lower nests. The solutions of the planting and natural disturbance models are embedded in the upper nest harvest decision using the nested logit structure (Train 2009). Climate enters into the planting and the natural disturbance nest, and also affects the harvest decision due to the inclusive value from the nested logit structure. Given our focus on how climate uncertainty might delay adaptation from hardwoods to pine, and given that pines are predominantly established through planting on cleared land, we define harvest as having received a clear-cut harvest. Any partial cuts are embedded in the "no-harvest" nest and we do not separately estimate drivers of partial cut harvests.

Planting Model

We define the planting decision as a binary choice between planting managed pine forests or natural hardwood forests. To construct our binary dependent variable, we assign forest type groups into two choice categories: managed pines and natural hardwoods[6]. Table A1 in the

[6] Of all the plots in our sample area that have been planted, we determine the proportion of plots in each forest group that were artificially regenerated (as opposed to naturally regenerated). Forest groups with more than 50 percent of planted plots that were artificially regenerated are categorized as "managed pine" while those with less than 50 percent of plots artificially regenerated are categorized as "natural hardwood".

appendix presents the results of this categorization. Conditional on harvesting, a landowner can choose to either plant a managed pine stand or regenerate natural hardwoods. We assume that the plots of land must remain in forests, which eliminates the option of converting the land to another use[7].

Post-harvest, a landowner of plot *n* 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:

$$V_{njt}^{ph|h} = \beta_0 + \beta_{1j}\overline{wtmax}_{nt} + \beta_{2j}\overline{precip}_{nt} + \beta_{3j}land_n + \beta_4 NR_{r(n)jt} + \beta_5 NR_{r(n)jt} * \overline{wtmax}_{nt} + \beta_{6j}var(wtmin)_{nt} + \beta_{7j}var(wtmin)_{nt} * \overline{wtmax}_{nt} + \varepsilon_{njt} \quad (4)$$

For $ph = plant|clear - cut$

Where $\overline{wtmax}_{nt}$ represents the average wintertime maximum temperature from the 30 years prior to *t*, $\overline{precip}_{nt}$ represents average annual precipitation from the 30 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. It is well known in the forest biology literature that the distribution of southern pine species is limited to the north by cold temperatures and to the west by low levels of precipitation (Schmidtling 2001; Lu et al. 2021).

[7] Inclusion of the choice to convert land to other uses 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 groups and its interaction with climate.

The variable $land_n$ is an indicator of land quality measured with the FIA's site class[8], and $NR_{r(n)jt}$[9] is the average net returns to forest group j for plot n in region[10] r. The key explanatory variable measuring climate uncertainty is $var(wtmin)_{nt}$, which is the variance of minimum daily wintertime low temperature in the 20 years prior to year t. The interaction term between $var(wtmin)_{nt}$ and $\overline{wtmax}_{nt}$ allows the effect of $var(tmin)_{nt}$ to vary across different climates as illustrated by Figure 2. The interaction $NR_{r(n)jt} * \overline{wtmax}_{nt}$ scales the regional average net return based on plot-level variation in $\overline{wtmax}_{nt}$. Finally, there are unobservable factors that drive management choice j (e.g. landowner skill) 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. This relationship arises because climate conditions such as temperature and precipitation are key factors that affect the growth of trees and, consequently, the value of the forestland (Hashida and Lewis 2019; Schmidtling 2001; Lu et al. 2021). While the climate variables 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. If 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. On the other hand, a hardwood forest type may not be well suited to warmer climates and in that case, we would expect a negative relationship between temperature and land values for plots with that forest type.

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[8] 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.

[9] Due to the timeframe between planting and harvest, forest owners only have an expectation of their profits from planting a given forest type. As such, we construct an expected net returns variable to approximate how a landowner may assess the economic tradeoffs of different replanting choices, a key determinant of their replanting decision and the overall value of a parcel of forestland. As net returns to forest type *j* increase, the value of a parcel of land with forest type *j* will also increase. Therefore, if a landowner's expectations of net returns to forest type *j* increase, the probability that they choose to replant *j* also increases. We assume that the relationship between expected net returns and the replanting decision does not vary across forest types and therefore we do not index its coefficient by *j*.

[10] 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. See Figure 1 for map of the study area with the price regions displayed.

The planting model is estimated using a pooled cross-sectional dataset of harvested plots. Due to the timespan of our sample, we only observe one harvest for any one of these plots. We recognize that with pooled cross-sectional data, our estimation is more susceptible to omitted variable bias compared to a panel data with plot fixed-effects. While we expect some omitted variables in ε_{njt} such as management experience, risk preferences, and reasons for owning land to affect the planting decision, it is unlikely that these characteristics are correlated with climate or climate uncertainty. As such, their exclusion from the model would not bias our estimates of the coefficients on our variables of interest ($var(wtmin)_{nt}$, $\overline{wtmax}_{nt}$, and $\overline{precip}_{nt}$).

Natural Disturbance 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 estimate this probability in the second lower nest. 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 the disturbance caused substantial damage to the stand. The probability of disturbance, conditional on a plot not being harvested, is a function of climate variables, ownership, elevation, and location. Disturbance is estimated with the following latent value binary outcome specification:

$$V_{nt}^{ph|h} = \beta_0 + \beta_1 elevation_n + \beta_2 private_n + \beta_3 \overline{tmean_{nt}} + \beta_4 \overline{ngprecip_{nt}} + \beta_5 state_{s(n)} + \varepsilon_{njt} \quad (5)$$

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

Where $disturb_n$ is a binary variable equal to 1 if the plot has been naturally disturbed and 0 if not; *elevation* is the plot's elevation; $private_n$ is a binary variable indicating whether the plot is privately owned or otherwise; $\overline{tmean_{nt}}$ is the mean annual temperature; $\overline{ngprecip_{nt}}$ is the average precipitation during non-growing season; and $state_{s(n)}$ is a vector of dummy variables indicating the plot's state. It is widely established in forest ecology that climate variables such as temperature and precipitation can affect forests' susceptibility to damage from pests and disease, their ability to suppress fires, as well as damage from weather events such as freezing temperatures, ice, flooding and drought (Mattson and Haack 1987; Weed et al. 2013).

Harvest Model

The harvest decision is estimated as the upper nest, which embeds the solutions from the lower nest planting and disturbance models. Given a plot of forestland, the landowner can choose to harvest or let their stand grow for another period. The harvest decision is a function of the estimated revenue from the associated harvest decision and the inclusive values from the planting and disturbance models:

$$V_{nkt}^{h} = \beta_0 + \beta_{1j} rev_{nkt} + \beta_{2j} \Delta rev_{nkt} \tag{6}$$

Where $k = \begin{cases} 1 \; if \; clear \; cut \\ 0 \; otherwise \end{cases}$

And rev_{nkt} is the revenue associated with the harvest decision. For the clear-cut decision, revenue is calculated as the price times the volume of wood on the plot – what the landowner would receive if they clear cut their plot today. The term Δrev_{nkt} reflects the additional revenue the landowner would receive if they let their trees grow another period. As shown in Eq. (1), the harvest decision is dependent on both V_{nkt}^{h} and on the optimized post-harvest value function, represented in the nested logit model by the inclusive values formed from the planting and natural disturbance nests [$I_{nkt}^{h} = ln \sum_{j=1}^{2} exp\left(V_{njt}^{ph|h} / \lambda_k\right)$]. The inclusive value is the optimized value of the respective lower nest model. The nested logit model embeds I_{nkt}^{h} into the harvest model as a set of independent variables for each k. 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):

$$Prob_{njt} = Prob_{nkt}^{h} \cdot Prob_{njt|k}^{ph|h} = \frac{\exp\,(V_{nkt}^{h} + \lambda_k I_{nkt}^{h})}{\sum_{k=1}^{K} \exp\,(V_{nkt}^{h} + \lambda_k I_{nkt}^{h})} \cdot \frac{\exp\,(V_{njt}^{ph|h} / \lambda_k)}{\sum_{j=1}^{J} \exp\,(V_{njt}^{ph|h} / \lambda_k)} \tag{7}$$

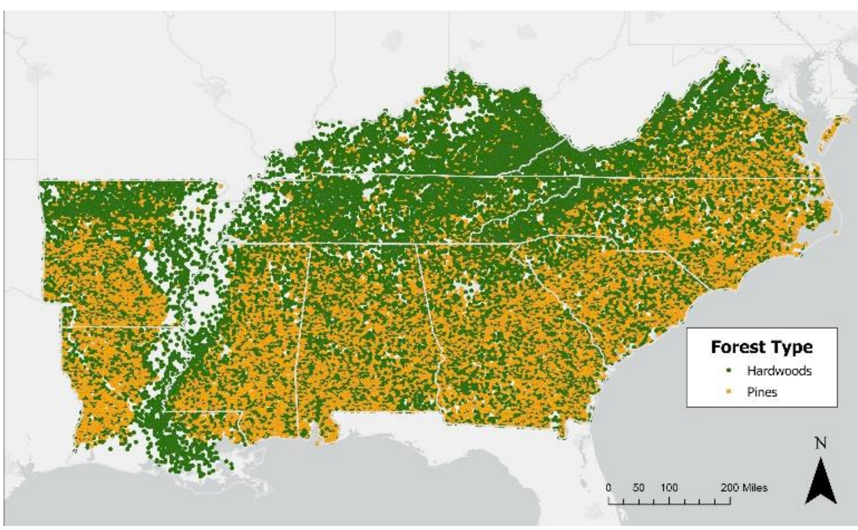
The advantage of the nested logit model is that the empirical structure of the model reflects the theoretical nesting structure from Eq. (1) – the optimized post-harvest decision affects the harvest decision directly. The data used to estimate the harvest decision is an unbalanced panel since we observe the harvest decision at least twice on a majority of the plots (84%) in our sample.

6. Data and Study Area

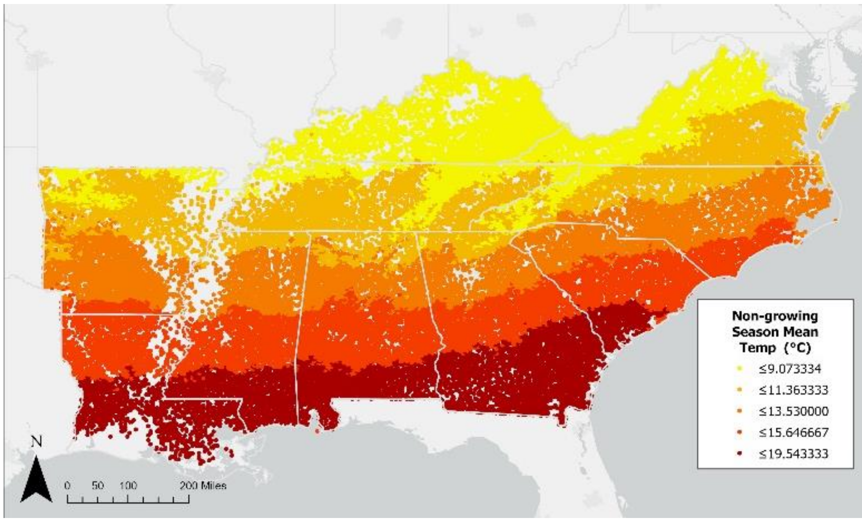
6.1. Study area

Our study area comprises 11 states in the southeast and mid-Atlantic United States and has some key characteristics that make it an ideal location to study the effects of option value 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) of landowners. Second, the most valuable trees are in warmer locations in the south while the cooler regions in the inland mid-Atlantic (Kentucky and Tennessee in particular) are dominated by less valuable hardwood forests (Fig. 3A and 3B). Comparing Fig. 3A and 3B, we see a relationship between the location of pine forests and higher temperatures. The majority of pine forests are located in the deep south (LA, GA, AL) and nearer the coast throughout the Carolinas and Virginia, whereas states such as Tennessee and Kentucky have relatively fewer pine forests. Third, there is distinct spatial heterogeneity in our key measure of climate uncertainty (Fig. 3C): the variance of the wintertime cold temperatures is notably lower in the region east of the Appalachian Mountains and much higher north and west of those mountains. This variation in climate uncertainty is critical for identifying its impact on forest management decisions.

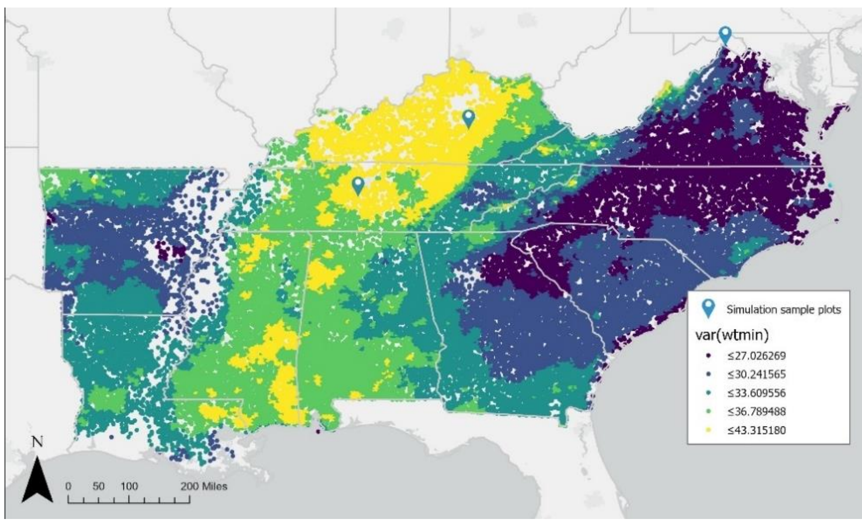
Figures 3A-C: FIA forest plots in the southeastern and mid-Atlantic United States



A: Current distribution of hardwoods and pines (see Table A1 for the categorization of forest types into these choice groups).



B: Current mean temperature during the non-growing season



C: Current level of climate uncertainty, measured by variance in wintertime low temperatures, $var(wtmin)$. This map also indicates the approximate location of the three sample plots used in our simulation of future adaptation decisions (see Section 8).

As temperatures warm under climate change, areas in the mid-Atlantic United States are expected to reach temperatures similar to the region directly south. Consequently, landowners in the mid-Atlantic will be presented with economic incentives to plant pine forests in favor of hardwood forests (Figure 1). Including southern states in our study, such as Alabama, Georgia, Louisiana, and Mississippi, gives us the range of climate data needed to estimate the relationship between warmer temperatures not currently seen in the mid-Atlantic and observed planting decisions. This aspect of our data overcomes a common challenge in empirically estimating climate adaptation decisions which is the fact that historical climate has not experienced the changes that are projected to occur into the 21st century. Empirically estimating this relationship is difficult if researchers aim to predict how people will adapt to never-before-seen climate (Massetti and Mendelsohn 2018). The diverse climate and forest management decisions within our study area overcome this challenge. Our identification of the effects of climate on management decisions relies primarily on the spatial variation in long-term climate variables, including our measure of climate uncertainty.

6.2. Data

We use plot-level panel data with 61,540 observations of forest management decisions across 30,903 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 region so each plot in this region is measured approximately once every five years. 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[11], and other plot characteristics. We combine these data with downscaled climate data from the Parameter-elevation Regressions on Independent Slopes Model (PRISM), as well as data on annualized net returns to forestry developed by Mihiar and Lewis (2021). A full list of data and sources are found in Table A2 of the Appendix.

Of the 61,540 observations of management decisions, 3,131 (5.1%) of those are harvests[12] and are used to estimate our planting model. Because of the time-span of our data set and the rotation lengths, we only observe the planting decision once for any given harvested plot, leaving us with a cross-sectional dataset to estimate this model. The remaining 58,409 observations are non-harvests and are used to estimate the disturbance model. All observations are used to estimate the upper nest harvest model. Both the disturbance model and harvest model are estimated with

[11] Volume 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 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).

[12] We define a harvested plot as one that has been clear cut. Plots that have been partially cut are not included in our definition of harvested.

unbalanced panel datasets as there are 9,668 plots (16% of the total observations) that have only been measured once.

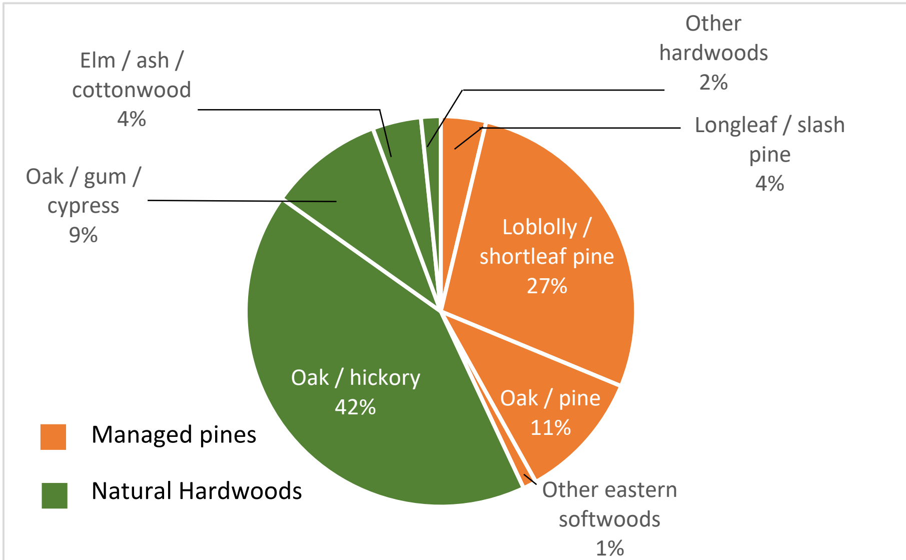
As discussed in section 6.1, we categorize planting decisions into our two choice groups: planted pines and hardwoods (Table A1). Fig. 3A shows how these forest types are distributed across the study area. Table A3 presents the proportion of plots in each forest group for each state and the whole sample. Planted pine forests make up 43% of our sample, while natural hardwood forests make up the other 57 % (Figure 4). When broken down by state, this distribution changes. In Kentucky, for example, only 5 percent of the plots are in planted pine, compared to South Carolina where 43 percent of plots are in planted pine, and Georgia where 55% of plots are in the pine choice group (Table A5).

PRISM Climate Data:

We map downscaled climate data (800m resolution) from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) to our FIA plots. Using daily historical climate data, we construct 30-year means for the following climate variables: mean daily maximum temperature during the non-growing season ($\overline{wtmax}$), mean annual temperature ($\overline{tmean}$), mean annual precipitation ($\overline{precip}$), and mean non-growing season total precipitation ($\overline{ngprecip}$). We also utilize daily historical climate data from PRISM to construct our measure of climate uncertainty[13], ($var(wtmin)$)(Fig. 3C).

[13] We test three different uncertainty variables: variance in minimum wintertime temperature (MWT) over the years 1990:2015, variance in minimum non-growing season temperature of the 5 years preceding the year the plot was measured, (for example, if a plot was measured in 2005, we take the variance of non-growing season minimum temperatures over 2000-2004 and yearly average number of days below 0° C.

Figure 4: Proportion of forest groups in the study area



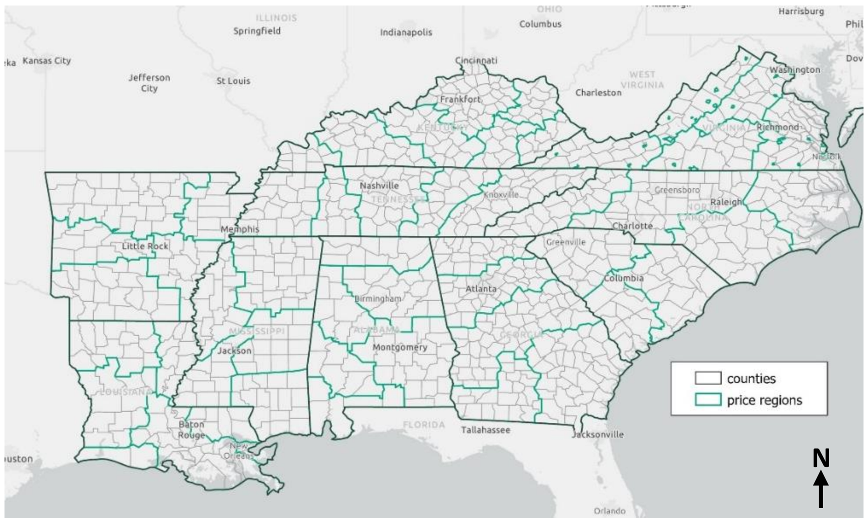
Net Returns to Forestry and Stumpage Price Data:

We use a county-level data set of the annualized net economic returns to forestland for each year from 1998-2014 (Mihiar and Lewis 2021). These returns are calculated using observed local stumpage prices georeferenced to the county level, and rotation lengths that are empirically observed using the FIA data. The rotation lengths are forest type-specific and observed at the state level. One advantage of using observed rotation lengths is that we do not have to impose an assumption about future climate in determining rotation length, as would be the case if an optimal Faustmann rotation were used. To avoid the identification issues that stem from a lack of within-county climate variation[14], we aggregate these net returns data to a regional level for each of these two categories of forests. Regions are defined by the FIA survey groups. There are 21 regions in our data set, with an average of 20 counties per region (Fig. 5). This aggregation of net returns is advantageous for two main reasons: first, the within-region climate variation is now much greater than within-county climate variation; second, we lose fewer observations as a result of missing county-level net returns data. From these data, we construct a measure of expected net returns to each replanting choice by taking an average of the net returns from the five years preceding time *t*. Ultimately, this results in expected net returns data for the years 2002-2014

[14] Net returns data do not exist for every forest group in every county. This could either be because price data was not collected or reported in a county or because there is minimal to no market activity for a forest group in a county (in other words, a very small amount of trees of a forest group are being bought and sold in that county or that forest group is not even growing in that county) (Mihiar and Lewis 2021).

which varies across regions and the two planting choices. Additionally, we use the recorded stumpage price data from this dataset to calculate the marginal costs and benefits of harvesting used to estimate our harvest model. Prices are recorded at the county-level annually from 1998-2014 and matched to each tree species group.

Figure 5: Price Regions



In the case of our study area, pine forests are the more valuable forest type with average net returns of $23.12 per acre compared to an average net return of $9.36 per acre of hardwood forests. The values of these forests vary spatially as well. Net returns to pines vary from an average of $12.34 in Virginia to an average of $29.33 in Tennessee. Summary statistics for all explanatory variables are provided in Table A5 and summary statistics for selected variables across forest types are found in Table A4 in the Appendix**.**

7. Econometric Estimation Results

Our planting model is estimated using 3,131 observations of *harvested* plots. We estimate two different planting models: our preferred model that includes var(*wtmin*) as an explanatory variable (column (1) in Table A6), and an alternative model that does not include var(*wtmin*) (column (2) Table A6). The disturbance model is estimated using the remaining 58,409 observations of plots that were not harvested. Finally, we estimate the harvest model (upper nest) using our panel of 61,540 observations.[15] The full set of parameter estimates are presented in Table A6 of the appendix while estimated partial effects are presented in Table A7. Using the

[15] Approximately 16% of plots are only observed once in the data, while the remaining 84% of plots are observed at least twice each.

average climate of each state and the whole sample as the baseline, we estimate the partial effects of the average projected climate changes for the region (2 °C increase in wintertime temps 80 mm increase in precipitation) and a two standard deviation increase in *var(wtmin)* for each state and the sample as a whole. A few key results are discussed below.

The statistically significant parameters ($p<0.05$) of the planting model include the parameters on *var(wtmin)*, precipitation, temperature, net returns, the interaction between *var(wtmin)* and temperature, and site class. All signs are as expected and intuitive, e.g. higher net returns to a forest type increases the probability of choosing that forest type for replanting. The parameter estimate for var(*wtmin*) is negative and significant ($p<0.01$) indicating that uncertainty lowers the probability of planting pine, while the interaction between variance and temp is positive and significant ($p<0.01$), implying that the warmer a location is during the winter, the larger effect var(*wtmin*) will have on the decision to plant pines. The positive parameter on this variance-temperature interaction confirms our hypothesis that wintertime low temperature variance is likely to have a larger effect on plots that are closer to the adaptive margin between hardwoods and pines. All parameters in the harvest model are statistically significant ($p<0.05$) and intuitive, while the statistically significant parameters ($p<0.05$) in the disturbance model are the parameters on elevation, ownership, and the dummy variables for Louisiana, Mississippi, and South Carolina.

Given the non-linearity and interactions in the econometric model, we examine estimated partial effects in Table A7, which are evaluated at the average climate of each state in our sample. Key results include the following. First, an increase in wintertime maximum temperatures raises the probability of planting pines and the probability of harvesting in all states except Arkansas and South Carolina where there is no significant impact. There is no significant impact on the probability of natural disturbance. The partial effect of a 2°C increase in temperature increases the probability of planting pine by between 2.8% (Virginia) and 7.8% (Mississippi). Second, an increase in precipitation raises the probability of planting pines and the probability of harvesting in all states but has no significant impact on the probability of natural disturbance. The partial effect of an increase of 80mm of precipitation (the projected average increase for this region) increases the probability of planting pine by between 2.2% (Kentucky) and 5.7% (Alabama, Arkansas, Georgia, Mississippi, North Carolina, and South Carolina). Third, and most important for this study, an increase in the variance of wintertime low temperatures has a large negative effect on the probability of planting pines and the probability of harvesting in all states. An increase in *var(wtmin)* of two standard deviations is estimated to decrease the probability of planting pines by between 7.3% (Kentucky) and 21% (Arkansas and North Carolina). It reduces the probability of planting pines by 18% when calculated for the whole sample. Given that *var(wtmin)* varies considerably from state to state (Table 1 and A5, Figure 3), it is difficult to compare these partial effects across states. Two standard deviations is a relatively large change for states such as the Carolinas and Virginia where mean *var(wtmin)* is around 26 but a smaller change for states such as Kentucky and Tennessee where mean *var(wtmin)* is around 36.

8. Future climate simulation

The marginal effects from the econometric model provide insight as to how climate and climate uncertainty affect the probabilities of harvesting and planting pine forests, but do not explicitly indicate when those decisions may happen. However, because we have explicitly modeled climate uncertainty in our econometric model, we are able to simulate how changes in uncertainty alter the time path of adaptation into the future. We simulate the forest management decisions for three sample plots under climate change. The 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. The fact that harvests and subsequent plantings happen infrequently and after long periods of growth does not get captured in the econometric results. Furthermore, by simulating the results across sample plots, we can model the results of spatially heterogeneous future climate projections.

8.1. Simulation methodology

The simulation works as follows. For a given sample plot *n*, the econometric model provides an estimated probability of harvest choice *k* ($\widehat{Prob}_{nkt}^{h}$) and estimated probabilities of post-harvest management choice *j* ($\widehat{Prob}_{njt}^{ph|h}$). Our sample plots are currently in oak-hickory (*t=0* in the simulation) with an observed growing stock volume that generates an expected revenue upon harvest (rev_{njt}) or an expected revenue growth if not harvested (Δrev_{njt}), which plug in to $\widehat{Prob}_{nkt}^{h}$ and provide us with an estimated harvest probability conditional on the plot's current state in *t*=0. A uniformly distributed random number *r* between 0 and 1 is drawn and compared to $\widehat{Prob}_{nkt}^{h}$, and if $r < \widehat{Prob}_{nkt}^{h}$ the plot is harvested and if $r \geq \widehat{Prob}_{nkt}^{h}$ it is not harvested. If the plot is not harvested in $t=0$, then we use estimated timber yield functions from Mihiar and Lewis (2021) to determine how the plot grows until the next period when the harvest decision is considered again. If the plot is harvested in t=0, then we draw a different random number r^{ph} and plant pines if $r^{ph} < \widehat{Prob}_{njt}^{ph|h}$ and plant hardwoods if $r^{ph} \geq \widehat{Prob}_{njt}^{ph|h}$. If pine is planted, we assume that the plot will remain in pine and the simulation stops. If a hardwood forest is planted, we use the hardwood yield functions from Mihiar and Lewis (2021) to determine how the stand grows until the next period. Repeating this process over multiple time periods and with many different random draws generates a simulated distribution of outcomes. Since these estimated timber management probabilities are functions of climate, we use climate projections to determine how they evolve over time. 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 years) relative to the scenario of no climate change and graph the results (Figure 4).

The sample plots were chosen as ones that have a similar climate to their state's average climate. The three sample plots are in Kentucky, Tennessee, and Virginia. The key climate measures of these plots are presented in Table 2. Kentucky and Tennessee are states currently dominated by hardwoods and on the adaptive margin where forest transitions are most likely to occur. The plot in Virginia was chosen as a point of comparison – it is the northernmost plot in our sample, in a region where we expect temperatures to be too cool under climate change for landowners to plant pines. 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.[16] [17] All plots are expected to become warmer and wetter. We do not present the future projections of $var(wtmin)$ in Table 2 as they deviate significantly from their current level and show no clear trend through time or across climate models (Fig. A1).

[16] The results presented here use climate projections based on the Can ESM2 model.
[17] Each future year's climate measure is an average of the climate of the preceding 20 years.

Table 2: Current and future climate projections of simulation sample plots

	Current Climate (PRISM)				Projected 2099 Climate (RCP 8.5 MACA)		
State	$\boldsymbol{var(wtmin)}$	$\boldsymbol{wtmean}$ **(°C)**	$\boldsymbol{\overline{tmean}}$ **(°C)**	$\boldsymbol{\overline{precip}}$ **(mm)**	$\boldsymbol{wtmean}$ **(°C)**	$\boldsymbol{\overline{tmean}}$ **(°C)**	$\boldsymbol{\overline{precip}}$ **(mm)**
TN	37.31	9.35	14.49	1358.6	13.85	20.13	1579.3
VA	26.81	5.47	11.18	995.6	9.58	17.16	1141.8
KY	40.58	7.56	13.10	1227.4	11.38	18.67	1408.9

8.2. The effects of current levels of climate uncertainty on adaptation

A primary goal of the simulations is to isolate the effects of climate uncertainty on the time-path of adaptation from hardwoods to pine forests. The first approach we take is to explore how the current spatial variation in *var(wtmin)* affects the time-path of adaptation for our three sample plots. Our study area has a wide range of *var(wtmin)* with mean *var(wtmin)* being lower in the coastal states, particularly North Carolina and Virginia, and higher just west of the Appalachian Mountains (Figure 3C, Table 3). To explore the effects of different levels of *var(wtmin*), we simulate the time-path of adaptation under climate change while first holding var(*wtmin*) fixed at its current level, and then repeating the simulation for each sample plot but replacing its var(*wtmin*) with both the largest and smallest var(*wtmin*) in the study area (45.5 in Kentucky and 20.9 in North Carolina). The results from these scenarios are graphed alongside the baseline scenario (Figure 4).

Table 3: Min, max, and mean var(*wtmin*) across states

	Var(wtmin) by state									
	AL	**AR**	**GA**	**KY**	**LA**	**MS**	**NC**	**SC**	**TN**	**VA**
Min	24.4	25.9	23.4	27.1	27.5	26.8	20.9	22.3	26.9	21.2
Max	44.5	38.9	36.9	45.6	39.0	40.1	40.3	31.8	43.3	39.8
Mean	34.7	30.7	29.1	36.9	32.7	35.1	25.9	26.6	34.8	26.8

Figure 4: Simulation Results

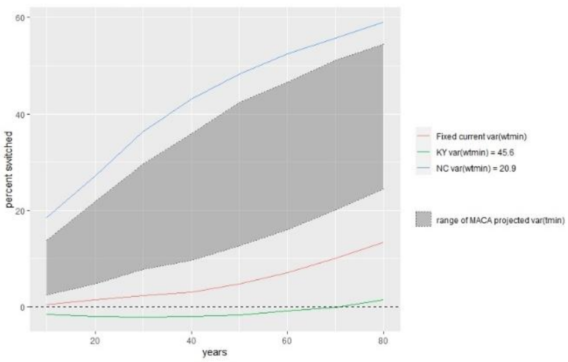
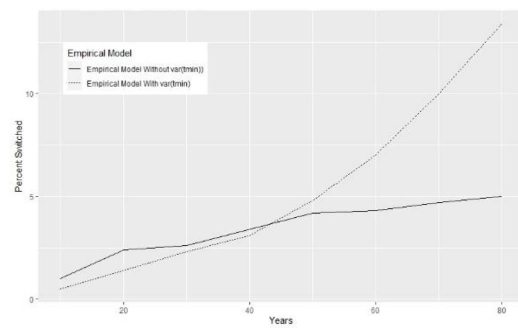
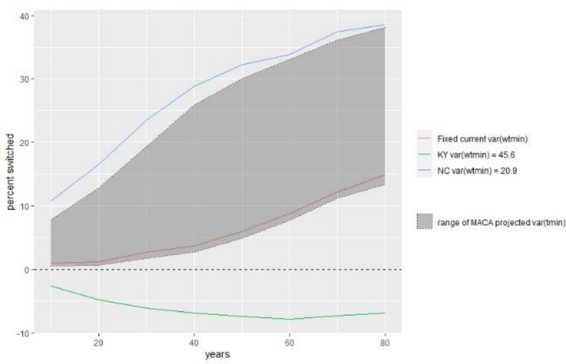
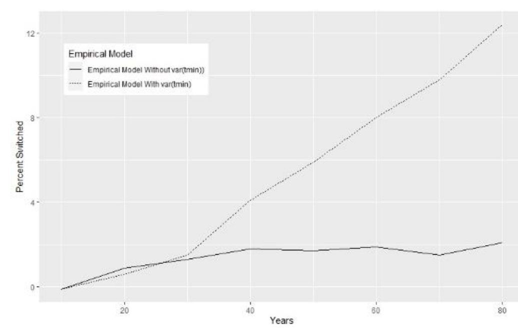
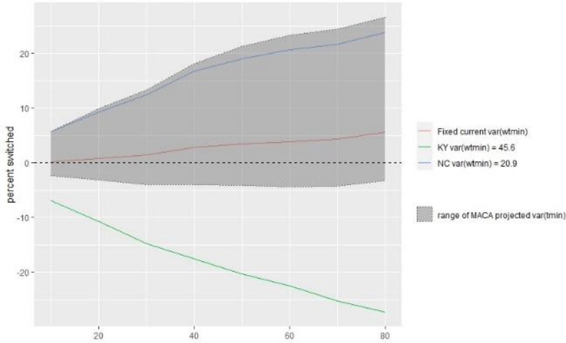
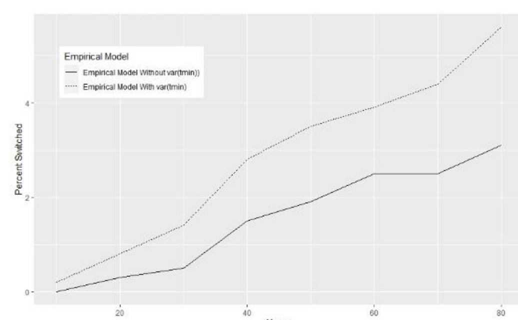
	A: Adaptation paths under different levels of uncertainty	**B: Adaptation paths when uncertainty is excluded from empirical model**
Kentucky		
Tennessee		
Virginia		

Figure 4: Results of the simulation for selected sample plots. Column (A) presents the different adaptation paths that result from replacing a plot's var(wtmin) with that of another location. It also shows the range of adaptation paths that could occur given the range in projected var(tmin) across time and across different climate models. Column (B) presents the results of the full empirical model and the empirical model that ignores variance in the non-growing season low temperature.

There are three main takeaways from the simulation results presented in Column A of Fig. 4.

1) All else equal, increased climate uncertainty slows adaptation:

These results are consistent across all three sample plots. For all three sample plots, when a larger var(*wtmin*) is substituted, the speed of adaptation diminishes relative to the baseline scenario. On the other hand, when a smaller var(*wtmin*) is substituted, the speed of adaptation increases relative to the baseline. The effects of a larger var(*wtmin*) are very pronounced in this simulation. A larger var(*wtmin*) leads to less adaptation under climate change (relative to the no-climate change scenario).

2) Climate uncertainty has larger impacts in regions where the value of adaptation is high:

Looking at the baseline outcomes under climate change, we see that the sample plots in Kentucky and Tennessee have the fastest rate of adaptation. By 2100, the probability of switching to pine forests increases from around 0% to 12.5% for these two plots whereas the sample plot in Virginia only sees an increase from about 0% to 5%. Once a low var(*wtmin*) is substituted, the probability of switching to pine forests increases substantially for the sample plot in Kentucky. We estimate that within 10 years (by the year 2030), the probability of this plot converting to pine will be just under 20% which is a 20 percentage point increase from the baseline scenario. By 2100, that probability increases to a whopping 59%. These probabilities for plots in Tennessee and Virginia are 32% and 24% respectively. These results illustrate the finding that uncertainty has less of an impact on adaptation decisions in places that are further from the adaptive margin. It is most relevant in areas that are already on the threshold of adaptation.

3) Modeling climate uncertainty generates different adaptation paths than ignoring uncertainty

Column B of Figure 4 shows the results of an additional simulation which uses the empirical planting model *without* var(*wtmin*) included as an independent variable, alongside the baseline results using the fully specified planting model that includes var(*wtmin*) in the set of independent variables. The simulation results are similar across the two models during the early years of the simulation, but the results diverge towards the end of the simulated time-period. This illustrates the importance of accounting for climate uncertainty in modeling irreversible adaptation decisions. While not including uncertainty in the empirical model may lead to some effects of climate uncertainty being embedded in other parameter estimates, ignoring uncertainty can lead to quite different projections of the rate of adaptation.

8.3. The effects of projected levels of climate uncertainty on adaptation

A second goal of this simulation is to predict the adaptation paths of each of these plots given future projected var(*wtmin).* We first calculate the future yearly projections of var(*tmin)* from 2020 to 2100 for each plot using three different climate models[18]. However, because these projections vary considerably across climate models and show no clear trend over time (Figure A1), using the time series of projections in the simulation is not informative in isolating particular changes in variance. Rather, we simulate the time-paths of adaptation under climate change using scenarios that fix the plot's uncertainty at the minimum and maximum projected var(*wtmin)* under the MACA projections (Figure 4).

The main takeaway from this approach is that adaptation paths are highly sensitive to the range of climate uncertainty in the MACA projections. These simulations produce a wide range of adaptation paths for each of the sample plots, which is due entirely to differences in var(*wtmin*). We estimate that by the year 2100, the probability of the sample plot in Kentucky switching to pine ranges from 24% to 55% across the two var(*wtmin*) scenarios, while the probability for the plots in Tennessee and Virginia range from 13% to 38% and -3% to 27% respectively. To illustrate the magnitude of this range of outcomes, take Kentucky, a state with one of the most diverse mix of hardwood species in the U.S. and where 88% (10.9 million acres) of its forests are privately owned (Brandeis et al. 2016). Given our simulation results, by 2100, between roughly 2.6 and 6 million acres of hardwood forests could be converted to pine forests - that's between 10% and 22% of the state's area. Therefore, there is significant uncertainty in the future composition of forestland that is driven by uncertainty in the eventual time path of daily variation in wintertime low temperatures. Given the fact that biodiversity is significantly lower in pine plantations relative to natural forests (Haskell et al. 2006), our results imply large uncertainties in conservation outcomes that are driven by economic uncertainties in adaptation behavior of forest landowners.

[18] the Canadian Fourth Generation Global Climate Model (CanESM2/CGCM4), the Community Climate System Model version 4 (CCSM4), and the Hadley Centre Global Environment Model version 2 (Hadley)

9. Discussion

Our results indicate that climate uncertainty slows adaptation and that proximity to the adaptive margin influences the magnitude of this effect. In an application to forest management in the eastern U.S., we find that the closer a landowner is to the adaptive margin, the more likely climate uncertainty impacts their planting and harvesting decisions. Whereas previous studies on climate adaptation in forestry have identified the effects of climate on these decisions and the economic benefits of adaptation, none have addressed how climate uncertainty affects the timing or any potential barriers to adaptation. This is a key piece of information for climate policy and conservation policy design. Because adaptation decisions are irreversible and future climate is uncertain, option value theory tells us that there would be an incentive to delay the decision to adapt to climate change by harvesting a plot of hardwood forest and converting it to a pine forest. This decision hinges on the fact that at the adaptive margin (in our case, states like Kentucky), landowners are faced with the fact that a warming climate increases the economic value of planting cold-sensitive pine species, and so converting their land to highly valuable pine forests becomes increasingly viable as the region warms. Under the assumption of costless adaptation, these landowners would be expected to convert their forests as soon as the returns to pine forests surpass that of hardwoods. While the payoff from converting to pine forests could be substantial, it is also uncertain whether or not planting a pine forest will be more profitable than the existing hardwood forests due to uncertainty in the occurrence of cold temperatures that can harm young pines. The combination of irreversibility with climate uncertainty is what gives rise to the incentive to delay the adaptation decision.

The results in this paper have implications for the many external ecosystem service benefits provided by privately-owned forests, as well as for conservation policy. The distinction between the two replanting decisions (hardwoods or pines) is important in this context. Pine forests are heavily managed and commonly occur as plantations, whereas hardwood forests tend to be naturally regenerated with much less management and greater diversity of tree species. As such, landowners' decisions to convert hardwood forests to pine plantations in response to a changing climate is a land-use change that could negatively affect biodiversity as well as alter the level of other forest ecosystem services (Paillet et al. 2010; Carnus et al. 2006; Haskell et al. 2006). Our results suggest a wide range of outcomes in the time-path of forest composition between pines and hardwoods that are driven by projected variation in daily wintertime low temperatures. Thus, our results suggest that an important source of future conservation uncertainty arises from the economic response of private forest landowners to climate uncertainty in making adaptation decisions.

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 conservation planning. From the perspective of a conservation planner, knowing the timing of land-use change – such as conversions of hardwood forests to pine forests – greatly impacts the timing of optimal conservation decisions (Costello and Polasky 2004). In particular, conservation actions that conserve 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 uncertainty in wintertime low temperatures actually evolve, highlighting the importance of accounting for uncertainty when assessing the urgency of conservation actions.

The literature has made clear that adaptation must be accounted for in climate change impact studies as adaptation affects the net damages from climate change (Auffhammer 2018; Guo and Costello 2013). Generally, studies have found that adaptation induced by private incentives reduces the damages to climate change, but adaptation decisions can have environmental consequences and produce social costs (Fezzi et al.). 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 climate uncertainty affects the private benefits from adaptation, there are potentially many social cost implications arising from these adaptive behaviors.

There are numerous other climate adaptations where we would expect an option value to exist - situations where the decision to adapt is irreversible and potentially affected by climate uncertainty. These decisions can include coastal armament and managed retreat in response to sea level rise, investments in various forms of infrastructure, and agricultural decisions that require land-use or systems changes to name a few. These are all adaptation decisions that may have an option value that incentivizes decisionmakers to delay adaptation. Depending on the context, this behavior could have detrimental effects if the adaptation were one that results in reduced climate change damages. Some of these adaptation decisions are mostly private (e.g. agricultural management); other adaptation decisions are public decisions made by governments, like beach nourishment (Gopalakrishnan et al. 2018); and others are private decisions that generate externalities, like private shoreline armoring (Dundas and Lewis 2020). Our paper models the private adaptation decisions of landowners and shows how option values can affect these decisions. That climate uncertainty can slow adaptation is consistent with prior analyses of real options theory (Mezey and Conrad 2010), and future work should explore the implications of this finding in settings where the adaptation decision being made is not a private one.

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 var(*wtmin*) under future climate, 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, 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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Appendix

Table A1: Planting model choice group definitions

Planting Model Choice Group Assignments		
Forest Group Name	Proportion Artificially Regenerated	Choice group assignment
White / red / jack pine group	66.7%	Managed Pine
Longleaf / slash pine group	86.5%	Managed Pine
Loblolly / shortleaf pine group	79.8%	Managed Pine
Other softwoods group[19]	16.7%	Natural Hardwood
Oak / pine group	60.8%	Managed Pine
Oak / hickory group	22.4%	Natural Hardwood
Oak / gum / cypress group	21.6%	Natural Hardwood
Elm / ash / cottonwood group	20.3%	Natural Hardwood
Maple / beech / birch group	0.0%	Natural Hardwood
Other hardwoods group[20]	17.2%	Natural Hardwood

Table A2: List of data used and sources

Data used in estimation

Variable	Description	Units	Source
Clear Cut	1 if clear-cut; 0 if not	binary	FIA
Disturbed	1 if plot is disturbed and experienced negative growth; 0 if not	binary	FIA
mgd_pine	1 if a managed pine species is planted; 0 if not	binary	FIA
hardwood	1 if a hardwood species is planted; 0 if not	binary	FIA
site class	Measure of a plot’s quality on a scale from 1 (highest quality) to 7 (lowest quality)	categorical	FIA
Elevation	Elevation	ft	FIA
Private	1 if land is privately owned; 0 if not	binary	FIA
State dummy	Binary variables indicating the plot's state	binary	FIA
Stand volume	Per acre volume calculated by multiplying the plot's measured trees by their trees/acre expansion factor (TPA) and summed for the plot	MBF/acre	FIA

[19] The ‘Other softwoods’ classification includes the following forest groups: Spruce-Fir, other eastern softwoods, Pinyon-Juniper, and exotic softwoods.
[20] The ‘Other hardwoods’ classification includes the following forest groups: Aspen-Birch, other hardwoods, tropical hardwoods, and exotic hardwoods.

Stand growth	Per acre volume growth calculated by multiplying each tree's recorded annual growth by their TPA and summed for the plot	MBF/acre/ year	FIA
Clear Cut Revenue	Timber price multiplied by stand volume	$/acre	FIA, Mihiar and Lewis 2021
No-cut benefit	Timber price multiplied by stand growth	$/acre	FIA, Mihiar and Lewis 2021
Net Returns	Annualized net returns per acre	$/acre/year	Mihiar and Lewis 2021
Wtmax	Average maximum daily temperature Dec.-Feb.	Degrees Celcius	PRISM
Annual precip	Mean annual precipitation	mm	PRISM
Var(wtmin)	Variance in minimum daily temperature Dec.-Feb. of the previous 20 years		PRISM
Mean(temp)	Mean daily temperature Mar.-Nov.	Degrees Celcius	PRISM
ngprecip	Average total precip from Dec.-Feb.	mm	PRISM
	Data used in simulation		
Projected wtmax	Average maximum daily temperature Dec.-Feb.	Degrees Celcius	MACA
Projected annual precip	Mean annual precipitation	mm	MACA
Projected mean(temp)	Mean daily temperature Mar.-Nov.	Degrees Celcius	MACA
Projected ngprecip	Average total precip from Dec.-Feb.	mm	MACA
Stand growth	Per acre volume growth calculated by multiplying each tree's recorded annual growth by their TPA and summed for the plot	MBF/acre/ year	FIA

Acronyms found in the Units and Source column are as follows: Forest Inventory and Analysis (FIA), Parameter-elevation Regressions on Independent Slopes Model (PRISM), and Multivariate Adaptive Constructed Analogs (MACA)

Table A3: Forest composition across states

	Choice Group: Pine			
State	**White, Red, Jack Pine**	**Longleaf, Slash Pine**	**Loblolly, Shortleaf Pine**	**Oak, Pine**
AL	0.0%	4.9%	35.6%	12.9%
AR	0.0%	0.0%	30.5%	10.6%
GA	0.2%	13.8%	29.9%	10.9%
KY	0.4%	0.0%	1.7%	4.6%
LA	0.0%	5.1%	37.3%	8.4%
MS	0.0%	4.4%	38.7%	10.4%
NC	0.8%	1.6%	29.1%	13.0%
SC	0.2%	3.4%	41.2%	12.3%
TN	0.7%	0.0%	7.7%	7.7%
VA	1.3%	0.0%	20.3%	10.3%
Whole Sample	0.4%	3.7%	27.3%	10.6%

			Choice Group: Hardwood			
State	**Other Softwoods**[21]	**Oak, Hickory**	**Oak, Gum, Cypress**	**Elm, Ash, Cottonwood**	**Maple, Beech, Birch**	**Other Hardwoods**[22]
AL	0.3%	32.4%	9.8%	2.9%	0.0%	0.2%
AR	1.8%	41.6%	9.9%	4.9%	0.0%	0.2%
GA	0.0%	27.6%	14.1%	2.1%	0.0%	0.3%
KY	2.1%	74.5%	1.0%	6.3%	8.3%	0.6%
LA	0.0%	12.7%	24.7%	9.0%	0.0%	1.8%
MS	0.4%	26.2%	12.4%	6.1%	0.0%	0.5%
NC	0.2%	40.6%	9.5%	3.0%	0.4%	0.9%
SC	0.2%	23.8%	14.9%	3.2%	0.0%	0.2%
TN	2.0%	70.7%	2.4%	5.6%	2.2%	0.6%
VA	0.6%	58.9%	2.6%	3.1%	2.0%	0.5%
Whole Sample	0.7%	41.5%	9.4%	4.0%	1.1%	0.5%

[21] The 'Other softwoods' classification includes the following forest groups: Spruce-Fir, other eastern softwoods, Pinyon-Juniper, and exotic softwoods.
[22] The 'Other hardwoods' classification includes the following forest groups: Aspen-Birch, other hardwoods, tropical hardwoods, and exotic hardwoods.

Table A4: summary stats of selected variables by forest type

	Forest type	$\overline{wtmax}$ (°C)	$\overline{tmean}$ (°C)	$\overline{ngprecip}$ (mm)	$\overline{precip}$ (mm)	var(wtmin)	Net Returns to Pines	Net Returns to Hardwoods
Managed Pines	"White / red / jack pine group"	8.36	12.6	321.1	1306	30.3	$ 14.00	$ 6.70
	"Longleaf / slash pine group"	16.6	18.8	327.4	1335	31.5	$ 21.40	$ 10.90
	"Loblolly / shortleaf pine group"	13.6	16.9	332.0	1306	30.1	$ 24.00	$ 9.94
	"Oak / pine group"	12.7	16.2	326.3	1298.5	30.3	$ 22.70	$ 9.44
	"Other softwoods group"	9.65	14.50	307.5	1247.55	33.75	$ 20.80	$ 8.05
	Group Total	**13.6**	**16.9**	**330.1**	**1306.6**	**30.3**	**$ 23.44**	**$ 9.90**
Hardwoods	"Oak / hickory group"	10.5	14.8	321.7	1284.2	31.5	$ 22.10	$ 8.45
	"Oak / gum / cypress group"	14.6	17.7	330.2	1318.9	30.3	$ 25.60	$ 10.90
	"Elm / ash / cottonwood group"	11.9	16.1	331.9	1294.4	31.3	$ 27.40	$ 10.50
	"Maple / beech / birch group"	7.5	12.7	309.0	1257.3	35.2	$ 18.30	$ 6.61
	"Other hardwoods group"	11.3	15.0	346.6	1384.0	31.1	$ 21.30	$ 9.22
	Group Total	**11.2**	**15.3**	**323.6**	**1290.7**	**31.4**	**$ 22.89**	**$ 8.97**

Table A5: Summary stats by state

State	Var(wtmin)	$\overline{tmean}$ (°C)	$\overline{wtmax}$ (°C)	$\overline{precip}$ (mm)	Net Returns ($/acre) Hardwoods	Pines	Pine-hw	% Pines	Site Class
AL	34.70	17.34	14.33	1427.39	$ 10.50	$ 28.18	17.68	53%	4.83
AR	30.74	16.03	11.32	1320.41	$ 6.93	$ 29.26	22.33	41%	5.01
GA	29.14	17.69	15.14	1256.74	$ 10.78	$ 23.15	12.37	55%	4.28
KY	36.90	13.19	7.61	1211.27	$ 6.39	$ 19.13	12.74	6%	4.99
LA	32.70	18.84	15.83	1491.26	$ 13.58	$ 28.76	15.18	51%	4.06
MS	35.09	17.72	14.43	1477.72	$ 13.84	$ 26.98	13.14	53%	4.09
NC	25.92	15.05	11.48	1253.44	$ 9.39	$ 16.53	7.14	44%	4.70
SC	26.60	17.16	14.25	1195.77	$ 9.08	$ 20.51	11.42	57%	4.41
TN	34.75	14.21	9.42	1363.47	$ 11.75	$ 29.33	17.58	15%	4.80
VA	26.83	13.11	8.52	1129.59	$ 4.86	$ 12.34	7.48	31%	4.90

Table A6: Parameter Estimates of Nested Logit Model

	Planting pine post-clear cut	
	(1)	(2)
Constant	2.80	-2.40***
	(1.81)	(0.57)
$\overline{wtmax}$	-2.78 *	0.81*
	(1.29)	(0.32)
$\overline{Precip}$	2.88 ***	1.34***
	(0.47)	(0.30)
Net Returns	0.79 *	-0.09
	(0.36)	(0.30)
Net Returns*$\overline{wtmax}$	-0.49	0.08
	(0.27)	(0.23)
Site Class	-0.17 ***	-0.14**
	(0.05)	(0.04)
Var(wtmin)	-2.73 ***	
	(0.60)	
Var(wtmin)*$\overline{wtmax}$	1.43 **	
	(0.45)	
Observations: 3,131 plots that were clear cut		

	Natural Disturbance if not clear cut *(on server excel file "results all3 models" disturbance sheet date 8/11")*
Constant	**-4.75** ***
	(1.17)
Elevation	**0.27** *
	(0.12)
Private land dummy	**-0.95** ***
	(0.10)

$\overline{wtmean}$	8.97	
	(6.12)	
$\overline{ngprecip}$	-2.17	
	(1.15)	
AR dummy§	-0.03	
	(0.20)	
GA dummy	-0.01	
	(0.18)	
KY dummy	-0.27	
	(0.31)	
LA dummy	**0.47**	*
	(0.24)	
MS dummy	**-1.05**	**
	(0.34)	
NC dummy	0.06	
	(0.23)	
SC dummy	**-1.00**	***
	(0.26)	
TN dummy	-0.17	
	(0.24)	
VA dummy	-0.02	
	(0.32)	

Observations: 58,409

§ Alabama is the omitted state

	Harvest (clear-cut = 1, no clear-cut = 0) *(results on server in planting results 7-14 excel file, harvest sheet)*			
Clear cut constant	-1.644	***	-4.35	***
	(0.067)		(0.07)	
Clear cut revenue	0.097	***	0.05	***

	(0.008)		(0.01)	
No cut benefit waiting	-4.095	***	2.16	***
	(0.297)		(0.09)	
No cut benefit waiting^2	4.467	***	-4.26	***
	(0.528)		(0.30)	
Planting IV	-0.595	***	4.62	***
	(0.023)		(0.53)	
Disturbance IV	34.048	***	33.80	***
	(4.415)		(4.29)	
Observations: 61,540				

***0.10%

**1%

*5%

Table A7 Estimated Partial Effects

	$\overline{wtmax}$ up by 2°C					
	Planting Pines		Natural Disturbance		Clear Cut	
State	**Avg. ME**	**Std. Error**	**Avg. ME**	**Std. Error**	**Avg. ME**	**Std. Error**
AL	0.0655***	0.0123	0.0016	0.0012	0.0104***	0.0026
AR	0.0254	0.0157	0.0019	0.0014	0.0029	0.0018
GA	0.0390***	0.0097	0.0020	0.0015	0.0058**	0.0018
KY	0.0380***	0.0050	0.0013	0.0010	0.0016***	0.0003
LA	0.0525***	0.0085	0.0028	0.0021	0.0179***	0.0043
MS	0.0780***	0.0125	0.0006	0.0005	0.0166***	0.0034
NC	0.0286*	0.0133	0.0021	0.0016	0.0036*	0.0017
SC	0.0231	0.0126	0.0008	0.0006	0.0031	0.0018
TN	0.0557***	0.0089	0.0015	0.0011	0.0045***	0.0007
VA	0.0283**	0.0092	0.0019	0.0014	0.0020***	0.0006
Whole Sample	**0.0469*****	**0.0087**	**0.0015**	**0.0011**	**0.0052*****	**0.0010**

	$\overline{precip}$ up by 80mm					
	Planting Pines		Natural Disturbance		Clear Cut	
State	**Avg. ME**	**Std. Error**	**Avg. ME**	**Std. Error**	**Avg. ME**	**Std. Error**
AL	0.0574***	0.0093	-0.00034	0.00019	0.0089***	0.0018
AR	0.0568***	0.0093	-0.00040	0.00021	0.0071***	0.0015
GA	0.0574***	0.0093	-0.00042	0.00023	0.0088***	0.0017
KY	0.0224***	0.0049	-0.00027	0.00015	0.0010***	0.0003
LA	0.0524***	0.0075	-0.00057	0.00033	0.0180***	0.0046
MS	0.0567***	0.0089	-0.00012	0.00007	0.0115***	0.0026
NC	0.0571***	0.0094	-0.00044	0.00024	0.0077***	0.0018
SC	0.0573***	0.0093	-0.00016	0.00009	0.0079***	0.0016
TN	0.0483***	0.0085	-0.00030	0.00016	0.0040***	0.0009
VA	0.0485***	0.0076	-0.00040	0.00022	0.0036***	0.0007
Whole Sample	**0.0560*****	**0.0092**	**-0.00032**	**0.00017**	**0.0063*****	**0.0012**

	var(wtmin) increase by 2 standard deviations (9)					
	Planting Pines		Natural Disturbance		Clear Cut	
State	**Avg. ME**	**Std. Error**	**Avg. ME**	**Std. Error**	**Avg. ME**	**Std. Error**
AL	-0.1433***	0.0323	0.0000	0.0000	-0.0146***	0.0026
AR	-0.2084***	0.0272	0.0000	0.0000	-0.0162***	0.0023
GA	-0.1206**	0.0381	0.0000	0.0000	-0.0126***	0.0036
KY	-0.0731***	0.0103	0.0000	0.0000	-0.0028***	0.0005
LA	-0.1019*	0.0452	0.0000	0.0000	-0.0221*	0.0091
MS	-0.1458***	0.0356	0.0000	0.0000	-0.0185***	0.0037
NC	-0.2096***	0.0284	0.0000	0.0000	-0.0174***	0.0026
SC	-0.1428***	0.0325	0.0000	0.0000	-0.0134***	0.0029
TN	-0.1749***	0.0149	0.0000	0.0000	-0.0102***	0.0012
VA	-0.1878***	0.0256	0.0000	0.0000	-0.0097***	0.0017
Whole Sample	**-0.1800*****	**0.0224**	**0.0000**	**0.0000**	**-0.0134*****	**0.0014**

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

Figure A1. Projected variance of wintertime low temperatures across three climate models and an aggregate of the three for sample plots in Tennessee, Kentucky, and Virginia