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Prescribed fires as a climate change adaptation tool ☆

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ABSTRACT

Climate change has been shown to increase wildfire risk, while prescribed burning is a potential management action that landowners can perform to adapt to such climate-driven changes in risk. This study builds off natural resource economic theory to illustrate how wildfire is jointly determined with privately optimal prescribed burn decisions by landowners. We use panel data on prescribed burn permits across the southeastern U.S. states to empirically estimate (i) how climate and previous large wildfire events affect prescribed burn decisions and (ii) how climate and prescribed burning affect the occurrence of large wildfires. Based on an instrumental variables identification strategy, our estimated simultaneous system finds that a hotter and drier climate will increase prescribed burning, with landowner adaptation to corresponding wildfire risk being a key mechanism. By 2050, we find that a hotter and drier future climate will increase the number of large wildfires from 27 per year under current conditions to 36 per year with climate change but no climate adaptation, and 29 large wildfires per year with both climate change and climate adaptation. This paper provides intuition and quantitative evidence regarding the interaction between climate, wildfire, and landowner management adaptation.

1. Introduction

Prescribed fires, also known as prescribed burns or controlled burns, are fires purposefully ignited under controlled conditions by fire experts (e.g., certified burners) to clear ground fuel and for a diversity of outcomes in terrestrial ecosystems. Prescribed fires remove fuels and contribute to mitigating the spread of wildfires (Kobziar et al., 2009; Prichard et al., 2010), and there is evidence that the areas treated by prescribed fires burn less intensively during wildfire events (Ryan et al., 2013). Since wildfires are expected to increase in frequency and intensity with climate change (Abatzoglou and Williams, 2016) and due to prior fire suppression efforts (Kreider et al., 2024), fuel management will be a critical land management option for private landowners to adapt to climate change (Sample et al., 2022). Increasing the use of prescribed fires rather than aggressively suppressing wildland fires can promote adaptive resilience as the climate continues to warm (Schoennagel et al., 2017). Prescribed fire is also widely noted to contribute to ecosystem restoration, wildlife species habitat, and recreational benefits (Engstrom et al., 1984; Cox and Jones, 2007; Ulyshen et al., 2022).[1]

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[1] For example, longleaf pine (*Pinus palustris*) forests, native to southeastern states, depend on frequent fire, while the wildlife and plants found in longleaf pine forests have adapted to frequent fire. Ecosystem restoration efforts of longleaf pine ecosystems typically include prescribed fires. In the southeast, private

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Prescribed fires exhibit a characteristic of private provision of public goods, where landowners conducting prescribed burns reduce wildfire risks on their lands in addition to their neighbors' land. Fire management decisions that include prescribed fires depend on the private economic costs and benefits that arise from both long-term climate shifts and short-term weather realizations, and the privately optimal amount of fire management is lower than the social optimum when fire management creates external benefits to neighboring landowners through lower wildfire spread (Lauer et al., 2017). Incentives for fire management are also affected by legal liability if intentionally set prescribed fires escape to neighboring land. Despite the numerous benefits of prescribed fires, the current literature lacks the critical economic link between climate, prescribed fire usage, and wildfire mitigation. While federal agencies, such as the USDA Forest Service, have been actively conducting prescribed burns under the Wildland Fire Use policy (Schoennagel et al., 2017), recent estimates indicate that 84% of prescribed fire occurs on state and private lands, of which private lands comprise by far the largest share (Melvin, 2022). Developing an understanding of how private landowners make prescribed burn decisions along with the implications of their actions on wildfire outcomes is essential when the coordination between private and public sectors is called for to mitigate the increasing rate and intensity of wildfires.

The purpose of this study is to estimate (i) the impact of wildfire, climate, and other factors on prescribed burning, and (ii) the impact of prescribed burning, climate, and other factors on wildfires. The key data we exploit is burn permit data acquired by the Tall Timbers Research Station for seven southeastern US states across eleven years (2010–2021) (Cummins et al., 2023). This spatially and temporally rich data allows us to develop panel measures of county-level prescribed fire acreage on forestland. Our empirical analysis is motivated by a simple theory depicting an equilibrium between a region's wildfire arrival and its prescribed burning effort aimed at managing fuels. To understand the factors that influence prescribed burn decisions, we first estimate the effects of climate, biophysical conditions, and past wildfire events on a dependent variable of county-level prescribed fire acreage. Next, we estimate the effects of prescribed fires, climate, and biophysical conditions on wildfire occurrence.

Our research design combines fixed effects and instrumental variables. We capture a range of spatially-varying and time-varying unobservables by including fixed effects defined for each combination of state, level III eco-region, and year. Eco-regions contain similar ecosystem components, including types of vegetation such as dominant forest types that strongly correlate with certain forest management strategies like planting.[2] We also apply instrumental variables methods to account for remaining unobserved time and spatially-varying drivers of wildfire and controlled burning decisions, and to be consistent with our theoretical setup showing that wildfire and prescribed burning are simultaneously related. In particular, we instrument for wildfire in the prescribed burning equation with a variable depicting naturally-caused (e.g., lightning) wildfire events, with the identifying assumption being that the count and location of naturally-caused ignitions affect prescribed burning decisions only through the occurrence of wildfires. We instrument for prescribed burning in the wildfire equation with a variable measuring the number of establishments in the forestry sector in the county, with the identifying assumption that forestry sector establishments affect wildfire occurrence only by affecting the availability and cost of labor resources needed to conduct prescribed burning.

Our analysis focuses on the southeastern United States (Fig. 1), where prescribed burns have been widely used in private forestland. The southeast is the largest regional supplier of timber in the country, producing 60% of all U.S. timber harvests (Vose et al., 2019). Here, many species have adapted to fires; Loblolly pine (*Pinus taeda*) and longleaf pine (*Pinus palustris*) are both fire-adapted species, and both species benefit from fire's effects on reducing competition (Burns and Honkala, 1990). Although moderate to high-severity wildfires have been rare, the U.S. southeast is also a region that is increasingly exposed to wildfire, as it has experienced a 271% increase to an average of 286,000 ha per year burned since 2000, which represents a larger proportional increase than the two western regions (U.S. Department of Agriculture and Forest Service, 2023a). While wildfire prevention is the primary reason for prescribed fires, private landowners' prescribed burning also maintains hunting game species habitat, reduces competing plants, and helps with pest and disease control (Kolden, 2019). This is also the case in the southeast, where the intended purposes of prescribed burning reported in state permit data include hazard reduction and removal, silvicultural site preparation, wildlife habitat improvement, and other ecological purposes. This region leads the nation in prescribed burning, with total acres treated at approximately 6–7 million acres annually (Melvin, 2021).

Although the regional focus of this study is the southeast U.S., our methodology and findings could be applied in other settings. The use of prescribed fires mostly occurs on federal land in the western U.S., mainly because federal agencies own the majority of forestland and because the liability statutes in the western states are often more stringent for forest owners compared to the southeast, discouraging the active prescribed burning by private landowners (Miller et al., 2020). However, prescribed fires are increasingly recognized as a useful, integral part of managing resilient forest systems, as shown in recent efforts to revive the traditional use of fires by the tribes in California (Wigglesworth, 2022).

Our results show that counties that have experienced recent large wildfire events of at least 500 acres conduct more prescribed burns; the occurrence of a recent large wildfire within the prior three years leads to 1.7 times more prescribed burn acreage. Hotter and drier conditions, measured by maximum vapor pressure deficit (VPD), also lead to an increase in prescribed fire acreage with an elasticity of about 2.5–2.8. We also find evidence that prescribed fires reduce the probability of a large wildfire occurring, as a 1% increase in prescribed burning acreage reduces the probability of large wildfire by 0.09 percentage points — for reference,

landowners also use prescribed fires to create game hunting grounds, such as bobwhite quail and white-tailed deer, which generate substantial economic benefits to the local economy. Further, some federally listed endangered species, like red-cockaded woodpeckers (*Dryobates borealis*) and gopher tortoises (*Gopherus polyphemus*), are closely tied to frequent prescribed fires.

[2] In our study region, planting – and thus, managed planting density – is heavily concentrated in pine forests rather than hardwoods (Johnson and Lewis, 2024).

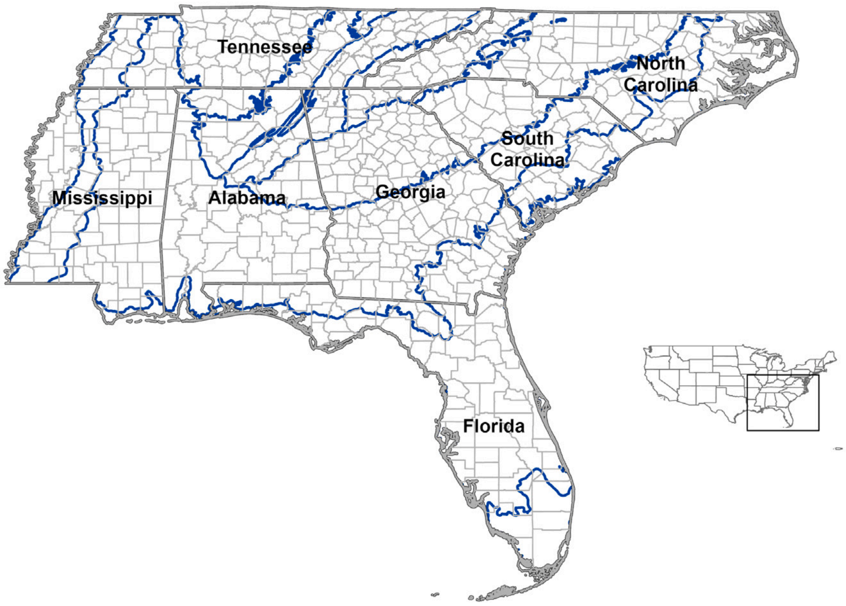

Fig. 1. Study area. Counties, shown as the smallest polygons, are the units of observation in our study. The ecoregion borders are shown in blue lines. The ecoregion-state is a spatial scale used to define fixed effects in our econometric models.

the mean county-level annual probability of a large wildfire is approximately 5% in our study region. Results show that hotter and drier conditions strongly increase wildfire probability, as a 1% increase in VPD raises the probability of a large wildfire by 0.36 percentage points. We also conducted a simulation exercise to project how future wildfire occurrence would change as the climate changes and as landowners adapt to a changing climate. Our simulation indicates that wildfires will increase as a direct result of an increasingly warmer and drier climate, though prescribed burning adaptation by landowners mitigates much of the increase in large wildfire occurrence. By 2050, our simulation projects that a hotter and drier future climate will increase the number of large wildfires from an average 27 per year under current conditions to an average of 36 per year under a scenario with climate change but no climate adaptation (i.e., fixed prescribed burning at the current level). When we use our model to simulate climate adaptation with climate change, we project a lower average of 29 large wildfires per year.

Much of the previous empirical economic literature on wildfire focuses on suppression issues (Plantinga et al., 2022; Baylis and Boomhower, 2023), fuel management (Wibbenmeyer et al., 2019), outdoor recreation (Gellman et al., 2022), projection of future wildfires (Prestemon et al., 2016), public health issues related to smoke (Mccoy and Zhao, 2021; Wen and Burke, 2022; Heft-Neal et al., 2022, 2023), residential property values (McCoy and Walsh, 2018), timberland property values (Wang and Lewis, 2024), voluntary adaptation (Baylis and Boomhower, 2022), and self-protection behavior (Burke et al., 2022). In contrast, empirical economic studies looking at forest management decisions on fire mitigation are scarce, though there is a significant set of theoretical and numerical economic studies of fire mitigation that informs our conceptual setup (e.g. Reed and Apaloo, 1991; Yoder, 2004; Amacher et al., 2005). In economic studies of liability rules, Langpap and Wu (2021) provides a theoretical framework for wildfire risk mitigation choices when the incentive is provided through liability rules and voluntary cost-sharing agreements. Another study examines the effect of liability laws and regulations on the incidence and severity of escaped prescribed fires (Yoder, 2008). Wonkka et al. (2015) study the effect of prescribed fire statutory variations across six states in the southeastern U.S. on prescribed fire application. Using the analysis of state legislation, prescribed fire records, and stakeholder interviews, a recent paper provides a policy recommendation for reducing legal barriers to prescribed burns specific to California (Miller et al., 2020). The recommendation includes a collaboration among multiple stakeholders, including private landowners.

To our knowledge, there is no empirical analysis in economics linking private burning decisions, climate or weather outcomes, and wildfire outcomes. Our study's primary contribution is to provide the first empirical economic analysis of how climate change affects the linkages between private landowners' resource management action, wildfire mitigation, and landscape-level wildfire outcomes using large-scale burn permit and wildfire outcome data. This is the first economics paper to empirically show the reduction in wildfires as a function of climate adaptation through prescribed fires. Our result is relevant to current policy discussions advocating for increased prescribed fires, mostly in the western U.S. Our results are also novel, showing the landowners' prescribed burning behavioral response to drier conditions and past wildfire events. The paper also contributes to an existing climate literature that links econometrically-estimated parameters to project future outcomes (Hashida and Lewis, 2019; Dundas and Von Haefen, 2020).

2. Economic models of prescribed burning and wildfire

2.1. Theoretical foundation of costly protection in the presence of fire risks

In the presence of catastrophic events such as wildfires, the forest landowner has two decision variables, rotation age and protection effort (Amacher et al., 2009). Key protection efforts include prescribed fires that the landowner can undertake to reduce fuels in a way that reduces the probability that a wildfire will arrive,[3] which reflects the probability of ignition at the landowners site plus the probability that a wildfire spreads from a neighboring site. Here, we focus on how a landowner's optimal protection from conducting prescribed burning interacts with the local wildfire arrival rate, building off Reed (1984)'s seminal study of the economics of wildfire. We keep notation similar to Amacher et al. (2009)'s comprehensive review of forest management under risk of catastrophic events (Ch. 10).

Suppose a forest stand grows according to yield function $F(t)$, where t indicates the age of the stand. Upon harvest, the landowner sells timber at a unit price of p and replants the stand with cost c_1. The landowner faces the possibility of a regular catastrophic wildfire, which arrives according to a homogeneous Poisson process described by the Poisson parameter λ (Reed, 1984). Destruction of the stand by wildfire leaves no salvage value from the timber and requires the landowner to pay cost c_2 to clear burned timber and regenerate the stand. If the landowner can adapt to wildfire only by adjusting rotation length, then Reed (1984) shows that the landowner's effective discount rate is raised by λ, and therefore the optimal rotation length is diminishing in λ.

The first extension to Reed (1984) to consider other types of costly protection (e.g., prescribed burning) was Reed (1987), which has served as the foundation for many subsequent theoretical analyses of protection effort (e.g., Reed and Apaloo, 1991; Yoder, 2004; Amacher et al., 2005). Following Amacher et al.'s (2009) depiction, suppose the landowner considers a prescribed burning action PB that reduces the probability that wildfires arrive. For simplicity, assume this action has no impact on forest growth $F(t)$, but comes at an increasing marginal cost that is borne during replanting such that $c_1(PB)$, where $c_1'(PB) > 0$ and $c_1''(PB) > 0$. Once the prescribed burning action is taken, there is a decrease in the wildfire arrival rate such that:

$$\lambda = \lambda(PB), \text{ where } \lambda'(PB) < 0 \tag{1}$$

To consider how the landowner's optimal prescribed burning is affected by climate-induced changes in wildfire, let the wildfire arrival rate be a function of both prescribed burning PB and a climate variable such as temperature or vapor pressure deficit (C), such that $\lambda = \lambda(C, PB)$ and $\frac{\partial \lambda}{\partial C} > 0$.

Given the above setup, the expected bare land value of the stand is

$$V = \frac{\left[r + \lambda(C, PB)\right]\left[pF(T) - c_1(PB)\right] e^{-[r+\lambda(C,PB)]T}}{r\left(1 - e^{-[r+\lambda(C,PB)]T}\right)} - \frac{\lambda(C, PB)}{r} c_2 \tag{2}$$

where T is rotation age, and r is discount rate.

And the optimal amount of prescribed burning is found from the first-order condition with respect to PB:

$$\begin{aligned} V_{PB} = &\left(r + \lambda(C, PB)\right) c_1'(PB) + \\ &\lambda'(C, PB)\left([pF(T) - c_1(PB)] - \frac{[r + \lambda(C, PB)][pF(T) - c_1(PB)]}{r(1 - e^{-[r+\lambda(C,PB)]T})} - \frac{c_2}{r} \right) = 0 \end{aligned} \tag{3}$$

where T is the optimal rotation age that is solved from the first-order condition with respect to rotation length:

$$V_T = pF_T - \frac{\left[r + \lambda(C, PB)\right]\left[pF(T) - c_1(PB)\right]}{\left(1 - e^{-[r+\lambda(C,PB)]T}\right)} = 0 \tag{4}$$

At the margin, the landowner chooses PB by equating the marginal cost of protection to the marginal increase in the expected net return that comes from a lower wildfire arrival rate. Relevant to empirical work, Eq. (3) shows that the prescribed burn decision should be affected by all variables that affect both protection costs and the expected net return from timber harvest. Variables that affect prescribed fire decisions include biophysical conditions of the forest (e.g., stand volume, age, slope, elevation, soil productivity), climate conditions, past wildfire events that indicate risks, and regulatory requirements that impact the costs of conducting prescribed fires.

For further clarity using a specific functional form, assume the following logistic form:

$$\lambda = \lambda(C, PB) = \frac{1}{\left[1 + e^{(\alpha_0+\alpha_1 C+\alpha_2 PB)}\right]}, \text{ where } \alpha_1 < 0, \alpha_2 > 0 => \frac{\partial \lambda}{\partial C} > 0 \text{ and } \frac{\partial \lambda}{\partial PB} < 0 \tag{5}$$

In Eq. (5), the exogenous portion of the wildfire arrival rate is the wildfire arrival rate in the absence of prescribed burning ($PB = 0$) and is defined as λ_0, which is an increasing function of the climate variable C:

$$\lambda_0 = \lambda(C, PB = 0) = \frac{1}{\left[1 + e^{\alpha_0+\alpha_1 C}\right]} \tag{6}$$

[3] Another fuels management strategy for planted forests is to reduce stocking density (Amacher et al., 2005).

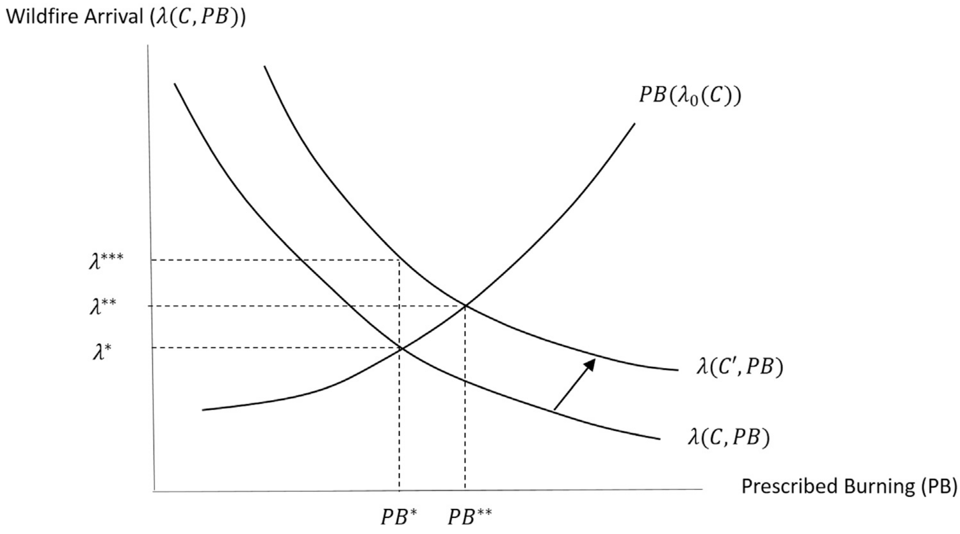

Fig. 2. Relationship between wildfire arrival and optimal prescribed burning λ_0 is the exogenous wildfire arrival rate in the absence of prescribed burning, $PB = 0$. C is a climate variable at current condition, and C' is new climate condition.

By assuming that the forest growth function is a conventional von Bertalanffy function used elsewhere in forest economics (e.g., Hashida and Lewis, 2019) of the form $F(T) = a(1 - e^{-bT})^3$, along with an increasing marginal cost of prescribed burning, the optimal amount of prescribed burning as a function of C and λ_0 can be numerically solved for a reasonable range of parameters and shown that:

$$\frac{\partial PB}{\partial C} > 0 => \frac{\partial PB}{\partial \lambda_0} > 0 \tag{7}$$

In Appendix B, we show example numerical calculations of the optimal amount of prescribed burning for two representative counties based on climate, prescribed burning, and wildfire arrival rate.

Intuitively, changes in the climate variable C that raise the exogenous wildfire arrival rate λ_0 will spur a response from the optimizing landowner to increase the amount of protective prescribed burning. Fig. 2 illustrates the general intuition. The curve $PB(\lambda_0(C))$ describes the landowner's optimal amount of prescribed burning as an increasing function of the exogenous component of wildfire arrival, λ_0, which is only the climate variable C. In this simplified model, climate C only affects land value through the wildfire arrival rate λ and not through the forest growth function $F(t)$, thus changes in climate C only facilitate movement along the $PB(\lambda_0(C))$ curve rather than a shift in the curve. When evaluated at a particular climate C, Fig. 2 illustrates the presence of an equilibrium amount of prescribed burning and wildfire (PB^*, λ^*). Consider the mechanism for how equilibrium is achieved. Suppose an exogenous climate shock changes C to C', which increases the wildfire arrival curve such that the wildfire arrival rate increases to above the equilibrium amount if prescribed burning were held fixed at PB^*, such that $\lambda^{***} > \lambda^*$. However, the landowners would respond to the climate-induced shift in wildfire by increasing their optimal amount of prescribed burning until a new equilibrium is achieved (λ^{**}, PB^{**}). Thus, the landowners prescribed burning adaptation ($PB^{**} - PB^*$) reduces wildfire arrival by ($\lambda^{***} - \lambda^{**}$). Empirical analysis is needed to estimate the slopes of the $PB(\lambda_0(C))$ and $\lambda = \lambda(C, PB)$ functions, which can then facilitate how prescribed burning is affected by wildfire and how wildfire is affected by prescribed burning.

2.2. Testable hypotheses and empirical goals

The theoretical model above sets a foundation for the simultaneous relationship between a region's wildfire arrival and prescribed burning effort, with key hypotheses that (i) prescribed burning is an increasing function of exogenous drivers of wildfire arrival, (ii) wildfire arrival is a decreasing function of prescribed burning, (iii) the equilibrium amount of wildfire and prescribed burning is a function of climate, and (iv) prescribed burning adaptation can mitigate some of the climate-induced increase in wildfire arrival. An empirical test of these hypotheses requires data on prescribed burning and wildfire in an econometric framework that consists of a prescribed burning equation with wildfire as an independent variable, along with a wildfire equation with prescribed burning as an independent variable. Another key goal of empirical estimation is to estimate the effects of prescribed burning on the probability of wildfire arrival, and the elasticity of prescribed burning with respect to wildfire arrival. The econometric literature on simultaneous equations provides a foundation for testing the relationships in this section, along with tests of how climate can impact equilibrium prescribed burning and wildfire.

Based on our theoretical model, we estimate two models: a model with prescribed burn decisions as the dependent variable and a second model with wildfire as the dependent variable. The first model estimates the prescribed burn decision as a function of realized climate variables, previous wildfire events, biophysical conditions, and owner characteristics. The second model estimates the impact of prescribed fires on wildfire events while controlling for the climate and biophysical conditions. The estimated system indicates how climate affects prescribed burn decisions directly and indirectly through wildfire. The system also indicates how climate affects wildfire events directly and indirectly through landowners adapting to climate through their prescribed burn decisions.

2.3. Key empirical features of measures of prescribed burning and wildfire occurrence

A key data source is prescribed fire permit data collected from state forestry agencies[4] summarized in Cummins et al. (2023), which serves as the empirical foundation to identify the location and magnitude of prescribed fire usage. The authors' personal conversations with fire experts in the Forest Service and university fire extension experts confirmed that burn permit data is the most accurate data source for capturing prescribed fire activities on private land. The historical prescribed fire data covers twelve southeastern U.S. states based on permits that landowners file with state agencies. Of the twelve states collected in Cummins et al. (2023), we use seven states (AL, GA, FL, MS, NC, SC, TN) that require burn permits, creating 2.1 million permit records. We focus on the states that require burn permits because the requirement makes it more likely that we accurately measure prescribed burning activity in these states than in states without permit requirements. We further subset the data to non-agricultural fires and non-sugarcane fires, resulting in about 1.6 million records over 11 years.[5]

The permit data includes descriptions of burn activity that are consistently applied across the states, including what burners report in their permit request: "burn type" describing the type or purpose of the burn (e.g., broadcast burning, wildlife management), date of ignition, acres treated, and latitude and longitude. Although the burners provide the coordinates, there may be measurement error in the coordinates. We aggregate the individual permit data into total prescribed fire acreage at the county level to minimize potential measurement error associated with the self-reported location of individual records. Furthermore, the aggregation to the county scale allows us to match the prescribed fire activities in the area with the occurrence of large wildfire events at the same scale. The final data set includes acreage of total forestland treated in prescribed fires in each year between 2010 and 2021 across seven states.

The burn permit data indicate that 162 out of the 615 counties (26%) had at least one year with zero acreage in prescribed burning, whereas every other county saw a non-zero amount of prescribed burning in every year. Of the 162 counties that had some years with no prescribed burning, 141 (87%) were in the two most northern states of Tennessee and North Carolina. Another feature of the prescribed burning data is a right-skew with some high outliers. While an inverse hyperbolic sine (IHS) transformation is one candidate for normalizing the right-skew of this variable that also contains a non-trivial amount of zero values, caution is warranted due to the sensitivity of the IHS transformation to the scale of measurement (Chen and Roth, 2024). Therefore, in order to focus on the "intensive margin" of marginal changes in prescribed burning, and to use a log transformation to normalize the right-skew of the data, we use data on those counties that always have a positive amount of prescribed burning in every year when estimating prescribed burning as the dependent variable.

Wildfire occurrence for each county is based on the wildfire perimeter records from Monitoring Trends in Burn Severity (MTBS). The MTBS includes all fires larger than 500 acres since 1984. We further subset the MTBS records to incident type "wildfire". Using the full dataset, we see that large wildfires occur during 5.1% of the county-year observations. For those large wildfires that do occur, the average size is 10,515 acres with a range between 506 acres and 358,048 acres. Therefore, given the low probability of observing a large wildfire in a county in a given year, we measure wildfire as a dummy variable equal to one if county c had a large wildfire in year t, and zero otherwise.

Some simple descriptive statistics set up the estimation challenge. First, the average acreage in prescribed burning is 12,923 acres (6,046 acres) for counties that experienced (did not experience) at least one large wildfire during our study period. So, prescribed burning acreage and the occurrence of large wildfires are positively correlated. Second, conditional on the set of counties that experience at least one large wildfire during our study period, the average acreage in prescribed burning is 16,224 acres (9,919 acres) if that large wildfire occurred (did not occur) within the last 3 years. So, prescribed burning acreage is much higher within the first few years after a large wildfire, suggesting that landowners might be responding to the recent occurrence of a large wildfire with more prescribed burning. Finally, for the set of counties that experience at least one large wildfire during our study period, the average acreage in prescribed burning during the three years that precede a large wildfire is 14,618 acres, while the average acreage in prescribed burning in other periods is 9,368 acres. Thus, multiple confounding factors will likely need to be accounted for if estimation is to uncover evidence in support of the hypothesized negative impact of prescribed burning on the probability of large wildfire.

2.4. Estimating the effects of previous wildfire events and climate variables on the prescribed burn decision

Our first estimating equation (Eq. (8)) uses the natural logarithm (log hereafter) of county c's prescribed fire acreage in time t as the dependent variable, with a set of independent variables that represent key attributes influencing timber productivity and risk

[4] Alabama Forestry Commission, Florida Forest Service, Georgia Forestry Commission, Mississippi Forestry Commission, North Carolina Forest Service, South Carolina Forestry Commission, and Tennessee Division of Forestry

[5] We removed agricultural fires by removing permit records that have any mention of "agriculture" or "agricultural" in the reported burn type. For the remaining permit records, we did not differentiate the intended purposes, whether hazard mitigation or wildlife management, for example, mainly to minimize the measurement errors of relying on reported burn types (e.g., misreporting the main purpose, multiple purposes). Indeed, about 17% of the permit records are missing the burn type altogether.

as discussed above. As wildfire risk, we use the binary wildfire occurrence indicator along with a measure of hot and dry climate conditions, giving us the following specification:

$$log(PB_{ct}) = \gamma_1 \widetilde{WB_{ct-\tau}} + \gamma_2 C_{ct} + \gamma_3 F_{ct} + \alpha_{est} + \epsilon_{ct} \tag{8}$$

where PB_{ct} is the prescribed burned acreage in county c in year t; $\widetilde{WB_{ct-\tau}}$ is the instrumented binary wildfire occurrence variable that is equal to one if county c experienced a large wildfire during the previous τ number of years and zero otherwise; C_{ct} is a measure of hot and dry climate conditions for county c in year t; F_{ct} is a vector of geophysical variables for county c in year t; α_{est} indicates ecoregion-state-year fixed effects; and ϵ_{ct} represents the error terms that are clustered by ecoregion-state. Ecoregions from the U.S. Environmental Protection Agency (EPA) group regions into distinct ecosystem patterns and have been used in numerous wildfire pyrogeography assessments (Iglesias et al., 2022; Donovan et al., 2017). We use level III ecoregions to account for the unobserved ecosystem characteristics (e.g., dominant forest type) that affect prescribed burn decisions. We further interact ecoregions with state and year to capture unobservable heterogeneity across states (e.g., variations in relevant regulations) and time (e.g., time-varying unobserved weather conditions or change in biophysical ecosystems). The ecoregion-state-year fixed effects capture state and time-varying unobserved elements of wildfire risk that influence prescribed burning for counties that have similar ecosystem characteristics. Clustering standard errors by ecoregion-state allows for arbitrary heteroskedasticity and spatial correlation across counties within ecoregions, along with arbitrary serial correlation across time for counties.

Since wildfire events may be driven by the same county-level time-varying unobservables that affect prescribed burns, we apply an instrumental variable approach and use naturally caused wildfires (e.g., ignited by lightning) as an instrument for the large wildfire variable. Importantly, our IV is the count of naturally caused wildfires of any size, not just large wildfires. For a preliminary look at the relevance of this instrument, we compute that counties that had at least one large wildfire during our study period saw an average of 9.85 naturally caused wildfires (of any size) per year, while counties that had no large wildfires only saw an average of 1.32 naturally caused wildfires per year. The ignitions (count) of naturally caused wildfires are time and county-varying variables that are driven by random weather events rather than suppression efforts and mitigation activities. Our first-stage equation uses the count of naturally caused wildfires as an excluded instrument for the large wildfire occurrence dummy variable (Eq. (9)) in an application of the two-stage least-squares method.

$$WB_{ct-\tau} = \beta_1 Z_{ct-\tau} + \beta_2 C_{ct} + \beta_3 F_{ct} + \alpha_{est} + \epsilon_{ct} \tag{9}$$

where $WB_{ct-\tau}$ is the binary indicator of wildfire occurrence in the previous τ number of years in county c; $Z_{ct-\tau}$ is the rolling average count of naturally-caused wildfires as an instrument for wildfires in previous τ number of years in county c. The remaining variables are the same as in Eq. (8). We include $\widetilde{WB_{ct-\tau}}$, a variable measuring recent exposure of county c to wildfire within two and three years prior to year t, excluding the current year, which allows us to estimate how prescribed burning responds to current wildfire occurrence, conditional on other factors that influence fire risk.

Building off the theory above, additional independent variables capture drivers of timber productivity and include annual maximum vapor pressure deficit (VPD) to measure the combination of hot and dry weather in C_{ct}, along with soil productivity, stand age, stand volume, slope, elevation, and ownership type in F_{ct}. Guidance from theory is that climate affects prescribed burning decisions through its impact on both productivity and risk of disturbance. The natural science literature finds strong evidence that higher levels of VPD – indicating hotter and drier conditions – have a strong impact on wildfire risk (Zhuang et al., 2021). However, it is unclear whether we should measure climate with long-term averages or as short-term weather events, so we use the machine learning k-fold cross-validation technique to evaluate which choice predicts the data better: a long-term 30-year representation of climate or a short-term annual representation of weather. We will also test different lengths of wildfire time frames, 2 years and 3 years. The standard errors are clustered at the ecoregion-state level, and each observation is weighted by the forested acres at each county to account for the variation in suitable land for burning (e.g., urban areas are less suitable for burning).

2.5. Effects of prescribed fires on the occurrence of large wildfires

Following the theoretical foundations above, we also estimate an equation with wildfire as the dependent variable, measured as a binary indicator of large (> 500 acre) wildfire occurrence at the county-year level, with recent prescribed fire acreage included in the set of independent variables. We use the inverse hyperbolic sine transformation of prescribed burning acreages that allows us to include the small number of observations with meaningful zero values and yields a similar interpretation to a model with a logged dependent variable (Bellemare and Wichman, 2020).[6]

As prescribed burns are likely correlated with unobservable drivers of wildfires (e.g., unmeasured weather events), we use the number of establishments in the forestry sector as a time and county-varying instrument in a fixed effects — instrumental variable (IV) estimation. Prescribed burning is labor-intensive and highly dependent on the availability of expertise in the forestry sector. Personal correspondence between the authors and local fire experts in the study area confirms that the implementation costs are one of the key determinants for prescribed burn decisions. The fire experts also explained that 50%–70% of prescribed burns in this area are conducted by contractors who are employed as forestry consultants. The number of establishments in the forestry

[6] In our data, only 6% of the sample has a 2-year rolling average of zero acres in prescribed burning. It is rare for any county in the study area to have two consecutive years with no prescribed burning. Therefore, we argue that the issue of zeros for the use of inverse hyperbolic sine transformation is mostly irrelevant in our wildfire model.

sector represents competitiveness, expertise, and availability of support for conducting prescribed burning. We present evidence in Section 4.2 that strongly supports the relevance of using forestry establishments as an instrument. Another identifying assumption is that the establishment count is uncorrelated with unobserved drivers of wildfire occurrence.[7] The exogeneity of our IV is supported by the observation that timber activity is the primary driver of establishments, rather than wildfire activity. In particular, the annual acreage subjected to timber harvest in our study region is roughly ten times as large as the annual acreage burned in large wildfires. Further, the forestry establishment count variable has a strong positive correlation with harvested acreage, with a correlation coefficient of approximately 0.6. In summary, our IV strategy rests on the assumption that the number of forestry establishments in a county affects wildfire occurrence only through its effects on landowner prescribed burning acreage.

In our main second-stage model (Eq. (10)), we estimate a Probit model with the large wildfire dummy variable that indicates whether each county c had a large wildfire in year t as the dependent variable. The wildfire indicator is modeled as a function of weather variables, biophysical conditions, and the inverse hyperbolic sine of acres treated in prescribed fires in the previous years, instrumented in the first-stage model (Eq. (11)). To alleviate the incidental parameters problem arising from including a large number of fixed effects in a non-linear model, we implement the correlated random effects approximation of fixed effects by including the Mundlak device with variables that represent the averages of all explanatory variables within each ecoregion-state-year (Mundlak, 1978). Formally, our main wildfire model is:

$$Prob(WB_{ct} = 1 | PB_{ct-\tau}, C_{ct}, F_{ct}, \overline{X_{est}}) = \Phi(\eta_1 \widetilde{PB_{ct-\tau}} + \eta_2 C_{ct} + \eta_3 F_{ct} + \eta_4 \overline{X_{est}}) \tag{10}$$

where WB_{ct} is equal to 1 if there is a wildfire in county c in year t; $\widetilde{PB_{ct-\tau}}$ is the instrumented inverse hyperbolic sine of rolling average acres treated in prescribed fires in the previous τ years in county c (excluding the current year); $\overline{X_{est}}$ is the average value of all explanatory variables for each ecoregion-state-year (the Mundlak device); and other variables are the same as in the prescribed fire estimating equation above. Standard errors are clustered at the ecoregion-state level.

The first-stage equation used to instrument for prescribed fire activities is:

$$PB_{ct-\tau} = \delta_1 Z_{ct-\tau} + \delta_2 C_{ct} + \delta_3 F_{ct} + \delta_4 \overline{X_{est}} + \epsilon_{ct} \tag{11}$$

where $PB_{ct-\tau}$ is inverse hyperbolic sine of rolling average acres treated in prescribed fires in the previous τ years in county c; $Z_{ct-\tau}$ is the number of establishments in the forest sector in the previous τ years in county c as IVs for prescribed fires. Estimation of parameters in the instrumental variables Probit model is conducted with full information maximum likelihood and weighted by forested acreage in each county, such that the equation of interest and first stage parameters are estimated jointly using Stata's (V. 18) ivprobit command.[8]

3. Data and variable measurement issues

The climate/weather data comes from the PRISM database at Oregon State University, and we use annual realized climate measures in maximum vapor pressure deficit (VPD). VPD is a measure of air moisture, and high values of VPD are associated with drought and have been linked to more extreme fire weather (Zhuang et al., 2021). The climate variables for year t are measured as averages between $t-30$ and t for long-term climate (30-year normal), and as annual average at t for short-term weather. As mentioned above, we test whether long-term climate or short-term weather representations predict the dependent variables better using k-fold validation. The wildfire variable used as an explanatory variable in the prescribed burn model for year t is measured as a binary wildfire occurrence between $t-\tau$, for $\tau = 1, 2, 3$ (excluding the current year t to alleviate concerns about reverse causality). The prescribed burn variable used as an explanatory variable in the wildfire model for year t is measured as a rolling average between $t-\tau$, for $\tau = 1, 2, 3$ (excluding the current year t to alleviate concerns about reverse causality).

Biophysical conditions of forestland come from the USDA Forest Service's Forest Inventory and Analysis (FIA) data. The ownership information is based on a geospatial data set created by the US Forest Service, which identifies private ownership categories (family, corporate, TIMO, REIT, and others), public categories (federal, state, local), and Native American tribal land (Sass et al., 2020).

Finally, to construct our instrument using the count of naturally-caused wildfires (i.e., wildfires that are started by non-human causes such as lightning) within each county, we use the USDA Forest Service's "Spatial wildfire occurrence data for the United States, 1992–2020" (Short, 2017). We construct instrumental variables representing the number of establishments in the forestry sector (NAICS 113 Forestry and logging) from the US Bureau of Labor Statistics (BLS) Quarterly Census of Employment and Wages.[9] The data is collected for each county for each year. In accordance with BLS's confidentiality policy, BLS generally withholds the publication of employment and wage data for any industry level in a county if the number of survey responses for the county is below a certain level. The number of establishments data does not have such confidentiality constraints.

The final panel data set used to estimate the prescribed burning decision consists of 5,197 county-year observations across seven southeast U.S. states over the period 2010–2021, while the data used to estimate the binary wildfire occurrence model consists of

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[7] One concern is that these forest sector indicators are also correlated with the wildfire suppression costs. Unlike wildfire extent (e.g., acreage burned), wildfire occurrence is more exogenous and not as correlated with suppression efforts. Furthermore, the costs of wildfire suppression spending in the southeast are much smaller and comprise only 1% of Forest Service suppression costs, compared to 20% in the Southwest and Pacific Southwest (U.S. Department of Agriculture and Forest Service, 2023b).

[8] See https://www.stata.com/new-in-stata/new-in-instrumental-variables-analysis/.

[9] Available at https://www.bls.gov/cew/.

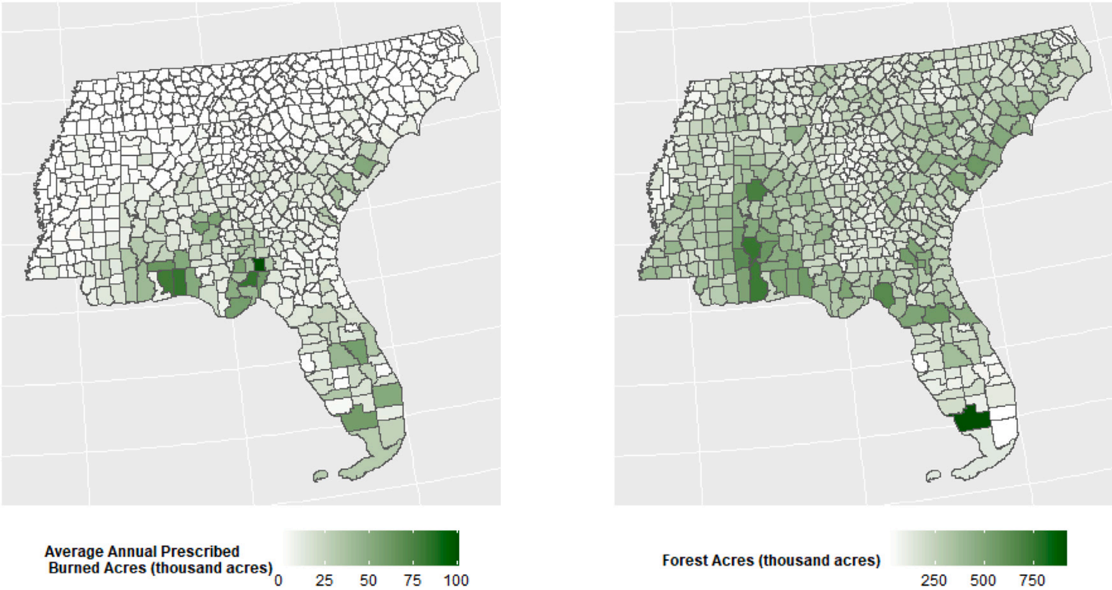


Fig. 3. Average annual prescribed fire application by county (left) and forested acres (right).

Table 1
Summary of prescribed fire permits by state.

	AL	FL	GA	MS	NC	SC	TN
Number of permits ('000)	141.7	432.0	861.5	41.1	8.3	144.9	4.0
Total acres ('000)	9,977	16,388	16,698	4,173	965	5,333	213
Annual avg acres ('000)	907	1,365	1,391	347	120	484	23

Note: The number of permits is the total number of permits submitted during 2010–2021. Total acres are areas burned in prescribed fires during this period. Annual avg. acres are the average acres burned during this period.

Table 2
Summary statistics of key variables.

	Avg.	Std.Dev
Average max vapor pressure deficit (hPa)	16.21	2.43
30-year moving avg max vapor pressure deficit (hPa)	16.25	2.01
Projected change in vapor pressure deficit 2030–2050 (%)	9.69	1.89
Saw timber volume MBF per acre	6.14	2.55
Total forest (thousand acres)	210.67	122.84
Private forest (thousand acres)	177.38	105.71
Average stand age (years)	42.30	16.06
Average siteclass (Best:1 to Worst:7)	4.53	0.60
Average slope (%)	10.15	11.79
Average elevation (feet)	560.94	621.62
Share of family ownership (%)	64.13	21.35
Number of prescribed burn permits	266.15	370.27
Acres burned annually in prescribed fires	7891.85	13 394.68
=1 if large wildfire happens	0.05	0.22
20-year moving avg count of wildfires	0.10	0.29
Number of forestry sector establishments	5.29	5.09

5,559 county-year observations for the preferred model with the key independent variable measured as a 2-year rolling average of prescribed burning acreage. The prescribed burning decision uses only counties that have non-zero prescribed burning in each year of 2010–2021, allowing us to use a log transformation and focus on the intensive margin of changes in prescribed burning acreage, rather than the extensive margin of whether to conduct any prescribed burning at all. Fig. 3 shows the spatial distribution of prescribed fire application (annual average acreage burned) at the county level in our study area, together with the forested areas (in acres). Table 1 summarizes state-level prescribed fire activities.

Table 2 summarizes the key variables used in our analysis. More than 80% of forests in the study area are privately owned, 64% of which are family-owned. The areas treated by prescribed fires dwarf the size of areas burned in wildfires in this region, which is starkly different than in the western U.S. Appendix Figure A1 shows spatial variation in VPD for the years 2010, 2015, and 2020.

4. Results

4.1. Prescribed fire decision

Our fixed effects — IV results for the prescribed fire equation are presented in Table 3. The table shows the results across different specifications of the prescribed burning equation using various climate and wildfire time frames, along with the first-stage results. The first results use short-term weather (annual) and recent wildfire events (previous 2-year moving average). The second results use short-term weather (annual) and recent wildfire events (previous 3-year moving average). The third results use a long-term climate variable (30-year normal) and recent wildfire events (previous 3-year moving average). We conducted the machine learning technique K-fold cross-validation to test which model fits the data better; the results are represented as mean squared error measures in the table. Representing climate as a short-term measure and using the previous 3 years as the wildfire event window (Model 2) fits the data best. All results use ecoregion-state-year fixed effects to account for unobserved variables that vary across ecoregion-state and by year. The standard errors are clustered at the ecoregion-state level.

As suggested in the basic summary statistics, counties that have had a recent large wildfire respond with a significant increase in prescribed fire acreage. Counties that had at least one large wildfire within the prior 3 years respond by approximately 1.7 times their prescribed burning acreage.[10] Prescribed fire acreage also responds to climatic measures of fire risk, as the elasticity of prescribed fire acreage with respect to vapor pressure deficit (VPD) is around 2.5. Thus, results provide clear evidence that warmer and drier conditions (higher VPD) spur private landowners to undertake additional prescribed burning, with one possible mechanism being that landowners view higher VPD as a signal of higher wildfire risk.

The test for weak instruments suggests that the instrument (naturally-caused wildfire count) is relevant as an instrument for the endogenous variable (large wildfire occurrence). The count of naturally-caused wildfires is strongly correlated with wildfire occurrence. The estimated impacts of wildfires on prescribed burning are smaller in magnitude when wildfire is not instrumented (column 1 in Table A1), indicating that the IV meaningfully changes results.

We ran several alternative specifications as robustness checks based on the short-term weather specification model (Appendix Table A1). In the Appendix Table A1, we find similar (but smaller) estimates of the effects of wildfire occurrence and VPD when using ecoregion-state-year fixed effects but no instrument (column 1), insignificant effects of wildfire occurrence when using annual temperature and precipitation rather than VPD (column 2), statistically insignificant parameter estimates for everything when using county rather than ecoregion-state-year fixed effects (columns 3, 4), similar inference when clustering standard errors by county (column 5), and somewhat larger (smaller) estimates of wildfire occurrence (VPD) when using only ecoregion-state fixed effects in an IV estimation (column 6). The results with the county fixed effects (columns 3, 4) are not close to statistical significance at any reasonable significance level, which suggests that the county fixed effects might absorb most of the usable variation in the data. To explore this further, we regress log(prescribed burn acres) on county fixed effects alone and find that the R-squared is 0.83, while the equivalent R-squared when we regress the outcome on county and year fixed effects is 0.84. We conclude that there is too little usable variation to include fixed effects defined at the county level.

4.2. Effect of prescribed fires on wildfire occurrence

The next results show estimates of marginal effects from the equation where wildfire is the dependent variable — the binary wildfire occurrence (=1 if a large wildfire occurred, 0 otherwise). In Table 4, column 1 presents an uninstrumented Probit model with the Mundlak device approximating ecoregion-state-year fixed effects. Column 2 presents estimates from an IV Probit without the Mundlak device, while column 3 presents our preferred estimates from an IV Probit with the Mundlak device. Column 4 is also an IV Probit with the Mundlak device, but we use prescribed burn acreage in the past 1 year instead of 2 years. Similarly, column 5 uses the past 3 years of prescribed burn acreage. The coefficient estimates and the first-stage results for the IV models are included in Tables A2 and A3, respectively. Importantly, the F-statistic for the null that the excluded instrument (plus its Mundlak mean) is jointly zero is well above the weak instrument threshold of 10, indicating strong evidence in support of the relevance of the instrument. The uninstrumented results (column 1) show that prescribed fires increase the probability of wildfire events, contradicting the premise that prescribed fires mitigate wildfire risks, but consistent with the positive correlation between prescribed burning acreage and large wildfire occurrence from the descriptive statistics. However, when we use the number of establishments in the forest sector as an instrument, combined with the Mundlak device (column 3), the estimated marginal effect estimates for the prescribed fire acreage variable (2-year rolling average acres) become intuitively negative and statistically significant ($p < 0.05$). In particular, a 1% increase in prescribed fire acreage lowers the probability of a large wildfire by approximately 0.085 percentage points in our preferred Model (Table 4 column 3). Consistent with prior natural science research, estimates also indicate that VPD strongly increases the probability of a large wildfire occurrence - a 1% increase in VPD raises the probability of a large wildfire by 0.355 percentage points in our preferred specification.

Our preferred marginal effect estimates show how prescribed burning can be used to adapt to the increasing wildfire risk from climate changes that result in hotter and drier conditions through increased VPD. In particular, a 4.18% increase in prescribed burning acreage would lower the probability of a large wildfire by approximately 0.355 percentage points, which would perfectly

[10] This is calculated as $exp(\beta) - 1$ with β being the parameter estimate of the wildfire variable.

Table 3
Prescribed Burn Decision: Different Weather/Climate Observation Length and Wildfire Event Window.

	Model 1		Model 2		Model 3	
	First stage	Second stage	First stage	Second stage	First stage	Second stage
=1 if it had a wildfire in previous 2yrs		0.856**				
		(0.317)				
=1 if it had a wildfire in previous 3yrs				1.004***		1.054***
				(0.323)		(0.346)
Log(Avg max vapor pressure deficit)	−0.222	2.496***	−0.295	2.597***		
	(0.211)	(0.831)	(0.307)	(0.917)		
Log(30yr max vapor pressure deficit)					−0.246	2.839**
					(0.437)	(1.161)
Saw timber volume MBF per acre	−0.014*	0.010	−0.021**	0.020	−0.021**	0.022
	(0.008)	(0.042)	(0.010)	(0.043)	(0.010)	(0.042)
Avg siteclass	0.079***	0.061	0.107***	0.019	0.107***	0.022
	(0.021)	(0.102)	(0.024)	(0.100)	(0.025)	(0.094)
Avg stand age (10 years)	0.029*	0.175***	0.037*	0.164***	0.037*	0.166***
	(0.016)	(0.037)	(0.019)	(0.036)	(0.019)	(0.036)
Avg slope (%)	−0.002	−0.024	−0.001	−0.024	−0.001	−0.024
	(0.001)	(0.014)	(0.002)	(0.014)	(0.002)	(0.015)
Avg elevation (100 ft)	−0.001	−0.086*	0.000	−0.086*	0.000	−0.083*
	(0.007)	(0.044)	(0.010)	(0.043)	(0.012)	(0.043)
Share of family ownership	−0.205***	−0.592*	−0.256***	−0.517*	−0.259***	−0.480
	(0.055)	(0.309)	(0.066)	(0.301)	(0.065)	(0.300)
2yr avg count of naturally-caused wildfires	0.009***					
	(0.001)					
3yr avg count of naturally-caused wildfires			0.010***		0.010***	
			(0.002)		(0.002)	
Ecoregion-state-year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,197	5,197	5,197	5,197	5,197	5,197
MSE (cross-validation)		1.354		1.345		1.348
R^2	0.35111	0.57124	0.37309	0.56953	0.37200	0.56602
Within R^2	0.06212	0.13493	0.07453	0.13149	0.07291	0.12441
F-test (IV only), p-value	1.12×10^{-33}	0.00250	1.33×10^{-29}	0.00025	2.93×10^{-29}	0.00013
Wald (IV only), p-value	9.27×10^{-16}	0.00687	2.38×10^{-7}	0.00186	1.52×10^{-7}	0.00234

Note. The dependent variables for the first stages are: "=1 if it had a wildfire in previous 2yrs" (Model 1), "=1 if it had a wildfire in previous 3yrs" (Model 2), and "=1 if it had a wildfire in previous 3yrs" (Model 3). The dependent variable for the second stage is "Log(Prescribed burn acres)" for all three models. Standard errors are clustered at the ecoregion-state level.

* $p < 0.1$.

** $p < 0.05$.

*** $p < 0.01$.

Table 4
Marginal Effect of Prescribed Fire on Probability of Wildfire Events: Probit Model with Prescribed Fire Instrumented by the Number of Establishments in the Forestry Sector.

Marginal effects	Model 1	Model 2	Model 3	Model 4	Model 5
Prescr Burn Acres rolling avg past 2 years	0.022***	−0.012	−0.085**		
	(0.008)	(0.017)	(0.040)		
Prescr Burn Acres past 1 year				−0.094**	
				(0.038)	
Prescr Burn Acres rolling avg past 3 years					−0.061
					(0.043)
Log(Avg max vapor pressure deficit)	0.081	0.342**	0.355**	0.365**	0.279*
	(0.114)	(0.152)	(0.173)	(0.182)	(0.170)
Observations	5559	5559	5559	6185	4941
IV	No	Establish	Establish	Establish	Establish
Mundlak FE Approx (ecoregion-state-year)	Yes	No	Yes	Yes	Yes
Standard-Error Clustering			Ecoregion-state		
F stat (1st stage) for within-varying plus Mundlak mean IVs	NA	NA	26.93	31.89	23.98
F stat (1st stage) for within-varying IVs only	NA	266.31	48.21	55.66	42.69

Note. Establish: The number of establishments in the forestry sector.

* $p < 0.1$.

** $p < 0.05$

*** $p < 0.01$.

offset the higher wildfire risk that arises from a 1% increase in VPD. Therefore, our results provide an estimate as to how much extra prescribed burning effort is needed to keep a region's large wildfire probability fixed under a hotter and drier climate.

The marginal effect of prescribed fires is robust to including wildfire suppression efforts (see note on Appendix Table A4 for details) or naturally-caused wildfire count as additional independent variables. Therefore, since we find that results are largely invariant to the omission or inclusion of wildfire suppression or naturally caused wildfire ignitions, this provides suggestive evidence that our excluded IV (forestry sector establishments) is likely to be uncorrelated with unmeasured drivers of wildfire. We also assess the use of county fixed effects rather than ecoregion-state-year fixed effects, shown in Table A5. We find that the use of county fixed effects leads to a marginal effect estimate for the prescribed burning variable that is far from statistical significance at any reasonable significance level, suggesting that there is too little usable within-county variation. To explore this possibility further, we find that the correlation coefficient between the prescribed burn acreage variable and its Mundlak-average variable is 0.96, indicating very little within county variation in prescribed burn acreage. The F-statistic for the first stage indicates minimal IV relevance once we approximate for county fixed effects with the Mundlak county averages, which is in contrast to the main specification that proxies for ecoregion-state-year fixed effects. In contrast, we have more within county variation in the log(VPD) variable, as the correlation coefficient between log(VPD) and its Mundlak-average is 0.84.

4.3. Simulation of prescribed fires and wildfires

To better understand the extent to which climate adaptation by prescribed burning can be expected to mitigate wildfire acreage, we use our estimation results to simulate how prescribed fire acres, wildfire probability, and the realized wildfire count co-evolve when the climate gets warmer and drier. We simulate the projected warmer and drier climate change by increasing VPD according to the average downscaled output from four Global Climate Models (GCMs) projection (Abatzoglou and Brown, 2018) for all counties in the study area. These GCMs (CCSM4, HadGEM, CNRM, and CSIRO) were selected as they were ranked as some of the best climate projections for reproducing observed climate in the southeast U.S. (Rupp, 2016). According to the RCP 8.5 climate projection based on these models, counties in the study areas expect to see a change in VPD in the range of +3 to +13% (average +9.6%) between 2030 and 2050.[11] The change is spatially and temporally heterogeneous (see Figures A2–A3 for projected VPD changes spatially and Table A6 for each state).

We first project annual prescribed fire acreage as a function of only the projected change in VPD for the next 20 years starting in the year 2030. Using the estimates from our IV model results for prescribed fires (Table 3 column 4) and wildfires (Table 4 column 3),[12] we simulate how prescribed fire acreage and large wildfire occurrence would change in response to each county's projected increase in VPD. The prescribed fire acreage is updated every year according to projected VPD and our estimate that links VPD and the prescribed burn decision. We define a baseline projection where prescribed burning responds directly to changes in VPD through our estimate of γ_2 in Eq. (8), and wildfire responds directly to changes in VPD through our estimate of η_2 in Eq. (10). Importantly, our baseline projection does not let prescribed burning and wildfire affect each other in the simultaneous equations system - i.e., $\widetilde{WB}_{ct-\tau}$ is held fixed in Eq. (8) and $\widetilde{PB}_{ct-\tau}$ is held fixed in Eq. (10). Our approach of using econometric estimates along with projected changes in VPD to simulate future wildfires under climate change is similar in spirit to Burke et al. (2023), who also use projected changes in VPD to simulate future wildfire smoke under climate change.

Next, we go beyond prior literature like Burke et al. (2023) to simulate the full simultaneous change between prescribed burning and wildfire, where increases in VPD raise both prescribed burning and wildfire, while prescribed burning acreage changes in response to wildfire, but wildfire also changes in response to prescribed burning i.e., $\widetilde{WB}_{ct-\tau}$ is not held fixed in Eq. (8) and $\widetilde{PB}_{ct-\tau}$ is not held fixed in Eq. (10). The difference between this simultaneous change projection and the baseline projection quantifies how climate adaptation in prescribed burning affects the change in wildfire acreage, as shown conceptually in Fig. 2. Specifically, prescribed fire acreage is updated every year based on our estimates for Eq. (8). Using a Monte Carlo simulation to generate realizations of wildfire occurrence from our probit model of the probability of large wildfires, we draw a random uniform number at each time period to compare to the wildfire probability and determine the wildfire occurrence.[13] We repeat the same process each year for each county, and then we repeat the whole process 500 times to take the average of simulated results.

We begin our presentation of the simulation results by showing an illustrative example of how prescribed fire and wildfire evolve over time in our simulation using two representative counties, Polk and Santa Rosa, both located in Florida (Fig. 4). In Fig. 4, the blue line shows prescribed fire acreage when landowners respond only to an increase in VPD, while the gray line shows prescribed fire acreage when landowners respond both to VPD and the corresponding increase in wildfires that also comes from an increase in VPD. The difference between the gray line and blue line at any point in time is the additional prescribed fires induced by wildfire outcomes. On the other hand, the orange line shows the large wildfire probability when there is no climate adaptation through prescribed burning, and the yellow line shows the large wildfire probability when landowner-prescribed burns mitigate some of the wildfire increase as a climate adaptation response. The difference between the orange and yellow lines at any point in time represents the wildfire mitigation benefits from the climate adaptation of prescribed burning.

[11] RCP or Representative Concentration Pathways portray possible future greenhouse gas emission scenarios. RCP 8.5 is the highest baseline emissions scenario, in which emissions continue to rise throughout the 21st century. Although we use RCP 8.5 projection in our main results, Appendix has results based on RCP 4.5 (Table A7 and Figure A4). RCP 4.5 is considered as a moderate scenario where emissions peak around 2040. Compared to RCP 8.5 scenario, projected VPD increase during 2030–2050 in RCP 4.5 scenario is much more moderate, with just 0.1% change in 2030–2050.

[12] To calculate the predicted probabilities, we use the two-step coefficient estimates for the IV Probit model for simplicity. Estimated marginal effects are consistent across the two-step and full information maximum likelihood estimates.

[13] If wildfire happens in $t-1$ following a year without a wildfire, the county increases prescribed fires by 173%. On the other hand, if the county had no wildfires in $t-1$ although it had wildfires in the previous year, it reduces its prescribed burning by 63%. If the wildfire occurs consecutively or no wildfires at all consecutive years, its prescribed acreage changes according to changes in VPD only.

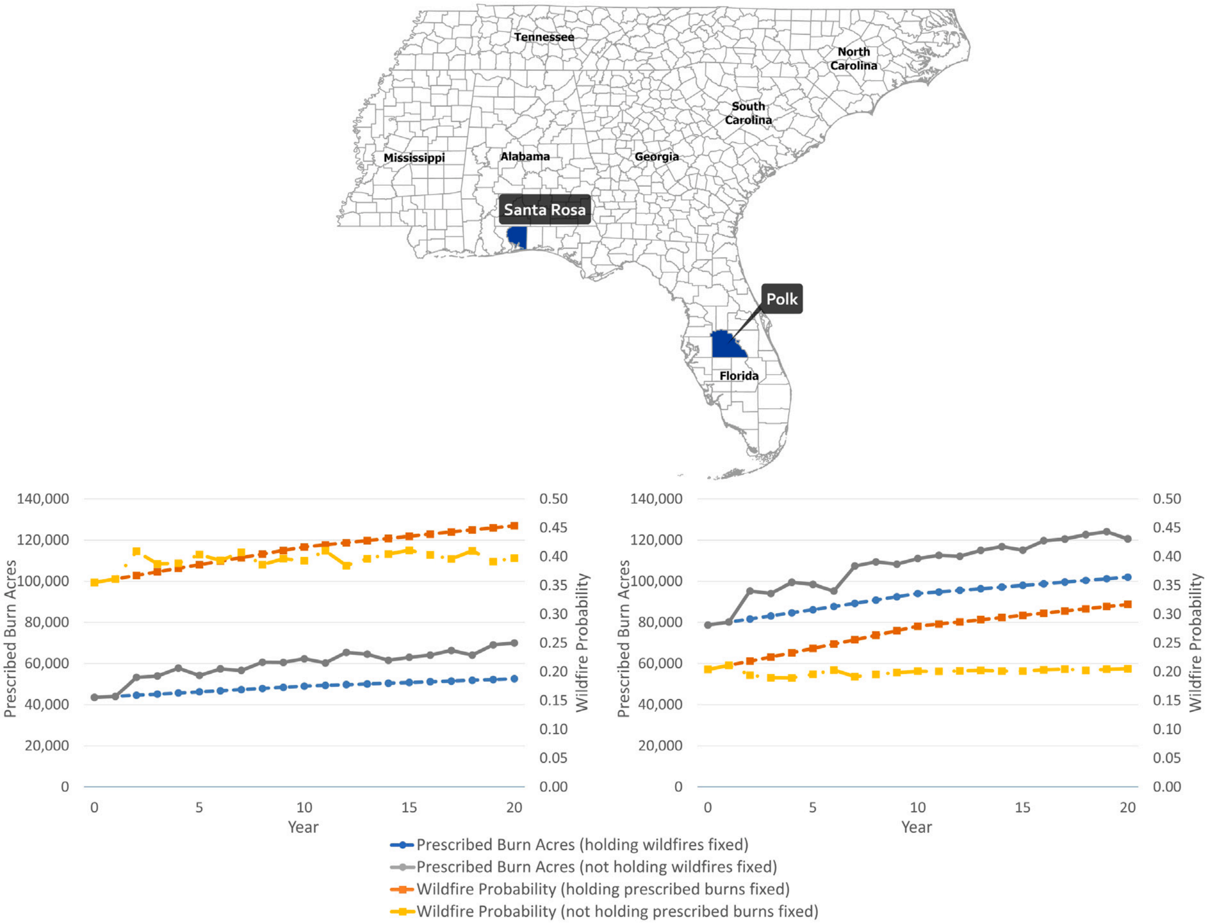
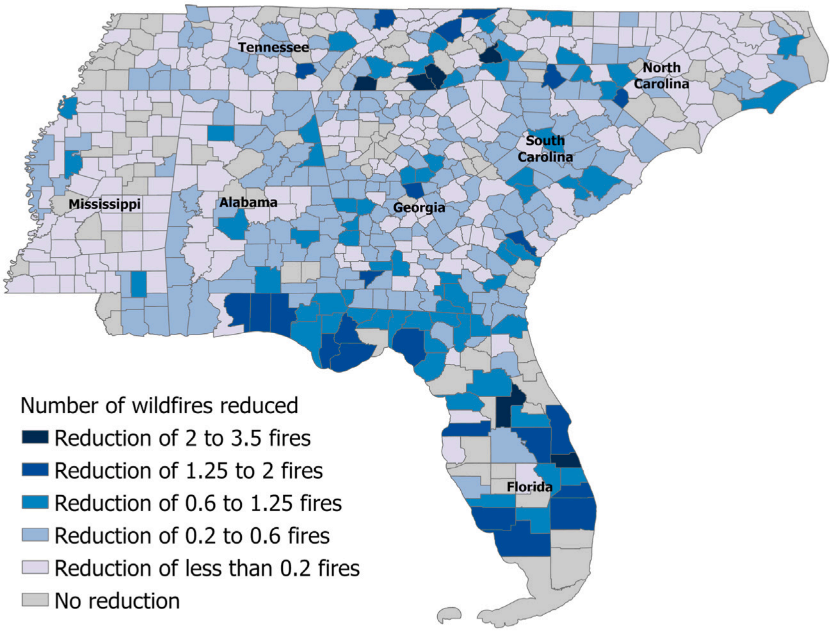


Fig. 4. Simulated change in prescribed fire and wildfire probability in Polk County, FL (left) and Santa Rosa County, FL (right). The blue lines are prescribed burn acreage when landowners respond only to a change in VPD (while holding the wildfires fixed), the gray lines are prescribed fire acreage when landowners respond both to VPD and the corresponding increase in wildfires that are also affected by an increase in VPD, the orange lines are the large wildfire probability when there is no climate adaptation through prescribed burning, and the yellow lines are the large wildfire probability when prescribed burns mitigate some of the wildfire increase. Parameter estimates used in the simulation are based on Table 3 Model 2 for prescribed fire acreage and Table A2 column 3 for wildfire probability. Note that the coefficient estimates in Table A2 column 3 are adjusted with predicted values from the first-stage model to calculate the wildfire probability. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The wildfire mitigation effect from climate adaptation is aggregated to the entire study area. In aggregate, the number of large wildfires is projected to be an average of 712 over 20 years (36 per year) if we only account for a change in VPD. However, the number of large wildfires is mitigated by the increase in prescribed burns, resulting in only 572 fires (29 per year), a reduction of 140 fires in the next 20 years (a reduction of 7 fires per year). Thus, the climate adaptation tool of prescribed burning is projected to reduce the number of large wildfires by about 20% of the total projected number of wildfires in the baseline scenario. As a reference, if we assume the current level of VPD remains constant in the next 20 years, the projected number of large wildfires is 530 (27 per year). Further, prescribed fire acreage will increase by 30% in 20 years due to an increase in VPD alone in our baseline scenario and by 41% if we account for the simultaneous relationship with wildfire. Thus, the 41% projected increase in prescribed burning mitigates the projected annual change in wildfires from +9 per year to +2 per year, mostly offsetting the higher wildfire risk resulting from the 9.6% increase in VPD from climate change.

The top map in Fig. 5 shows the spatial distribution of the results depicting how climate adaptation from prescribed burning mitigates growth in wildfires, calculated as the difference in wildfire count in the next 20 years between the baseline scenario and full scenario (i.e., avoided wildfires due to prescribed fires). The bottom map presents the number of avoided wildfires divided by the total number of wildfires by 2050 in the baseline scenario.

Table 5 summarizes the aggregate simulation results for each state, and each column represents: (1) the difference in prescribed fire acreage between the baseline and full simultaneous scenarios in 2050 (i.e., impact of wildfires in inducing more prescribed burns), (2) the difference in large wildfire probability between the baseline and full simultaneous scenarios in 2050 (i.e., impact of prescribed fires in reducing large wildfires), (3) the difference in total number of large wildfires over the next 20 years between baseline and full scenarios (i.e., avoided large wildfires due to prescribed fires), (4) the avoided large wildfires (column 3) expressed



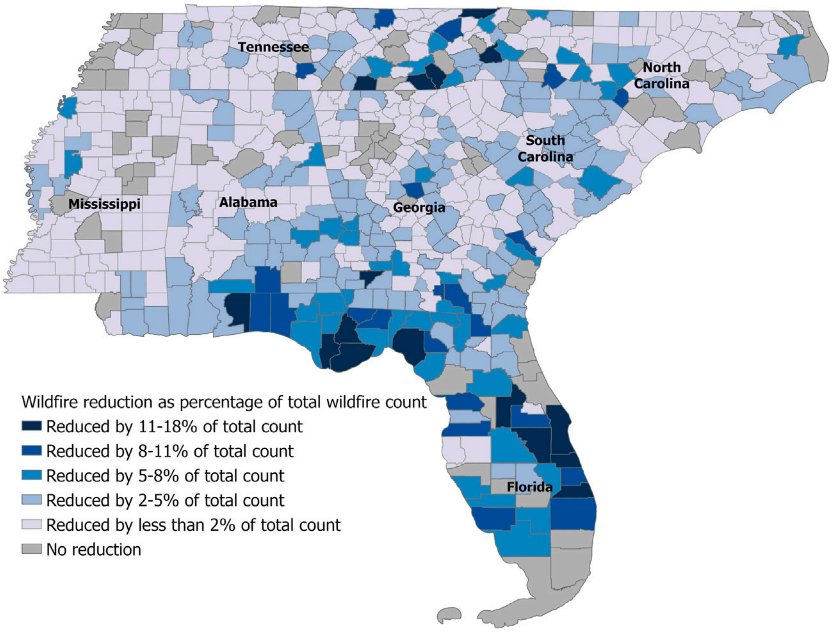


Fig. 5. Top: Reduction in wildfire count due to prescribed fires by 2050. Bottom: Reduction in wildfire due to prescribed fires as a percentage of total projected wildfire count by 2050.

as a percentage of total number of large wildfires in the baseline scenario over the next 20 years, (5) the percentage increase in prescribed burning in the full scenario outcome in 2050 relative to the current level, and (6) the percentage change in projected VPD by 2050. We see some heterogeneity across states in Table 5. The effectiveness of increased prescribed burning in reducing wildfire acreage depends on the change in VPD, as well as the level of prescribed burns and wildfires. South Carolina, for example, is currently an active prescribed burn user despite the state having the lowest number of acres burned in wildfires in the past 20 years. With its relatively high projected VPD increase of 10.3% by 2050, prescribed fires are expected to have a sizable mitigation potential in reducing the number of large wildfires. With the highest projected increase in VPD (+11%), Georgia will also have the largest mitigation benefits (40 wildfires or 43% of total wildfires mitigated) from prescribed burning. It is worth mentioning that the largest

Table 5
Simulation results by state.

State	Delta prescribed burn (PB) acres	Delta wildfire (WF) probability	Delta WF count	Delta as % of total WF count	PB acres increase	VPD change by 2050
All	507,310	−2.0%	−140	−20%	41%	9.6%
AL	93,938	−2.2%	−18	−26%	42%	10.2%
FL	327,086	−5.6%	−35	−10%	50%	9.0%
GA	45,874	−2.0%	−40	−43%	37%	11.1%
MS	7,845	−0.7%	−8	−34%	33%	10.4%
NC	9,890	−1.4%	−16	−18%	34%	8.9%
SC	20,787	−2.4%	−15	−45%	34%	10.3%
TN	1,889	−0.7%	−9	−21%	31%	7.3%

Note: Column 1 shows the difference in prescribed burn acres between the baseline (holding prescribed fire fixed) and full scenario (not holding prescribed fire fixed) outcomes in 2050: full scenario PB — baseline PB. Column 2 shows the difference in wildfire probability between the baseline and full scenarios in 2050: full Prob(WF) - baseline Prob(WF). Column 3 shows the difference in the number of wildfires between the baseline and full scenarios over the next 20 years: full WF count — baseline WF count. Column 4 shows the percentage of wildfire mitigation (column 3) relative to the total number of wildfires in baseline case over the next 20 years. Column 5 is the percentage increase in prescribed burn in full scenario outcome in 2050 relative to the current level, and column 6 is the percentage change in the projected vapor pressure deficit between 2030 and 2050.

prescribed burn acreage projected is in wildfire-prone areas of Florida by 2050, but it will only constitute 12% of the current forested area, indicating the further potential of prescribed fires as an adaptation tool.

5. Conclusion

As climate change intensifies, policy and land management have started to focus on increasing the adaptive resilience of forest ecosystems to new fire regimes of more intense and frequent wildfires. Rather than suppressing all fires, this approach includes active use of prescribed fires to reduce fuel loads and mitigate large wildfires. In contrast to wildfires, the risks of prescribed fires spreading into out-of-control fires are relatively low, and more than 99% of prescribed fires are held within planned perimeters successfully (Ryan et al., 2013). However, in the western U.S., the use of prescribed fires has been generally confined to federal land, and an evidence-based understanding of its wildfire mitigation benefits based on empirical data has been lacking, with only some very recent work (e.g. Stephens et al., 2023.)

Natural resource economic theory shows that prescribed burning on timberland is an economic decision and is influenced by all conventional drivers of the economic value of timberland (e.g., growth parameters, stumpage prices, reforestation costs, etc.). Our theoretical framework shows how climate shocks that increase a region's wildfire risks will induce more prescribed burning efforts by optimizing timberland owners. Thus, if wildfires are slowed by prescribed burning, then a region's equilibrium amount of wildfire and controlled burning is determined by the interaction between climate, wildfire, and the optimizing decisions of private timberland owners. Using large-scale panel data on burn permits in the southeastern U.S., we conduct the first econometric analysis to estimate the impact of climatic, wildfire, and other factors on prescribed fire acreage. We also estimate the effect prescribed burns have on wildfire incidents to assess the wildfire mitigation benefits of prescribed fires.

By applying ecoregion-state-year fixed effects and instrumental variables to this simultaneous equations system with county-level panel data, our approach accounts for endogeneity concerns arising from unobservable factors that affect both wildfires and prescribed burn decisions. We find that hotter and drier climate conditions strongly increase both wildfires and prescribed fires, as is predicted by theory. Recent occurrences of large wildfires, which arguably proxy for recent wildfire risk, are also found to sharply increase prescribed fire use, indicating the interactive relationship between prescribed fire and large wildfires. Our findings are consistent with Wibbenmeyer et al. (2019) finding that recent wildfire occurrences generate increased fuel management projects (like prescribed burning) on federal lands in the western U.S. Wibbenmeyer et al. (2019) argue that since recent wildfires reduce fuels, then risk should be lower after wildfires and therefore demand for fuels management should decrease rather than increase; which leads them to interpret their findings as evidence of a bias resulting from salient events like wildfires. In contrast to some of the extremely large wildfires that occur in the western U.S., the large wildfires in our study region burn on average less than 9% of forestland in counties that receive large wildfires, and so over 90% of forests – and fuel – remain post wildfire. Thus, we interpret recent large wildfire occurrences in the eastern U.S. as a reasonable signal for increased wildfire risk.

We also find evidence that prescribed fires reduce wildfires. Our simulation projects future large wildfires over a 20-year horizon under a range of climate change and climate adaptation scenarios, including (i) 27 large fires per year if current conditions hold, (ii) 36 large fires per year when VPD increases by almost 10% on average while prescribed burning is held fixed at current levels, and (iii) 29 large fires per year under both climate change (10% higher VPD) and climate change adaptation (41% increase in prescribed burning). Thus, our projected climate change adaptation of prescribed burning lowers the 20-year cumulative total number of wildfires by 20%, and lowers the projected increase in wildfires from 9 additional fires per year down to 2 additional fires per year (a 78% reduction). While our findings show that landowners respond to a hotter and drier climate with an increase in prescribed fires, our results show that wildfires themselves also increase as a direct result of a hotter and drier climate, which is strongly consistent with the natural science literature (e.g., Abatzoglou and Williams, 2016). The novelty of our simulated projection of large wildfires is incorporating explicit estimates of the economic choice of how to adapt to climate change through prescribed burning that manages fuel loads.

It is worth noting, however, that our main findings are specific to the study area and constrained by the variability present in our empirical data. First, we did not have enough within-county variation to estimate parameters with a combination of county and year fixed effects, so our results instead rely on a broader spatial scale of fixed effects that use a combination of level III ecoregion, state, and year. Second, we chose the U.S. Southeast for its prevalent use of prescribed fires and the availability of extensive burn permit data, but the region has not experienced large wildfires to the same extent as the western U.S., especially with regards to moderate and high severity wildfires. Therefore, we cannot generalize our findings in other regions where prescribed fire is part of active policy discussion, including the western U.S. states. However, our research methods can be applied elsewhere with location-specific context, including differences in liability stipulations across states. California historically used strict liability for cases when prescribed fire escapes, which places the burden of restitution for damages on the burner regardless of any actions taken by the burner to avoid damages. But California recently amended the law (California SB926) to gross negligence, which requires the complainant to show the damage resulting from the burner having a conscious and voluntary disregard for the need to use even reasonable care. Unlike southeastern states, however, the western coastal states (CA, OR, WA) require a permit application fee, which often amounts to a considerable sum (Wood and Varner, 2023). The southeastern states, on the other hand, have either a gross negligence clause or slightly stricter simple negligence, and none of them require permit application fees. In most states where gross negligence applies, there are typically statutorily prescribed fire standards and certification requirements that a burner must follow in order to receive the benefit of gross negligence standards (Weir et al., 2020).

Our results indicate that prescribed fires reduce the occurrence of large wildfires and will play an increasing role in climate change adaptation. They provide other ecological benefits, such as soil restoration and regeneration, which are critical functions for many fire-dependent ecosystems. Future fire regimes will require a holistic land management strategy that includes a range of adaptation options, including thinning, restoring diverse species adapted to fires, and preserving healthy forest ecosystems. Our research is the first study to econometrically estimate the simultaneous interaction between prescribed fires and wildfires, with an emphasis on how prescribed fires can be viewed as a climate adaptation tool.

A few avenues for future research are worth mentioning. Prior theoretical work (e.g., Lauer et al., 2017) indicates there is a socially optimal level of fire management that accounts for externalities across landowners. Future research could compare the socially optimal level with the actual level of fire management to empirically examine the under-provision of the public good nature of prescribed fires. Prescribed fires might not be feasible if conditions become too dry and hot, so there might be an upper limit to VPD where prescribed burning is possible. Indeed, a recent study evaluated differences in burn days between the present (2006–2015) and future conditions (2051–2060) and found that burn days will decrease in the Southeastern U.S. due to rising maximum temperatures and declining moisture, limiting prescribed burn opportunities (Jonko et al., 2024). However, the study also concludes that the future climate in many areas of the western U.S. presents opportunities to expand prescribed fire applications. Fine-tuning the situations (locations and timing) where prescribed fires can mitigate wildfires could be an interesting addition to our analysis. Furthermore, the effect of wildfires could also work to reduce the imminent need to treat fuels as they naturally clear fuel loads. Our model uses past wildfire events as a measure of wildfire risk that landowners respond to mitigate, but analysis at a more spatially granular scale could distinguish these different signals from wildfires that result in the spatially and temporally different impacts of wildfires in implementing prescribed fires over time. The future policy environment could also play an important role in promoting or restricting prescribed fire management options for private landowners. Coincidentally, the Environmental Protection Agency (EPA) has recently proposed (EPA-HQ-OAR-2015-0072) more stringent national ambient air quality standards (NAAQS) for particulate matter (PM), and some advocates for prescribed burns have been opposing the policy change on the grounds that it would restrict the use of prescribed fires for private landowners. Prescribed fire advocates recommend exempting all prescribed fires on private lands from the proposed rule based on the premise that prescribed fires would reduce total PM pollution by abating emissions from wildfires. Future studies could build off our findings and examine the magnitude of emission reduction benefits from prescribed burning to examine how such regulatory exemptions impact net emissions.

CRediT authorship contribution statement

Yukiko Hashida: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **David J. Lewis:** Writing – review & editing, Validation, Methodology, Formal analysis, Conceptualization. **Karen Cummins:** Writing – review & editing, Data curation.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: The authors declare no financial and personal relationships that could inappropriately influence or bias their work. The corresponding author, Yukiko Hashida, was supported by the USDA Forest Service Joint Venture Research Agreement (23-JV-11330180-079).

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jeem.2024.103081.

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