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The Impacts of Climate-induced Insect Damage on Timberland Values in the Southeastern U.S.

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Abstract: This paper estimates the impacts of insect damage on private timberland values in the Southeastern U.S. using a large, pooled cross-section of parcel-level timberland transaction price data and county-level insect damage data. Our econometric analysis indicates that a 1,000 acre increase in a county's average insect damage acreage reduces timberland prices by approximately 1%. Using a variety of approaches to estimate the link between seasonal precipitation, temperature, and insect damage acreage, we project an average increase of between 168 and 550 additional acres of annual insect damage per county under future climate projections to 2050 relative to the current climate. Using our econometric estimates, the predicted acreage increase in insect damages will lead to an approximate 0.2% ($6/acre) to 0.5% ($14/acre) reduction in weighted timberland prices, resulting in total losses of between $1 billion to $2.5 billion for the entire timberland population in the Southeastern U.S. The methods and results highlight how to use empirical data to project future natural disturbance risk from climate change on the economic value of forested natural capital.

JEL Codes: Q23, Q51, Q54

Keywords: Climate change; Forests; Insect; Climate econometrics, Natural capital

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Declaration of Competing Interest

The authors declare no known conflicts of interest related to this manuscript.

1 Introduction

Over the past few decades, climate-induced natural disturbances have become more frequent and severe, posing significant threats to U.S. forests and causing substantial damage to forest productivity and ecosystem services (Dale et al., 2001; Gan, 2004; Abatzoglou and Williams, 2016; Westerling, 2016; Seidl et al., 2017). Among these disturbances, insects and pathogens can be particularly damaging and costly, leading to widespread tree mortality and subsequent economic costs (Dale et al., 2001). For example, the outbreak of the southern pine beetle (SPB) in the southeastern U.S. has resulted in considerable timber losses, tree mortality, and millions of dollars in economic damages (Pye et al., 2011), and SPB outbreaks and damages have been moving northward since 2001 (Costanza et al., 2023). Ecological studies have identified several factors influencing the patterns and behaviors of insect activities such as climate/weather, landscape patterns, host tree characteristics, and natural enemies (Costanza et al., 2023). Among these factors, ongoing climate shifts have been recognized as the most significant driver in shifting insect population dynamics and range expansions (Gan, 2004; Duehl et al., 2011; Harvey et al., 2023), and future climate changes are expected to further alter insect spread (Seidl et al., 2017; Lehmann et al., 2020). For instance, ecological studies find warmer winter temperatures have reduced the cold limitations on the southern pine beetle, which originally thrived in the southern U.S. This has led to its gradual expansion into northern states, including New Jersey, New York, and Connecticut, posing new challenges to forest management in these regions (Weed et al., 2013; Lesk et al., 2017; Heuss et al., 2019; Costanza et al., 2023). Economic analyses of such climate-related costs of insects remain limited, and no studies, to our knowledge, have linked insect outbreaks with the economic value of forests.

Timberland prices arise from interactions between buyers and sellers in a competitive land market which reflects expectations regarding external risks that influence timberland management and investment. Natural resource economic theory suggests that timberland prices capitalize the risks posed by pests, with a higher likelihood of catastrophic infestations leading to greater discounting of future timber rents and therefore, declines in forestland prices (Reed and Errico, 1987). The theoretical impact of insect activities on timberland values (Reed and Errico, 1987), combined with evidence suggesting that climate change has modified the patterns and frequency of insect dynamics (Seidl et al., 2017; Lehmann et al., 2020; Harvey et al., 2023), suggests a need for information on how the timberland market responds to climate-induced shifts in insect risks. A better understanding of market responses to climate-related disturbances informs i) private decisions regarding timberland investment and management (Sun and Zhang, 2001), ii) private costs associated with climate-related natural disasters, and iii) the net benefits associated with policies designed to mitigate the impacts of climate extremes.

This study uses econometric methods to estimate the relationship between insect damage and the market price of timberland in the southeastern U.S., a region ideal for this analysis due to its history of insect outbreaks, significant private timberland ownership, transaction data availability, and diverse local climate. Using a pooled cross-sectional dataset of over 30,000 timberland transactions across 10 states in the southeastern U.S., we estimate how prices for timberland respond to insect damages that were present on local forestland just before each land transaction was made. The timberland price model uses county and year fixed effects to control for time-invariant county-specific omitted variables plus time-varying but spatially-invariant omitted variables. Our identification of the price impacts of insect damage relies on within-county variation in insect damaged forest acreage and timberland prices. To predict changes in forest insect damage under the future climate model CCSM4 with the RCP 8.5 scenario (high emission pathway) relative to the current climate condition, we estimate the response of insect damage to seasonal temperature and precipitation using a 16-year county-level panel dataset. In this analysis, insect-damaged forest acreage serves as the dependent variable, while quadratic functions of four seasonal variables for both mean temperature and total precipitation across winter (December -February), spring (March-May), summer (June to August), and fall (September to November) are included as key independent variables. In addition to conventional regression, we use the machine learning method Lasso along with a Tobit approach to estimate insect damage model across 10 states in the southeastern U.S. using insect and climate data from 2004 to 2019. Finally, we use the estimated insect damage forest model to predict the effects of projected climate change on future forest area damaged by insects, and we use the econometric timberland price model to project the monetary damages of the resulting climate-induced insect damages on the economic value of timberland.

Our findings indicate that larger areas of insect damage generate a negative impact on timberland prices, although the magnitude is relatively small. Specifically, a thousand-acre increase in annual average forest acreage damaged by insects leads to a roughly 1% decrease in timberland prices. It is important to note that the negative impact of insect damage on timberland prices captures an average effect that arises from two mechanisms – direct damage to the growing stock volume on existing timberland plus any potential change in landowners' perceived risk of owning timberland assets under the threat of insect outbreaks. We then project that future climate change leads to an average increase of between 168 and 550 acres of insect damage per county under the CCSM4 climate model with RCP 8.5 emissions scenario relative to the current climate condition. This predicted increase in insect damage is expected to reduce timberland values by a modest amount of approximately 0.2% ($6/acre) to 0.5% ($14/acre), which translates to an overall loss of approximately $1 billion to $2.5 billion across the entire landscape of timberland. The spatial distribution of price impacts resulting from these predicted changes varies by prediction method, with some evidence of higher damages in the northern portion of the southeastern U.S.

Our study makes several contributions to literature. First, we contribute to an emerging empirical literature that estimates the economic costs of climate change that operate through natural disturbances. Specifically, we provide the first empirical estimates of the impacts of climate-related insect damage on the economic value of timberland, using parcel-level timberland prices across 10 southeastern U.S. states spanning over 17 years. As disturbance regimes have changed dramatically due to the warming climate over the past decades (Seidl et al., 2017), a growing effort has been devoted to advancing our knowledge regarding the economic impacts of natural disturbances within the natural resource economics literature. For example, some studies have investigated the implications of forest wildfires for damage to structures, recreation opportunities, and residential property values (McCoy and Walsh, 2018; Kim and Jakus, 2019; Bayham et al., 2022). Among these studies, several wildfire hedonic studies find that wildfire activities cause a significant but short-lived reduction in housing prices in the wildland-urban interface (WUI) areas in the western U.S. (Loomis, 2004; Donovan et al., 2007; Mueller et al., 2009; McCoy and Walsh, 2018). The most closely related study to ours is by Wang and Lewis (2024), which estimates drought and wildfire impacts on timberland transaction prices in the Pacific states of the U.S. In contrast, the economics literature is relatively sparse on the impact of insect outbreaks on timberland values. We build upon previous studies that examine the economic costs of forest disturbances like wildfire to provide the first empirical estimates of the impacts of insect damage on the economic value of timberland as revealed by observed prices. Furthermore, our findings of timberland value losses due to projected increases in insect damage under future climate scenarios add evidence regarding the social costs posed by climate change that operate through natural disturbances, which highlights the net benefits of mitigating such destructive events.

Second, we show how to use our econometric model to project future climate-change driven impacts of insects on the economic value of timberland. Natural science studies demonstrate that climate and seasonal variations, especially winter climatic conditions, significantly influence the succession and expansion of bark beetles in the western U.S. (Bentz et al., 2010; Preisler et al., 2012; Bentz and Klepzig, 2014). However, quantitative evidence on the relationship between climate/weather and insect events in the southeastern U.S. is limited (Asaro et al., 2017). Most existing work in this area is illustrative and qualitative, with only a few empirical efforts attempting to understand the effects of climate/weather on insect outbreaks at a large scale in the southeastern U.S. (Gan, 2004; Duehl et al., 2011; Munro et al., 2022). Gan (2004) developed a panel estimate of the relationship between climate and SPB risks across 11 states in the southeastern U.S. using state-level data from 1973 to 1996, though it relied on coarse data that may overlook fine-scale variation of climate within each state. In contrast, our contribution employs recent county-level panel data on insect damage across a large spatial area, and we use three different estimation techniques including conventional fixed effects regression, machine learning methods, and a Tobit model to predict changes in forest acreage damaged by insects under future climate scenarios relative to current climate condition. This predictive capability is essential for integrating with our timberland price estimates to project future climate change costs on forests that operate through insect outbreaks.

2 Timberland market and insect damage in the Southeastern U.S.

2.1 Timberland market

We study timberland prices in the southeastern region of the U.S., specifically focusing on ten states: Alabama (AL), Arkansas (AR), Florida (FL), Georgia (GA), Louisiana (LA), Mississippi (MS), North Carolina (NC), South Carolina (SC), Tennessee (TN), and Virginia (VA). The states of Kentucky and West Virginia in the southeastern U.S. were not included because of the limited number of timberland transactions observed during our study period between 2004 and 2020. The selection of this spatial and temporal scale covers a wide spatial area and ensures sufficient variation in timberland prices, insect damage, and local climate conditions. Additionally, the 2004-2020 timeframe aligns with the availability of insect damage data taken from the Forest Inventory and Analysis (FIA) data. We collect timberland transaction data for ten states from the real estate data vendor CoreLogic, which provides the most recent and comprehensive land transaction records for various land use types, including residential, forest, and agricultural, across the U.S. over an extended period. CoreLogic's property database includes both the latest transaction records and a separate database with historical transaction information. However, for this study, we focus primarily on the most recent transactions to compile a pooled cross-sectional dataset, using the latest sale data for timberland parcels. The CoreLogic database contains detailed parcel information such as sale price, sale date, geographic coordinates, land use codes, seller and buyer names, and various parcel attributes like acreage and zoning codes[2].

We apply several filters to select forest-related land transaction records. First, we use CoreLogic's land use codes, which classify properties into categories like agricultural, commercial, residential, and forest, to extract forest-related parcels from the database. Specifically, we include both parcels explicitly coded as forestland and those coded as vacant, resulting in approximately 252,379 observations. We include vacant parcels to account for possible differences in labeling styles employed by different counties, as some vacant-coded parcels might actually be forested or recently clear-cut land. Next, to ensure that our selected parcels are private timberland, we geolocate each parcel using its geographic coordinates and conduct a quality check. We overlay the selected forest parcels with two additional geospatial datasets: the National Land Cover Database (NLCD) and the USGS Protected Areas Database (PAD), which distinguish between forest cover and public vs. private ownership. This cross-referencing allows us to only include the extracted forest-related CoreLogic parcels that are forestland and privately owned. By measuring parcels' spatial proximity to their nearest private timberland areas derived using NLCD and PAD maps, we exclude parcels that do not overlap with private timberland areas. This step removed about 54% of the observations (53% being vacant parcels located outside of timberland areas and 1% being forest-coded parcels not within timberland areas). Additionally, we exclude parcels smaller than 5 acres (removing 12%) and those within 5 km of urban areas (removing 9%), as these lands are more likely to be valued for development potential rather than timber production. Lastly, we filter out non-arm's-length transactions – defined as those with prices below \$100/acre – along with extremely high priced transactions above \$50,000/acre (removing 8%). After applying these filters, we are left with approximately 45,000 observations[3].

In addition to the filtering rules discussed above, we refine our dataset further by integrating land cover information from the USGS National Land Cover Dataset (NLCD) to determine the exact land cover class for each parcel at the time of sale. This integration allows us to assign a specific NLCD-derived land use category to each parcel during the transaction period. Given that NLCD data is available only for specific years (2004, 2006, 2008, 2011, 2013, 2016, and 2019), we assign the most recent or prior year's NLCD land cover class to parcels lacking NLCD information for the specific transaction year. For example, if a sale took place in 2005, the land cover class is derived from the 2004 NLCD map. We find that the majority of our sample aligns with forest categories in the NLCD[4]. Parcels classified under non-forest uses in the NLCD (approximately 30%) are excluded from our sample to maintain a clear focus on timberland-specific transactions. This process results in a final sample of 31,084 observations. Table 1 summarizes timberland prices by state within our study region. Given our interest in estimating the effects of insect damage on the average acre of timberland, we weight the data by acres in our later empirical estimation to give less weight to small acreage transactions and more weight to large acreage transactions. Table 1 shows how weighted average timberland prices are

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[2] While CoreLogic captures seller information at the time of the transaction, it does not explicitly differentiate between industrial and nonindustrial private forestland.

[3] More details about the process of applying each filter rules can be found in Wang (2023).

[4] The NLCD categorizes forest land cover into three types: deciduous forest, evergreen forest, and mixed forest. The remaining categories include non-forest land cover types such as shrubland, pasture/hay, and water.

lower than unweighted prices, indicating that smaller acreage land is worth more on the land market, a result that likely is driven by the closer proximity of smaller acreage land to urban areas with correspondingly higher potential for future development rents (Brorsen et al. 2015).

Table 1: Summary of timberland transaction prices by state within the study region

State	Obs	Unweighted mean ($/acre in 2020 U.S. dollars)	Acres-weighed mean ($/acre in 2020 U.S. dollars)
Alabama	5,662	3,545	2,531
Arkansas	1,713	2,905	2,392
Florida	5,065	5,689	3,168
Georgia	1,987	4,405	2,631
Louisiana	2,804	4,152	3,064
Mississippi	396	3,929	2,898
North Carolina	4,306	4,784	3,209
South Carolina	1,859	5,013	3,109
Tennessee	5,430	4,133	2,666
Virginia	1,862	5,931	3,847
Total	31,084	4,479	2,840

Note: Weight is the parcel size measured in acres.

Figure 1 illustrates the spatial distribution of private timberland and timberland transactions observed across our study region[5]. Our transaction sample provides broad geographic coverage of timberland areas across the study region, although forested transactions are relatively sparse in the CoreLogic data in certain states (e.g. Arkansas and Virginia) and are absent in certain counties within North and South Carolina and Mississippi.

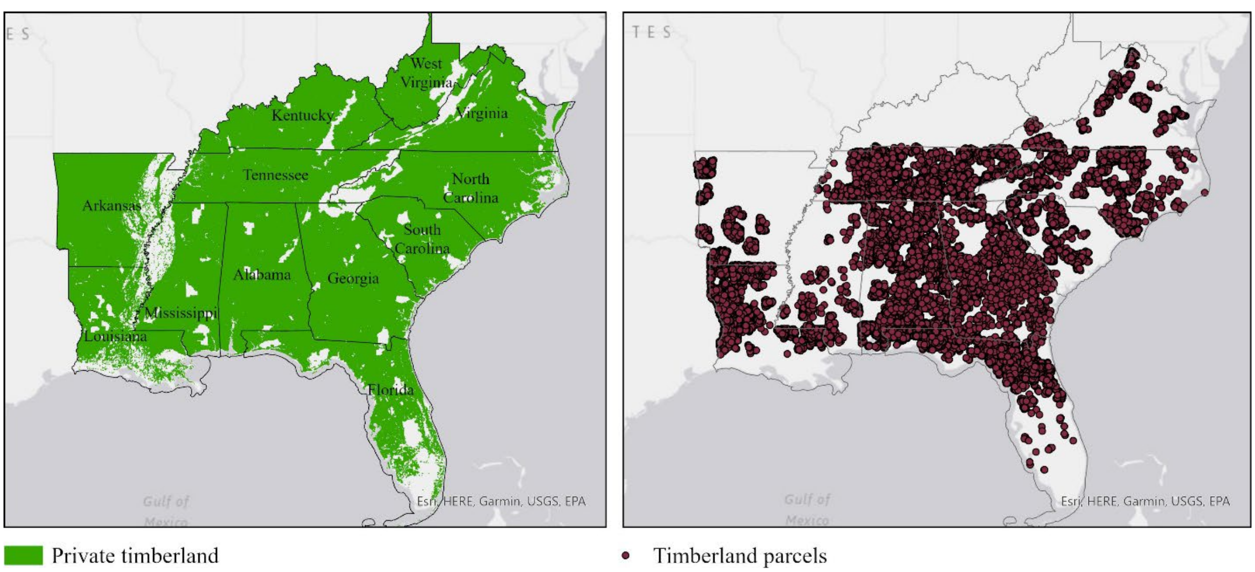

Figure 1: Map of private timberland and timberland market transactions across the study region.

[5] Private timberland map in Fig.1 is developed using both the National Land Cover Database (NLCD) and the USGS Protected Areas Database (PAD).

2.2 Insect damage

There are various native and nonnative insect species impacting forests in this area, with the most common agents being Gypsy moth (GM), Emerald ash borer (EAB), Hemlock woolly adelgid (HWA), and Southern pine beetle (SPB). Among these, SPB is widely recognized as the most destructive native bark beetle that causes periodic extensive damage and widespread mortality in the commercially valuable pine-dominant forests throughout the southeastern U.S. (Ungerer et al., 1999; Gan, 2004; Pye et al., 2011).

To measure insect damage in this region, we collect county-level data on insect damaged forest areas from the USDA Forest Service's Forest Inventory Analysis (FIA) across 10 states from 2004 to 2019. To ensure data integrity and comparability, we excluded FIA data prior to 2000 due to the inconsistencies in plot designs, inventory frequencies, methodology, and attribution definitions across states. In 1999, standardized plot designs and data collection standards were implemented nationwide to enhance consistency among FIA work units. The insect damage data represents the annual total acreage of forests damaged by severe insect activities in each county and does not differentiate the damage caused by specific insect agents.

As shown in Fig. 2, the annual acreage impacted by insects has generally increased over time across the 10 southern states. However, individual states exhibit varied trends; some show gradual increases or flat patterns, while Tennessee and Virginia experience declines followed by a resurgence. This variability suggests that private timberland owners have faced both rising and emerging risks from insect damage over the past two decades. Additionally, Fig. 2 highlights the substantial spatial and temporal variation in insect damage, which is critical for our empirical analysis.

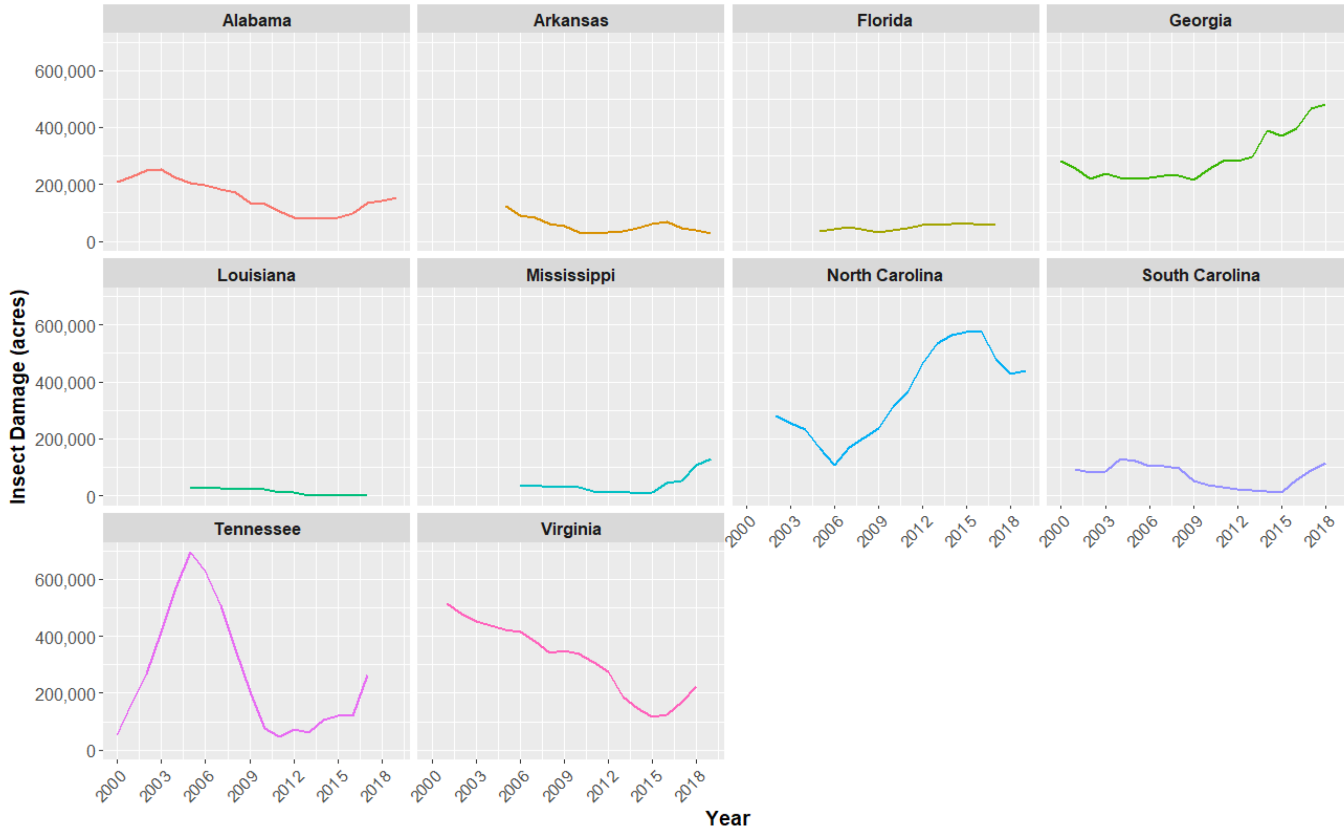

Figure 2. Annual acreage of forests damaged by insects across states, 2000–2019

3 Impacts of climate-induced insect damage on timberland prices

3.1 Mechanism for impact of insect damage

To better understand the increasing risks posed by climate-related natural disturbances like wildfires, insect outbreaks, and droughts, Reed (1984) first incorporated wildfire risk into the traditional Faustmann model to study how wildfires influence landowners' harvest decisions. Building upon Reed's model, Reed and Errico (1987) examined the effects of insect hazards on timber supply in an analytical model by introducing a combined hazard factor into the Faustmann model to represent both wildfires and insect infestations. In this context, suppose a stand can either be harvested at age T or be destroyed by fire or infestation before reaching the harvest age within a single rotation. The combined hazard factor is then expressed as follows:

$$h_c = \begin{cases} \lambda + h & a < T \\ \infty & a = T \end{cases} \tag{1}$$

Where λ is the probability of wildfire occurrence, h is the insect infestation rate, a is the age of the stand, and T is the harvest age that maximizes land value. The value of bare timberland can be written as based on forest economic theories (Reed, 1984; Zhang and Hall, 2020; Zhang, 2021):

$$V^{bare} = f(P, vol(C, sq, a), R, \lambda, h, \gamma, SC) \tag{2}$$

Where P is the timber price, $vol(C, sq, T)$ is the timber volume for the stand of soil quality sq growing in climate C, R is the regeneration cost, γ is the discount rate, and SC is the post-disturbance salvage cost. A higher insect infestation rate h lowers the bare land value V^{bare} since landowners are less certain of receiving future timber rents. As such, insect risks affect bare land values in Eq. (2) in a similar way to how fire risk affects bare land values in Reed (1984), by implicitly raising the discount rate used by landowners to assess future economic returns from timber harvest. Insects can spread across space in a similar manner to wildfire, although insect populations have more complex spatial dynamics as they are influenced by a range of local biological and ecological factors such as forest structure, landscape pattern, and natural enemies (Tobin et al., 2023). Consequently, landowners seeing an increase in local insect damages may adjust their expected infestation rate h, and so their bare land value may be reduced even if the stand is not directly damaged by insects.

For stands that are not bare land and which have a positive age (volume) a, the land value equation must be modified to reflect the value of the standing stock. If insect damages are catastrophic, the landowner either harvests the stand in T-a years in the absence of insect infestations or experiences a complete loss of timberland value if infestations occur before reaching the optimal harvest age. This first rotation payoff is represented by:

$$V1(a) = \begin{cases} P * vol(C, sq, T) - R & if\ T^f >= T - a \\ -SC & if\ T^f < T - a \end{cases} \tag{3}$$

Where T^f is the random time of the insect infestation. Once a harvest or infestation occurs on the age a stand, the stand value returns to bare land value in Eq. (2). Therefore, the land value of a stand of age a can be written as a sum of the expected present value of future harvest of the age a growing stock plus the expected present value of bare land after the first disturbance:

$$V = E[e^{-\gamma T^f}]V1(a) + E[e^{-\gamma T^f}]V^{bare} \tag{4}$$

Where E is the expectation operator over the random variable T^f. According to Eq. (4), if a stand with a positive age a is catastrophically damaged by insects, its value will consist of only the value of bare land Eq. (2). Conversely, the value of a stand with a positive age growing stock that is unaffected by insects will be higher since they have to wait less time for the first harvest revenue (Eq. (4)). Therefore, stands that are catastrophically damaged by insects have a lower value than those that are not directly affected, even if there is no change in the expected insect infestation rate h.

In summary, as demonstrated in Eq. (4), insects affect timberland values through two mechanisms: by directly damaging the existing growing stock in stands of age a, or by altering landowners' expectations of insect risks h.

3.2 Empirical analysis

In moving to empirical analysis, we follow Wang and Lewis (2024) and write a general statement of the timberland value function:

$$price = V(P, vol(C, sq, a), R, \lambda(fire, C), h(insect, C), SC, \gamma, U;\ \boldsymbol{\beta}) \tag{5}$$

Where most variables are defined above, but where the wildfire arrival rate λ is a function of nearby fire occurrences ($fire$) and climate (Wang and Lewis 2024), and the insect arrival rate h is a function of nearby insect outbreaks (*insect*) and climate. One additional variable added to Eq. (5) is U, which represents the future value of developing the forestland into urban uses. The parameter vector $\boldsymbol{\beta}$ translates changes in any independent variable into land price.

To disentangle the impacts of insect damage on timberland prices, we explicitly account for climate variables, wildfire risks, development pressures, and land attribute variables such as slope, elevation, and soil quality that may influence timberland prices. We control for time-invariant county unobservables (e.g., accessibility to a port) with county fixed effects and we control for time-varying but spatially invariant unobservables (e.g., interest rates) with year fixed effects. By explicitly accounting for those variables, our identification of insect impacts relies on spatial and temporal variation in insect damage and timberland prices within counties.

By using the standard log-linear reduced form function commonly employed in hedonic and Ricardian studies on land prices (Stetler et al., 2010; Hansen et al., 2014; Mendelsohn and Massetti, 2017), we specify our pooled cross-sectional model with spatial and temporal fixed effects as:

$$Log\ (price_{it}) = \beta_0 + \beta_1 Insect_{c(i)t} + \boldsymbol{\beta_2} g(Climate_{it}) + \boldsymbol{\beta_3} f(Fire_{it}) + \boldsymbol{\beta_4} X_i + Year_t + \mu_{c(i)} + \varepsilon_{it} \tag{6}$$

Where our dependent variable $price_{it}$ is per-acre value of timberland sale i in year *t* with inflation adjusted prices (in 2020 U.S. dollars). $Insect_{c(i)t}$ is the annual insect damage in county *c* where each parcel i is located in year *t*. The function *g()* is a quadratic function of the 30-year average climate variables evaluated for parcel i at time *t*, while the function *f()* is a vector of large wildfire arrival risk for parcel i at time *t*. The vector X_i denotes land attributes of each parcel i, such as slope, elevation, and distance to road (Zhang et al., 2013). The term $\mu_{c(i)}$ represents a fixed effect for county *c* that contains parcel *i*, while time fixed effects are captured by $Year_t$. Finally, ε_{it} is an idiosyncratic parcel-time error term.

3.2.1 Measurement of timberland prices

We obtain the most recent timberland transaction data from CoreLogic covering the period from 2004 to 2020 for ten southern states: Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, and Virginia. As discussed in Section 2.1, our sample includes approximately 31,084 private timberland parcels, which is about 12% of the original raw CoreLogic sample after applying our filtering rules to create a refined dataset that consists only of parcels in a forested use rather than used for a non-forested use like residential or agriculture. The dependent variable in our analysis is the per-acre price of timberland in 2020 U.S. dollars.

3.2.2. Measurement of insect damage

Various metrics have been employed in the existing literature to evaluate insect risks, such as the annual infestation rate, probability and magnitude of insect outbreaks, as well as the proportion of insect-induced damages against the growing stocks of trees (Reed and Errico, 1987; Gan, 2004; Munro et al., 2022). Ideally, we can estimate insect impacts that arise from direct damage to the stand separately from nearby damage that may influence landowners' risk expectations, as discussed in Sec. 3.1. However, knowing the spatial extent of insect damage is necessary for identifying which land parcels were directly damaged by insects. Unfortunately, the absence of detailed spatial data on insect damage restricts our ability to identify whether any particular timberland parcel was damaged by insects[6]. Instead, we process comprehensive insect data on total insect damaged forest areas at the county level, which allows us to identify whether all parcel transactions are within counties that have experienced insect damage (Fig. 2). Given our use of county-level insect damage, disentangling the price effects of direct insect damage from changes in insect risk expectations is not possible with the data we use. Rather, any impact we estimate from insect damage represents the average effect of direct damage and changes in risk expectations arising from insect outbreaks.

Our independent variable measuring county-level average annual insect damages is constructed using data from the U.S.D.A. Forest Service's FIA database. For each parcel, we calculate the average forest acreage damaged by insects in the county where it is located, using data from the five years preceding the sale date. The FIA program conducts annual surveys covering approximately 20% of all plots in most southeastern U.S. states, resulting in a full survey every five years (Arkansas Department of Agriculture)[7]. By averaging observations over the last five years, we incorporate all available FIA sample plots within each county in constructing our insect damage variable. For counties with missing insect data in specific years, we calculate the average annual insect damage by averaging over the available data years.

[6] We discussed the availability of alternative spatial insect damage dataset and why it is not appropriate for our analysis. Detailed discussion can be found in the Appendix B.

[7] Although the 1998 Farm Bill specified that 20% of plots within each state should be surveyed annually, FIA's sampling intensity varies by region and county, typically covering around 10–20% of plots each year due to funding limitations (Woudenberg et al., 2010).

3.2.3. Measurement of climate

Natural science and econometric studies suggest that the growth and survival of southern pine forests in our study region of the southeastern U.S. is sensitive to minimum winter temperatures and extreme heat (Schmidtling, 2001; Chen et al., 2012; Lu et al., 2021; Johnson and Lewis 2024). Thus, to explicitly account for such climate impacts on the economic value of timberland, we calculate 30-year average of winter minimum temperature and growing season maximum temperatures (March-November) preceding the sale date of parcel i, using monthly historical climate data derived from Oregon State University's PRISM database. We incorporate a quadratic form of those climate variables into our model to account for potential non-linear climate impacts.

3.2.4. Measurement of wildfire risk

In comparison to the western U.S., where wildfires are infrequent but often severe, the eastern U.S. experiences a higher frequency of low severity wildfire (Wibbenmeyer and McDarris, 2021). We obtain wildfire data from the Monitoring Trends in Burn Severity (MTBS) dataset, which includes all large wildfires greater than 500 acres in the eastern U.S. since 1984. Fig. 3 illustrates the number of large wildfires that occurred from 1984 to 2020 in 12 states within the southeastern U.S. Unlike the western U.S., where there is a notably upward trend of large and severe wildfires, the southeastern U.S. has not been exposed to a big change in large and severe wildfires (Costanza et al., 2023). An interesting exception is a surge in large wildfires in Florida between 2008 and 2011 (Fig. 3), though most of these Florida fires were concentrated in the southern region of Florida where private timberland transactions are scarce. So, timberland resources in the southeastern U.S. have not been exposed to as much change in large wildfire patterns in the last two decades as timberland has in the western U.S.

We include independent variables that measure potential large wildfire impacts on timberland values by calculating the wildfire arrival rates on each parcel, as well as within a 15 km buffer around each parcel, using MTBS wildfire data and using the same wildfire metrics developed by Wang and Lewis (2024). In particular, we measure the number of wildfires that have occurred directly on or within 15km of each timberland parcel during the 20 years preceding each parcel's date of sale.

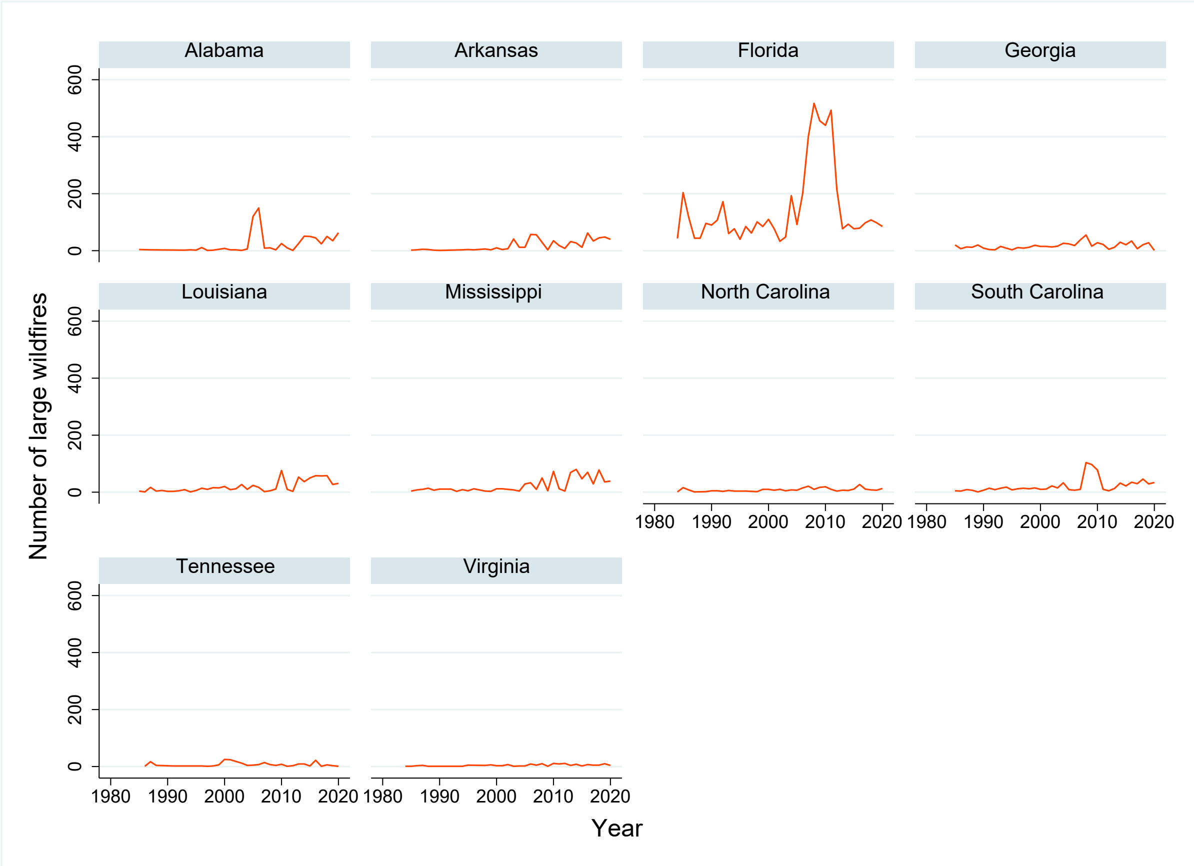

Figure 3: Annual number of large wildfires (>500 acres) occurred in the southeastern U.S. from 1984 to 2020

3.2.5 Measurement of other land attributes

For each parcel i, we also compile a vector of land characteristics to capture factors that influence timberland productivity (e.g., soil quality, elevation, slope, distance to the nearest road) and development pressure (e.g., distance to the nearest urban areas). We calculate the non-irrigated land capability class for each parcel using the soil survey data from the Gridded National Soil Survey Geographic Database (gNATSGO) database at a 10m resolution. Slope and elevation for each parcel are derived from the national Digital Elevation Model (DEM) model at a 1-arc (30m) resolution. We measure the distance between each parcel and its nearest road using the spatial map of major roads of the United States 2014 (U.S. Geological Survey, 2014). We also measure the distance between each parcel to the boundary of its nearest urban areas (including both urbanized areas (UAs) of 50,000 or more people and urban clusters (UCs) of at least 2,500 and less than 50,000 people) using the U.S. 2010 Census Urban Area shapefiles. More detail on the data construction process can be found in Wang (2023). Table 2 provides the summary statistics of the dependent and independent variables used in the analysis.

Table 2: Summary statistics of dependent and independent variables

Variable	Obs	Min	Max	Mean	Weighted mean
Timberland price ($/acre)	31,084	100.006	49806.61	4478.669	2840.142
Insect damage (thousand acres)	29,636	0	60.563	2.335	1.978
Max temp in growing season (Degree C)	31,084	17.730	31.044	26.145	26.612
Min temp in winter (Degree C)	31,084	-6.676	15.206	1.031	1.638
Large wildfires per decade on parcel	31,084	0	1	0.001	0.005
Large wildfires per decade nearby (0-15 km away)	31,084	0	81.5	0.531	0.951
Soil (non-irrigated land capability class)	29,775	1	8	5.033	5.129
Elevation (km)	31,084	0	1374.803	181.254	151.372
Slope (degree)	31,084	0	42.220	5.619	5.071
Distance to the nearest road (km)	31,084	0.001	19.141	2.599	2.836
Distance to the nearest urban area (km)	31,084	5.000	67.212	13.762	14.479

Note: The weight is the parcel size measured in acres.

3.3 Estimation strategy

We use ordinary least squares with standard errors clustered by county to estimate parameters in Eq. (6) using our pooled cross-sectional dataset. There is a tradeoff between choosing a coarser spatial scale or a more granular spatial scale with which to define spatial fixed effects for parcel-level analysis in a pooled cross-section. Considering that the expansion and dynamics of insect outbreaks correlate with local forest structure and composition, their severity and frequency often vary within a state. As a result, adopting a coarser spatial scale fixed effect may not adequately capture all potential local factors associated with insect activities. Therefore, we use county-level fixed effects to account for unobserved, time-invariant location-specific factors that are likely to influence insect outbreaks such as local forest structure and composition, land topography, and demographic characteristics. Moreover, the inclusion of county fixed effects helps address potential concerns about landowners' adaptations to increasing insect damage, which could influence the likelihood and severity of future outbreaks through changes in timberland management. Since insect infestations typically occur and spread at a local scale (Duehl et al., 2011), it's reasonable to assume that landowners within the same county would respond similarly to local outbreaks. By incorporating county fixed effects, we effectively capture these adaptation strategies adopted in the same county. We also include year fixed effects to capture macroeconomic factors that change over time and affect all timberland transactions (e.g., interest rates).

To ensure robust inference, we cluster standard errors at the county level to allow for any arbitrary heteroscedasticity and spatial/temporal correlations that may exist across parcels within the same county. Lastly, to avoid our estimates being disproportionately driven by a large number of small-sized parcels, we estimate Eq. (6) weighted by acres to obtain marginal effects for the average timberland acre rather than the average timberland parcel.

3.4 Estimation results

Table 3 presents the coefficient estimates for our main Eq. (6) using the full sample of sales prices in the southeastern U.S. We present two sets of results with model (1) including coarser state fixed effects and model (2) including a smaller spatial-scale county fixed effect definition. As previously discussed, we favor the results obtained with county fixed effects in model (2).

Estimated parameters indicate a significant negative impact of insect damage on timberland prices ($p<0.05$). Specifically, a thousand-acre increase in insect damage within a county leads to an approximate 1% decrease in the per-acre market price of that county's timberland as shown in model (2). It is crucial to highlight that our insect damage variable is computed using aggregated county-level data, which prevents us from directly observing whether insect damage has occurred on or near each parcel. Therefore, our insect result reflects an average effect arising from the two mechanisms discussed in Sec. 3.1 - direct damage to existing stocks for parcels that have experienced infestations, as well as alterations in expectations of risks for parcels that have not been directly affected by infestations but are close to areas with insect damage. Importantly, insect outbreaks exhibit significant within-county variation over time, which is why the insect damage parameter can be estimated precisely with county fixed effects. We note that the difference in the insect parameter value between the state fixed effects estimation (model 1) and the county fixed effects estimation (model 2) highlights potential omitted variable bias with defining coarser state fixed effects.

Given the quadratic specification of climate variables, we examine the marginal effects of climate on timberland prices using the average marginal effects (AME) presented in the bottom of Table 3. With more coarse state fixed effects in model (1), the AME indicates that maximum growing season temperature has a decreasing effect on timberland prices of -12.8% per degree C ($p<0.05$), while minimum winter temperatures have no statistically significant AME ($p<0.05$). However, Fig. A.1 in Appendix A indicates that the AME of minimum winter temperatures is positive when evaluated at a warmer temperature. Notably, there is no statistical significance of the AMEs for the two temperature variables when using the finer-scale county fixed effects ($p<0.05$), highlighting the lack of within county variation in these temperature variables. Given the small size of most southeastern U.S. counties, the lack of within county variation in temperature is unsurprising. Fig. A.1 and Fig. A.2 present the AMEs for each temperature variable evaluated at different levels of temperature for the state and county fixed effect definitions in models (1) and (2).

Table 3: Estimation results of the full sample of sales prices in southeastern U.S.

Log (price per acre)	Model (1)	Model (2)
Average insect damage (thousand acres)	0.002	-0.010**
	(0.005)	(0.004)
Max Temp in Growing Season	0.809**	-0.455
	(0.410)	(0.648)
Max Temp in Growing Season Squared	-0.018**	0.008
	(0.008)	(0.014)
Min Temp in Winter	0.018	0.090
	(0.045)	(0.065)
Min Temp in Winter Squared	0.010**	0.004
	(0.005)	(0.011)
Large wildfires per decade on parcel	0.135	0.552
	(0.549)	(0.536)
Large wildfires per decade nearby (0-15 km away)	-0.005	0.006
	(0.011)	(0.009)
Soil quality (1=best, 8=worst)	-0.032**	-0.024
	(0.016)	(0.016)
Elevation (km)	0.000	-0.001*
	(0.000)	(0.000)
Slope	-0.004	-0.005
	(0.004)	(0.004)
Distance to road (km)	-0.011	-0.001
	(0.010)	(0.009)
Distance to urban area (km)	-0.010***	-0.008**
	(0.004)	(0.004)
Constant	-1.298	14.317*
	(5.279)	(7.484)
Year FE	Yes	Yes
State FE	Yes	No
County FE	No	Yes
Observations	28,433	28,433
R-squared	0.038	0.214
Average Marginal effects (AME)		
AME of Tmax_grow	-0.128*	-0.033
	(0.076)	(0.115)
AME of Tmin_winter	0.048	0.103
	(0.036)	(0.075)

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the county level.

We fail to reject the null hypothesis that large wildfire occurrences have no effect on timberland prices in the southeastern U.S. ($p<0.05$). Large wildfire frequency in the southeastern U.S. has not experienced a large change in recent decades (Fig.3), and so wildfire risk expectations are likely not changing. Further supporting this interpretation is the fact that southeastern U.S. wildfires have not been as severe as those in the western U.S. (Costanza et al., 2023). Thus, we interpret our results to indicate that recent large wildfires in the southeastern U.S. have not (yet) signaled enough of a change in wildfire risk to alter landowner risk expectations in a way that would affect timberland prices.

Our analysis also reveals significant impacts of land attributes on timberland prices, though the significance depends on the fixed effect definition we use with the exception of proximity to urban areas. Specifically, timberland prices are higher in areas that are closer in proximity to urban areas ($p<0.05$). A 1 km increase in distance to urban areas lowers timberland prices by 1% in model (1) or 0.8% in model (2), which suggests that timberland parcels capitalize future development potential consistent with conventional urban economic theory.

3.5 Robustness checks

We conduct several sensitivity analyses to assess the robustness of our findings. First, natural science studies suggest that wildfire activities can interact with bark beetle outbreaks because fires make stands more vulnerable to bark beetle attacks (see Fettig et al. 2022 for a review). This interaction may lead to a multicollinearity problem in estimation. To investigate this, we conduct an additional analysis examining the correlation between insect damage and all wildfire arrival rates. The results reveal a low correlation coefficient of less than 0.02, indicating no significant collinearity between insect damage and wildfire variables. To further validate the robustness of our results, we re-estimated the impact of insects without including the wildfire variables in the model and found robust insect results as shown in Appendix Table A.1.

Second, to further explore a potential endogeneity concern arising from landowners' local adaptation to insect damage, we re-estimate the main Eq. (6) by introducing a set of finer spatial scale fixed effects than the county. These fine-scale spatial fixed effects are designed to capture the potential adaptation practices employed by landowners within the same spatial unit. We create evenly distributed grid cells organized into 50 rows and 50 columns, with each grid cell covering approximately 46*46 km (labeled as Grid50 FE). Additionally, we implement an even finer-scale set of spatial grids with 60 rows and 60 columns, covering approximately 36*36 km per grid cell (labeled as Grid60 FE). The results are presented in Appendix Table A.2, which demonstrates the robustness and reliability of our initial findings to alternative spatial fixed effects.

Third, to address potential biases from timberland parcels with high development pressure near urban boundaries, we exclude parcels within 5 km of urban boundaries in the main estimation. This 5 km buffer is informed by prior research indicating that development values decline with distance from urban centers (Plantinga et al., 2002). To test the robustness of our findings, we conducted sensitivity analyses using larger radii of 10 km and 15 km from urban boundaries. The results, detailed in Appendix Table A.3, consistently indicate a negative impact of insect damage on timberland market prices across all thresholds. However, at the 15 km radius, the insect damage effect becomes insignificant, likely due to a substantial reduction in sample size (nearly two-thirds of observations are excluded with the 15 km filter), which limits variation in key variables and introduces more noise. Despite this, our conclusions regarding the negative impact of insect damage remain robust with the 10 km radius.

Fourth, given that larger timberland properties are typically traded at a lower price per acre due to the presence of fewer buyers of large properties, we also included a dummy variable distinguishing between large (≥1,000 acres) and small parcels (≤1,000 acres) to assess potential price differences between the markets for small and large forested parcels. Results, shown in Appendix Table A.4, indicate that while larger parcels do tend to sell for lower prices, the dummy indicator for larger timberland parcels is not statistically significant in our preferred model (2). Importantly, adding the large property dummy variable does not change the estimated effects of insect damage, confirming the robustness of our earlier findings.

Finally, since most of our sample consists of small parcels, we prefer to estimate Eq. (6) using parcel acres as a weighting factor to mitigate the disproportionate influence of these smaller parcels, as discussed in Section 3.3. However, we assess the robustness of our findings by comparing them to estimates that do not employ acreage weighting. The results, presented in Appendix Table A.5, consistently demonstrate a negative impact of insect damage, albeit at a slightly reduced magnitude.

4 Price impacts due to future changes in insect damage driven by climate change

Natural science studies suggest that climate warming is expected to further influence insect spread, such as the projected northward expansion of the southern pine beetle (SPB) in the coming decades (Weed et al., 2013; Lesk et al., 2017; Seidl et al., 2017; Lehmann et al., 2020). In this section, we develop an econometric model to estimate parameters that govern how insect damage is affected by seasonal variability in temperature and precipitation by regressing county annual insect damage on seasonal mean temperature and total precipitation using panel data from 2004 to 2019 across 10 southeastern U.S. states. We then use these estimated parameters to predict changes in insect damage under future average seasonal temperature and precipitation projections (2021-2050) relative to current average seasonal conditions (1991-2020). Finally, we quantify timberland price responses to predicted changes in insect damage using our estimates from Eq. (6). The future temperature and precipitation projections to 2050 are derived from the downscaled Multivariate Adaptive Constructed Analogs (MACA), utilizing high-resolution data from the Community Climate System Model version 4 (CCSM4) under the Representative Concentration Pathways (RCP) 8.5 scenario (a high-emission pathway).

4.1 Predicting changes in insect damage under future climate projections

Drawing upon key insights from the existing natural science literature, we use insect damage $Insect_{ct}$ in county *c* and year *t* as the dependent variable, with a range of seasonal temperature and precipitation variables used as independent variables to estimate the relationship between insect damage and seasonal variability in temperature and precipitation. The rationale for choosing these seasonal climatic factors is discussed in more detail in Appendix B. Considering insect populations are often affected by a number of local biological and ecological factors, such as host tree characteristics, landscape patterns, natural enemies, and local competitors (Asaro et al., 2017), we incorporate county fixed effects into our model to account for unobserved location-specific variables that may influence insect activities and evolve slowly over time. Given there is no well-defined theoretical framework guiding the functional form between insect damage and seasonal variability in temperature and precipitation, we adopt a linear-in-parameters quadric function to allow for potential nonlinear effects of weather on insect damage. Our model specification is written as follows[8]:

[8] We do not specifically model and control for drought effects in the model because we find summer drought indicator measured as summer average vapor pressure deficit is highly correlated with summer mean temperature. This potential multicollinearity issue leads to imprecise estimates and makes it difficult to accurately isolate the effects of drought and summer temperature.

$$Insect_{ct} = \alpha_0 + \alpha_1 f(P_{ct}) + \alpha_2 g(T_{ct}) + \alpha_3 h\left(T_{c,t-m}\right) + \omega_c + \epsilon_{ct} \quad (7)$$

Where $f(P_{ct})$ is a quadratic function of current seasonal total precipitation in county c and year t; $g(T_{ct})$ is a quadratic function of current seasonal mean temperature in county c and year t; and $h\left(T_{c,t-m}\right)$ is a quadratic function of lagged seasonal mean temperature in county c and year t-m, where m is the number of years lagged from the current year. The term ω_c represents county fixed effects and ϵ_{ct} is an idiosyncratic error term.

We estimate the parameter vectors $\boldsymbol{\alpha}$ and $\boldsymbol{\omega}$ in Eq. (7) using three different estimation approaches: ordinary least squares (OLS), the Lasso machine learning method, and a Tobit model. OLS is a conventional estimation approach widely used for linear regression equations like Eq. (7). However, the Lasso method offers an alternative approach, particularly suited for cases with numerous potential covariates and unclear theoretical structures (Muthukrishnan and Rohini, 2016; Ranstam and Cook, 2018), as in our study. Lasso automatically selects independent variables from the large set of potential seasonal variables in Eq. (7) based solely on their statistical explanatory power and suppresses irrelevant variables. This feature improves interpretability and enhances out-of-sample prediction performance by mitigating overfitting. In contrast, OLS prediction includes all potential weather and climate variables, which may increase the risk of overfitting and reduce the accuracy of out-of-sample predictions. The Tobit model is particularly suitable for our analysis due to the presence of a zero-censored dependent variable (insect damage). Unlike OLS and Lasso, Tobit explicitly accounts for censoring in the data, ensuring that predictions for the dependent variable align with the observed data structure. While OLS and Lasso may generate negative prediction outcomes—unrealistic in the context of insect damage—the Tobit model avoids this issue by appropriately handling the zero-censoring structure in both estimation and prediction. In summary, OLS provides a traditional regression framework but may suffer from overfitting in the presence of numerous predictors. Lasso addresses overfitting by selecting variables based solely on statistical performance, which enhances prediction accuracy but does not necessarily align with theoretical considerations for variable selection. Tobit is advantageous when dealing with censored data, such as the zero-censored dependent variable in this study. Additionally, since Lasso selects variables automatically, depending on the specific combinations of weather and climate predictors, it can yield different magnitudes and spatial patterns of insect damage compared to OLS and Tobit.

However, the inclusion of numerous county fixed effects in our model increases computational costs when using Lasso with our large dataset, and Lasso's penalty can shrink fixed effects coefficients to zero, potentially biasing estimates by omitting key local variation. To keep county fixed effects in the model but still use Lasso, we employed a two-stage approach by first regressing insect damage on county fixed effects to account for the effects of time-invariant location-specific variation on insect damage, and then obtain residuals that capture the remaining variation in insect damage that can be partially explained by time and county varying weather variables. We then apply Lasso to select relevant seasonal temperature and precipitation covariates that best explain the within-county varying residuals after the initial fixed effects estimation. Finally, we regress insect damage on the set of Lasso-selected independent seasonal variables along with the full set of county fixed effects to estimate parameters in Eq. (7). For our third method, we use the Tobit model to account for the fact that nearly half of the observations in our estimation data report zero insect damage. The Tobit method's primary advantage is the ability to explicitly model such censored data in cases with many zero values, such as our setting.

We evaluate the predictive performance of OLS, Lasso, and Tobit through a split-sampling approach which assesses how well each model predicts out-of-sample[9]. We divide our sample into two datasets: a training set used for estimation (2004–2016), and a validation set used for assessing out-of-sample prediction (2017–2019). Parameters are estimated on the training data and predictions are made on the validation data using the estimated coefficients from the training data. We assess the models' performance by comparing the predicted values of the *insect* dependent variable to its actual values in the validation data, using the metrics root mean squared error (RMSE) and R-squared (R^2). Table 4 summarizes the out-of-sample test results for each estimation method. Among the three estimation methods, Lasso has the lowest RMSE and highest R-squared for the validation data, although the results are only slightly different from OLS and Tobit. The R-squared values across all models are expected, as our approach primarily relies on weather and location-specific time-invariant variables to explain variations in insect damage. Other local biological and ecological factors, such as host tree species and interactions with natural enemies and competitors (Asaro et al., 2017), also play important roles. However, incorporating these environmental variables and obtaining their future projections is challenging due to data limitations across the large geospatial scope of this study (Munro et al., 2022).

Table 4: Out-of-sample test results across different models

Estimation Method	Sample	RMSE	R-squared	Obs
OLS	Training	1.761	0.578	10,008
	Validation	2.596	0.486	1,802
Lasso	Training	1.732	0.573	10,008
	Validation	2.358	0.497	1,802
Tobit	Training	1.461	0.594	10,008
	Validation	2.396	0.381	1,802

To evaluate the impact of climate change on insect damage, we use our parameter estimates from Eq. (7) to predict insect damage using average seasonal temperatures and precipitations under current climate conditions (1991-2020) and projected future average seasonal conditions (2021-2050) under climate change, respectively[10]. We then calculate the difference between the two predictions to determine the expected changes in insect damage for each county that are due to climate change. Table 5 summarizes the predicted changes in annual insect damage under future projections to 2050, using the CCSM4 climate model with the RCP 8.5 scenario, compared to current seasonal conditions. On average, the OLS estimates predict an increase in insect damage of around 550 acres per county per year, while Lasso and Tobit predict a relatively smaller increase in insect damage of approximately 168 acres and 450 acres per county, respectively.

[9] For the lasso regression, we use the adaptive lasso option, an extension of lasso that applies an alternative penalty weighting approach to perform variable selection and shrinkage (Zou, 2006).

[10] We predict changes in insect damaged area based on long-term average seasonal temperatures and precipitation to avoid the influence of extreme seasonal variations in specific years, which may not be representative of long-term trends.

The predictions show a wide range under the OLS and Tobit models, indicating significant spatial heterogeneity, while the Lasso approach exhibits much less variation.

Table 5: Predicted Changes in Annual County Average Insect Damage

Variable	Obs	Mean	Std. dev.	Min	Max
Insect Damage w/ OLS (thousand acres)	885	0.549	1.853	-3.589	7.081
Insect Damage w/ Lasso (thousand acres)	885	0.168	0.094	-0.188	0.480
Insect Damage w/Tobit (thousand acres)	885	0.450	2.322	-7.676	17.727

Fig. 4 illustrates the spatial distribution of predicted changes in insect-damaged forest acreage for each county based on the results from the three prediction methods. All three predictions suggest that cooler northern areas are expected to see a larger increase in insect damage, while the warmer, wetter southern areas may experience declines as rising temperatures hinder insect growth and activity. Overall, our predictions are consistent with findings from natural science research predicting the northward expansion of the southern pine beetle (SPB), which has historically been confined to pine forests in the southeastern U.S. (Weed et al., 2013; Bentz and Klepzig, 2014; Dodds et al., 2018). The warming climate facilitates the SPB's range expansion by removing climatic barriers that have limited the SPB's survival and spread. Our findings are also consistent with prior economic research that shows how a warming climate in the northern part of our study region will see landowner adaptation from hardwood to pine forests (Johnson and Lewis, 2024), suggesting that landowner planting decisions will alter the composition of the forest towards pine trees that are more susceptible to SPB.

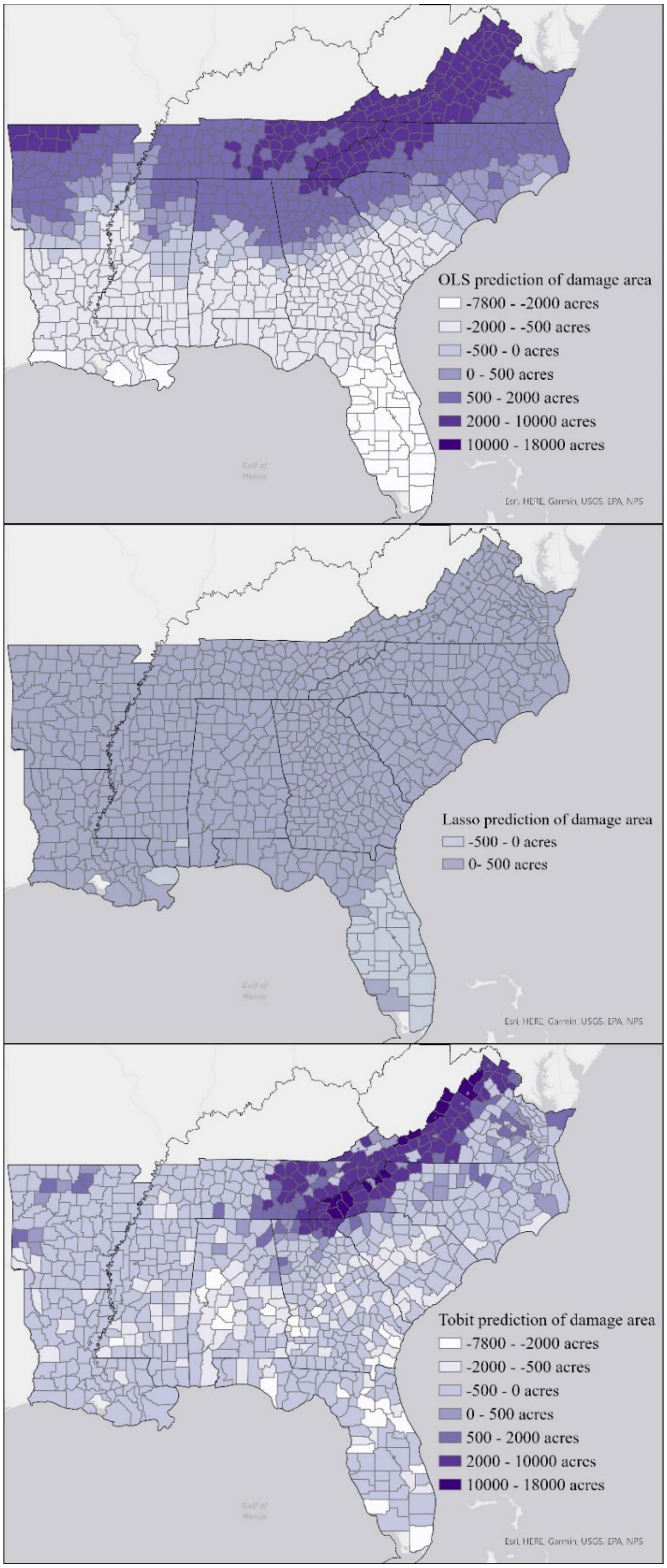

Figure 4. Spatial distribution of predicted changes in annual county average insect damage acreage under different prediction methods. These predicted changes are from an RCP 8.5 climate change scenario relative to a scenario with no changes in climate.

4.2 Estimating timberland price impacts from climate-induced changes in insect damage

Based on our estimated predicted changes in insect damage in Sec 4.1 (as shown in Fig. 4), we can quantify how such changes further alter the economic value of timberland based on the estimated timberland price model in Eq. (6). Considering the log-linear relationship between insect damage and timberland prices, the price impacts on parcel i from changes in insect damage equals[11]:

$$Est.\%\,Insect\;\;impact\colon \%\Delta price_i = 100(\exp(\widehat{\beta_1}(Insect_{c(i),2050} - Insect_{c(i),2020})) - 1) \quad (8)$$

Where $\widehat{\beta_1}$ is the estimated coefficient of insect damage from our preferred model (2) in Table 3. $Insect_{c(i),2020}$ represents predicted average insect-damaged forest acreage under the current average seasonal conditions (1991-2020) in county c where parcel i is located and $Insect_{c(i),2050}$ represents predicted average insect-damaged forest acreage under the projected future average seasonal conditions (2021-2050) in county c where parcel i is located.

Table 6 summarizes the estimated losses in timberland prices resulting from predicted average changes in insect damage under future seasonal conditions (2021–2050) compared to current seasonal conditions (1991–2020) using our three prediction approaches: OLS, Lasso and Tobit. The results indicate that price impacts vary across states and by estimation method, though the variations remain within a reasonable range. For example, in Alabama, the predicted changes in insect-damaged forest acreage under future seasonal conditions compared to current seasonal conditions lead to a timberland price increase of 0.04% or a decrease of 0.12%, depending on whether insect damage is predicted using the OLS or Lasso method. While specific state-level impacts exhibit some variation depending on the method employed, the overall pattern across the southeastern region shows consistent negative effects on timberland prices. On average, the OLS-based predictions show that the projected change in insect damage leads to an average reduction of approximately 0.5% in timberland prices. In contrast, the smaller average Lasso and Tobit predictions of climate-induced changes in insect damage lead to a slightly smaller average decrease of about 0.2% and 0.34% in timberland prices. These variations in predicted outcomes reflect the trade-offs (variable selection and censored data structure) associated with each model, as discussed in Section 4.1. Thus, no single model emerges as definitively "best" in this analysis. Exploring alternative methods could enhance the robustness of these results and provide additional insights.

Since our dataset of parcel transactions covers the entire geographical extent of our study region (Fig. 1), we extend our estimates to the population of private timberland throughout the 10 southeastern states. Based on timberland data from the federal Forest Inventory and Analysis Data (FIA), there are about 174,226,300 acres of private timberland in total across the ten southeastern states. By leveraging the proportion of timberland in each individual state within this region, we calculate population-weighted timberland value losses due to anticipated insect damage shifts driven by future climate projections, which is about 0.5% based on OLS, 0.2% based on Lasso and 0.35% based on Tobit.[12] Since a 0.5% (0.2% or 0.35%) drop in timberland

[11] Eq. (8) is derived based on the exact change in price in response to a change in insect damage.

[12] The weights for the states - AL, AR, FL, GA, LA, MI, NC, SC, TN, VA - are as follows: 0.13, 0.11, 0.09, 0.14, 0.08, 0.11, 0.10, 0.07, 0.08, and 0.09, respectively, determined by the proportion of timberland within each state in relation to the overall timberland within this region.

values equates to approximately $14 ($6 or $10) per acre, the total losses in timberland values amount to roughly $2.5 billion ($1 billion or $1.7billion) across the ten southeastern states, which is equivalent to our estimated reduction in per acre value – -$14/acre (OLS) or -$6/acre (Lasso) or -$10/acre (Tobit) – multiplied by the total acres (174,226,300 acres) of private timberland.

Table 6: Summary of predicted insect impacts on timberland prices under three alternative methods for predicting future changes in acreage damaged by insects from climate change

State	Obs	OLS	Lasso	Tobit
		Mean	Mean	Mean
Alabama	5,662	0.04%	-0.12%	0.68%
Arkansas	1,713	-0.70%	-0.29%	0.18%
Florida	5,065	1.79%	-0.08%	0.83%
Georgia	1,987	0.16%	-0.19%	0.26%
Louisiana	2,804	1.07%	-0.16%	0.28%
Mississippi	396	0.72%	-0.14%	0.40%
North Carolina	4,306	-1.78%	-0.19%	-1.77%
South Carolina	1,859	-0.26%	-0.14%	0.03%
Tennessee	5,430	-1.88%	-0.17%	-0.91%
Virginia	1,862	-3.99%	-0.28%	-4.32%
Total	31,084	-0.45%	-0.16%	-0.34%
Population-weighted		-0.43%	-0.18%	-0.35%

Fig. 5 illustrates the spatial pattern of predicted insect damage impacts on parcel-level timberland prices using OLS, Lasso, and Tobit predictions. Under future climate projections, the price impacts suggest that northern areas of the region are generally expected to experience a greater decline in timberland values due to increased insect damage. In contrast, southern states, such as Florida, may see a rise in timberland value due to reduced insect activities.

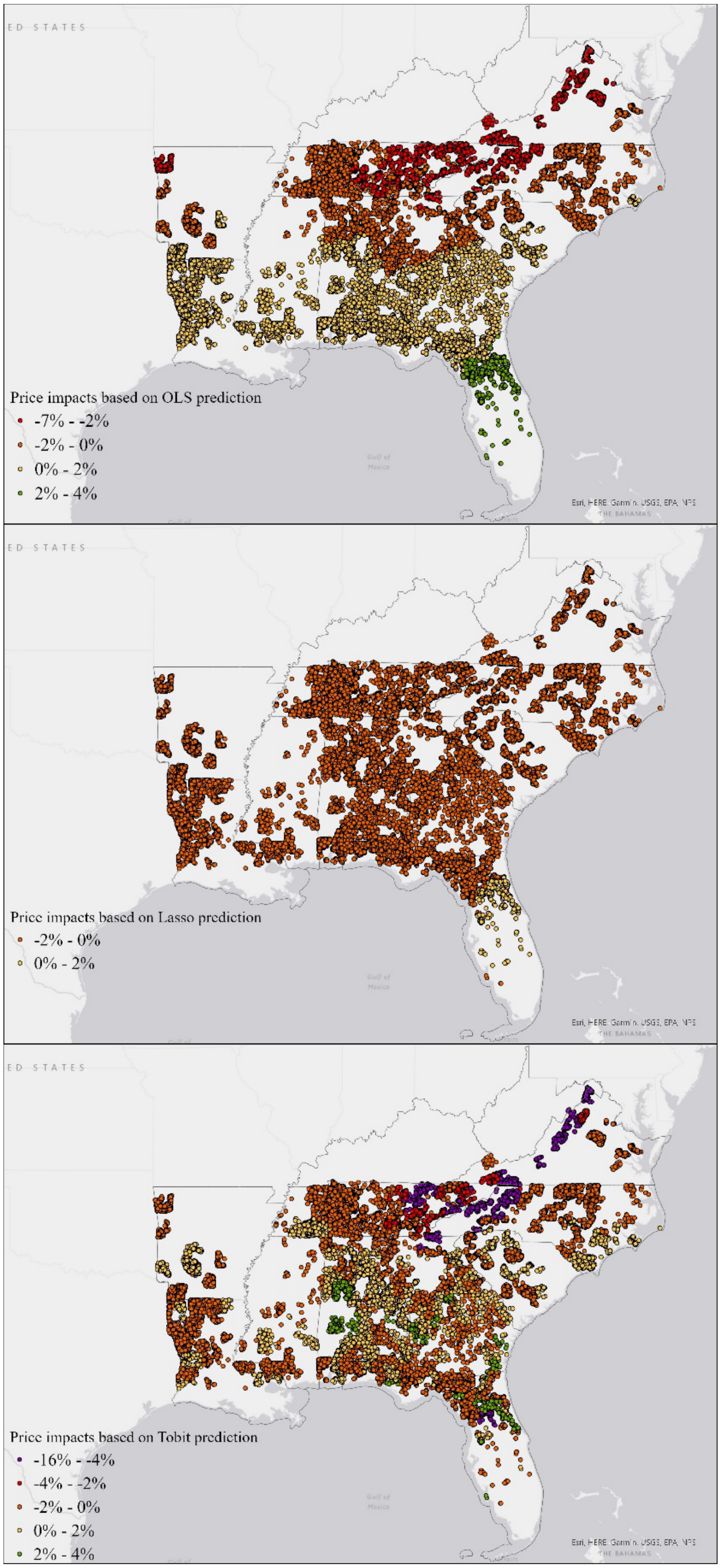

Figure 5: Spatial distribution of predicted insect damage impacts on timberland prices using OLS, Lasso, and Tobit predictions of physical acreage damage from climate change.

5 Conclusion and discussion

The forest resources in the southeastern U.S. are valuable stocks of natural capital that provide numerous ecosystem services, support regional biodiversity, and contribute to the regional economy through timber production (Zhang, 2022; McIntosh and Zhang, 2024). However, recent observed and projected changes in local climate patterns have sparked growing concerns about the increasing risk of climate-induced natural disturbances, such as wildfires, insect outbreaks, and hurricanes, which could severely impact forested natural capital stocks in this region (Parks and Abatzoglou, 2020; Anderegg et al., 2022). For example, the warming climate is expected to increase the likelihood of southern pine beetle (SPB) outbreaks, one of the most common and destructive forest insect agents, and expand their range northward (Ungerer et al., 1999; Gan, 2004). Thus, economic projections of landowner incentives to adapt to climate change by planting pines in the northern part of the southeastern U.S. (Johnson and Lewis, 2024) are expected to occur alongside a northward expansion of pine pests like SPB. Despite numerous natural science studies highlighting the adverse effects of insect outbreaks on forest structures (Lesk et al., 2017; Dodds et al., 2018; Heuss et al., 2019), their impact on timberland markets in the southeastern U.S. still remains unclear.

This paper provides a framework to estimate the impacts of insect damage on the market price of timberland using a pooled cross-section of parcel data covering almost 30,000 timberland transaction prices from 2004 to 2020 across ten states in the southeastern U.S. We employ a reduced-form linear econometric model with spatial and temporal fixed effects to estimate the impacts of insect damage on timberland prices. Identification is facilitated by county and year fixed effects that control for location-specific and year-specific unobserved factors that could otherwise confound our analysis, enabling us to isolate the impact of insect damage on timberland values. Our full sample results indicate that a thousand-acre increase in insect damage within a county decreases that county's timberland prices by about 1%, holding all other factors constant. Since our insect damage data is county level and does not enable us to identify which parcels within a county are directly damaged by insects, the insect damage result reflects two channels, i) the direct impact of insect damage on existing timber growing stock, and ii) any potential change in landowners' risk expectations of owning timberland assets within the county.

In order to predict changes in forest area damaged by insects under future climate projections relative to the current climate condition, we estimate the relationship between insect damage and seasonal temperature and precipitation using a 16 year-panel with the county-year as the unit of observation across 10 states in the southeastern U.S. We employ three different estimation techniques including OLS, the machine learning approach Lasso, and a Tobit model to estimate parameters and predict changes in insect damages under the CCSM climate projections with the RCP 8.5 scenario relative to the current climate. We find that future climate change leads to modest average increases in insect damage across the southeastern U.S., with an average expansion of between 168 acres and 550 acres per county per year, depending on which estimation method we use. Notably, the northern area of the study region is expected to see a larger increase in insect damage than the southern portion, consistent with recent findings from natural science studies (Weed et al., 2013; Lesk et al., 2017). The price impacts resulting from these projected changes in insect damage indicate a modest population-weighted average decline of between 0.2% and 0.5% in timberland values, depending on which method is used to project insect damage. When translated to a population-level damage in dollars, the projections of insect damage translate to an overall loss of between \$1 billion and \$2.5 billion.

Our findings of modest negative price impacts from insect damage contribute to the growing body of knowledge on economic impacts of climate change on natural resources through natural disturbances, including the social costs that climate change poses for private timberland management. In comparison to wildfire impacts on the value of forests, we find that climate-induced changes in insect damage are expected to have a much lower impact on the economic value of forests in the U.S. southeast (~0.2% to 0.5% reduction) than the estimated impact of changes in recent wildfire risk has already had on the economic value of forests in the Pacific states of the western U.S. (~10% reduction) (Wang and Lewis 2024). Focusing on comparing the impacts of wildfire across regions, we note that while acreage burned from large wildfires has increased in both the western and southeastern U.S., the acreage that has burned with moderate and high severity has increased by much more in the western U.S. than in the southeastern U.S. (Costanza et al. 2023). In estimating timberland price impacts from large wildfires, we find that timberland prices do not respond to local wildfire events, which suggests that landowner expectations of wildfire arrival rates have likely not changed in the southeastern U.S. One interpretation is that since there have been minimal changes in moderate to high severity wildfires in the southeast, then landowners have rationally not shifted their expectations of wildfire arrival in that region. In contrast, Wang and Lewis (2024) find that timberland prices fall when exposed to nearby large wildfire events in the Pacific states of the western U.S., a result they attribute to landowners updating their expectations of wildfire arrival rates in response to the large increase in high severity large wildfires that has already occurred in that region.

There are several caveats to our study that are worth mentioning. First, our insect damage data at the county level are limited in terms of identifying damage to individual parcels or distinguishing between damage caused by different insect agents. Thus, in the future, improved spatial data on the damage caused by various insect agents will enable a better understanding of how timberland markets respond to diverse insect risks. Second, our finding of price impacts of climate-induced insect damage should be viewed as a lower bound as we are not able to account for the losses of many non-market goods and ecosystem services provided by forests associated with insect damage. Moreover, similar to other Ricardian studies of climate impacts on land values (Mendelsohn and Massetti, 2017), our approach does not account for general equilibrium impacts that result from future shifts in the price of timber. Lastly, we project insect damage using three methods: conventional OLS estimation, the machine learning approach Lasso, and the Tobit model. While Lasso offers the highest prediction accuracy, it involves trade-offs between improving prediction performance and identifying key explanatory variables. We leave it to future research to evaluate which approach is preferred.

References

Abatzoglou, J. T., and Williams, A. P. 2016. Impact of anthropogenic climate change on wildfire across western US forests. *Proceedings of the National Academy of Sciences*, 113(42), 11770-11775. https://doi.org/10.1073/pnas.1607171113

Anderegg, W. R., Chegwidden, O. S., Badgley, G., Trugman, A. T., Cullenward, D., Abatzoglou, J. T., ... and Hamman, J. J. 2022. Future climate risks from stress, insects and fire across US forests. *Ecology letters*, 25(6), 1510-1520. https://doi.org/10.1111/ele.14018

Asaro, C., Nowak, J. T., and Elledge, A. 2017. Why have southern pine beetle outbreaks declined in the southeastern US with the expansion of intensive pine silviculture? A brief review of hypotheses. *Forest Ecology and Management*, *391*, 338-348. https://doi.org/10.1016/j.foreco.2017.01.035

Bayham, J., Yoder, J. K., Champ, P. A., and Calkin, D. E. 2022. The economics of wildfire in the United States. *Annual Review of Resource Economics*, 14, 379-401. https://doi.org/10.1146/annurev-resource-111920-014804

Bentz, B. J., Régnière, J., Fettig, C. J., Hansen, E. M., Hayes, J. L., Hicke, J. A., ... and Seybold, S. J. 2010. Climate change and bark beetles of the western United States and Canada: direct and indirect effects. *BioScience*, 60(8), 602-613. https://doi.org/10.1525/bio.2010.60.8.6

Bentz, B., and Klepzig, K. 2014. Bark beetles and climate change in the United States. US. Department of Agriculture, Forest Service, *Climate Change Resource Center*.

Brorsen, B.W., Doye, D. and Neal, K.B., 2015. Agricultural land and the small parcel size premium puzzle. *Land Economics*, 91(3), pp.572-585. https://doi.org/10.3368/le.91.3.572

Chen, G., Tian, H., Zhang, C., Liu, M., Ren, W., Zhu, W., ... and Lockaby, G. B. 2012. Drought in the Southern United States over the 20th century: variability and its impacts on terrestrial ecosystem productivity and carbon storage. *Climatic change*, 114, 379-397. https://doi.org/10.1007/s10584-012-0410-z

Costanza, J.K., et al. Disturbances to Forests and Rangelands. In: U.S. Department of Agriculture, Forest Service. 2023. Future of America's Forest and Rangelands: Forest Service 2020 Resources Planning Act Assessment. Gen. Tech. Rep. WO-102. Washington, DC: 5-1–5-55. Chapter 5.

Dale, V. H., Joyce, L. A., McNulty, S., Neilson, R. P., Ayres, M. P., Flannigan, M. D., ... and Wotton, B. M. 2001. Climate change and forest disturbances: climate change can affect forests by altering the frequency, intensity, duration, and timing of fire, drought, introduced species, insect and pathogen outbreaks, hurricanes, windstorms, ice storms, or landslides. *BioScience*, 51(9), 723-734. https://doi.org/10.1641/0006-3568(2001)051[0723:CCAFD]2.0.CO;2

Dodds, K. J., Aoki, C. F., Arango-Velez, A., Cancelliere, J., D’Amato, A. W., DiGirolomo, M. F., and Rabaglia, R. J. 2018. Expansion of southern pine beetle into northeastern forests: Management and impact of a primary bark beetle in a new region. *Journal of Forestry*, *116*(2), 178-191. https://doi.org/10.1093/jofore/fvx009

Donovan, G. H., Champ, P. A., and Butry, D. T. 2007. Wildfire risk and housing prices: a case study from Colorado Springs. *Land Economics*, *83*(2), 217-233. https://doi.org/10.3368/le.83.2.217

Duehl, A. J., Koch, F. H., and Hain, F. P. 2011. Southern pine beetle regional outbreaks modeled on landscape, climate and infestation history. *Forest Ecology and Management*, 261(3), 473-479. https://doi.org/10.1016/j.foreco.2010.10.032

Fettig, C. J., Runyon, J. B., Homicz, C. S., James, P. M., and Ulyshen, M. D. 2022. Fire and insect interactions in North American forests. *Current Forestry Reports*, *8*(4), 301-316. https://doi.org/10.1007/s40725-022-00170-1

Gan, J. 2004. Risk and damage of southern pine beetle outbreaks under global climate change. *Forest Ecology and Management*, 191(1-3), 61-71. https://doi.org/10.1016/j.foreco.2003.11.001

Johnson, K.K., and D.J. Lewis. 2024. Weather variability risks slow climate adaptation: An empirical analysis of forestry. *Journal of Environmental Economics and Management* 125: 103000. https://doi.org/10.1016/j.jeem.2024.103000

Kim, M. K., and Jakus, P. M. 2019. Wildfire, national park visitation, and changes in regional economic activity. *Journal of Outdoor Recreation and Tourism*, 26, 34-42. https://doi.org/10.1016/j.jort.2019.03.007

Hansen, W. D., Mueller, J. M., and Naughton, H. T. 2014. Wildfire in hedonic property value studies. In *Western Economics Forum* (Vol. 13, No. 1, pp. 23-35).

Harvey, J. A., Tougeron, K., Gols, R., Heinen, R., Abarca, M., Abram, P. K., ... and Chown, S. L. 2023. Scientists' warning on climate change and insects. *Ecological monographs*, 93(1), e1553. https://doi.org/10.1002/ecm.1553

Heuss, M., D'Amato, A. W., and Dodds, K. J. 2019. Northward expansion of southern pine beetle generates significant alterations to forest structure and composition of globally rare Pinus rigida forests. *Forest Ecology and Management*, 434, 119-130. https://doi.org/10.1016/j.foreco.2018.12.015

Jactel, H., Koricheva, J., and Castagneyrol, B. 2019. Responses of forest insect pests to climate change: not so simple. *Current opinion in insect science*, 35, 103-108. https://doi.org/10.1016/j.cois.2019.07.010

Lehmann, P., Ammunét, T., Barton, M., Battisti, A., Eigenbrode, S. D., Jepsen, J. U., ... and Björkman, C. 2020. Complex responses of global insect pests to climate warming. *Frontiers in Ecology and the Environment*, 18(3), 141-150. https://doi.org/10.1002/fee.2160

Lesk, C., Coffel, E., D'Amato, A. W., Dodds, K., and Horton, R. 2017. Threats to North American forests from southern pine beetle with warming winters. *Nature Climate Change*, 7(10), 713-717. https://doi.org/10.1038/nclimate3375

Loomis, J. 2004. Do nearby forest fires cause a reduction in residential property values?. *Journal of forest economics*, *10*(3), 149-157. https://doi.org/10.1016/j.jfe.2004.08.001

Lu, Y., Walker, T. D., Acosta, J. J., Young, S., Pandey, P., Heine, A. J., and Payn, K. G. 2021. Prediction of freeze damage and minimum winter temperature of the seed source of loblolly pine seedlings using hyperspectral imaging. *Forest Science*, 67(3), 321-334. https://doi.org/10.1093/forsci/fxab003

McCoy, S. J., and Walsh, R. P. 2018. Wildfire risk, salience & housing demand. *Journal of Environmental Economics and Management*, *91*, 203-228. https://doi.org/10.1016/j.jeem.2018.07.005

McIntosh, M. G., and Zhang, D. 2024. Cointegration of Timberland Value in the United States, South and Central America, and Oceania. *Forest Science*, fxae018. https://doi.org/10.1093/forsci/fxae018

Mendelsohn, R. O., and Massetti, E. 2017. The use of cross-sectional analysis to measure climate impacts on agriculture: theory and evidence. *Review of Environmental Economics and Policy*, 11(2), 280-298. https://doi.org/10.1093/reep/rex017

Mueller, J., Loomis, J., and González-Cabán, A. 2009. Do repeated wildfires change homebuyers' demand for homes in high-risk areas? A hedonic analysis of the short and long-term effects of repeated wildfires on house prices in Southern California. *The Journal of Real Estate Finance and Economics*, 38(2), 155-172. https://doi.org/http://dx.doi.org/10.1007/s11146-007-9083-1

Munro, H. L., Montes, C. R., and Gandhi, K. J. 2022. A new approach to evaluate the risk of bark beetle outbreaks using multi-step machine learning methods. *Forest Ecology and Management*, 520, 120347. https://doi.org/10.1016/j.foreco.2022.120347

Muthukrishnan, R., and Rohini, R. 2016. LASSO: A feature selection technique in predictive modeling for machine learning. IEEE International Conference on Advances in Computer Applications (ICACA), Coimbatore, India, pp. 18-20. https:// 10.1109/ICACA.2016.7887916

Parks, S. A., and Abatzoglou, J. T. 2020. Warmer and drier fire seasons contribute to increases in area burned at high severity in western US forests from 1985 to 2017. *Geophysical Research Letters*, 47(22), e2020GL089858. https://doi.org/10.1029/2020GL089858

Plantinga, A. J., Lubowski, R. N., and Stavins, R. N. 2002. The effects of potential land development on agricultural land prices. *Journal of urban economics*, *52*(3), 561-581. https://doi.org/10.1016/S0094-1190(02)00503-X

Preisler, H. K., Hicke, J. A., Ager, A. A., and Hayes, J. L. 2012. Climate and weather influences on spatial temporal patterns of mountain pine beetle populations in Washington and Oregon. *Ecology*, 93(11), 2421-2434. https://doi.org/10.1890/11-1412.1

Pye, J. M., Holmes, T. P., Prestemon, J. P., and Wear, D. N. 2011. Economic impacts of the southern pine beetle. *Southern pine beetle II*, 213-222.

Ranstam, J., and Cook, J. A. 2018. LASSO regression. *Journal of British Surgery*, *105*(10), 1348-1348. https://doi.org/10.1002/bjs.10895

Reed, W. J. 1984. The effects of the risk of fire on the optimal rotation of a forest. *Journal of environmental economics and management*, 11(2), 180-190. https://doi.org/10.1016/0095-0696(84)90016-0

Reed, W. J., and Errico, D. 1987. Techniques for assessing the effects of pest hazards on long-run timber supply. *Canadian Journal of Forest Research*, 17(11), 1455-1465. https://doi.org/10.1139/x87-224

Schmidtling, R. C. 2001. Southern pine seed sources (Vol. 44). US Department of Agriculture, Forest Service, Southern Research Station.

Seidl, R., Thom, D., Kautz, M., Martin-Benito, D., Peltoniemi, M., Vacchiano, G., ... and Reyer, C. P. 2017. Forest disturbances under climate change. *Nature climate change*, 7(6), 395-402. https://doi.org/https://doi.org/10.1038/nclimate3303

Stetler, K. M., Venn, T. J., and Calkin, D. E. 2010. The effects of wildfire and environmental amenities on property values in northwest Montana, USA. *Ecological Economics*, 69(11), 2233-2243. https://doi.org/10.1016/j.ecolecon.2010.06.009

Sun, C., and Zhang, D. 2001. Assessing the financial performance of forestry-related investment vehicles: capital asset pricing model vs. arbitrage pricing theory. *American Journal of Agricultural Economics*, 83(3), 617-628. https://doi.org/10.1111/0002-9092.00182

Tobin, P. C., Haynes, K. J., and Carroll, A. L. 2023. Spatial Dynamics of Forest Insects. In Forest Entomology and Pathology: Volume 1: *Entomology* (pp. 647-668). Cham: Springer International Publishing.

Ungerer, M. J., Ayres, M. P., and Lombardero, M. J. 1999. Climate and the northern distribution limits of Dendroctonus frontalis Zimmermann (Coleoptera: Scolytidae). *Journal of Biogeography*, 26(6), 1133-1145. https://doi.org/10.1046/j.1365-2699.1999.00363.x

U.S. Geological Survey, 2014, USGS Small-scale Dataset - 1:1,000,000-Scale Major Roads of the United States 201403 Shapefile: U.S. Geological Survey.

Wang, Y. 2023. Empirical analyses of the impact of climate-induced natural disturbances on the economic value of US forests (Doctoral dissertation, Oregon State University]. Campus Repository: https://ir.library.oregonstate.edu/concern/graduate_thesis_or_dissertations/q811kt20w

Wang, Y., and Lewis, D. J. 2024. Wildfires and climate change have lowered the economic value of western US forests by altering risk expectations. *Journal of Environmental Economics and Management*, 123: 102894. https://doi.org/10.1016/j.jeem.2023.102894

Weed, A. S., Ayres, M. P., and Hicke, J. A. 2013. Consequences of climate change for biotic disturbances in North American forests. *Ecological Monographs*, 83(4), 441-470. https://doi.org/10.1890/13-0160.1

Westerling, A. L. 2016. Increasing western US forest wildfire activity: sensitivity to changes in the timing of spring. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 371(1696), 20150178. https://doi.org/10.1098/rstb.2015.0178

Wibbenmeyer, M., and McDarris, A. 2021. Wildfires in the United States 101: Context and consequences. *Resources for the Future*.

Woudenberg, S. W., Conkling, B. L., O'Connell, B. M., LaPoint, E. B., Turner, J. A., and Waddell, K. L. 2010. The Forest Inventory and Analysis Database: Database description and users manual version 4.0 for Phase 2. *Gen. Tech. Rep. RMRS-GTR-245. Fort Collins, CO: US Department of Agriculture, Forest Service, Rocky Mountain Research Station. 336 p.*, *245*.

Zhang, D. 2021. From Backwoods to Boardrooms: The Rise of Institutional Investment in Timberland. Oregon State University Press.

Zhang, D. 2022. Institutional timberland investment in South and Central America. *Forest Policy and Economics*, *135*, 102663. https://doi.org/10.1016/j.forpol.2021.102663

Zhang, D., and Hall, R. W. 2020. Timberland Asset Pricing in the United States. *Journal of Forest Economics*, *35*(1), 43-67. http://dx.doi.org/10.1561/112.00000448

Zhang, D., Meng, L., and Polyakov, M. 2013. Determinants of the prices of bare forestland and premerchantable timber stands: a spatial hedonic study. *Forest Science*, *59*(4), 400-406. https://doi.org/10.5849/forsci.12-014

Zou, H. 2006. The adaptive Lasso and its oracle properties. *Journal of the American statistical association*, *101*(476), 1418-1429. https://doi.org/10.1198/016214506000000735