Wildfires and Climate Change Have Lowered the Economic Value of Western U.S. Forests by Altering Risk Expectations

Yuhan Wang[1], David J. Lewis[1]

Date of Draft: October 3rd, 2023

Abstract: There is a lack of evidence regarding how natural resource markets have responded to recent increases in climate-induced extreme events like wildfire. Wildfire can affect the economic value of forests by directly damaging the existing the existing tree stock and by altering landowner risk expectations of future wildfire arrival. This paper uses parcel data over a seventeen-year period to estimate the effects of large wildfires and drought stress on market prices for private timberland across the three Pacific states of the western U.S. In addition to estimating the land price impacts of wildfires on parcels that were directly burned, we identify changes in risk expectations by estimating the impacts from wildfires that burned in close proximity rather than directly on timberland that was sold in the land market. Results indicate that recent increases in large wildfires and drought stress over the past two decades have lowered the economic value of timberland by approximately 10%, or about $11.2 billion in damages across the three Pacific states, with approximately 5.5% (~$6.2 billion) due to climate change. Most of the wildfire damages arise from changes in risk expectations. Results provide evidence on the costs of climate-induced extreme events on natural capital that have already occurred.

JEL codes: Q23, Q54

Keywords: Climate change; Forests; Wildfire; Climate econometrics; Natural capital

Acknowledgements: We thank two anonymous reviewers and editor Roger H. von Haefen for their extremely constructive comments and suggestions. We acknowledge helpful comments from Dan Bigelow, Steve Dundas, and Jennifer Alix-Garcia, as well as seminar participants at the AERE summer conference and Oregon State University. We thank the Emery N Castle Chair in Resource and Rural Economics for funding this project. We acknowledge funding from the National Institute of Food and Agriculture (No. 2021-67023-33827).

Conflict of Interest Statement: The authors declare no known conflicts of interest related to this manuscript.

* Corresponding Author: Yuhan Wang, wangyuha@oregonstate.edu , Phone: 541-360-1315.
[1] Department of Applied Economics, Oregon State University, 213 Ballard Ext. Hall, Corvallis, OR 97331

1. Introduction

A large literature in environmental and natural resource economics has examined the impacts that climate change can have on natural resources through its effect on the productivity of agriculture (e.g., the review by Mendelsohn and Massetti, 2017) and timber (e.g., the review by Sohngen, 2020). While climate change can impact natural resources by altering growth functions for renewable resources, another important avenue of climate impact is through disturbance events. For example, climate change has triggered a significant increase in droughts and large wildfires across the western U.S. (Strzepek et al., 2010; Abatzoglou and Williams, 2016), spurring impacts on numerous public agencies and private sector activities (Bayham et al., 2022). Wildfire risk information has been shown to be priced in housing markets (Loomis, 2004; Donovan et al., 2007; Stetler et al., 2010; McCoy and Walsh, 2018), but it is unclear whether such changes in risk are reflected in natural resource markets. For forest stocks, a number of natural science studies have demonstrated that increasingly frequent droughts and wildfires have negatively impacted forest growth, timberland productivity, and tree mortality rates (Van Mantgem et al., 2009; Williams et al., 2010; Stevens-Rumann and Morgan, 2019), particularly for the commercially valuable Douglas-fir species (Weiskittel et al., 2012; Restaino et al., 2016). To illustrate the increasing large wildfire prevalence across the Pacific states of the western U.S., we calculate that privately owned parcels of timberland are about 8.25 km closer on average to the nearest large (>1,000 acres) wildfire event during the first two decades of the 21st century than they were during the last two decades of the 20th century. Thus, the problem of understanding how large wildfire and drought stress impact the economic value of western U.S. forests is one example of a broader social problem of estimating how disturbance risks from climate change are already impacting the economic value of important natural capital.

Estimating the impacts of climate change on the value of natural capital in forests has been identified as an important goal for the federal government (The White House, 2023), but a challenge with meeting this goal is the fact that forests produce some ecosystem services that are traded in markets (e.g., timber) and some ecosystem services that are not traded in markets (e.g., wildlife habitat, recreation, flood control, etc.). Among those ecosystem services, timberland prices emerge from broadly competitive markets and provide an avenue for estimating the impacts of climate change on at least one of the ecosystem services provided by forests. Economic theory suggests that the market price of timberland capitalizes landowner expectations of the present value of all factors that impact productivity, such as tree growth and stumpage prices. Natural resource economics also shows that the market price of timberland capitalizes landowner expectations of wildfire arrival rates (Reed, 1984), including risks from ignition on spatially proximate land (Lauer et al., 2017). Reed's (1984) seminal study shows that higher expected wildfire arrival rates on a piece of forest land effectively increase the discount rate used to compute the present value of future timber rents, and thus land values should be bid down as wildfire arrival rates increase. However, empirical observations of wildfire frequency vary significantly across space in regions with many micro-climates and individual landowners, and an open empirical question is whether the recently observed increases in large wildfire events have shifted landowner expectations of wildfire arrival rates enough to be capitalized in the land market. Further, despite significant theoretical work on how the spatial aspects of wildfire spread are important drivers of timberland values (e.g., Konoshima et al., 2008; Busby et al., 2012), an open empirical question is whether spatial proximity to changes in large wildfire arrival rates serves as an avenue for altering landowner expectations of such climate-induced disturbance events.

The purpose of this study is to estimate the effects of climate-induced large wildfires and drought stress on timberland prices in the Pacific states of the western U.S. – Washington (WA), Oregon (OR), and California (CA), a topographically and climatically diverse region with valuable natural capital embedded in forest resources. We begin with a simple depiction of Reed's (1984) theoretical model of wildfire impacts on timberland parameterized with local data to develop testable hypotheses about the magnitude of price impacts from observable recent increases in wildfires. The testable hypotheses are then brought to an empirical analysis of a pooled cross-sectional dataset of just over 9,000 transaction prices of timberland across the entire privately-owned forested region of the Pacific states over the period 2004-2020. We link each parcel transaction to empirical measurements of vapor pressure deficit (a drought stress measure) and large wildfire arrival rates (a wildfire exposure measure) using parcel locations combined with a climate raster and wildfire polygons. Our wildfire arrival rate measure captures the number of distinct fires that occurred both on and nearby each parcel over the 20 years prior to each parcel transaction. Our wildfire arrival rate variable takes advantage of the timing and spatial boundary of each wildfire to capture fine-scale temporal and spatial variation in wildfire activity. Using a range of spatial and temporal fixed effects in a linear econometric model, the identification of drought and large wildfire impacts on timberland values is based on within-county variation in prices, drought stress, and large wildfires. A key feature of the estimation strategy is separately estimating the effects of fires that occur directly on private timberland parcels from fires that occur nearby, thereby allowing us to test if spatially proximate fire serves as an avenue for updating timberland owners' expectations of large wildfire arrival.

Given the estimated econometric model parameters, we then estimate the extent of timberland value losses that have already occurred based on changes in drought stress and large wildfire arrival rates during the past two decades. Our results show that observed increases in drought stress have already reduced the economic value of timberland by approximately 1.04%. Recent increases in large wildfire arrival rates have reduced timberland values by an additional 8.74%. Importantly, most of the large wildfire-induced losses in timberland value occur from higher wildfire arrival rates on neighboring land that alter wildfire arrival expectations in the land market (leading to a decrease of 7.38%), rather than from direct burning on private timberland (leading to a decrease of 1.36%). Taken together, the increases in climate-induced drought stress and large wildfire events over the past two decades have led to a roughly 10% loss in timberland value per acre on average, about $11.2 billion losses in total across the three Pacific states. Building on prior climate change attribution studies that link recent changes in VPD and wildfires in the western U.S. to anthropogenic climate change (Abatzoglou and Williams, 2016; Zhuang et al., 2021), our results suggest that recent climate change is responsible for lowering timberland values by 5.5% (~$6.2 billion).

This paper makes several contributions to literature. The first contribution is providing empirical estimates of how increasingly frequent large wildfire arrival has affected the economic value of forests through two avenues: i) direct fire damage to the existing forest stock, and ii) neighboring fires that alter landowners' expectations of fire arrival. Most of the recent empirical work estimating wildfire impacts on land values has focused on residential housing markets near the wildland-urban interface (WUI) areas (see Hansen et al. (2014) for a comprehensive review). A key finding of these studies is that wildfires tend to have a short-lived negative effect on housing prices in WUI areas in the western U.S. (Loomis, 2004; Donovan et al., 2007; Mueller et al., 2009; Stetler et al., 2010; McCoy and Walsh, 2018). Given the distinct dynamics of rotational forestry (Conrad, 2010), along with evidence that government fire suppression efforts prioritize lowering risks in high-valued residential areas (Plantinga et al., 2022), wildfire impacts on timberland markets are likely to differ significantly from impacts on residential markets. Natural resource economic theory is clear that wildfire arrival expectations should be capitalized into timberland values and be a key determinant of forest management practices such as rotation length and planting density (Amacher et al., 2005), and there is a clear theoretical structure as to how higher fire expectations raise the discount rate used to weigh future timber rents (Reed, 1984). We build on past theoretical work by applying linear econometric techniques to estimate how natural resource market prices adjust to increasing wildfire occurrence that likely shifts expectations of wildfire arrival. The empirical methods allow us to test hypotheses regarding landowner expectations of wildfire arrival, in contrast to past natural resource economics literature that uses numerical methods to examine how management behavior can adapt to fires (e.g., Amacher et al., 2005; Konoshima et al., 2008; Busby et al., 2012; Lauer et al., 2017).

Our study contributes to the Ricardian literature by estimating how expectations of climate change can be transmitted to landowners through spatially proximate climate-driven disasters (wildfire) using the first parcel-level forestry Ricardian analysis based on market transaction prices of timberland. The Ricardian approach was first proposed by Mendelsohn et al. (1994) to examine the long-term impacts of climate change on the net rent or value of farmland by accounting for climate-induced adaptations. This approach has been widely adopted in the agricultural sector in various locations worldwide (Mendelsohn et al., 1994; Mendelsohn et al., 1996; Polsky, 2004; Seo et al., 2005; Schlenker et al., 2005; Sanghi and Mendelsohn, 2008; Massetti and Mendelsohn, 2011; Mendelsohn and Massetti, 2017). Ricardian studies of forestry are limited to Mihiar and Lewis (2021) and Hashida and Lewis (2022), who investigate the effect of climate change on measures of timberland rents that were constructed from tree growth and stumpage price observations rather than land transaction prices. Many Ricardian studies estimate how the current climate impacts agricultural and forestry land values, though a recent critique argues that land values should capitalize expected future changes in climate that may operate through scientific forecasts of climate change (Severen et al., 2018). We contribute to this work on expectations in Ricardian studies by estimating how local wildfire shocks – driven partly by climate change – serve as an avenue for updating landowner expectations as to how climate change creates risk that affects the value of their land assets.

Finally, our finding of land value losses that have already occurred because of climate-related disturbance shocks contributes to a broader understanding of the economic impacts of climate change on the value of natural capital. While significant research attention has focused on estimating future climate change impacts on economic measures (e.g., Hsiang et al., 2017; Auffhammer, 2018), less is known about the economic impacts of climate change that have already occurred. Some recent examples that have estimated the economic impacts of past climate change include studies of historical crop insurance losses (Diffenbaugh et al., 2021), changes in agricultural productivity growth (Ortiz-Bobea et al., 2021), global economic inequality (Diffenbaugh and Burke, 2019), and flood damage costs (Davenport et al., 2021). Through our analysis of the impacts of large wildfire and drought stress on timberland values, we contribute to this emerging field of study by quantifying the effects of historical climate shocks on the economic value of natural capital, as well as providing insights into the potential net benefits associated with actions to mitigate extreme weather events.

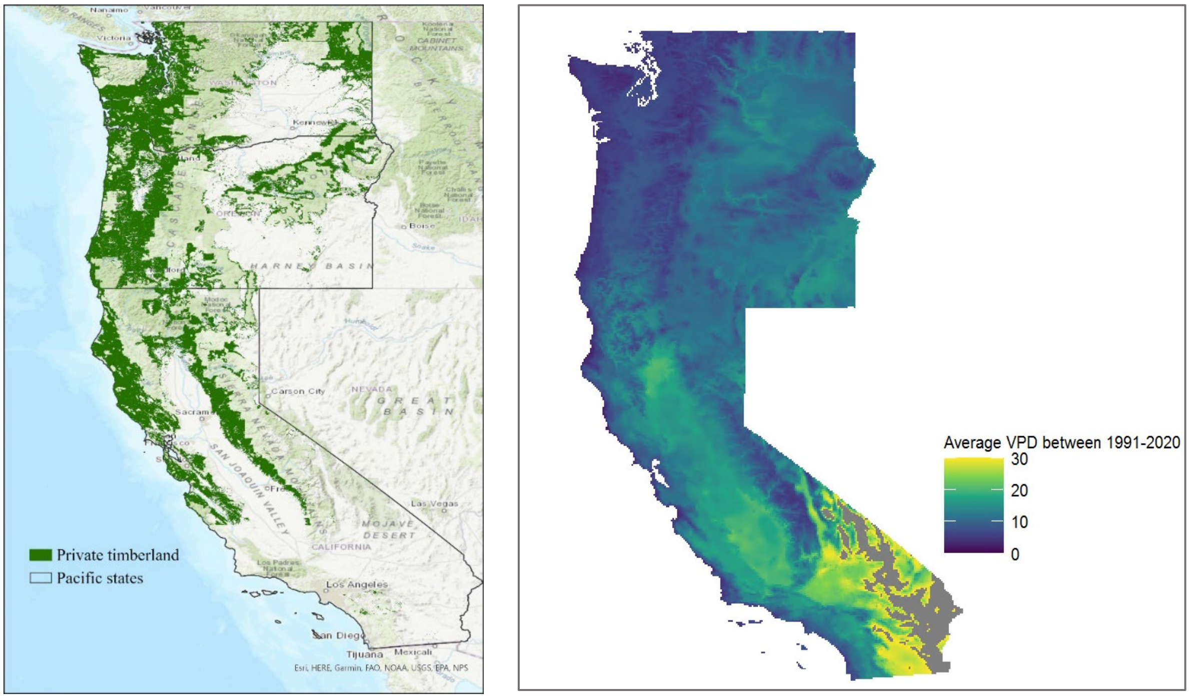
2. Large wildfire and timberland in the U.S. Pacific States Region

This paper studies timberland prices across three Pacific states of the western U.S., Washington, Oregon, and California, using data from 2004-2020. These temporal and spatial scales are chosen to provide significant empirical variation in timberland prices, large wildfires, and drought stress. Throughout our study region, about one-third of all forests are privately owned, while the remainder are owned by federal, state, and local governments. However, most of the timber harvested – and almost all timberland traded in the land market - comes from private timberlands. Harvest operations on federal lands have been greatly reduced since the 1990s under the federal Northwest Forest Plan. There are a variety of tree species in this study region, with Douglas-fir being the most prevalent. Some other tree species include ponderosa pine, lodgepole pine, coast redwoods, Engelmann spruce/subalpine fir, Sitka spruce, and selected hardwoods such as red alder. Douglas-fir is the most planted tree species by landowners, though recent natural science studies have found evidence of limited post-fire tree regeneration in low-elevation ponderosa pine and Douglas-fir forests due to low seed availability and high fire severity under regional climate change (Rother and Veblen, 2016; Davis et al., 2019; Kemp et al., 2019).

Privately owned commercial timberlands are used to produce marketable timber [2](Mei, 2019). Fig. 1 (a) presents a private timberland map for the study area.[3] Western Oregon and Washington have a large amount of private timberland. This region is also one of the largest national producers of timber products in the country, thanks to a mild and wet climate that is beneficial for growing the commercially valuable Douglas-fir species. In contrast, eastern Oregon and Washington are hotter and drier and have significantly less private timberland than

[2] Technically, timberland refers to forestland that is capable of producing more than 20 cubic feet of wood per acre per year (USDA 2007).
[3] To identify privately owned timberland, we first create a private forestland map by excluding publicly protected areas derived from the Protected Areas Database from the forested area derived from the 2016 National Land Cover Database. Then following the definition of timberland, Fig.1 (a) is constructed by overlapping the private forestland map with a county-level average site productivity class greater than 20 cubic feet per acre per year, where county-level weighted average forest productivity data is obtained from the Resource Planning Act 2012 Database.

western Oregon and Washington. Private timberland in California is concentrated in coastal areas and low-elevation areas near national forests.



(a) Private timberland (b) 30-year average annual VPD, 1991-2020

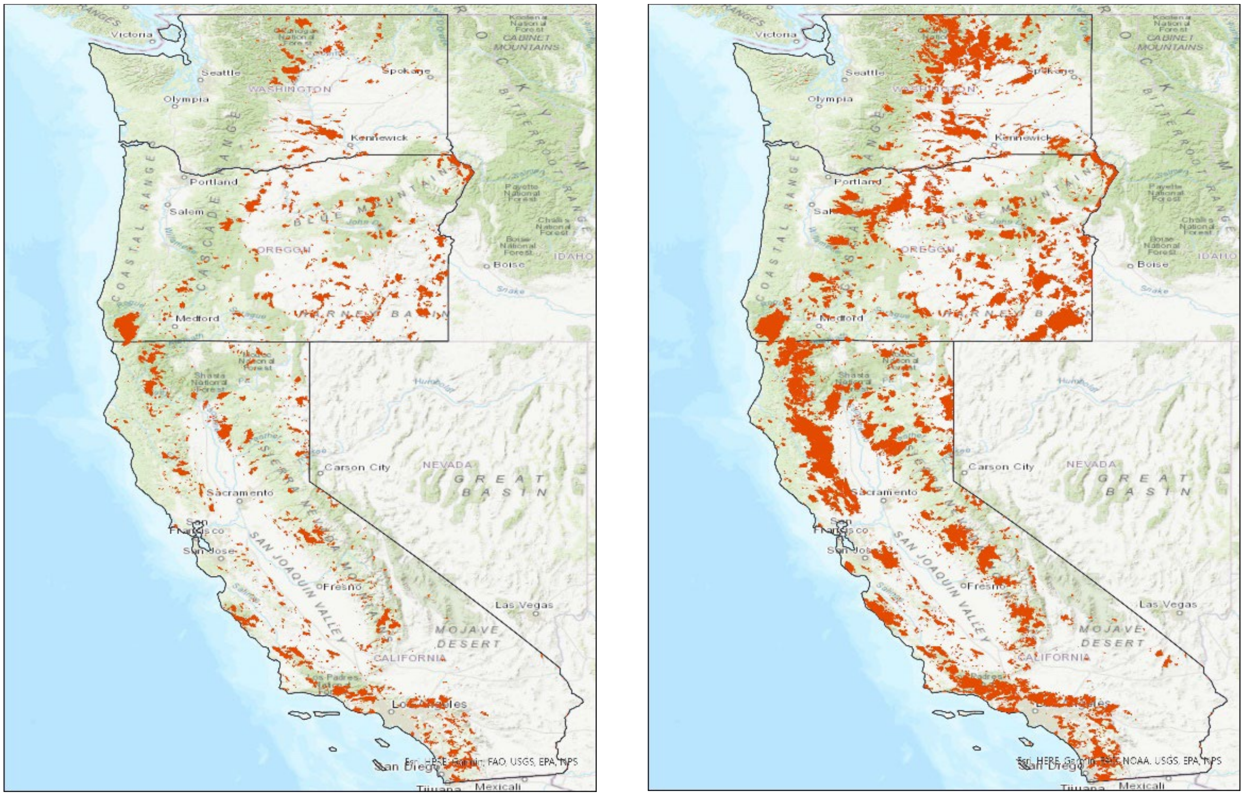
Figure 1. Private timberland and average annual VPD in the study area

The study region has experienced varying degrees of drought over the past two decades because of rising temperatures, including the widely publicized mega-drought (Williams et al., 2022). Western U.S. forests have been identified to be affected by a plant-relevant drought indicator known as the vapor pressure deficit (VPD) (Restaino et al., 2016). By definition, the VPD measures dryness and atmospheric aridity and integrates relative humidity and temperature.[4] When VPD is high, the air is relatively dry, causing plants to transpire and take in more water from their roots, eventually causing them to dry out and die. A 30-year average

[4] The vapor pressure deficit (VPD) is defined as the difference between the actual vapor pressure of the air and the saturated vapor pressure. Higher VPD indicates dry air and high transpiration rate, causing stomatal closure and hence limiting growth owing to reduced intake of CO_2 (Restaino et al., 2016).

annual VPD between 1991-2020 is shown in Fig. 1 (b). Private timberland is less likely to be found in areas with high levels of VPD.

In addition to drought stress, large wildfires are becoming more common and severe in the study area. The Monitoring Trends in Burn Severity (MTBS) data show that there have been more than 3,500 large wildfires of at least 1,000 acres reported between 1984 and 2020, resulting in the burning of over 42 million acres across the three states. Despite an overall increase in large wildfires over the region, there is a high level of regional variation in large wildfire occurrence (Fig. 2), which has been attributed to factors like climatic conditions and fuel loads (Abatzoglou and Kolden, 2013; Abatzoglou and Williams, 2016). Large wildfire activities also differ across private timberland, public forestland, and other land use types. The acreage burned in other land use types and public forestland is substantially higher than in private timberland (Fig. 3). However, there is significant spatial intermixing of private timberland with these other two uses, as we calculate that of all large fires that occurred within 15km of our sample of privately owned timberland parcels that have a transaction price between 2004-2020, 6% burned on private timberland, 26% burned on publicly owned forestland, and 68% burned on other land use types such as shrubland. This suggests an important empirical fact that although private timberland in the region has seen fewer recent large wildfires than other land uses and public forestland, this private timberland is surrounded by large fire risks that have been occurring on other land uses and public forestland.



(a) Large wildfires, 1984 - 2003

(b) Large wildfires, 2001-2020

Figure 2. Spatial distribution of large wildfires that have occurred in the past and current period

Note: Wildfire data come from MTBS.

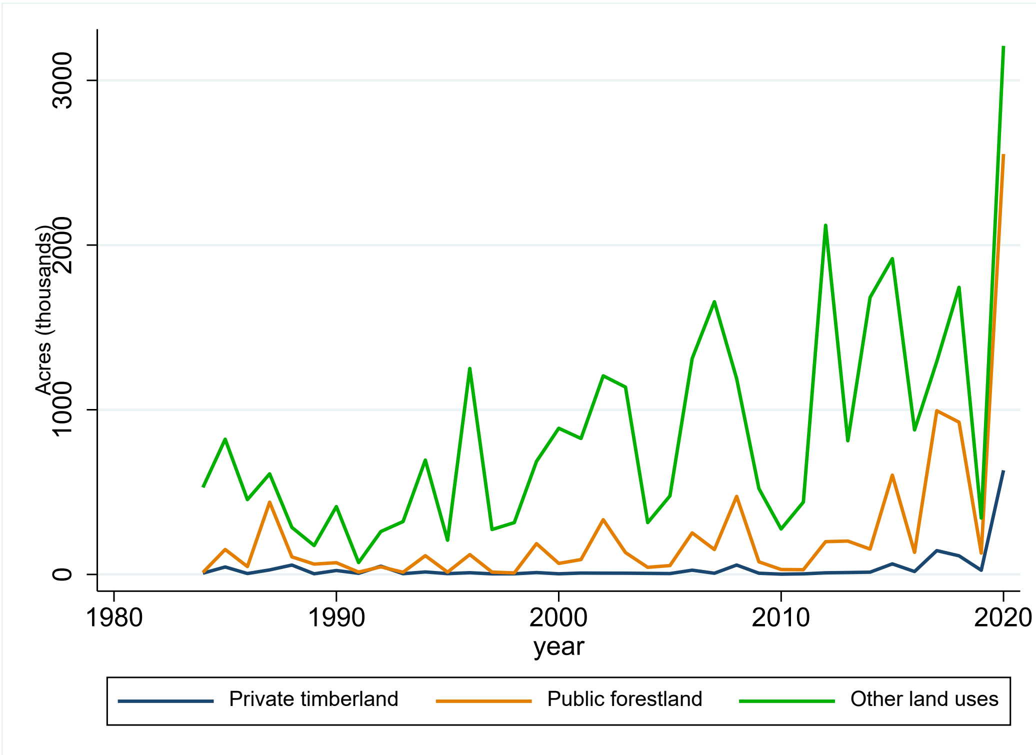


Figure 3. Annual acreage burned across private timberland, public forestland and other land uses

3. Theoretical underpinnings – Wildfire expectations and timberland prices

3.1 Faustmann and Reed model foundation

The foundational theory for timberland values rests on the Faustmann model, which assumes that landowners practice rotational forestry on land where tree volume for a stand of age a growing in climate conditions C is defined by $vol(C, a)$. The Faustmann model assumes clear-cut harvest with constant per-unit stumpage prices P, a stable climate and therefore constant growth function, a constant discount rate γ, and a constant regeneration cost R. While such assumptions can be relaxed to account for modern issues like climate change adaptation (e.g., Guo and Costello, 2013), we discuss the Faustmann model and its extension to wildfire to build the intuition needed for our empirical work. Under Faustmann assumptions, the landowner maximizes the value of their stand by selecting a constant rotation length T (Conrad, 2010), thereby resulting in a compact expression for the value of bare timberland:

$$V^{bare} = \frac{[P * vol(C,T) - R]e^{-\gamma T}}{1 - e^{-\gamma T}} \tag{1}$$

Key drivers of timberland values in the Faustmann setting are the landowners' expectation of stumpage prices, costs, and tree growth.

The expression in Eq. (1) assumes no fire risk, and thus the landowner's problem is deterministic. Reed (1984) presented the first extension of the Faustmann problem that incorporated risky natural disturbance by assuming that fire arrival is governed by a random Poisson process that occurs independently over time. Suppose the average arrival rate of a fire in any time period is determined by the Poisson parameter λ. A forest that burns once every T^f years would have a Poisson parameter of $\lambda = 1/T^f$. An additional assumption in the Reed model is that wildfire occurrence destroys any salvage value of the standing trees, which is known as catastrophic loss (Amacher et al., 2009). Combining the Reed assumption that catastrophic fires occur in a time-independent Poisson process with the original Faustmann assumptions of constant prices and a stable climate and tree growth function, the value of bare timberland can be written in a Faustmann-like expression (Conrad and Clark, 1987):

$$V^{bare} = \frac{(\gamma + \lambda)[P * vol(C,T) - R]e^{-(\gamma + \lambda)T}}{\gamma(1 - e^{-(\gamma + \lambda)T})} - \frac{\lambda}{\gamma} SC \tag{2}$$

Where SC is a salvage cost variable incurred to clear and regenerate trees after wildfire, and thus, $\frac{\lambda}{\gamma} SC$ is the expected present value of all future salvage costs. Reed's key insight was that the Poisson fire risk parameter λ implicitly increases the landowners' discount rate above the standard Faustmann case with no fire risk, thereby giving less weight to future harvest values and spurring the landowner to adapt to fire by shortening their rotation time T relative to the case without fire risk. Extensions have introduced other fire management adaptations besides harvest (e.g., Amacher et al., 2005).

Building off Reed's original model, the natural resource economics literature has emphasized that fire spread is a spatial process and fuel conditions and fire occurrence on one portion of a landscape can affect management and the market value of timberland on neighboring lands (Lauer et al., 2017). Recent numerical work in resource economics examines how optimal fire management can be designed given the spatial aspects of fire spread across landowners (Konoshima et al., 2008), and that fire management effort is lower in landscapes with fragmented ownership patterns, especially between private and public landowners (Busby et al., 2012). Given the importance of fire spread across landowners, an empirically relevant hypothesis is that landowner expectations of fire risk λ in Eq. (2) are likely influenced by wildfire activity and fuel loads on neighboring lands. Thus, one potential avenue for updated wildfire arrival expectations is through the patterns of fire activity on neighboring lands. If *fire* is a variable that represents recent fire occurrence on neighboring land, then $\lambda(fire)$.

One additional feature to lay out is the expression of land value for a stand that has an age (and volume) greater than zero (*a*>0), rather than Eq. (2)'s expression for bare land value. Given the assumptions above, the landowner will harvest the stand in *T-a* years in the absence of a catastrophic fire, or suffer a loss of all timberland value if the stand is burned prior to harvest age. The time of the fire event is a random variable defined as T^e, and the first rotation payoff is defined by:

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

Given the Poisson process governing fire arrival in the Reed model, the probability of $T^e < T - a$ is higher with a higher fire arrival rate λ. After either the harvest or fire event occurs, the land value will revert to the bare land value in Eq. (2). The land value of a stand of age a can thus be written as a sum of the expected present value of future harvest from the stand of age *a* plus the expected present value of bare land after the first disturbance:

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

Where E is the expectation operator over the random variable T^e. The main insight from Eq. (4) useful for empirical work is that land that has had its timber directly burned from a recent fire will be more likely to consist of bare land with a timberland value described by Eq. (2), and land that has not had a recent fire will be more likely to have a stock of trees with age *a*>0 with a timberland value described by Eq. (4). It should be noted that $V > V^{bare}$ since landowners that buy a stand with trees of age *a*>0 have to wait less time for the first harvest than owners of bare land. Thus, a recent fire on a parcel of land will lower that parcel's land value even without a change in expected fire arrival rate.

3.2 Testable hypotheses from the Reed model for the Pacific states: A numerical depiction

Fire arrival periods have shortened across the Pacific states, and this section parameterizes Reed's land value equation with local data. First, we determine how the wildfire arrival rate λ has changed over time on private timberland in our study region. We define two time periods (1984-2003 and 2001-2020) and calculate wildfire arrival rates in the two time periods, separately, using MTBS wildfire data. These two time periods are consistent with our empirical analysis in Sec. 6. For each privately owned timberland parcel *i* in our sample, we first calculate *i*'s wildfire arrival in the past period (1984-2003) using the total number of distinct fires that occurred directly on parcel *i* during that period divided by 20 years. Then we obtain the past wildfire arrival rate λ_{84-03} over our study region as an average across all parcels. We find λ_{84-03} is about 0.001 large fires per year. Similarly, we calculate the current wildfire arrival rate λ_{01-20}

between 2001 and 2020, which is about 0.003 large wildfires per year.[5] Wildfire arrival on private timberland has increased threefold during the first two decades of the 21st century compared to the last two decades of the 20th century.

We use the Reed equation Eq. (2) to assess how the present value of bare forest land changes as wildfire risk changes from λ_{84-03} to λ_{01-20}. We parameterize Eq. (2) with timber prices and yield functions for tree growth[6] across all major tree species in the Pacific region using data from Hashida and Lewis (2019). We assume that wildfire occurs independently over time and that wildfire impact is catastrophic with no salvage value of the standing trees (Reed, 1984). For simplification, we also assume zero replanting costs and zero post-fire salvage costs. With these simplified assumptions, the land value expression in Reed's Eq. (2) becomes:

$$V^{bare} = \frac{(\gamma+\lambda)\left[P*\alpha*\left(1-e^{-\delta*T}\right)^3\right]e^{-(\gamma+\lambda)T}}{\gamma\left(1-e^{-(\gamma+\lambda)T}\right)} \qquad (5)$$

Where α and δ are the estimated parameter values for the timber yield function that embed the climate conditions C of the Pacific U.S. where they were estimated. We use three different discount rates 1%, 3%, and 5%, separately, to calculate the optimized bare land value V^{bare} in the past and current period by solving for optimal rotation age T at the two different wildfire arrival rates of λ_{84-03} and λ_{01-20}. Given estimates of land value under the two different wildfire arrival rates, we compute the percentage change in present value that arises from the higher wildfire arrival rate λ_{01-20} compared to the lower level λ_{84-03}. Since our study area covers

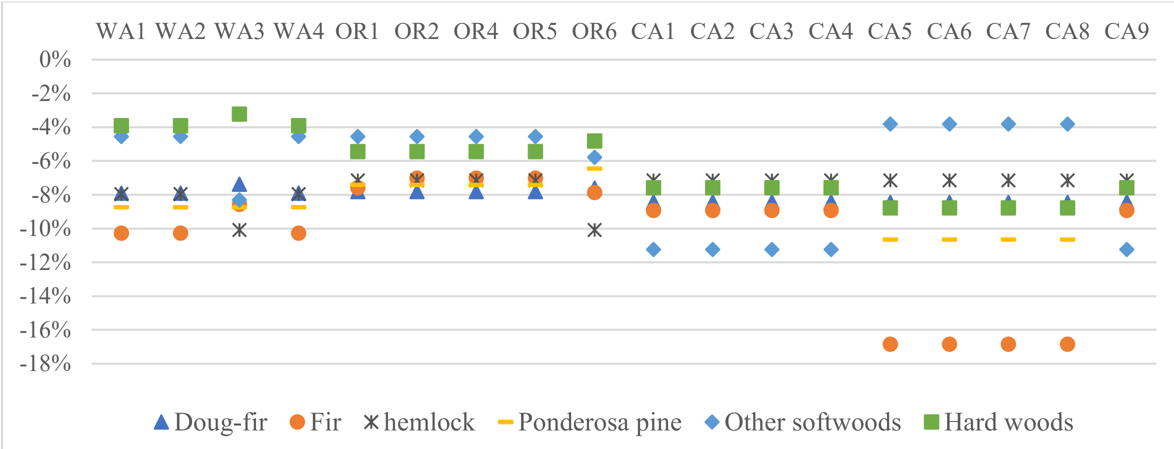
[5] Note that our numerical estimates of λ_{84-03} and λ_{01-20} are based only on wildfire data from the MTBS dataset and do not include small fires (less than 1000 acres). While small fires are more common than large wildfires, large wildfires are more likely to cause significant and catastrophic losses than small fires, so they better fit the assumptions of Reed's model.

[6] The von Bertalanffy growth function is used for tree growth, which is a conventional S-shaped function of volume as a function of stand age (Von Bertalanffy, 1938).

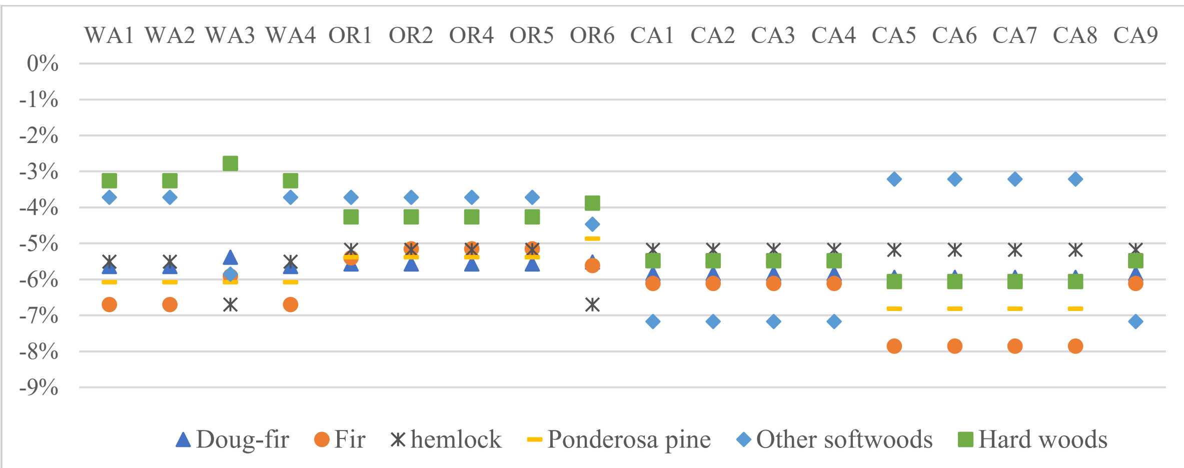
several forest types, we compute the percentage change in timberland value for all site classes and each major forest type across all eighteen price regions across the study area.[7]

Fig. 4 illustrates how the observed increases in wildfire arrival on private timberland would affect the economic value of timberland for all forest types in each price region. This numerical analysis shows that the increased fire risk would lead to timberland value losses ranging from 3% to 17% of land value with most impacts ranging from 4% to 9% of land value. Variations in the impacts from Fig. 4 arise from the assumed discount rate, forest type growth function, and price region. Thus, our numerical depiction of the Reed model generates a testable hypothesis that recent fire increases should lower land values somewhere in the range of 4% to 9%. A key point to make is that our hypothesized land value changes arise entirely from changes in landowner expectations of the wildfire arrival rate λ, since we use bare land value in Eq. (2) to compute the changes in Fig. 4. Empirical estimates of fire effects may differ from Fig. 4 because of many reasons, including i) many stands will have standing volume and will not be bare land, and ii) landowner expectations of wildfire arrival and other parameters may be heterogeneous.

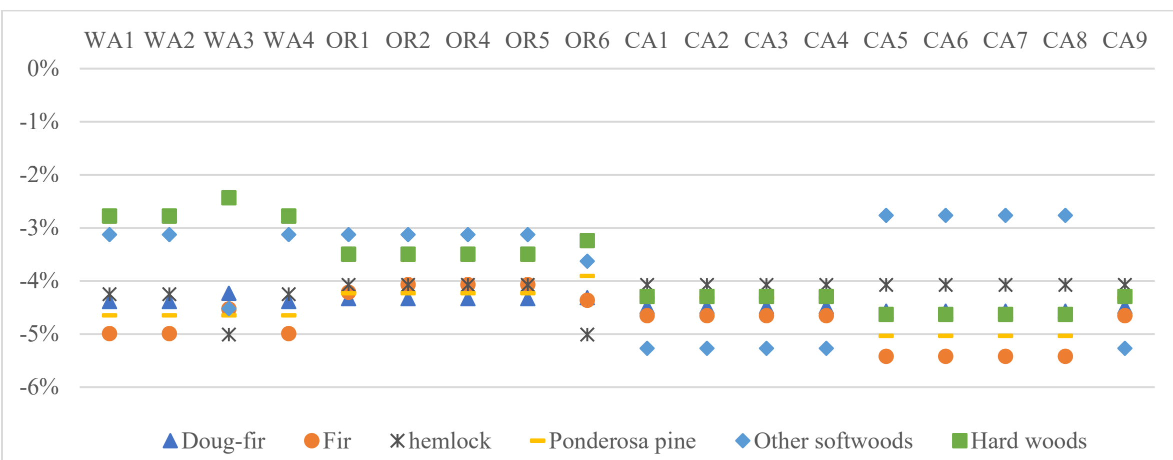
[7] Following Hashida and Lewis (2019), we have four stumpage price regions in WA, six price regions in OR, and nine price regions in CA. For each price region, we have six major forest types: (1) Douglas-fir, (2) fir/spruce/mountain hemlock, (3) hemlock/Sitka spruce, (4) ponderosa pine, (5) other softwoods, and (6) hardwoods. For each forest type, we then have three sets of different site classes that represents different land quality including high site class, middle site class, and low site class.



(a) Average % losses from more fires, all site classes, discount rate 0.01



(b) Average % losses from more fires, all site classes, discount rate 0.03



(c) Average % losses from more fire, all site classes, discount rate 0.05

Figure 4. Hypothesized range of expected percentage loss in timberland value from higher wildfire arrival rates in 2001-2020 compared to 1984-2003, across price region and forest type

3.3 Key insights and testable hypotheses for empirical analysis

The key insights from this theoretical section relevant to empirical work can be summarized as follows. First, fire arrival rates λ are expectations of landowners, which will be heterogeneous across space and capitalized into land values. Thus, the occurrence of a nearby individual wildfire event will have no impact on timberland prices if the event does not change the market's expectation of fire arrival rates. Second, if exogenous events like climate change increase wildfire events such that the market adjusts expectations of fire arrival rates, then participants in the land market should respond by bidding down land values since the ability to recover a long stream of future harvests becomes compromised with more wildfire. In sec 3.2, we combine observed changes in wildfire arrival rates with timber price and tree productivity parameters to generate a testable hypothesis that increased wildfire arrival rates would lower bare land values in our study region between 4% and 9%. Third, fires that occur nearby parcel *i* will lower *i*'s timberland values only if there is a shift in expectations of fire arrival rates, and the spatial aspects of fire spread imply that the presence of nearby fires is one avenue through which fire arrival expectations may shift. Finally, recent fires that occurred directly on parcel *i* with a positive age growing stock can lower *i*'s timberland value through destroying the existing stock on the stand, even if there is no change in expectations of fire arrival rate.

4. The empirical analysis

We conduct empirical analysis using land market data on timberland prices, and the key variables in Reed's model from Sec. 3 provide guidance on which independent variables influence prices. However, the explicit functional form from Eq. (4) may not hold if landowner assumptions deviate from some of Reed's assumptions. Therefore, a general statement of the value function that determines timberland prices is:

$$price = V(P, vol(a, C, sq), R, \lambda(fire, C), SC, \gamma, U;\ \boldsymbol{\beta}) \quad (6)$$

Where most variables in Eq. (6) are as described in Sec. 3, but with the addition of soil quality (sq), the observed arrival of nearby large wildfires (*fire*), and capitalized future urban development rents (*U*). The vector $\boldsymbol{\beta}$ represents parameters that translate the variables in Eq. (6) to $price$. Following Sohngen (2020), Eq. (6) posits that climate influences timberland prices through its effect on both the timber volume function $vol(a, C, sq)$ and through wildfire risk expectations. Following the logic of Sec. 3, wildfire expectations $\lambda(fire, C)$ depend on the observed rate of nearby wildfire occurrence and climate. While wildfire occurrence is related to climate *C*, it is also driven by fuel loads, vegetation conditions, and random ignition events (Abatzoglou and Kolden, 2013; Abatzoglou and Williams, 2016).

We use a standard log linear reduced-form model of land prices that is widely found in both wildfire hedonic analysis and Ricardian studies to estimate the relationship between land value and land attributes (Stetler et al., 2010; Mendelsohn and Massetti, 2017). Therefore, we specify our pooled cross-sectional model as follows:

$$Log\ (price_{it}) = \beta_0 + \boldsymbol{\beta_1} g(VPD_{it}) + \boldsymbol{\beta_2} f(Fire_{it}) + \beta_3 VLNF_{it} + \boldsymbol{\beta_4} X_i + Year_t + \mu_{c(i)} + \varepsilon_{it} \quad (7)$$

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), *g()* is a non-linear function of the climate measure vapor pressure deficit (VPD), and *f()* is a vector of large wildfire risk measures. A dummy variable depicting the presence of very large nearby fires (*VLNF*) is included to capture the heterogeneous effects of different sized nearby large wildfires. X_i denotes a vector of control variables that account for diverse land attributes such as slope and elevation. We use *c* to index counties, and thus $\mu_{c(i)}$ represents county fixed effects. Time fixed effects are captured by $Year_t$, and ε_{it} is an idiosyncratic error term.

4.1 Identification, fixed effect definitions and four main specifications

A range of temporal and spatial fixed effects (FE) is included in Eq. (7) to control for unobservables that may also affect timberland values. The presence of such temporal and spatial unobservables have been criticized for inducing omitted variable bias in cross-sectional Ricardian studies (Deschênes and Greenstone, 2007). The vector $Year_t$ is included in all main specifications and comprises year-specific FE to account for unobserved time-varying confounders that are common across space like timber demand, interest rates, macroeconomic fluctuations, and federal trade policy changes. The vector $\mu_{c(i)}$ is a location-specific FE that captures unobserved time-invariant but location-varying unobservables that influence timberland prices. A key role of location FE is to capture the baseline wildfire risk that exhibits significant spatial variations across space. For example, the coastal mountains in Western Oregon and Washington display a significantly lower wildfire risk compared to other areas in the region (Fig. 2).

Choosing the appropriate spatial level of location FEs induces a trade-off with our pooled cross-sectional data. Defining location FEs at too coarse a scale may fail to capture unobserved location-specific factors that vary within a large geographical area and are correlated with our key wildfire and drought stress variables. On the other hand, defining location FEs at too fine a scale may leave too little within variation in the key independent variables and thus lose precision in estimation. In our study, we illustrate the trade-off with the scale of spatial fixed effects by including state-level fixed effects (Model 1) and our preferred county-level FEs (Model 2). We prefer county-level FEs because they are sufficiently narrow to capture time-invariant local heterogeneous factors that may affect timberland values, such as baseline wildfire risk, local geography, topography, demographics, as well as aspects of climate (such as temperature and precipitation) which do not vary much within counties. State-level FEs may fail to capture the large variation in baseline large fire risk within the coastal and eastern portions of each state, leading to omitted variable bias. To further examine the sensitivity of large wildfire and VPD estimates to different levels of spatial FE, we conduct numerous robustness checks by including a range of location FEs at a finer scale than the county, such as census tracts and evenly distributed grid cells generated across our study region (Sec. 6.2).

We also test for robustness against unobservables that vary across counties and time by including a specification with county-specific time trends (Model 3). County-specific time trends capture factors like timber mill capacity that may change at a greater rate in some areas than others. And finally, Model (4) examines the robustness of our main large wildfire results to the inclusion of variables depicting small wildfire arrival rates (<1000 acres) in a model with county and year FEs.

4.2 Estimation strategy

To isolate the drought stress and large wildfire impacts on timberland values, we estimate Eq. (7) using ordinary least squares on the pooled cross-sectional data with the fixed effects defined above and with county clustered standard errors. Clustering standard errors at the county level allows inference robust to arbitrary heteroscedasticity and spatial correlation across parcels within the same county. We estimate Eq. (7) weighted by acres to minimize the influence from a large number of small-sized parcels and obtain marginal effects for the average timberland acre rather than the average timberland parcel.

5. Data

This section discusses data and measurement of the variables used in the empirical analysis.

5.1 Measurement of timberland prices

Timberland sales data is sourced from real estate transactions compiled by CoreLogic (CL), a private data provider that collects transaction records for the United States. Matching the time period of wildfire data, we include the most recent transactions for the universe of timberland parcels that were sold between 2004 and 2020. A transaction record includes parcel acreage, land use code, coordinates of the parcel centroid, price sold, date sold, and several other property attributes. According to the land use code associated with each parcel, we include either single parcel sales coded in forest use or multi-parcel sales with all parcels coded in forest use to ensure the land price mainly reflects forest use. In a single parcel sale, only one parcel is sold. In a multi-parcel sale, several parcels are sold together at a collective value.[8] The month and year of a transaction are derived from the sale date or, if there is no sale date, from the sale recording date.[9] For multi-parcel sales, we compute the corresponding transaction-level independent variable measures by averaging across those parcels that are part of the same transaction using weights equivalent to each parcel's acreage. Transactions with missing sale prices, location coordinates, acreages, or both sale and recording dates are removed from the dataset.

We further screen the data for outliers according to several rules to ensure that our sample focuses primarily on private timberland with timber production being a non-trivial part of its value. Importantly, we overlay parcel locations with our private timberland map described in

[8] To link parcels that belong to a common transaction, we use several relevant variables as an identifier to find those multi-parcel sales. These variables include county FIPS code, transaction batch date, sale recording document number, sale recording document book number, sale recording document page number, sale date, sale recording date, seller name, and sale price.

[9] When transaction dates include a year but lack date and month information, we assign June 1st as the date and month.

Sec. 2 (Fig. 1(a)) as a quality-control check to ensure each parcel is private timberland. We then drop parcels closer than 5km from the nearest urban area and parcels smaller than 10 acres. A detailed description of how we screen out outliers is included in the Appendix. The final transaction-level sample for our main results contains 9,145 transactions of timberland property. With our transaction data georeferenced in GIS (Fig. 5), we then connect each parcel with its site characteristics, wildfire indicators, drought stress, and other controls. Compared to the map of private timberland (Fig. 1(a)), we can see that parcel transactions cover the entire area where private timberland exists. Therefore, we conclude that our sample adequately represents the study area.

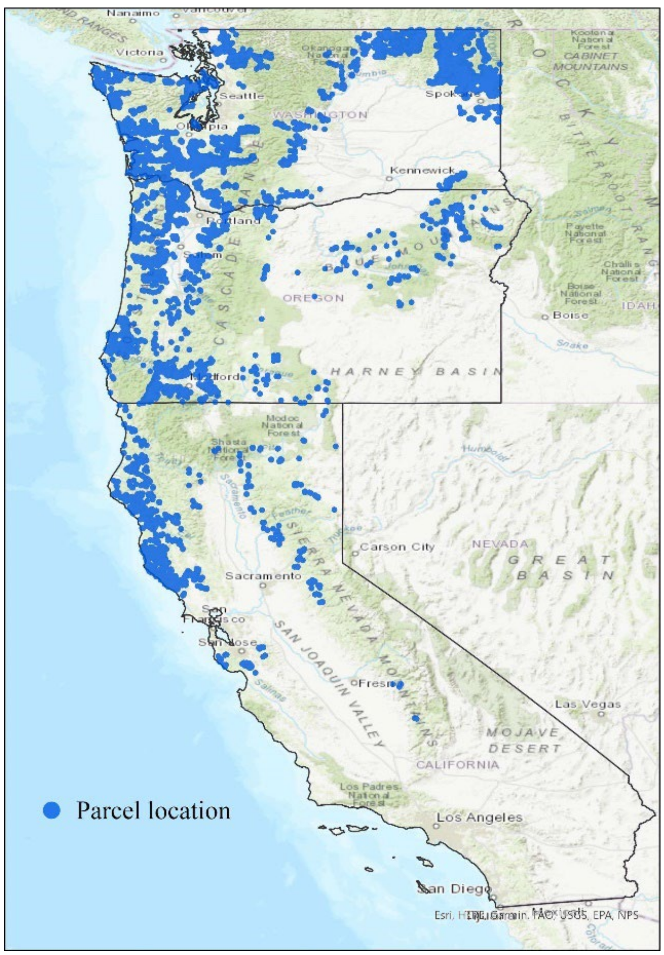


Figure 5. Spatial distribution of private timberland parcel transactions across the study area

5.2 Measurement of drought stress

We use a 30-year average VPD over the growing season (April to July) following Ricardian methods to measure the effects of climate-induced drought stress[10]. We choose the 30-year average not only because it is in line with the Ricardian tradition, but also because timberland is a long-term investment that makes it challenging for management to respond to short-term climate fluctuations (Mihiar and Lewis, 2021).[11] We choose VPD as our preferred drought stress variable for the following reasons. First, VPD is an effective indicator of drought conditions to assess and monitor moisture stress on vegetation and to predict drought impacts (Gamelin et al., 2022). Moreover, scientific studies suggest that this integrated plant-relevant variable performs better than the simplified temperature and precipitation indicator in reflecting how trees – especially the regionally-important Douglas-fir species – respond to extreme climate events such as droughts and heat (Restaino et al., 2016). Second, VPD is one of the key climatic factors that influence wildfire occurrence (Zhuang et al., 2021). Third, based on our pooled cross-sectional data structure, the inclusion of location fixed effects (FE) requires significant within variation in climate variables, and VPD shows more variation both within and across counties than other climate measures like mean temperature or total precipitation.

We specify *g()* as a quadratic form of VPD to capture the non-linear drought impacts in Eq. (7). The VPD is merged with each parcel i and measured as a 30-year average over the

[10] The Ricardian literature often uses measurements of long-term (e.g., 30 years) average measures of annual and seasonal temperatures and precipitations (Mendelsohn et al., 1994; Seo et al., 2005; Sanghi and Mendelsohn, 2008; Massetti and Mendelsohn, 2011; Mihiar and Lewis, 2021) or degree-days over the growing season to capture climate impacts on land values (Schlenker et al., 2006; Deschênes and Greenstone, 2007; Fezzi and Bateman, 2015).

[11] However, to assess whether land markets respond differently to drought conditions over shorter periods of time versus longer periods of time, we have also regressed land prices on alternative average VPD measures over 5, 10, and 20 years separately as robustness checks, which are discussed in more detail in Sec. 6.2.

growing season (April-July) in the year prior to when parcel i is sold.[12] Our VPD data is obtained from the Oregon State University Parameter-elevation Regressions on Independent Slopes Model's (PRISM) downscaled historical climate monthly database at a 4 km resolution.

5.3 Measurement of large wildfire risk

For wildfire variables, prior literature introduces several approaches for defining wildfire risks in forests, each of which captures a unique aspect of wildfire patterns. In wildfire hedonic studies, acreage burned, proximity to the nearest fire, and years since the most recent fire are common proxies for wildfire risks that are capitalized into nearby home prices (Mueller and Loomis, 2008; Mueller et al., 2009; Stetler et al., 2010; Mueller and Loomis, 2014; McCoy and Walsh, 2018). In theoretical and numerical studies of timber management, it is common to use measures of fire intervals/fire frequencies (the average number of years between fires in a defined area) or fire arrival rates (the number of fires occurring within a set time period) to predict the likelihood that wildfires may occur on specific stands (Reed, 1984; Amacher et al., 2005; Konoshima et al., 2008; Sheehan and Bachelet, 2019).

We specify a spatial wildfire arrival rate in Eq. (8) to capture landowner expectations of large wildfire risk in line with our theory section and wildfire numerical studies[13]:

$$fire_{i,t-20}^{r} = \frac{No.\ of\ distinct\ fires\ within\ radius\ r\ of\ parcel\ i\ during\ last\ 20\ years}{20\ years} \tag{8}$$

This metric produces the average annual fire arrival rate over the most recent 20-year period before parcel i is sold in year t. Wildfires are a natural part of the ecosystem in western U.S.

---

[12] For example, the mean VPD over the growing season (April-July) between 1974-2003 is computed for sales sold in 2004.

[13] To connect with the existing wildfire hedonic literature, we also specify a wildfire distance measurement that measures the proximity of each parcel to the nearest wildfires. We then perform a robustness check by replacing the wildfire arrival rates with this distance-based fire measurement to examine the wildfire effects. More details can be found in Sec. 6.2.

forests, and landowners know they regularly occur. Changes in wildfire behavior over a long period of time are likely to lead to a shift in expectations as landowners' perceptions of wildfire risk evolve based on their knowledge, experience, and social interactions (Brenkert-Smith et al., 2013). Thus, we prefer using a relatively long fire history (e.g., 20 years) to derive the average fire risk for each parcel to reflect the pattern and frequency of large wildfires that have prevailed around each parcel over a long period of time. Moreover, according to Shatford et al. (2007), natural conifer regeneration takes approximately 9-19 years following forest fires. Therefore, it is plausible that the impact of large wildfires that occurred greater than 20 years ago may diminish with tree regeneration.

We include three different independent variables in Eq. (7) to represent this large wildfire arrival rate building on three different radii from parcel i: r=0 to capture large fires that burn directly on parcel i, and extending rings to capture neighboring large fires of r=0-15km and r=15-30km.[14] An important feature of specifying wildfire as the linear sum of three different $fire_{i,t-20}^{r}$ variables using three different radii r is our ability to separately estimate price impacts from large wildfires that occur directly on the parcel (r=0) from large wildfires that occur on nearby land, which the theory in Sec. 3 suggests is important for identifying changing fire arrival expectations. One final note about Eq. (8) is that 94% of all large wildfires that occurred within 15km of each private timberland parcel in our sample burned on non-private timberland, with most (about 68%) burning on other land use types such as shrubland and the rest on public

[14] As a starting point, we use three rings, ranging from 0-5km, 5-10km, and 10-15km, to distinguish wildfire arrival rates at different distances. The rings are chosen arbitrarily. As shown in Appendix Table A1, we find no significant difference in wildfire effects among these three rings. Thus, we combine them into one wildfire variable within 0-15 km around the parcel to capture closer wildfire risks. For wildfire risks further away, we compute fire arrival rates within 15-20km and 20-30km but find no statistically significant difference between the two. Thus, we include a wildfire arrival rate within 15-30km to account for wildfire risks farther from the center.

forestland.[15] And so $fire_{i,t-20}^{0-15}$ should be primarily driven by factors exogenous to the private timberland market, such as meteorology, random ignition events, and fuels on non-private timberland.[16]

See Fig. 6 for a simple depiction showing how we construct the $fire_{i,t-20}^{r}$ in different radii r using MTBS wildfire polygon data. The dark area is the parcel perimeter created based on parcel coordinates and parcel acres. The green shaded areas represent 15 km rings mapped out from the parcel i. Suppose three different large wildfire events a, b, and c that have occurred on and nearby parcel i in the past 20 years before parcel i sold. Thus, based on equation Eq. (8), $fire_{i,t-20}^{0}$ would equal 1/20 (=0.05) fires per year since only one fire (c) intersects with parcel i. The variable $fire_{i,t-20}^{0-15}$ equals 0/20 (=0.00) fires per year to avoid double counting the arrival of fire (c). Likewise, $fire_{i,t-20}^{15-30}$ equals 2/20 (=0.1) fires per year since two new fires (a) and (b) intersect with the outer ring.

[15] We are interested in fire risks within 15 km of each parcel because we find that large wildfires between 15-30 km have no statistically significant effect on land values (see Table 2).
[16] However, large wildfires that occurred directly on the parcel may be endogenous to private timberland because of human-caused ignitions on private lands due to equipment use (Downing et al., 2022). To address this issue, we identify the cause of each wildfire using a spatial wildfire occurrence dataset. We find that among the 289 parcels (3% of our full sample) having at least one large wildfire directly occurred on them, 125 had at least one human-caused large fire. By excluding those parcels having at least one human-caused wildfires occurring directly on them from our sample, we find no significant difference in wildfire results (see Appendix Table A7), suggesting that this potential endogeneity concern is not a major issue in our study.

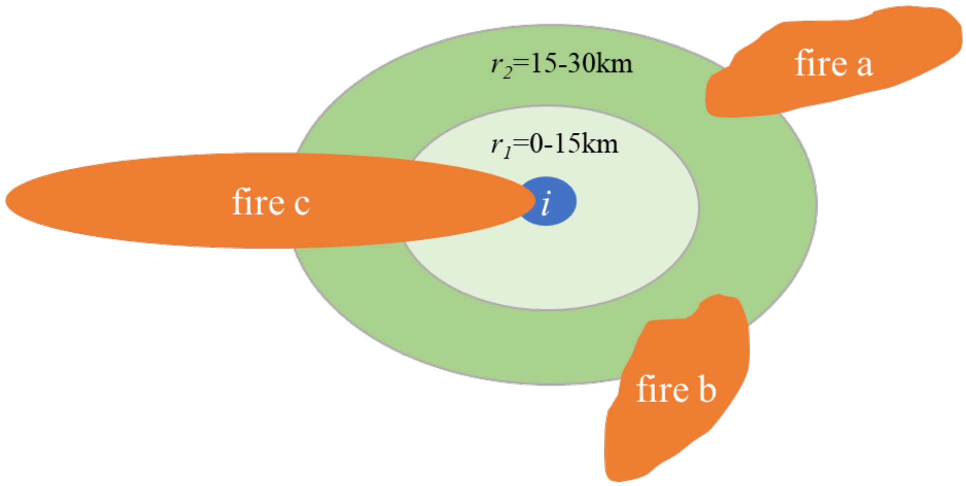


Figure 6. A simple map of fire area

Our large wildfire data are derived from the Monitoring Trends in Burn Severity (MTBS) database, which contains the most comprehensive and most up-to-date wildfire records dating back to 1984. This database contains information on the date, boundary, coordinates, and size of all large fires that have burned more than 1000 acres in the west. Each parcel's large wildfire arrival variable is computed separately. For each parcel, we keep large wildfires that happened from six months to 20 years prior to the sale date. The 6-month gap is chosen because we assume a land transaction can take up to 6 months to complete.

The MTBS fire data does not include information on small wildfires less than 1,000 acres in size, which can be common in the western U.S.[17] To account for these small wildfire impacts, we use additional wildfire data from the spatial wildfire occurrence dataset from 1992-2020 compiled by Short (2022) to calculate small wildfire arrival rates for each parcel based on the same spatial fire arrival measure in Eq. (8).[18] While Short's (2022) dataset does not include

[17] In our study region, small wildfires occur frequently, but their frequency and severity do not change much over time, as shown in Appendix Fig. A2.
[18] Since our transaction sample starts in 2004, we construct the small wildfire arrival rate using the most recent 10-year period rather than the most recent 20-year period considering the spatial wildfire occurrence dataset only dates back to 1992.

spatial boundaries of each wildfire like the MTBS, it does include information on the date, ignition coordinates, causes, and size of all geo-referenced wildfire records (including both large and small fires) across the country. While we prefer the MTBS data's exact spatial mapping of the boundaries of large wildfire events, we test robustness by including small wildfire arrival rates as additional controls. Detailed information can be found in Sec. 6.2.

Finally, in order to capture the heterogeneous fire effects from different sized wildfires like very large nearby wildfire ($VLNF$) events, we include a dummy variable $VLNF$ which equals one if the size of the nearest large wildfire to each parcel is greater than 5000 hectares (about 12355 acres), and zero otherwise[19]. Our definition of a very large nearby wildfire ($VLNF$) is based on Barbero et al.'s (2015) analysis of climate change and large U.S. wildfires. And since Busby et al. (2012) find that fire management effort is lower in landscapes with fragmented ownership between public and private landowners, we include a variable representing proximity to the nearest public land.

5.4 Measurement of other land attributes

For land attributes other than drought stress and wildfire that affect timberland values, we include a vector of variables in X_i for each parcel i that contains biophysical factors that affect timber productivity through the volume function (soil quality, slope, elevation), variables that represent pressure for urban development (distance to the nearest urban area), and a variable that represents costs of transporting timber (distance to the nearest road). We compile these land attributes from various publicly available data sources, and the process of their creation is described in greater detail in the Appendix.

[19] The construction of VLNF does not consider fires that occurred directly on the parcel, as direct fire damage to the parcel may not notably differ concerning the size of the wildfire—particularly for small parcels.

Table 1 provides summary statistics of the dependent and independent variables used in the analysis. Both the unweighted and weighted average timberland prices fall within our expectations. But the weighted average price appears to be more consistent with estimates provided by Mihiar and Lewis (2021) for net returns (rents) to forestry in western counties, as well as Hashida and Lewis (2022) for Douglas-fir mean rents.[20] Thus, we believe that our screening rules discussed in Sec. 5.1, combined with parcel acres weighting, produce reasonable timberland prices. As expected, the independent variables vary widely across sales.

Table 1. Summary statistics of dependent and independent variables

Variable	Obs	Min	Max	Unweighted		Weighted by acres	
				Mean	Std. dev.	Mean	Std. dev.
Timberland price per acre ($/acre)	9,145	103	59975	8314.686	9773.464	4357.170	5857.997
Large wildfires per decade on parcel	9,145	0	1.5	0.016	0.092	0.016	0.096
Large wildfires per decade near parcel (0-15 km away)	9,145	0	7.5	0.481	0.802	0.630	1.098
Large wildfires per decade distant (15-30 km away)	9,145	0	13	1.235	1.716	1.561	2.551
VPD over the growing season (hPa)	9,145	1.798	16.345	8.587	2.202	7.733	2.395
Equal 1 if a very large nearby fire (VLNF)	9,145	0	1	0.179	0.383	0.209	0.407
Elevation (km)	9,145	0	2.111	0.527	0.365	0.610	0.481
Slope (degree)	9,145	0	39.382	11.114	6.845	12.529	6.911
Soil (non-irrigated land capability class)	8,065	2	8	5.579	1.245	5.985	1.076
Distance to the nearest road (km)	9,145	0	31.529	4.987	4.496	7.010	7.491
Distance to the nearest urban area (km)	9,145	5.002	111.355	20.410	15.231	23.960	18.399
Distance to the nearest public forest (km)	9,145	0	9.101	0.913	1.212	0.856	1.087

Note: The unit of average annual large fire arrival rate variables was rescaled to a large wildfires per-decade measure to simplify the interpretation of estimated coefficients in empirical analysis.

6. Estimation results

Table 2 presents the coefficient estimates with the large wildfire arrival rates as the key fire variables using the full sample of sales prices. As discussed in Sec. 4, the four model specifications allow us to estimate results under alternative spatial scale definitions of fixed

[20] Suppose the discount rate is 3%, then the annualized rent would be $129 per acre for the average weighted timberland price of $4300 per acre. This is modestly higher than the bare land values from Mihiar and Lewis (2021) and Hashida and Lewis (2022), which is expected since our sample likely includes mostly parcels that are not bare land.

effects (Model 1 vs Model 2), with the control of county time trends (Model 3), and with the inclusion of the small fire arrival rate (Model 4).

6.1 Marginal effects of drought stress and large wildfire arrival

Since VPD enters the equation as a quadratic, it is more intuitive to interpret the results with the average marginal effect (AME) of VPD (see the bottom panel of Table 2). Across four model specifications, the AME of VPD is fairly consistent and statistically significant ($p<0.05$), with the exception of model (1) where the AME of VPD is positive and not statistically significant. The different estimate in model (1) may be due to state-level fixed effects being too coarse to account for all time-invariant unobserved factors, resulting in omitted variable bias. According to our preferred Model (2), the AME for VPD suggests that, on average, one hPa increase in mean VPD over the growing season will decrease timberland values per acre by 5.8%. Appendix Fig. A1 shows a larger negative drought impact in current warmer and drier areas. Higher levels of VPD over the growing season negatively impact timberland prices regardless of the current VPD level, but this impact is only significant in the current VPD range of 7-14 hPa, which is the majority of the sample. Inspection of Eq. 6 indicates that the marginal effect of VPD on timberland prices operates through productivity effects on the tree volume function and through landowner expectations of wildfire risk.

In terms of large wildfire impacts, we observe significant ($p<0.05$) negative impacts of large wildfire arrival that occurs either on the parcel or on spatially adjacent land within 15km (Table 2). We find no evidence that timberland prices are affected by either i) nearby small wildfires that occur at any distance away (Table 2 Model 4), or ii) large wildfires that occur beyond 15km from each parcel transaction. It is not surprising that timberland markets do not respond significantly to small wildfires as they are likely less destructive than large fires, and their occurrence is relatively stable over time (Appendix Fig. A2). We also find that our preferred large wildfire and VPD estimates (Model 2) are robust to the inclusion of county-trends (Model 3) and small wildfire arrivals (Model 4).

The largest negative impact from large fires is from fires that occur directly on the private timberland parcel, as an increase in the fire arrival rate of one fire per decade will reduce timberland value by 61.6% based on our preferred model (2)[21]. This result confirms our theoretical findings in Sec. 3 that fires which occur directly on parcels with a positive age growing stock will have a larger negative effect on timberland values due to the fire damaging the existing tree stock on the stand. The negative price impact of spatially proximate large wildfire arrival rates within 0-15km provides evidence that the occurrence of spatially proximate fire does serve as an avenue for updating timberland owners' expectations of wildfire risk. Furthermore, the results show a negative and statistically significant ($p<0.05$) estimate of the very large nearby fire (*VLNF*) effect, suggesting that timberland values are about 12.1% lower when a very large fire (greater than 5000 hectares) occurs nearby. One interpretation is that very large fires within close proximity are more salient and thus have a large impact on timberland values through shifting landowner's risk expectations.

In terms of the other independent variables, timberland values are lower in high-elevation and steep-sloped areas ($p<0.05$). Soil quality data is missing for about 12% of the sample and so is not included in our main estimation results. Estimation results for the sub-sample that includes soil quality can be found in Appendix Table A9, but indicate no statistically significant impact of soil quality at any reasonable significance level. In addition, we find that longer distance to roads

[21] Fires that happened directly on private timberland may have varying impacts on timberland values as the trees regenerate (Shatford et al., 2007). However, in our case, only 289 parcels (about 3% of our sample) have experienced fires in the preceding 20 years, and this limited number of observations includes insufficient variation to empirically test the dynamic effects of direct wildfire damage.

and urban areas negatively affect the value of timberlands ($p<0.05$), which suggests that timberlands located near roads and urban areas generally have a higher land value as a result of lower delivery costs and higher development value for other uses. Distance from public forests has a positive and significant effect ($p<0.05$) on timberland values, consistent with Busby et al.'s (2012) finding that fire management effort is lower (and fire risk is higher) when public and private lands are more fragmented.

Table 2. Estimated coefficients of full sample results

Log (price per acre)	Model (1)	Model (2)	Model (3)	Model (4)
Mean VPD (hPa)	0.148**	0.008	-0.008	-0.002
	(0.065)	(0.092)	(0.088)	(0.093)
Mean VPD square	-0.009**	-0.004	-0.003	-0.004
	(0.004)	(0.005)	(0.005)	(0.005)
Large wildfires per decade on parcel	-0.370	-0.616***	-0.634***	-0.635***
	(0.239)	(0.193)	(0.209)	(0.187)
Large wildfires per decade nearby (0-15km away)	-0.174***	-0.149***	-0.137***	-0.142***
	(0.029)	(0.027)	(0.031)	(0.025)
Large wildfires per decade distant (15-30km away)	-0.032**	-0.017	-0.018	-0.013
	(0.015)	(0.013)	(0.012)	(0.015)
Very large nearby fires (VLNF) =1	-0.078	-0.121**	-0.162***	-0.115**
	(0.062)	(0.051)	(0.058)	(0.052)
Small wildfires per decade on parcel				-0.099
				(0.066)
Small wildfires per decade nearby (0-15km away)				-0.000
				(0.000)
Elevation (km)	-0.561***	-0.564***	-0.557***	-0.563***
	(0.140)	(0.156)	(0.152)	(0.158)
Slope (degree)	-0.002	-0.020***	-0.020***	-0.020***
	(0.006)	(0.006)	(0.006)	(0.006)
Distance to the nearest road (km)	-0.023***	-0.014**	-0.014**	-0.014**
	(0.006)	(0.005)	(0.005)	(0.006)
Distance to the nearest urban area (km)	-0.013***	-0.008***	-0.008***	-0.007***
	(0.002)	(0.002)	(0.002)	(0.002)
Distance to the nearest public forest (km)	0.063***	0.044**	0.047**	0.046**
	(0.019)	(0.021)	(0.021)	(0.021)
Constant	8.348***	9.808***	10.496***	9.789***
	(0.366)	(0.435)	(0.422)	(0.449)
State and year FE	Yes			
County and year FE		Yes		Yes
County, year, and county-trends FE			Yes	
Observations	9,145	9,145	9,145	9,145
R-squared	0.467	0.544	0.562	0.545
Average Marginal effects (AME)				
AME of VPD	0.011	-0.058**	-0.058**	-0.059**
	(0.021)	(0.026)	(0.027)	(0.026)

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the county level. The unit of average annual fire arrival rate variables was rescaled to a fires per-decade measure to simplify the interpretation of estimated coefficients.

6.2 Robustness checks

We employ several checks to analyze the robustness of our results. The Appendix contains the full results, and here we discuss the main points. First, we replace the wildfire arrival rates with smaller distance bins from each parcel transaction (0-5km, 5-10km) and we find no significant difference within the different 5km bins that are less than 15km from the parcel (Table A1), confirming our choice of defining fire proximity with 15km bins. Second, we replace the wildfire arrival rates with a variable indicating proximity to the nearest large wildfire, a measure that is common in residential hedonic literature (e.g., Stetler et al., 2010; McCoy and Walsh, 2018). The results are shown in Appendix Table A2 and the AME of distance to fire shows that timberland values will increase by 0.3% for each 1 km distance further from the nearest fire. In addition, an interaction term between VPD and fire distance shows that large wildfires have a greater impact in high VPD areas where the climate is drier and warmer (Table A2).

Third, we examine the robustness of our results to alternative screening rules used to create the full sample. We increase the minimum size of parcels in the sample from 10 to 20 acres, and we increase the minimum distance of each parcel to nearby urban areas from 5km to 10km. Despite the reduced sample size from these restrictions (Appendix Table A3), results still indicate a similar magnitude negative price impact from large wildfires that occur on and nearby parcels (see Fig. 7).

Fourth, since VPD is one of the key factors associated with higher wildfire risks (Mueller et al., 2020), one may be concerned that wildfire arrival rates may be too correlated with VPD for precise estimation. To examine this concern, we first note that the correlation coefficients between all large wildfire variables and VPD are modest (less than 0.25). We also re-estimate the wildfire impacts without VPD included as an independent variable but find a minimal impact on the fire arrival conclusions when dropping VPD (see Fig. 7).

Fifth, since there is minimal theoretical guidance on how and which climate variables enter Ricardian models (Mendelsohn and Massetti, 2017), we employ the machine-learning technique double-selection lasso to estimate the wildfire effects by examining all possible selected parcel and climate variables (including both nonlinear and interaction terms) (Appendix Table A4).[22] Wildfire impacts conducted with double-selection lasso are very similar to our main results (see Fig. 7).

Sixth, we explore alternative time period definitions used to compute our drought measure VPD and wildfire arrival rates. Appendix Table A5 presents the results using different calculations of the VPD variable, where this measure is computed using the 5, 10, 15, or 20 years prior to each parcel's sale, as opposed to our main results that compute this measure using 30 years prior to each parcel's sale. The AMEs of VPD are largely the same across all definitions of time period (Appendix Table A5), and the R^2 measure is insensitive to the different calculations. Appendix Table A6 displays the results using different calculations of large wildfire arrival rates, where this fires/decade measure is computed only using fires over the 5, 10, or 15 years prior to each parcel's sale, as opposed to our main results that compute this measure using fires over the 20 years prior to each parcel's sale. We continue to observe negative and decreasing fire impacts as fires occur farther away, though the estimates contain more noise when using short and recent time windows. An important point is that goodness-of-fit is worse when replacing the fire arrival rate variables with similar calculations that use shorter time periods of less than 20 years.

[22] In addition to VPD, we include 30-year averages of annual and seasonal mean temperatures and precipitations, as well as mean temperature and precipitation over the growing season (April-July).

We also examine a concern that large wildfires that occurred directly on parcels may be endogenous if caused by humans on that parcel. We identify the cause of each large wildfire using the spatial wildfire occurrence data and then drop parcels having human-caused large wildfires that occur directly on them from our sample and re-estimate our wildfire effects. Appendix Table A7 shows no significant differences in coefficients after dropping those parcels.

Finally, we assess the robustness of results to different location fixed effect definitions by estimating the main Eq. (7) with a series of alternative spatial fixed effects. While our main results use county fixed effects, here we define census tract fixed effects as well as randomly distributed grid cells across the study region (Appendix Table A8). We create evenly distributed grid cells formed by 25 rows and 25 columns (about 40*72 km per grid cell, labeled as Grid25 FE), and a finer-scale 50 rows*50 columns set of spatial grids (about 20*36 km per grid cell, labeled as Grid50 FE[23]). Importantly, we find strong robustness of our main large wildfire and VPD impacts to alternative definitions of spatial fixed effects (See Fig. 7). The VPD and large wildfire arrivals all negatively impact timberland values on a robust and significant basis, with similar magnitudes.

[23] See Fig. A4 in the Appendix for reference.

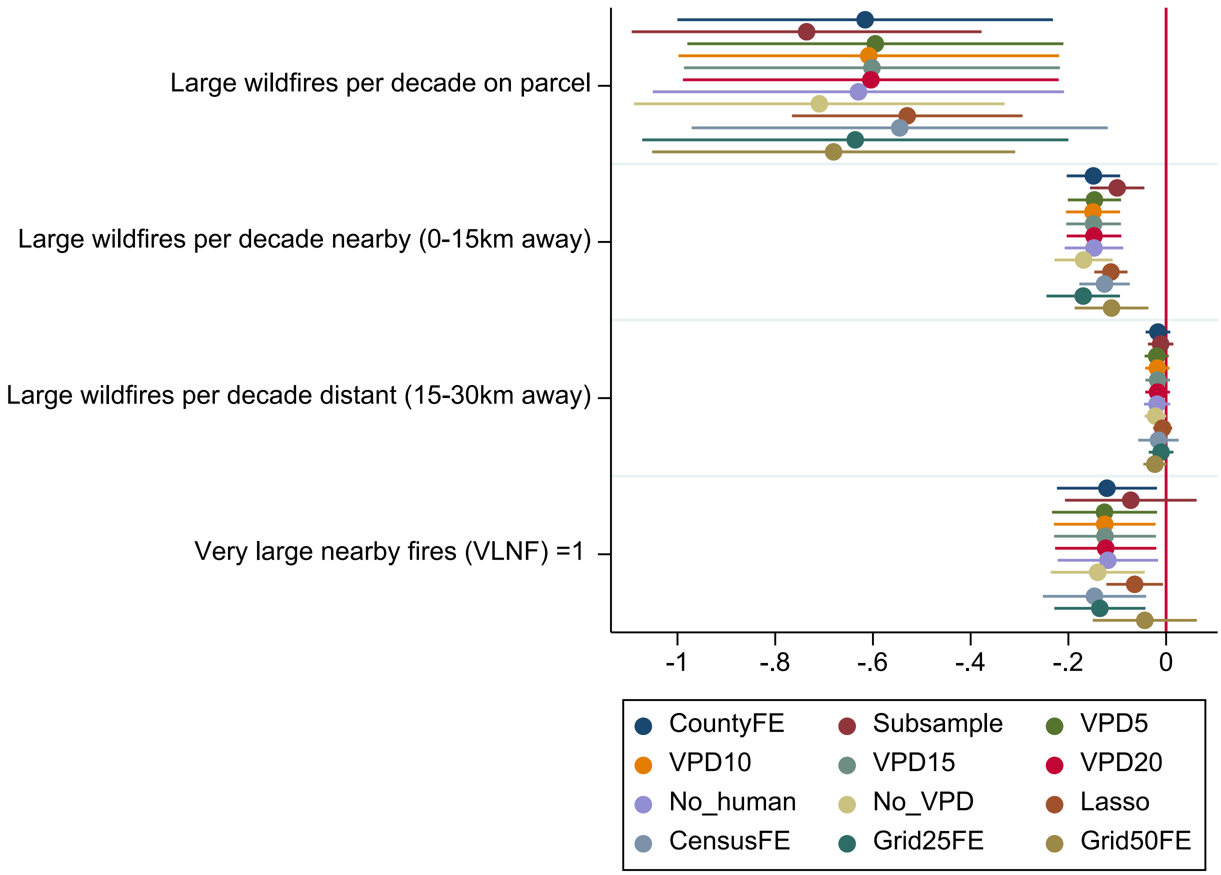


Figure 7. Marginal effects of large wildfire arrival rates in different robustness checks

Note: CountyFE represents the full sample estimators with our preferred county FE. Subsample represents the estimators with restrictive screening rules. VPD5, 10, 15, and 20 represent the full sample estimators with average VPD over the past 5, 10, 15, and 20 years, respectively. No_human represents the full sample estimators after dropping sales with at least one human-caused large wildfire occurred directly on them. No_VPD represents the full sample estimators after excluding VPD. Lasso represents the double-selection lasso estimators. The final three estimators represent the full sample estimators with different location FEs.

7. Capitalization impacts of historical changes in drought stress and large wildfire risks

In this section, we examine how observed changes in drought stress and large wildfire risks have contributed to the economic value of timberland over the past two decades. Specifically, by using estimated coefficients from our preferred model (2) in Table 2, we analyze how changes in the VPD and wildfire variables over the past two decades have affected the economic value of timberland. We focus on a comparison between 1984-2003 (past period) and 2001-2020 (current period). As our main Eq. (7) is a log-level regression, the capitalization impact on parcel i from changes in mean VPD and large wildfire arrival equals:

$$Est.\%\ Drought\ \ impact{:}\ \%\Delta price_{i,D} = \exp[\widehat{\beta_1}(VPD_{i,91-20} - VPD_{i,74-03})] - 1 \tag{9}$$

$$Est.\%\ Wildfire\ impact{:}\ \%\Delta price_{i,F} = \sum_r \{\exp[\widehat{\beta_2}(fire^r_{i,01-20} - fire^r_{i,84-03})] - 1\} + \exp[\widehat{\beta_3}\big(VLNF_{i,01-20} - VLNF_{i,84-03}\big) - 1 \tag{10}$$

$$Est.\%\ Total\ capitalization\ impact\ for\ parcel\ i = \%\Delta price_{i,D} + \%\Delta price_{i,F} \tag{11}$$

Where $\widehat{\beta_1}$ represents the vector of estimated coefficients of mean VPD, $\widehat{\beta_2}$ is the vector of estimated coefficients of large wildfire arrival rate in different radii *r*, and $\widehat{\beta_3}$ is the estimated coefficient of *VLNF* from our preferred model (2) in Table 2. Because our sample starts in 2004 and ends in 2020, we define the mean VPD in the past period as a 30-year average over the growing season between 1974 and 2003, and the mean VPD in the current period as a 30-year average over the growing season between 1991 and 2020. In a similar manner, we calculate the large wildfire arrival rate within different radii in the past period using large wildfire records between 1984 and 2003, and during the current period using records between 2001 and 2020. Also, we use large wildfire records between 1984 and 2003 to compute the *VLNF* variable in the past, and use large wildfire records between 2001 and 2020 to compute the *VLNF* variable in the current period. Fig. 2 and Fig. A3 in the Appendix show the spatial distribution of wildfires and mean VPD during the past and current period, respectively.

Table 3 summarizes the mean drought impacts, large wildfire impacts, and total capitalization impacts across different subregions within our study area. As examined in Sec. 6.1, we calculate the drought impact using Eq. (9) only for those parcels having statistically significant VPD impacts and set the drought impact to zero for those parcels that have statistically insignificant VPD effects. On average, the results show that changes in VPD between the 1974-2003 and 1991-2020 time periods have resulted in a 1.78% loss in timberland value per acre for the full sample, with some regional heterogeneity.

For wildfire impacts, on average, we see that increasing wildfires between the 1984-2003 and 2001-2020 periods led to an 8.01 % reduction in timberland value per acre for the full sample, with regional heterogeneity. We also decompose the overall large wildfire impacts across fires that occurred on each parcel, spatially proximate fires that occur nearby, and very large nearby fires. A key finding is that increases in fires that directly occurred on timberland parcels lowered land values by about 1%, while increases in neighboring fires (including very large nearby fires) accounted for the majority of the land value losses, collectively lowering land values by approximately 7% (Table 3). While fires that directly burn a parcel have a much larger per-acre impact than nearby fires (Table 2), this region simply contains more private timberland that is close to nearby wildfires than private timberland that is directly burned. As we argued in Sec. 3, spatially proximate fires that don't directly burn a private parcel should impact land values through increases in the expected wildfire arrival rate. Our finding of a 7% land value reduction due to higher neighboring wildfire arrival rates also confirms our testable hypothesis from Sec. 3.2, which was that the observed increase in landowners' expectations of wildfire rates would lower timberland values between 4% and 9%, and provides evidence that risk expectations from wildfire arrival are being updated through the more frequent occurrence of nearby fires. In addition, we should note that a portion of our estimated damages from drought stress (-1.78%) and from fires that directly burn private timberland parcels (-1.09%) could also embed changes in landowner risk expectations along with productivity effects and direct damages to the existing stock. As noted by Eq. (6), climate variables like VPD affect the timberland value function through both productivity effects on the volume function and through wildfire risk expectations. Nevertheless, a primary finding from Table 3 is that changes in risk expectations account for the majority of estimated damages from recent changes in wildfire and drought stress.

To scale our estimates up to the population of private timberland across the Pacific states, we note that the parcel transactions we use cover the entire geographical range of private timberland in this region, as illustrated in Fig. 5. According to federal Forest Inventory and Analysis Data (FIA), there are about 25,800,000 acres of private timberland across the three Pacific states. Using the share of timberland in each subregion as a weight, we then calculate the aggregated population-weighted drought stress, large wildfire, and total capitalization impacts for the entire Pacific region. We find that the increase in VPD and large wildfire arrival rates results in a 1.04% and 8.74% loss, respectively, in timberland value per acre for the full population. Overall, changes in drought stress and large wildfires lead to a total population-weighted loss of approximately 10% of timberland values, or approximately $436 per acre. Thus, the total losses in timberland values caused by changes in drought stress and large wildfires over the past two decades would be about $11.2 billion for the three Pacific states, equivalent to our estimated reduction in per acre value (-$436/acre) times the total acres (25,800,000 acres) of private timberland.

Table 3. Capitalization impacts of wildfire and drought changes between current period (2001-2020) and past period (1984-2003) across different subregions within the study area

	Full sample	California	Oregon		Washington		Population weighted
			West of Cascades	East of Cascades	West of Cascades	East of Cascades	
Drought stress impacts	**-1.78%**	**0.23%**	**-1.62%**	**-1.16%**	**-0.19%**	**-3.43%**	**-1.04%**
Total large wildfire impacts	**-8.01%**	**-13.74%**	**-8.42%**	**-3.26%**	**-5.02%**	**-8.15%**	**-8.74%**
From changes in large fires on each parcel	-1.09%	-3.77%	-0.39%	0.02%	0.04%	-1.36%	-1.36%
From changes in nearby large fires	-4.24%	-8.23%	-2.93%	-3.43%	-0.07%	-6.05%	-4.32%
From changes in nearby very large fires	-2.68%	-1.74%	-5.10%	0.15%	-4.99%	-0.72%	-3.06%
Total capitalization impacts	**-9.79%**	**-13.51%**	**-10.04%**	**-4.42%**	**-5.21%**	**-11.58%**	**-9.78%**

Note: We calculate the population-weighted drought stress, large wildfire, and total capitalization impacts based on weights of 0.28, 0.28, 0.08, 0.21, and 0.15, respectively, for California, West of Cascades Oregon, East of Cascades Oregon, West of Cascades Washington, and East of Cascades Washington.

Attributing our population-weighted drought stress and large wildfire damage estimates to climate change can be informed by two recent climate attribution studies. One study by Zhuang et al. (2021) finds that approximately two-thirds of the variation in VPD in the western U.S. between 1979 to 2020 is explained by anthropogenic climate warming, whereas the remaining one-third of the VPD trend is due to the natural variability of atmospheric circulation. Using this climate attribution evidence, our VPD-induced damages can be attributed to climate-induced damages (a loss of 0.69%, ~$0.8 billion) and non-climate-induced damages (a loss of 0.35%, ~$0.4 billion) as shown in Table 4. Another study by Abatzoglou and Williams (2016) suggests that ~55% of the increased western U.S. fuel aridity from 1979-2015 was due to anthropogenic climate change. If we attribute 55% of our estimated total large wildfire damages to climate change, then our results suggest a loss of 4.81% (~$5.4 billion) in timberland values comes from climate-induced increases in large wildfire arrival and a loss of 3.93% (~$4.4 billion) comes from non-climate-induced increases in large wildfire arrival (e.g., from increased fuels). In total, our results indicate that recent climate change is responsible for a reduction in timberland values by 5.5% ($6.2 billion) through climate-induced increases in large wildfires and vapor pressure deficits.

Table 4. Climate attribution for drought stress and large wildfire impacts

	Population weighted	California	Oregon		Washington	
			West of Cascades	East of Cascades	West of Cascades	East of Cascades
Attribution of drought stress impacts	-1.04%	0.23%	-1.62%	-1.16%	-0.19%	-3.43%
Climate change	-0.69%	0.15%	-1.07%	-0.77%	-0.13%	-2.26%
Non-climate change	-0.35%	0.08%	-0.55%	-0.39%	-0.06%	-1.17%
Attribution of large wildfire impacts	-8.74%	-13.74%	-8.42%	-3.26%	-5.02%	-8.15%
Climate change	-4.81%	-7.56%	-4.63%	-1.79%	-2.76%	-4.48%
Non-climate change factors	-3.93%	-6.18%	-3.79%	-1.47%	-2.26%	-3.67%
Total climate change impacts	-5.50%	-7.41%	-5.70%	-2.56%	-2.89%	-6.74%
Total non-climate change impacts	-4.28%	-6.10%	-4.34%	-1.86%	-2.32%	-4.84%

Note: Following Zhuang et al. (2021), about two-thirds of VPD impacts are attributed to anthropogenic climate warming, whereas the remaining one-third is due to the natural variability of atmospheric circulation. Following Abatzoglou and Williams (2016), about 55% of large wildfire impacts is explained by climate change, whereas the remaining is due to non-climate change factors that influence large wildfire occurrence.

8. Discussion

Natural resources have been adversely affected by a variety of climate-induced disturbances, including heatwaves, droughts, large wildfires, storms, and flooding. For example, the western U.S., a region with diverse climate regimes and valuable natural capital embedded in forest resources, has been suffering from drought and increasingly frequent large wildfires in recent years due to rising temperatures (Abatzoglou and Williams, 2016). However, it is unclear how natural resource markets have already responded to such climate shocks. To fill this gap in the literature, we develop an econometric analysis of wildfire and climate impacts on market prices for private timberland across the Pacific states in the western U.S. Our pooled cross-sectional data of over 9,000 individual timberland transactions from 2004-2020 across the entire Pacific coast of the U.S. allows us to control for a range of spatial and temporal fixed effects to help identify the effects of drought stress and large wildfire arrivals on timberland values. Our results indicate that increasingly frequent large wildfire arrival over the past two decades has already lowered the economic value of timberland through two avenues: i) a 1.36% reduction in land value due to direct fire damage on the existing forest stock, and ii) a 7.38% reduction in land value due to increasingly frequent neighboring fires that have altered landowners' expectations of fire arrival and increased the risk of investing in private timberland. Building off prior climate change attribution studies that link changes in VPD and large wildfires in the western U.S. to anthropogenic climate change (Abatzoglou and Williams, 2016; Zhuang et al., 2021), our results suggest that recent climate change is responsible for lowering timberland values in the Pacific states by 5.5% (~$6.2 billion).

Our findings illustrate that in comparison to the price reduction caused by direct burning of private timberland, the primary damage to timberland values arises from altered landowner's risk expectations in the land market. We contribute to recent calls for analyzing how markets capitalize and develop expectations of future climate change. While prior studies have emphasized how scientific forecasts of climate change can be capitalized into agricultural land markets (Severen et al., 2018), we show that locally increasing rates of climate-related natural disasters can serve as an avenue for altering landowner expectations of climate impacts and become capitalized into land values. We interpret this mechanism of local climate disasters impacting climate expectations and capitalizing into land values as an example of what Massetti and Mendelsohn (2018) call reactive adaptation, whereby people adjust to climate changes as those changes are observed. Local climate-induced natural disasters like wildfire, flooding, and wind damage are quite salient, and our results provide evidence that changes in their local frequency alter risk expectations for assets like land. Prior economic studies of future climate change on forestry differ in their assumptions of landowner expectations, ranging from numerical analyses that assume current landowners perfectly anticipate future climate change (e.g., Sohngen and Mendelsohn, 1998; Sohngen and Tian, 2016) to empirically-based simulations that assume landowners react to climate change as it occurs (Hashida and Lewis, 2019).

Given our application to timberland markets, our empirical estimates are strongly consistent with testable hypotheses that emerge from theoretical natural resource economic representations of wildfire. We show that our approximate 7% estimated land value loss arising from increasingly frequent local large wildfire arrival rates is supported by numerical parameterization of Reed's (1984) model with local data. Further, our finding that spatially proximate large wildfire events affect neighboring private timberland values is consistent with numerical studies that emphasize how spatial externalities associated with large wildfire spread from adjacent land in forests should be capitalized into land values (e.g., Konoshima et al., 2008; Busby et al., 2012; Lauer et al., 2017).

Our results also highlight the exposure of U.S. forestry to risk from wildfire, and the persistent and increasing problem arising from the lack of widespread markets to insure against losses to timber from wildfire (Chen et al. 2014). To the extent that some private landowners hold insurance for timber losses to fire, those insurance premiums should be capitalized into their land prices (Bin et al. 2008) and our results would be conditional on the current state of insurance. For many years, the State government in Oregon was the only state that had private insurance for wildfire suppression expenses, though that policy was dropped in 2023 as a result of rising premiums and deductibles due to increasing wildfire risk.[24]

[24] The decision to drop the private insurance was made on 4/3/2023 in a meeting of the Oregon Department of Forestry's Emergency Fire Cost Committee.

Our findings of how natural resource markets have already been affected by climate-induced shocks such as drought stress and wildfire risks have several important policy applications. First, by estimating how natural resource markets react to climate-induced disaster shocks, our results show how ongoing climate change can alter the value of natural capital, which can impact private investments made in natural capital and require public intervention to prevent unintended externalities from management changes. Second, we add new insights into existing estimates of wildfire damages, which focus on damages to air and water quality, property losses, health care costs, injuries, and fire suppression costs (Dale, 2010). Our findings add an additional cost of recent large wildfire events by showing how climate-induced increases in fire arrival change the land market's perceived risk of holding timberland assets, thereby generating costs for current timberland owners even if their land has not yet burned.

Caveats to our study include the following. First, our land price model does not consider future climate forecasts, which may affect current land prices (Severen et al., 2018). A challenge with incorporating climate forecasts would be matching the year of forecast availability to the year of each parcel transaction, which is more challenging in long pooled cross-sectional datasets like ours than it is in cross-sectional studies. Second, we would perceive our estimates of large wildfire impacts as a lower bound of impacts on forests since fire will also damage many non-market ecosystem services from forests like recreation (Gellman et al. 2022) that would not be accounted for in a study like ours that uses land market prices of timberland.

References

Abatzoglou, J. T., and Kolden, C. A. 2013. Relationships between climate and macroscale area burned in the western United States. *International Journal of Wildland Fire*, *22*(7), 1003-1020. https://doi.org/10.1071/WF13019.

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.

Auffhammer, M. 2018. Quantifying economic damages from climate change. *Journal of Economic Perspectives*, 32(4), 33-52. https://doi.org/10.1257/jep.32.4.33.

Amacher, G. S., Ollikainen, M., and Koskela, E. 2009. Economics of forest resources. Cambridge: Mit Press.

Amacher, G. S., Malik, A. S., and Haight, R. G. 2005. Not getting burned: the importance of fire prevention in forest management. *Land Economics*, *81*(2), 284-302. https://doi.org/10.3368/le.81.2.284.

Barbero, R., Abatzoglou, J. T., Larkin, N. K., Kolden, C. A., and Stocks, B. 2015. Climate change presents increased potential for very large fires in the contiguous United States. *International Journal of Wildland Fire*, 24(7), 892-899. http://dx.doi.org/10.1071/WF15083.

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. https://doi.org/10.1146/annurev-resource-111920-014804.

Bigelow, D. P., Plantinga, A. J., Lewis, D. J., and Langpap, C. 2017. How does urbanization affect water withdrawals? Insights from an econometric-based landscape simulation. *Land economics*, 93(3), 413-436. https://doi.org/10.3368/le.93.3.413.

Bin, O., Kruse, J.B. and Landry, C.E., 2008. Flood hazards, insurance rates, and amenities: Evidence from the coastal housing market. *Journal of Risk and Insurance*, *75*(1), pp.63-82. https://doi.org/10.1111/j.1539-6975.2007.00248.x.

Brenkert-Smith, H., Dickinson, K. L., Champ, P. A., and Flores, N. 2013. Social amplification of wildfire risk: the role of social interactions and information sources. *Risk analysis*, 33(5), 800-817. https://doi.org/10.1111/j.1539-6924.2012.01917.x.

Busby, G. M., Albers, H. J., and Montgomery, C. A. 2012. Wildfire risk management in a landscape with fragmented ownership and spatial interactions. *Land Economics*, 88(3), 496-517. https://doi.org/10.3368/le.88.3.496.

Chen, X., Goodwin, B.K. and Prestemon, J.P., 2014. Is timber insurable? A study of wildfire risks in the US forest sector using spatio-temporal models. *American Journal of Agricultural Economics*, *96*(1), pp.213-231. https://doi.org/10.1093/ajae/aat087

Conrad, J.M. and Clark, C.W., 1987. Resource Economics: Notes and Problems. Cambridge University Press.

Conrad, J.M., 2010. Resource economics. Cambridge university press.

Dale, L. 2010. The true cost of wildfires in the western US. Western Forestry Leadership Coalition. https://academiccommons.columbia.edu/doi/10.7916/c490-r123 (accessed 15 October 2022).

Davenport, F. V., Burke, M., and Diffenbaugh, N. S. 2021. Contribution of historical precipitation change to US flood damages. *Proceedings of the National Academy of Sciences*, *118*(4), e2017524118. https://doi.org/10.1073/pnas.2017524118.

Davis, K. T., Dobrowski, S. Z., Higuera, P. E., Holden, Z. A., Veblen, T. T., Rother, M. T., ... and Maneta, M. P. 2019. Wildfires and climate change push low-elevation forests across a critical climate threshold for tree regeneration. *Proceedings of the National Academy of Sciences*, 116(13), 6193-6198. https://doi.org/10.1073/pnas.1815107116.

Deschênes, O., and Greenstone, M. 2007. The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. *American economic review*, 97(1), 354-385. https://doi.org/10.1257/aer.97.1.354.

Diffenbaugh, N. S., and Burke, M. 2019. Global warming has increased global economic inequality. *Proceedings of the National Academy of Sciences*, *116*(20), 9808-9813. https://doi.org/10.1073/pnas.1816020116.

Diffenbaugh, N. S., Davenport, F. V., and Burke, M. 2021. Historical warming has increased US crop insurance losses. *Environmental Research Letters*, *16*(8), 084025. https://doi.org/10.1088/1748-9326/ac1223.

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.

Downing, W. M., Dunn, C. J., Thompson, M. P., Caggiano, M. D., and Short, K. C. 2022. Human ignitions on private lands drive USFS cross-boundary wildfire transmission and community impacts in the western US. *Scientific Reports*, 12(1), 2624. https://doi.org/10.1038/s41598-022-06002-3.

Fezzi, C., and Bateman, I. 2015. The impact of climate change on agriculture: nonlinear effects and aggregation bias in Ricardian models of farmland values. *Journal of the Association of Environmental and Resource Economists*, 2(1), 57-92. http://dx.doi.org/10.1086/680257.

Gamelin, B. L., Feinstein, J., Wang, J., Bessac, J., Yan, E., and Kotamarthi, V. R. 2022. Projected US drought extremes through the twenty-first century with vapor pressure deficit. Scientific Reports, 12(1), 8615. https://doi.org/10.1038/s41598-022-12516-7.

Gellman, J., Walls, M. and Wibbenmeyer, M., 2022. Wildfire, smoke, and outdoor recreation in the western United States. *Forest Policy and Economics*, *134*, p.102619. https://doi.org/10.1016/j.forpol.2021.102619.

Guo, C., and Costello, C. 2013. The value of adaption: Climate change and timberland management. *Journal of Environmental Economics and Management*, 65(3), 452-468. https://doi.org/10.1016/j.jeem.2012.12.003.

Hansen, W. D., Mueller, J. M., and Naughton, H. T. 2014. Wildfire in hedonic property value studies. In *Western Economics Forum* (Vol. 13, No. 1837-2016-151820, pp. 23-35).

Hashida, Y., and Lewis, D. J. 2019. The intersection between climate adaptation, mitigation, and natural resources: An empirical analysis of forest management. *Journal of the Association of Environmental and Resource Economists*, *6*(5), 893-926. http://dx.doi.org/10.1086/704517.

Hashida, Y., and Lewis, D. J. 2022. Estimating welfare impacts of climate change using a discrete-choice model of land management: An application to western US forestry. *Resource and Energy Economics*, *68*, 101295. https://doi.org/10.1016/j.reseneeco.2022.101295.

Hsiang, S., Kopp, R., Jina, A., Rising, J., Delgado, M., Mohan, S., ... and Houser, T. 2017. Estimating economic damage from climate change in the United States. *Science*, *356*(6345), 1362-1369. https://doi.org/10.1126/science.aal4369.

Kemp, K. B., Higuera, P. E., Morgan, P., and Abatzoglou, J. T. 2019. Climate will increasingly determine post-fire tree regeneration success in low-elevation forests, Northern Rockies, USA. *Ecosphere*, 10(1), e02568. https://doi.org/10.1002/ecs2.2568.

Konoshima, M., Montgomery, C. A., Albers, H. J., and Arthur, J. L. 2008. Spatial-endogenous fire risk and efficient fuel management and timber harvest. *Land Economics*, *84*(3), 449-468. https://doi.org/10.3368/le.84.3.449.

Lauer, C. J., Montgomery, C. A., and Dietterich, T. G. 2017. Spatial interactions and optimal forest management on a fire-threatened landscape. *Forest Policy and Economics*, *83*, 107-120. https://doi.org/10.1016/j.forpol.2017.07.006.

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.

Massetti, E., and Mendelsohn, R. 2011. Estimating Ricardian models with panel data. *Climate Change Economics*, 2(04), 301-319. https://doi.org/10.1142/S2010007811000322.

Massetti, E., and Mendelsohn, R. 2018. Measuring climate adaptation: Methods and evidence. *Review of Environmental Economics and Policy*. https://doi.org/10.1093/reep/rey007.

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.

Mei, B. 2019. Timberland investments in the United States: A review and prospects. *Forest Policy and Economics*, 109, 101998. https://doi.org/10.1016/j.forpol.2019.101998.

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.

Mendelsohn, R., Nordhaus, W. D., and Shaw, D. 1994. The impact of global warming on agriculture: a Ricardian analysis. *The American economic review*, 753-771. https://www.jstor.org/stable/2118029.

Mendelsohn, R., Nordhaus, W., and Shaw, D. 1996. Climate impacts on aggregate farm value: accounting for adaptation. *Agricultural and Forest Meteorology*, 80(1), 55-66. https://doi.org/10.1016/0168-1923(95)02316-X.

Mihiar, C., and Lewis, D. J. 2021. Climate, adaptation, and the value of forestland: A national Ricardian analysis of the United States. *Land Economics*, *97*(4), 911-932. https://doi.org/10.3368/le.97.4.011620-0004R1.

Mueller, J. M., and Loomis, J. B. 2008. Spatial dependence in hedonic property models: Do different corrections for spatial dependence result in economically significant differences in estimated implicit prices?. *Journal of Agricultural and Resource Economics*, 212-231. https://www.jstor.org/stable/41220624

Mueller, J. M., and Loomis, J. B. 2014. Does the estimated impact of wildfires vary with the housing price distribution? A quantile regression approach. *Land Use Policy*, 41, 121-127. https://doi.org/10.1016/j.landusepol.2014.05.008.

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/10.1007/s11146-007-9083-1.

Mueller, S. E., Thode, A. E., Margolis, E. Q., Yocom, L. L., Young, J. D., and Iniguez, J. M. 2020. Climate relationships with increasing wildfire in the southwestern US from 1984 to 2015. *Forest Ecology and Management,* 460, 117861. https://doi.org/10.1016/j.foreco.2019.117861.

Ortiz-Bobea, A., Ault, T.R., Carrillo, C.M., Chambers, R.G. and Lobell, D.B., 2021. Anthropogenic climate change has slowed global agricultural productivity growth. *Nature Climate Change*, 11(4), pp.306-312. https://doi.org/10.6077/pfsd-0v93.

Plantinga, A. J., Walsh, R., and Wibbenmeyer, M. 2022. Priorities and effectiveness in wildfire management: evidence from fire spread in the western United States. *Journal of the Association of Environmental and Resource Economists*, 9(4), 603-639. https://doi.org/10.1086/719426.

Polsky, C. 2004. Putting space and time in Ricardian climate change impact studies: agriculture in the US Great Plains, 1969–1992. *Annals of the Association of American Geographers*, 94(3), 549-564. https://doi.org/10.1111/j.1467-8306.2004.00413.x.

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.

Restaino, C. M., Peterson, D. L., and Littell, J. 2016. Increased water deficit decreases Douglas fir growth throughout western US forests. *Proceedings of the National academy of Sciences*, *113*(34), 9557-9562. https://doi.org/10.1073/pnas.1602384113.

Rother, M. T., and Veblen, T. T. 2016. Limited conifer regeneration following wildfires in dry ponderosa pine forests of the Colorado Front Range. *Ecosphere*, 7(12), e01594. https://doi.org/10.1002/ecs2.1594.

Sanghi, A., and Mendelsohn, R. 2008. The impacts of global warming on farmers in Brazil and India. *Global Environmental Change*, 18(4), 655-665. https://doi.org/10.1016/j.gloenvcha.2008.06.008.

Schlenker, W., Hanemann, W. M., and Fisher, A. C. 2005. Will US agriculture really benefit from global warming? Accounting for irrigation in the hedonic approach. *American Economic Review*, 95(1), 395-406. https://www.jstor.org/stable/4132686.

Schlenker, W., Hanemann, W. M., and Fisher, A. C. 2006. The impact of global warming on US agriculture: an econometric analysis of optimal growing conditions. *Review of Economics and statistics*, 88(1), 113-125. https://doi.org/10.1162/rest.2006.88.1.113

Seo, S. N. N., Mendelsohn, R., and Munasinghe, M. 2005. Climate change and agriculture in Sri Lanka: a Ricardian valuation. *Environment and development Economics*, 10(5), 581-596. https://doi.org/10.1017/S1355770X05002044.

Severen, C., Costello, C., and Deschenes, O. 2018. A Forward-Looking Ricardian Approach: Do land markets capitalize climate change forecasts?. *Journal of Environmental Economics and Management*, 89, 235-254. https://doi.org/10.1016/j.jeem.2018.03.009.

Shatford, J. P. A., D. E. Hibbs, and K. J. Puettmann. 2007. “Conifer Regeneration after Forest Fire in the Klamath-Siskiyous: How Much, How Soon?” *Journal of Forestry,* 105: 139–146. https://doi.org/10.1093/jof/105.3.139.

Sheehan, T., and Bachelet, D. 2019. A fuzzy logic decision support model for climate-driven biomass loss risk in western Oregon and Washington. *PloS one*, 14(10), e0222051. https://doi.org/10.1371/journal.pone.0222051.

Short, Karen C. 2022. Spatial wildfire occurrence data for the United States, 1992-2020 [FPA_FOD_20221014]. 6th Edition. Fort Collins, CO: Forest Service Research Data Archive. https://doi.org/10.2737/RDS-2013-0009.6

Sohngen, B. and Mendelsohn, R., 1998. Valuing the impact of large-scale ecological change in a market: The effect of climate change on US timber. *American Economic Review*, pp.686-710. https://www.jstor.org/stable/117001.

Sohngen, B. and Tian, X., 2016. Global climate change impacts on forests and markets. *Forest Policy and Economics*, *72*, pp.18-26. https://doi.org/10.1088/1748-9326/11/3/035011.

Sohngen, B., 2020. Climate change and forests. *Annual Review of Resource Economics*, *12*, pp.23-43. https://doi.org/10.1146/annurev-resource-110419-010208.

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.

Stevens-Rumann, C. S., and Morgan, P. 2019. Tree regeneration following wildfires in the western US: a review. *Fire Ecology*, *15*(1), 1-17. https://doi.org/10.1186/s42408-019-0032-1.

Strzepek, K., Yohe, G., Neumann, J., and Boehlert, B. 2010. Characterizing changes in drought risk for the United States from climate change. *Environmental Research Letters*, *5*(4), 044012. https://doi.org/10.1088/1748-9326/5/4/044012.

Van Mantgem, P. J., Stephenson, N. L., Byrne, J. C., Daniels, L. D., Franklin, J. F., Fulé, P.Z., ... and Veblen, T. T. 2009. Widespread increase of tree mortality rates in the western United States. *Science*, *323*(5913), 521-524. https://doi.org/10.1126/science.1165000.

Von Bertalanffy, L., 1938. A quantitative theory of organic growth (inquiries on growth laws. II). *Human biology*, 10(2), pp.181-213. https://www.jstor.org/stable/41447359.

Weiskittel, A. R., Crookston, N. L., and Rehfeldt, G. E. 2012. Projected future suitable habitat and productivity of Douglas-fir in western North America. *Schweizerische Zeitschrift fur Forstwesen*, *163*(3), 70-78. https://doi.org/10.3188/szf.2012.0070.

The White House. 2023. National Strategy to Develop Statistics for Environmental-Economic decisions. https://www.whitehouse.gov/wp-content/uploads/2023/01/Natural-Capital-Accounting-Strategy-final.pdf

Williams, A. P., Allen, C. D., Millar, C. I., Swetnam, T. W., Michaelsen, J., Still, C. J., and Leavitt, S. W. 2010. Forest responses to increasing aridity and warmth in the southwestern United States. *Proceedings of the National Academy of Sciences*, 107(50), 21289-21294. https://doi.org/10.1073/pnas.0914211107.

Williams, A. P., Cook, B. I., and Smerdon, J. E. 2022. Rapid intensification of the emerging southwestern North American megadrought in 2020–2021. *Nature Climate Change*, 12(3), 232-234. https://doi.org/10.1038/s41558-022-01290-z.

Zhuang, Y., Fu, R., Santer, B. D., Dickinson, R. E., and Hall, A. 2021. Quantifying contributions of natural variability and anthropogenic forcings on increased fire weather risk over the western United States. *Proceedings of the National Academy of Sciences*, 118(45), e2111875118. https://doi.org/10.1073/pnas.2111875118.

Appendix

In this section of the Appendix, we describe our data sources and data collection process in detail.

Timberland prices: The following screening rules are used to eliminate outliers and ensure our analysis primarily focuses on land with timber production being a non-trivial portion of its market value. We start by removing sales with land prices less than $100/acre or greater than $60,000/acre (in 2020 U.S. dollars) to make sure our sample consists of arm's length transactions within a reasonable price range. This upper price limit is detected by a box plot. To ensure each plot is private timberland, we then select parcels with distance to the nearest government-defined private timberland (see Sec. 2) less than 1 km as a quality-control check. To ensure land isn't primarily valued for future development, parcels with a distance to the nearest urban area less than 5 km or a sale size smaller than 10 acres are excluded. As a final step, we only keep sales starting in 2004 and ending in 2020 for the three Pacific states (Washington, Oregon, and California) to match the wildfire data which is only available between 1984 and 2020. Therefore, each sale is able to be matched with a wildfire history over the past 20 years to achieve consistency in wildfire measurements.

Land attributes: For each parcel, we also gather additional land characteristics from a variety of sources. We use non-irrigated land capability class as a proxy for soil quality, where this data is taken from the Gridded National Soil Survey Geographic Database (gNATSGO) database, which contains detailed soil information at a 10m resolution for all areas of the U.S. Land capability classes are represented by numbers 1 through 8, and the larger the number, the more restrictions the land has on its use. As soil data have a high resolution, assigning soil class to the parcel's centroid may not be accurate in determining soil quality for large parcels. So, we create a buffer around each parcel to estimate its boundary, with the buffer area equal to the total acreage of the parcel. Within each parcel, we calculate the area associated with each soil class. Following that, a spatial-weighted average based on the area of each soil class is computed to aggregate the soil classes to the parcel level. We also include slope and elevation variables using data derived from the national Digital Elevation Model (DEM) model at a 1-arc (30m) resolution. Each sale is assigned a slope and elevation corresponding to the centroid of the parcel. We use distance to the nearest road to approximate the costs of delivery for timber production, where distance is calculated in GIS using the map of major roads of the United States 2014. We measure the urban development potential of each parcel using the distance to the nearest urban area, which has been used in prior hedonic studies of land values (Bigelow et al., 2017). The distance to the nearest urban areas is computed in GIS using the U.S. 2010 Census Urban Area shapefiles, where urban areas include 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 as defined in the 2010 Census. While our main data filters described in Sec. 5.1 likely drop the forested parcels with the highest urban development potential, there likely remains some residual future development value embedded in our timberland transaction prices that will be captured in the distance to nearest urban area variable.

Appendix tables

Table A1: Results with finer scale of wildfire arrival rates

Log (price per acre)	Model (1)	Model (2)
Mean VPD (hPa)	0.003	0.007
	(0.093)	(0.092)
Mean VPD square	-0.004	-0.004
	(0.005)	(0.005)
Large wildfires per decade on parcel	-0.628***	-0.623***
	(0.189)	(0.190)
Large wildfires per decade nearby (0-5km away)	-0.177**	-0.164*
	(0.087)	(0.095)
Large wildfires per decade nearby (5-10km away)	-0.184***	-0.172***
	(0.042)	(0.043)
Large wildfires per decade nearby (10-15km away)	-0.144***	-0.122***
	(0.037)	(0.033)
Large wildfires per decade distant (15-20km away)		-0.010
		(0.038)
Large wildfires per decade distant (20-30km away)		-0.021
		(0.017)
Very large nearby fires (VLNF) =1	-0.122**	-0.120**
	(0.050)	(0.051)
Elevation (km)	-0.589***	-0.568***
	(0.156)	(0.156)
Slope (degree)	-0.020***	-0.020***
	(0.006)	(0.006)
Distance to the nearest road (km)	-0.015***	-0.014**
	(0.005)	(0.005)
Distance to the nearest urban area (km)	-0.008***	-0.008***
	(0.002)	(0.002)
Distance to the nearest public forest (km)	0.043**	0.044**
	(0.021)	(0.021)
Constant	9.811***	9.795***
	(0.436)	(0.440)
County and year FE	Yes	Yes
Observations	9,145	9,145
R-squared	0.544	0.544
Average Marginal effects (AME)		
AME of VPD	-0.060**	-0.058**
	(0.026)	(0.026)

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

Table A2. Results with distance to the nearest fire

Log (price per acre)	
Mean VPD (hPa)	-0.046
	(0.103)
Mean VPD square	-0.004
	(0.006)
Distance to the nearest large wildfire (km)	-0.005
	(0.006)
Distance to the nearest large wildfire square	-0.000
	(0.000)
Mean VPD * Distance to the nearest large wildfire	0.001
	(0.001)
Very large nearby fires (VLNF) =1	-0.084
	(0.052)
Elevation (km)	-0.574***
	(0.160)
Slope (degree)	-0.020***
	(0.006)
Distance to the nearest road (km)	-0.018***
	(0.006)
Distance to the nearest urban area (km)	-0.007***
	(0.002)
Distance to the nearest public forest (km)	0.042*
	(0.022)
Constant	9.626***
	(0.470)
County and year FE	Yes
Observations	9,145
R-squared	0.535
Average marginal effects (AME)	
AME of VPD	-0.060**
	(0.029)
AME of fire distance	0.003*
	(0.002)

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

Table A3. Results with alternative size and urban proximity specification

Log (price per acre)	
Mean VPD (hPa)	-0.086
	(0.078)
Mean VPD square	-0.000
	(0.004)
Large wildfires per decade on parcel	-0.736***
	(0.180)
Large wildfires per decade nearby (0-15km away)	-0.100***
	(0.028)
Large wildfires per decade distant (15-30km away)	-0.011
	(0.013)
Very large nearby fires (VLNF) =1	-0.072
	(0.068)
Elevation (km)	-0.507***
	(0.163)
Slope (degree)	-0.019***
	(0.006)
Distance to the nearest road (km)	-0.013**
	(0.006)
Distance to the nearest urban area (km)	-0.007***
	(0.002)
Distance to the nearest public forest (km)	0.019
	(0.021)
Constant	10.080***
	(0.445)
County and year FE	Yes
Observations	4,705
R-squared	0.584
Average Marginal effects (AME)	
AME of VPD	-0.093***
	(0.023)

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

Table A4. Results with and without VPD

Log (price per acre)	Model (1)	Model (2)
Large wildfires per decade on parcel	-0.710***	-0.530***
	(0.191)	(0.120)
Large wildfires per decade nearby (0-15km away)	-0.169***	-0.113***
	(0.030)	(0.017)
Large wildfires per decade distant (15-30km away)	-0.022*	-0.007
	(0.011)	(0.010)
Very large nearby fires (VLNF) =1	-0.140***	-0.064**
	(0.048)	(0.030)
Elevation (km)	-0.527***	
	(0.170)	
Slope (degree)	-0.020***	
	(0.006)	
Distance to the nearest road (km)	-0.013**	
	(0.006)	
Distance to the nearest urban area (km)	-0.008***	
	(0.002)	
Distance to the nearest public forest (km)	0.047**	
	(0.021)	
Constant	9.101***	
	(0.186)	
County and year FE	Yes	
Observations	9,145	9,145
R-squared	0.540	

Notes: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A5. Results with different time periods of average VPD

Log (price per acre)	Model (1)	Model (2)	Model (3)	Model (4)
Mean VPD over the past 5 years (hPa)	0.029			
	(0.068)			
Mean VPD over the past 5 years square	-0.005			
	(0.003)			
Mean VPD over the past 10 years (hPa)		0.018		
		(0.081)		
Mean VPD over the past 10 years square		-0.004		
		(0.004)		
Mean VPD over the past 15 years (hPa)			0.018	
			(0.081)	
Mean VPD over the past 15 years square			-0.005	
			(0.004)	
Mean VPD over the past 20 years (hPa)				0.013
				(0.085)
Mean VPD over the past 20 years square				-0.004
				(0.005)
Large wildfires per decade on parcel	-0.595***	-0.608***	-0.602***	-0.604***
	(0.193)	(0.196)	(0.193)	(0.193)
Large wildfires per decade nearby (0-15km away)	-0.147***	-0.150***	-0.148***	-0.148***
	(0.027)	(0.028)	(0.028)	(0.028)
Large wildfires per decade distant (15-30km away)	-0.019	-0.018	-0.017	-0.017
	(0.012)	(0.012)	(0.013)	(0.013)
Very large nearby fires (VLNF) =1	-0.126**	-0.126**	-0.125**	-0.124**
	(0.054)	(0.052)	(0.052)	(0.052)
Elevation (km)	-0.542***	-0.545***	-0.551***	-0.557***
	(0.157)	(0.156)	(0.155)	(0.156)
Slope (degree)	-0.020***	-0.021***	-0.021***	-0.020***
	(0.006)	(0.006)	(0.006)	(0.006)
Distance to the nearest road (km)	-0.015**	-0.014**	-0.014**	-0.014**
	(0.006)	(0.006)	(0.005)	(0.005)
Distance to the nearest urban area (km)	-0.008***	-0.008***	-0.008***	-0.008***
	(0.002)	(0.002)	(0.002)	(0.002)
Distance to the nearest public forest (km)	0.044**	0.044**	0.045**	0.045**
	(0.021)	(0.021)	(0.021)	(0.021)
Constant	9.716***	9.738***	9.776***	9.819***
	(0.398)	(0.404)	(0.397)	(0.407)
County and year FE	Yes	Yes	Yes	Yes
Observations	9,145	9,145	9,145	9,145
R-squared	0.544	0.544	0.544	0.544
Average Marginal effects (AME)				
AME of VPD	-0.047*	-0.050**	-0.055**	-0.057**
	(0.024)	(0.025)	(0.024)	(0.025)

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

Table A6. Results with different time periods of large wildfire arrival rates

Log (price per acre)	Model (1)	Model (2)	Model (3)
Mean VPD (hPa)	0.041	0.029	0.006
	(0.098)	(0.096)	(0.092)
Mean VPD square	-0.007	-0.006	-0.004
	(0.005)	(0.005)	(0.005)
Large wildfires per decade on parcel over the past 5 years	-0.202***		
	(0.069)		
Large wildfires per decade nearby (0-15km away) over the past 5 years	-0.014		
	(0.018)		
Large wildfires per decade distant (15-30km away) over the past 5 years	-0.019**		
Large wildfires per decade on parcel over the past 10 years		-0.368***	
		(0.104)	
Large wildfires per decade nearby (0-15km away) over the past 10 years		-0.036	
		(0.023)	
Large wildfires per decade distant (15-30km away) over the past 10 years		-0.025**	
		(0.012)	
Large wildfires per decade on parcel over the past 15 years			-0.561***
			(0.163)
Large wildfires per decade nearby (0-15km away) over the past 15 years			-0.118***
			(0.024)
Large wildfires per decade distant (15-30km away) over the past 15 years			-0.020*
			(0.011)
Very large nearby fires (VLNF) =1	-0.096*	-0.101*	-0.120**
	(0.055)	(0.054)	(0.053)
Elevation (km)	-0.564***	-0.557***	-0.557***
	(0.164)	(0.162)	(0.156)
Slope (degree)	-0.021***	-0.021***	-0.020***
	(0.006)	(0.006)	(0.006)
Distance to the nearest road (km)	-0.018***	-0.018***	-0.015***
	(0.006)	(0.006)	(0.006)
Distance to the nearest urban area (km)	-0.008***	-0.008***	-0.008***
	(0.002)	(0.002)	(0.002)
Distance to the nearest public forest (km)	0.045**	0.045**	0.046**
	-0.096*	-0.101*	-0.120**
Constant	9.320***	9.532***	9.745***
	(0.426)	(0.423)	(0.440)
County and year FE	Yes	Yes	Yes
Observations	9,145	9,145	9,145
R-squared	0.538	0.538	0.544
Average Marginal effects (AME)			
AME of VPD	-0.069***	-0.066***	-0.059**
	(0.025)	(0.025)	(0.026)

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

Table A7. Dropping sales with at least one human-caused large fire directly occurred on them

Log (price per acre)	
Mean VPD (hPa)	-0.008
	(0.090)
Mean VPD square	-0.003
	(0.005)
Large wildfires per decade on parcel	-0.630***
	(0.211)
Large wildfires per decade nearby (0-15km away)	-0.148***
	(0.030)
Large wildfires per decade distant (15-30km away)	-0.018
	(0.013)
Very large nearby fires (VLNF) =1	-0.119**
	(0.052)
Elevation (km)	-0.584***
	(0.158)
Slope (degree)	-0.020***
	(0.006)
Distance to the nearest road (km)	-0.014**
	(0.006)
Distance to the nearest urban area (km)	-0.008***
	(0.002)
Distance to the nearest public forest (km)	0.042*
	(0.021)
Constant	9.667***
	(0.448)
County and year FE	Yes
Observations	9,020
R-squared	0.545
Average Marginal effects (AME)	
AME of VPD	-0.059**
	(0.026)

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

Table A8: Results with different levels of location fixed effects

Log (price per acre)	Model (1)	Model (2)	Model (3)
Mean VPD (hPa)	-0.171**	-0.135*	-0.136
	(0.086)	(0.078)	(0.085)
Mean VPD square	0.006	0.003	0.004
	(0.005)	(0.005)	(0.005)
Large wildfires per decade on parcel	-0.545**	-0.636***	-0.680***
	(0.217)	(0.221)	(0.189)
Large wildfires per decade nearby (0-15km away)	-0.126***	-0.170***	-0.112***
	(0.026)	(0.038)	(0.038)
Large wildfires per decade distant (15-30km away)	-0.016	-0.010	-0.023*
	(0.021)	(0.013)	(0.012)
Very large nearby fires (VLNF) =1	-0.147***	-0.136***	-0.044
	(0.054)	(0.047)	(0.054)
Elevation (km)	-0.638***	-0.633***	-0.613***
	(0.127)	(0.136)	(0.167)
Slope (degree)	-0.023***	-0.030***	-0.029***
	(0.005)	(0.004)	(0.005)
Distance to the nearest road (km)	-0.012*	-0.005	-0.004
	(0.007)	(0.005)	(0.007)
Distance to the nearest urban area (km)	-0.006***	-0.005**	-0.006
	(0.002)	(0.002)	(0.004)
Distance to the nearest public forest (km)	0.038	0.067***	0.094***
	(0.026)	(0.023)	(0.026)
Constant	9.699***	11.593***	11.438***
	(0.420)	(0.429)	(0.532)
Census tracts and year FE	Yes		
Grid25 and year FE		Yes	
Grid50 and year FE			Yes
Observations	9,145	9,145	9,145
R-squared	0.591	0.581	0.627
Average Marginal effects (AME)			
AME of VPD	-0.072***	-0.081***	-0.068***
	(0.023)	(0.019)	(0.023)

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

Table A9. Results with soil quality

Log (price per acre)	
Mean VPD (hPa)	0.009
	(0.096)
Mean VPD square	-0.004
	(0.005)
Large wildfires per decade on parcel	-0.589***
	(0.191)
Large wildfires per decade nearby (0-15km away)	-0.166***
	(0.028)
Large wildfires per decade distant (15-30km away)	-0.010
	(0.013)
Very large nearby fires (VLNF) =1	-0.114**
	(0.047)
Elevation (km)	-0.576***
	(0.158)
Slope (degree)	-0.019***
	(0.006)
Distance to the nearest road (km)	-0.016**
	(0.007)
Distance to the nearest urban area (km)	-0.009***
	(0.002)
Distance to the nearest public forest (km)	0.044**
	(0.022)
Soil quality (nirr)	-0.009
	(0.032)
Constant	9.922***
	(0.464)
County and year FE	Yes
Observations	8,065
R-squared	0.365
Average Marginal effects (AME)	
AME of VPD	-0.055**
	(0.027)

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

Appendix figures

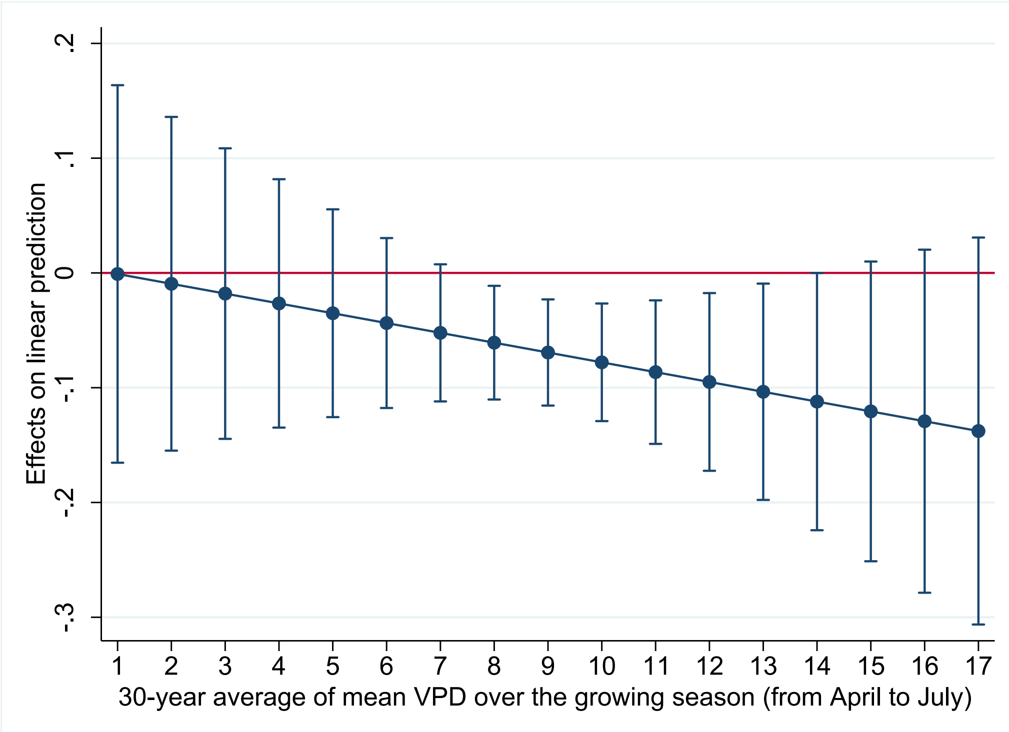


Figure A1. Estimated marginal effects of mean VPD

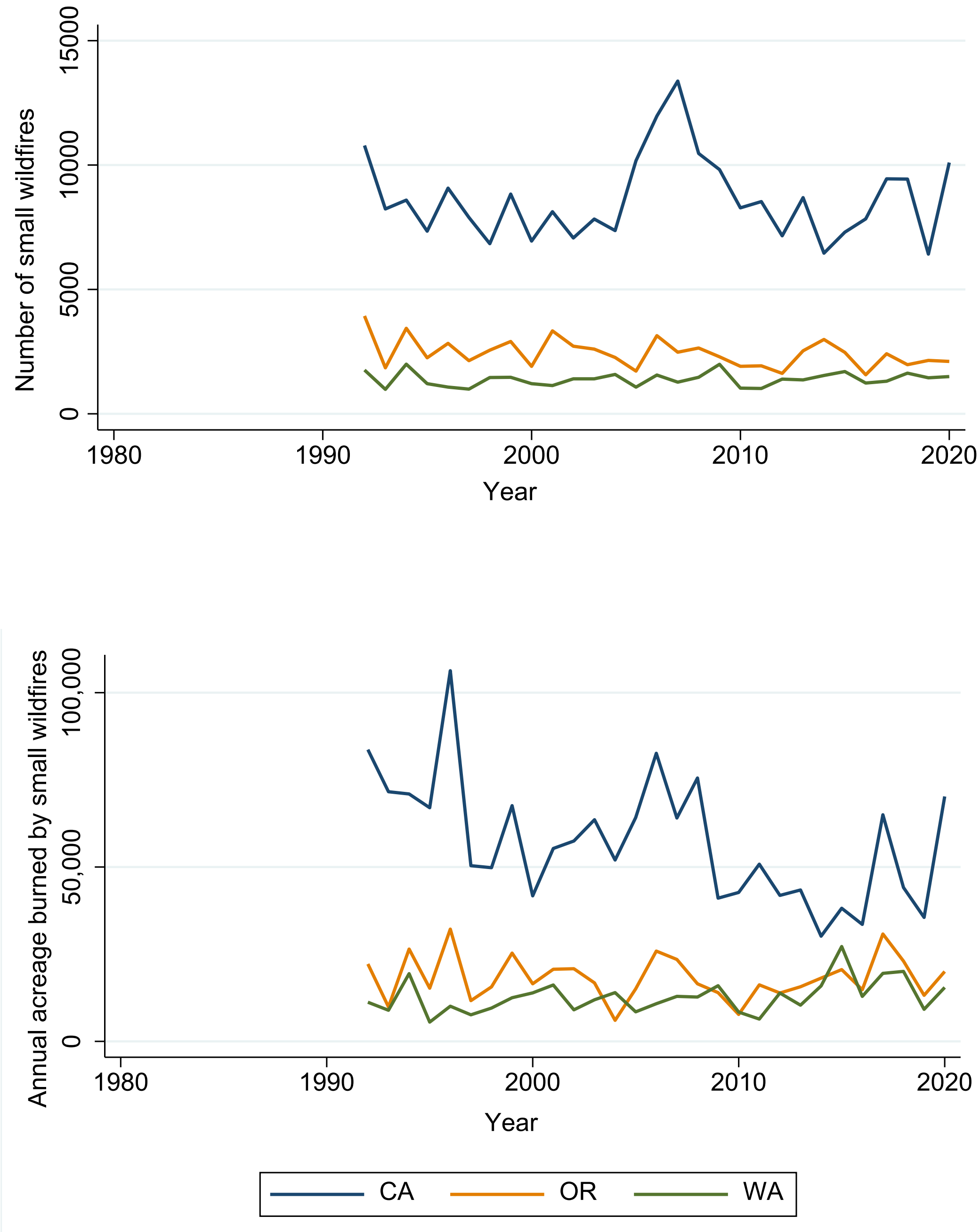
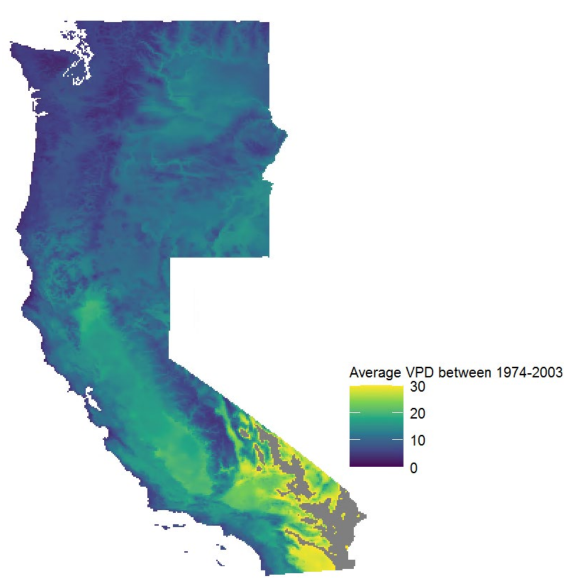


Figure A2. Frequency (above) and severity (below) of small wildfires by state and year

Note: Small wildfires (less than 1000 acres) not included in the MTBS data are derived from the USFS spatial wildfire occurrence database.



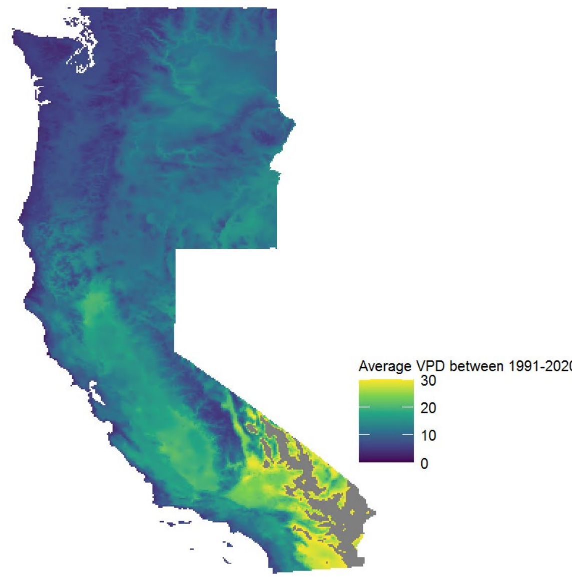


Figure A3. Spatial distribution of 30-year average VPD in the past and current period

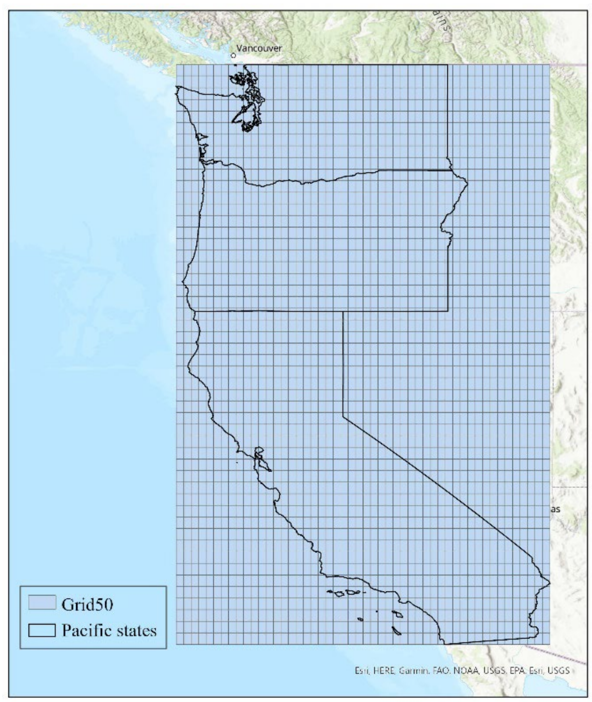


Figure A4. Grid25 and Gird50 grid cells, respectively