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 then use panel data on prescribed burn permits across the southeastern U.S. states to empirically estimate i) how climate and previous wildfire events affect prescribed burn decisions and ii) how climate and prescribed burning affect wildfire extent and ignition. Based on a fixed effects – instrumental variables identification strategy, our estimated simultaneous system finds that a hotter and drier climate will increase the use of prescribed burning, with landowner adaptation to corresponding wildfire risk being a key mechanism. Further, we find that a hotter and drier future climate will increase wildfires, though climate adaptation by landowners will mitigate the growth in wildfire acreage from a 17% increase down to a 14% increase. Our findings also indicate that policies that increase regulatory costs of prescribed fire have a strong negative impact on prescribed fire acreage. This paper provides intuition and quantitative evidence regarding the interaction between climate, wildfire, and landowner management adaptation.

Keywords: Prescribed fire, Controlled burn, Wild fire mitigation, Climate Change, Forest

JEL Codes: Q23, Q24, Q28, Q54

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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 (Fountain, 2022; Regan, 2022). Since wildfires are expected to increase in frequency and intensity with climate change (Abatzoglou and Williams, 2016), fuel management will be a critical land management option for private landowners to adapt to climate change. 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]

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, no empirical economic studies examine prescribed burn decisions at a scale larger than a single burn location. The current literature lacks the critical economic link between climate, prescribed fire

[1] For example, longleaf pine 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 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 and gopher tortoises, are closely tied to frequent prescribed fires.

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 percent 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, climatic and other factors on prescribed burning, and ii) the impact of prescribed burning, climatic and other factors on wildfires. The key data we exploit is burn permit data acquired by the Tall Timbers Research Station for ten 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. To understand the factors that influence prescribed burn decisions, we first estimate the effects of climate, biophysical conditions, regulatory stringency, 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 acreage. We exploit the panel nature of the data by including county and time fixed effects. We also apply a range of instrumental variables to account for the fact that unobserved time-varying drivers of wildfire may also impact controlled burning decisions. In particular, we instrument for wildfire in the prescribed burning equation with variables depicting natural-caused (e.g., lightning) wildfire events, and we instrument for prescribed burning in the wildfire equation with variables measuring forest sector wages and the quality of land for hunting.

Our analysis focuses on the southeastern United States (Figure 1), where prescribed burns have been widely used on private forestland. The southeast is the largest regional supplier of timber in the country, producing 60 percent of all U.S. timber harvests (Vose et al., 2019). Here, many species have adapted to fires; Loblolly pine and longleaf pine 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 percent 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, 2023). Although 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 region leads the nation in total acres treated with prescribed fires (around 6-7 million acres annually) (Melvin, 2021). As a comparison, wildfires, which are uncontrolled and unprescribed, burn only 1 million acres annually in the southeast (Barbero et al., 2015).

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 western states are often more stringent for the 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).

Figure 1: Study area

Our results show that counties with more recent wildfire events conduct more prescribed burns (around 1.3 - 2 elasticity), while stricter regulatory restrictions (permit requirement) reduce the rate of responsiveness to wildfires by prescribed burning (-0.6 - -1.5 elasticity). Hotter and drier conditions, measured by maximum vapor pressure deficit, increase prescribed fire acreage at a larger magnitude with an elasticity of about 4 - 7.6. We also find evidence that prescribed fires reduce wildfire acreage, though the magnitude is small (-0.1 - -0.2 elasticity). Hotter and drier conditions strongly increase wildfire extent. Further, prescribed fires reduce wildfire ignition incidents, although the magnitude is much smaller (-0.02 - -0.04 elasticity). Our finding that prescribed fires reduce the extent of wildfire rather than the incidence of wildfire is intuitive since prescribed fires remove fuels. We also conducted a simulation exercise to project how future acreage burned in wildfires would change as climate changes and landowners adapt to a changing climate. Our simulation indicates that wildfires will change as a direct result of realized climate conditions and as an indirect result of active wildfire mitigation actions by the landowners. In particular, the simulation shows that a hotter and drier future climate will increase wildfires, though climate adaptation by landowners will mitigate the growth in wildfire acreage from a 17% increase down to a 14% increase.

Much of the previous empirical economic literature on wildfire focuses on suppression issues (Plantinga et al., 2022), outdoor recreation (Gellman et al., 2022), projection of future wildfires (Prestemon et al., 2016), public health issues related to smoke (Wen and Burke, 2022), residential property values (McCoy and Walsh, 2018), timberland property values (Wang and Lewis, 2023), 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 which 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 that estimates the economic incentives driving private landowner decisions regarding prescribed burning, nor empirical work 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.

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). A key protection effort includes prescribed fires that the landowner can undertake to reduce fuels in a way that reduces the probability that a wildfire will arrive. 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:

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

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

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

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:

$$V_{PB} = (r+\lambda)c_1^{'}(PB) + \lambda^{'}(PB)\Bigg([pF(T) - c_1] - \frac{[r+\lambda(PB)][pF(T)-c_1]}{r(1-e^{-[r+\lambda(PB)]T)}} - \frac{c_2}{r}\Bigg) = 0 \tag{3}$$

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

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

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.

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 $\partial\lambda/\partial C > 0$. For further clarity using a specific functional form, assume the following logistic form:

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

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:

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

By assuming that the forest growth function is a conventional von Bertallanfy 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:

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

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. Figure 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. 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 (λ^{***}-λ^{**}). 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.

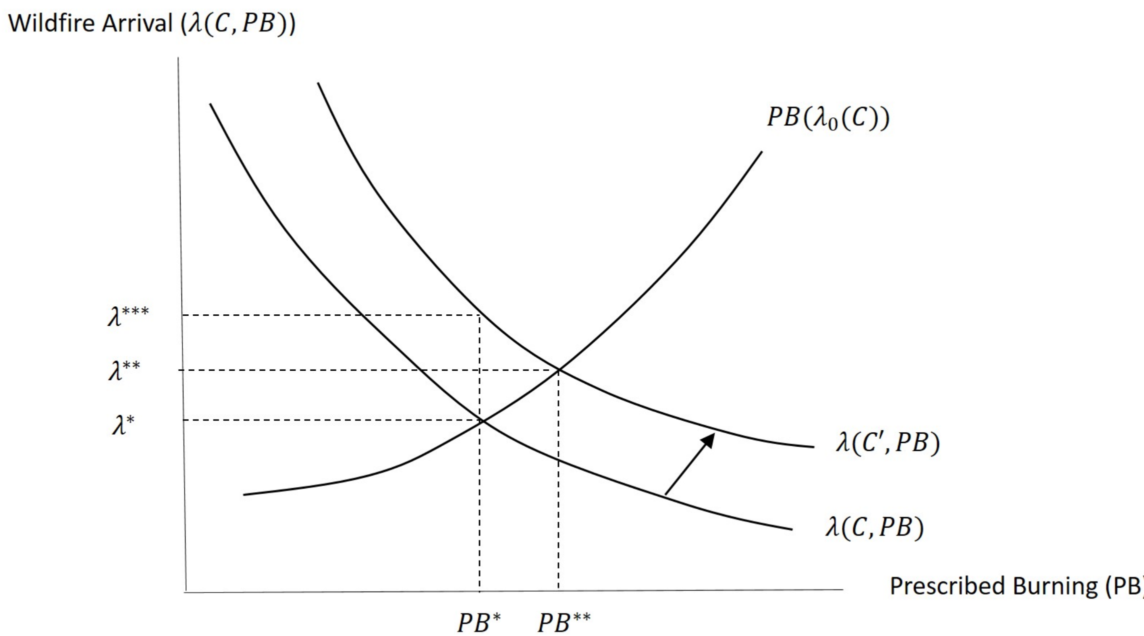


Figure 2: Relationship between wildfire arrival and optimal prescribed burning Note: λ_0 is the exogenous wildfire arrival rate in the absence of prescribed burning, $PB = 0$. C is a climate variable at current condition, and C' is new climate condition.

2.2 Testable hypotheses and empirical goals

This section provides a theoretical 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 elasticity of wildfire arrival with respect to prescribed burning, 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 Estimating the effects of previous wildfire events and climate variables on the prescribed burn decision

Our first estimating equation (eq.(8)) uses the inverse hyperbolic sign 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 as discussed above.

$$PB_{ct} = \gamma_1 \widetilde{WB_{cRAt-2}} + \gamma_2 R_{s(c)} * \widetilde{WB_{cRAt-2}} + \gamma_3 C_{ct} + \gamma_4 F_{ct} + \alpha_c + \upsilon_{st} + \epsilon_{ct} \quad (8)$$

where PB_{ct} is the inverse hyperbolic sine of prescribed burned acreage in county c in year t; $\widetilde{WB_{cRAt-2}}$ is the fitted value of acres burned in wildfires in previous two years in county c from the first-stage model that uses an instrument (eq.(9)); $R_{s(c)}$ is a vector of dummy variables for state regulations that affect the costs of prescribed burning, including a permit dummy to indicate whether a burn permit is mandated, and a smoke dummy to indicate whether a smoke management plan is mandated in state s that contains county c; C_{ct} is a vector of climate variables for county c in year t; F_{ct} is a vector of geophysical variables for county c in year t; α_c indicates county fixed effects; v_{st} indicates state-year fixed effects; and ϵ_{ct} is the error terms that are clustered by county. The inverse hyperbolic sine transformation of prescribed burning allows us to include observations with meaningful zero values and yields a similar interpretation to a model with a logged dependent variable (Bellemare and Wichman, 2020).

A key feature of Eq. 8 is the use of county fixed effects, which capture time-invariant county unobservable drivers of prescribed fire acreage. The baseline wildfire risk for county c arises from its long-term wildfire arrival rate and is embedded in the fixed effect for county c. We therefore include $\widetilde{WB_{cRAt-2}}$, a variable measuring recent exposure of county c to wildfire within two years prior to year t, which allows us to estimate how prescribed burning responds to current wildfire occurrence, conditional on baseline fire risk. The regulatory stringency dummy variables - whether each state requires a burn permit and smoke management plan - are interacted with the acreage burned in wildfires to capture how regulatory stringency would affect prescribed fire responses to recent wildfire occurrence. Building off the theory above, additional independent variables capture drivers of timber productivity and include annual realized weather variables (annual temperature, precipitation, and vapor pressure deficit (VPD)), forest type indicators, soil productivity, stand age, stand volume, slope, elevation, and ownership type. Guidance from theory is that climate affects prescribed burning decisions through its impact on both productivity and risk of disturbance. 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 20-year representation of climate or a short-term

2-year representation of weather. We also control for time-variant macro-level unobservables that differentially affect states with year-state fixed effects. The standard errors are clustered at the county 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).

Since wildfire events may be driven by the same time-varying unobservables that affect prescribed burns, we apply an instrumental variable approach and use naturally-caused wildfires as an instrument for the wildfire variable. Naturally-caused wildfires (e.g., ignited by lightning) 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 wildfire acreage. The fitted values from the first stage defined as eq. (9) are used in our main second-stage model in an application of the two-stage least-squares method.

$$WB_{cRAt-2} = \beta_1 Z_{cRAt-2} + \beta_2 C_{ct} + \beta_3 F_{ct} + \alpha_c + v_{st} + \epsilon_{ct} \tag{9}$$

where WB_{cRAt-2} is inverse hyperbolic sine of 2-year rolling avg burned acreage in wildfires in county c; Z_{cRAt-2} is 2-year rolling avg count of naturally-caused wildfires as an instrument for wildfires. The remaining variables are the same as in eq.(8).

2.4 Effects of prescribed fires on wildfire event

Following the theoretical foundations above, we also estimate an equation with wildfire events as the dependent variable, measured as both burned acreage and as a discrete count of fires at the county-year level, with recent prescribed fire acreage included in the set of independent variables. As prescribed burns are likely correlated with unobservable drivers of wildfires (e.g. like unmeasured weather events), we explore using forest sector wages and deer harvest counts as time and county-varying instruments in a fixed effects - instrumental variable (IV) estimation. Forest sector wages capture labor costs associated with employing fire experts and certified burners who conduct prescribed burns. Likewise, a county's deer harvest count is a good indicator of the quality of game hunting conditions, which is one of the known objectives for conducting prescribed burns in the study region. An identifying assumption is that neither forest sector wages nor deer harvest counts are correlated with unobserved drivers of wildfire. In our main second-stage model (eq. (10)), we estimate the acreage burned in wildfire each year in each county as a function of weather variables, biophysical conditions, and the fitted values for acres treated in prescribed fires in the previous years, instrumented in the first-stage model (eq. (11)). Formally, our main wildfire model is:

$$WB_{ct} = \eta_1 \widetilde{PB_{cRAt-2}} + \eta_2 C_{ct} + \eta_3 F_{ct} + \alpha_c + v_{st} + \epsilon_{ct} \tag{10}$$

where WB_{ct} is the acreage burned in (or count of) wildfires in county c in year t; $\widetilde{PB_{cRAt-2}}$ is the instrumented acres treated in prescribed fires in the previous two years in county c; and other variables are the same as in the prescribed fire estimating equation above. Note that this estimation equation includes county and state-year fixed effects.

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

$$PB_{cRAt-2} = \delta_1 Z_{cRAt-2} + \delta_2 C_{ct} + \delta_3 F_{ct} + \alpha_c + v_{st} + \epsilon_{ct} \tag{11}$$

where Z_{cRAt-2}: Forest sector wage and deer harvest counts are IVs for prescribed fires.

Altogether, our system estimates how climate and prior wildfires affect prescribed fire effort, along with estimates of how climate and prescribed burning affect wildfire events. Identification is based on a fixed effects IV strategy and exploits the significant temporal and spatial variation in both prescribed burning and wildfires.

3 Data and Variable Measurement Issues

A key data source is prescribed fire permit data collected from state forestry agencies[2] 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, we use ten states (AL, AR, GA, FL, LA, MS, NC, SC, TN, and VA) that have consistent records, creating 2.1 million permit records. We further subset the data to non-agricultural fires and non-sugar cane fires, resulting in about 1.6 million records over 11 years.

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 and the extent and ignition of 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 ten states.

The climate/weather data comes from the PRISM database at Oregon State University, and we use annual realized climate measures in temperature, precipitation, and maximum vapor pressure deficit (VPD). Vapor pressure deficit 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). All climate variables for year t are measured as averages between $t - 20$ and t for long-term cli-

[2] Alabama Forestry Commission, Arkansas Forestry Commission, Florida Forest Service, Georgia Forestry Commission, Louisiana Department of Agriculture and Forestry, Mississippi Forestry Commission, North Carolina Forest Service, South Carolina Forestry Commission, Virginia Department of Forestry, and Tennessee Division of Forestry

mate, and as averages between $t-2$ and 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 variables measuring wildfire risks are represented by both the extent (acres burned) and incident (count) burned in wildfires in the previous years for each county based on the wildfire perimeter records from Monitoring Trends in Burn Severity (MTBS). MTBS includes all fires larger than 500 acres since 1984. 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.

We use two variables to account for the variation in laws and regulations pertaining to the prescribed fire application across states: whether the state requires burn permits and whether the state requires a smoke management plan. Other stipulations, such as the requirement for certified burners and written burn prescriptions, or availability of funding (e.g., cost share program), do not have significant variation across states as most states require certified burners and written prescriptions, as well as provide cost share programs. We define a dummy variable to distinguish states that require permits from those that only require notifications (AR, LA, SC, and VA). Similarly, we define a dummy variable to differentiate states that require smoke management plans or compliance with state laws on smoke (FL, GA, NC, SC, VA) from others that do not mandate them.

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). Similarly, we construct instrumental variables representing forest sector wages from the US Bureau of Labor Statistics Quarterly Census of Employment and Wages. The instrumental variable depicting annual deer hunting harvest records is collected from state wildlife agencies individually, mainly through email correspondence.[3]

[3]Not all state agencies provided harvest data. Those that disclosed data are the Tennessee Wildlife Resources Agency, Georgia Department of Natural Resources, Louisiana Wildlife and Fisheries, South Carolina Department of

The final panel data consists of about 10,000 county-year observations across ten southeast U.S. states over the period 2010 – 2021. Figure 3 shows the spatial distribution of prescribed fire application (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.

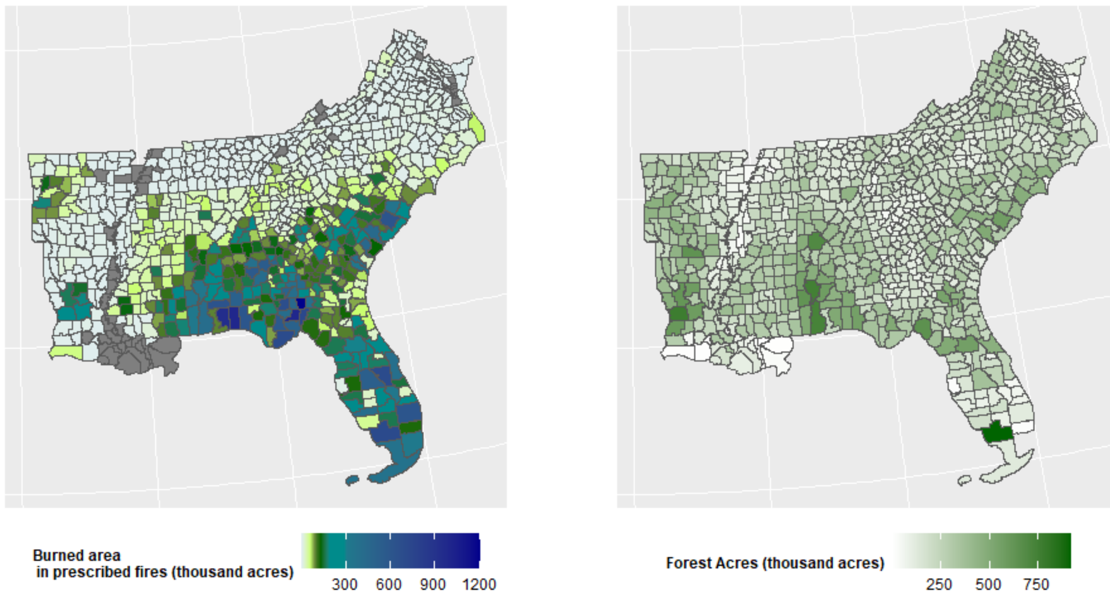


Figure 3: Cumulative prescribed fire application by county (left) and forested acres (right)

Table 1: Summary of prescribed fire permits by state (all numbers are in thousands)

	AL	AR	FL	GA	LA	MS	NC	SC	TN	VA
Number of permits	141.7	3.9	433.0	861.5	2.7	41.1	8.3	144.9	4.0	2.6
Total acres	9977	1219	16696	16699	1089	4173	965	5332	212	206
Annual avg. acres	831	101	1391	1391	90	347	80	444	17	17

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 per year during this period.

Table 2 summarizes the key variables used in our analysis. More than 80 percent of forests in the study area are privately owned, 63 percent of which are family-owned. The areas treated

Natural Resources, Virginia Department of Wildlife Resources, Florida Fish and Wildlife Conservation Commission, and North Carolina Wildlife Resources Commission.

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 Figures A1-3 show spatial variation in temperature, precipitation, and VPD for the years 2010, 2015, and 2020.

Table 2: Summary statistics of key variables

	Avg.	Std.Dev
Average annual precipitation (mm)	1427.06	293.98
Average annual temperature (C)	17.06	2.62
Average max vapor pressure deficit (hPa)	15.88	2.51
30-year moving average precipitation (mm)	1325.39	149.66
30-year moving average temperature (C)	16.68	2.54
30-year moving average max vapor pressure deficit (hPa)	15.92	2.04
Projected change in vapor pressure deficit by 2050 (%)	0.12	0.06
Saw timber volume MBF per acre	6.43	3.10
Total forest (thousand acres)	210.37	125.69
Private forest (thousand acres)	175.99	107.81
Average stand age (years)	43.83	16.76
Average siteclass (Best:1 to Worst:7)	4.57	0.63
Average slope (%)	10.30	11.96
Average elevation (feet)	556.80	641.05
Share of family ownership	0.63	0.23
Share of corporate ownership	0.26	0.21
Share of TIMO/REIT ownership	0.08	0.12
Wildfire arrival rate	0.01	0.10
Number of prescribed burn permits	211.98	346.05
2-year moving average acres burned in wildfires	424.62	5465.81
20-year moving average acres burned in wildfires	522.46	3963.48
Acres burned annually in prescribed fires	5839.37	11837.11
Forest sector wage (thou$)	34.59	15.65
Deer harvest count	1844.41	1462.22

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. The first column uses short-term weather (annual) and short-term wildfire variables (previous 2-year moving average). The second column uses a long-term climate variable (30-year normal) and a short-term wildfire event. The third column uses short-term weather and long-term wildfire variables (20-year moving average). The last column uses long-term climate and long-term wildfire variables. 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 both climate and wildfire as long-term measures (column 4) fits the data best. All results use county fixed effects to account for time-invariant county unobservables and state-year fixed effects to account for unobserved variables that vary across states and by year. The standard errors are all clustered at the county level. Note that the time-invariant state-level permit and smoke plan requirement variables drop out due to the inclusion of state-year fixed effects. We ran several alternative specifications (e.g., using temperature and precipitation and including forest types) based on the short-term wildfire and weather specification model, as presented in Appendix Table A2. We also present a naive model that does not instrument for the wildfire variable in Appendix Table A3.

Prescribed fire acreage is extremely elastic with respect to increases in vapor pressure deficit (VPD), with results varying between 4.035 and 7.613. Thus, results provide clear evidence that warmer and drier conditions (higher VPD) signal higher wildfire risk that spurs private landowners to undertake additional prescribed burning. Table 4 summarizes the marginal effects of wildfire acreage burned on prescribed burning, accounting for different permit requirements across states. For states where burn permits are not required, the elasticity of prescribed burning with respect to wildfire ranges between 1.02 - 1.81 depending on whether long-term or short-term climate is used, while states with permit requirements see a much smaller elasticity of 0.31 - 0.42. Thus, results provide clear evidence that permit requirements impart significant costs that reduce prescribed burning response to recent wildfires.

Both the Wald test for weak instruments and a Wu-Hausman test for endogeneity suggest that the instrument (naturally-caused wildfire count) is relevant as an instrument for the endogenous variable (acreage burned in wildfires). The estimated impacts of wildfires on prescribed burning are much smaller in magnitude when wildfire is not instrumented (Table A3), indicating that the IVs significantly change results.

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

	Log(Acres burned in prescribed fire)			
	(1)	(2)	(3)	(4)
Fitted log(2yr avg acres burned in wildfire)	1.947***	1.963***		
	(0.355)	(0.362)		
Fitted permit x Log(2yr avg acres burned in wildfire)	-1.483**	-1.456**		
	(0.573)	(0.579)		
Smoke plan required x Log(2yr avg acres burned in wildfire)	-0.266	-0.308		
	(0.405)	(0.403)		
Fitted log(LT t∼t-20 avg acres burned in wildfire)			1.348***	1.331***
			(0.175)	(0.172)
Fitted permit x Log(LT t∼t-20 avg acres burned in wildfire)			-0.598***	-0.565***
			(0.211)	(0.206)
Smoke plan required x Log(LT t∼t-20 avg acres burned in wildfire)			-0.576**	-0.603***
			(0.232)	(0.221)
Log(Avg max vapor pressure deficit)	4.035***		5.448***	
	(1.023)		(0.871)	
Log(30-year max vapor pressure deficit)		5.874***		7.613***
		(1.358)		(1.272)
Saw timber volume MBF per acre	0.023	0.031	0.141**	0.146***
	(0.055)	(0.055)	(0.054)	(0.054)
Avg siteclass	-0.254**	-0.233**	-0.338**	-0.304**
	(0.115)	(0.113)	(0.142)	(0.138)
Avg stand age (10 years)	-0.129**	-0.117**	-0.084	-0.066
	(0.055)	(0.055)	(0.052)	(0.052)
Avg slope (%)	-0.023	-0.025	-0.042***	-0.044***
	(0.017)	(0.017)	(0.014)	(0.014)
Avg elevation (100 feet)	0.004	0.027	-0.005	0.023
	(0.030)	(0.032)	(0.024)	(0.026)
Share of family ownership	1.262**	1.253**	1.926***	1.860***
	(0.632)	(0.626)	(0.708)	(0.706)
Wildfire var	short-term	short-term	long-term	long-term
Climate var	short-term	long-term	short-term	long-term
county FEs	Yes	Yes	Yes	Yes
state-year FEs	Yes	Yes	Yes	Yes
Observations	9,612	9,612	9,612	9,612
R^2	0.37756	0.37794	0.57709	0.58440
Mean MSE (cross validation)	2.7	2.69	2.56	2.54
Wald (1st stage), p-value, Log(2yr avg acres burned in wildfire)	1.41×10^{-11}	1.86×10^{-11}		
Wald (1st stage), p-value, Permit required x Log(2yr avg acres burned in wildfire)	4.77×10^{-6}	4.02×10^{-6}		
Wald (1st stage), p-value, Smoke plan required x Log(2yr avg acres burned in wildfire)	0.00023	0.00020		
Wald (1st stage), p-value, Log(t t-20 avg acres burned in wildfire)			4.11×10^{-27}	4.08×10^{-28}
Wald (1st stage), p-value, Permit required x Log(t t-20 avg acres burned in wildfire)			2.32×10^{-16}	6.76×10^{-17}
Wald (1st stage), p-value, Smoke plan required x Log(t t-20 avg acres burned in wildfire)			2.21×10^{-11}	1.53×10^{-11}

Table 4: Marginal Effects of Wildfire Acreage Burned

	ST weather/ST wildfire window	LT climate/ST wildfire window	ST weather/LT wildfire window	LT climate/LT wildfire window
Permit not required	1.810***	1.804***	1.050***	1.019***
	(0.468)	(0.470)	(0.176)	(0.171)
Permit required	0.314*	0.333*	0.424***	0.425***
	(0.170)	(0.174)	(0.077)	(0.077)

4.2 Effect of Prescribed Fires on Wildfire Extent and Incidents

The next set of results shows estimates of parameters from the equation where wildfire is the dependent variable - wildfire acreage is the dependent variable in Tables 5 and 6, while the count of distinct wildfire incidents is the dependent variable in Table 7. The results shown in Table 5 (dependent variable is wildfire acres) use forest sector wage as an instrument for prescribed fires, while the results shown in Table 6 use both forest sector wage and deer harvest count as instruments for prescribed fires. In Table 7, the dependent variable is wildfire incident (count of fires), and we use both instruments. In Appendix A4 (acreage) and A5 (incident), we included uninstrumented results as a reference, which show an inconclusive effect of prescribed fire on wildfire extent or incidents, contradicting the premise that prescribed fires mitigate wildfire risks. However, when we instrument prescribed fire acreage with forest sector wages (Table 5) or both forest sector wages and deer harvest count (Table 6), the estimated coefficient estimates for the prescribed fire acreage variable become intuitively negative and statistically significant ($p<0.1$) for all specifications. In particular, a 1 percent increase in prescribed fire acreage lowers wildfire acreage by 0.13 to 0.24 percent (Table 5, Table 6) and lowers the number of wildfires by 0.02 to 0.03 percent (Table 7). Consistent with prior natural science research, estimates also indicate that VPD strongly increases wildfire acreage with an elasticity of 2 to just over 4 (Table 6), and VPD also increases the number of wildfires with an elasticity of 0.2 to 0.6 (Table 7). The magnitude of the elasticity of prescribed burning is larger when explaining wildfire acreage than wildfire incidents, suggesting that prescribed fires may have a larger effect on reducing wildfire spread rather than wildfire ignitions.

Table 5: Effect of Prescribed Fire on Wildfire Acreage: Prescribed Fire Instrumented by Forest Sector Wage

	Log(Acres burned in wildfire)				
	(1)	(2)	(3)	(4)	(5)
Fitted log(2yr avg acres burned in prescribed fire)	-0.237*	-0.245**	-0.236*	-0.226**	-0.128*
	(0.120)	(0.123)	(0.122)	(0.111)	(0.069)
Log(Avg max vapor pressure deficit)	1.803***	2.376***		3.779***	3.425***
	(0.658)	(0.473)		(0.874)	(0.790)
Avg annual temperature (C)	0.279*	0.252*	0.368***		
	(0.148)	(0.143)	(0.141)		
Log(Avg annual precipitation)	-0.476*		-1.000***		
	(0.262)		(0.174)		
Saw timber volume MBF per acre	-0.053*	-0.053*	-0.063**	-0.071*	-0.091***
	(0.029)	(0.029)	(0.027)	(0.036)	(0.028)
Avg siteclass	0.534***	0.560***	0.494**	0.519***	0.577***
	(0.188)	(0.191)	(0.192)	(0.182)	(0.158)
Avg stand age (10 years)	0.115***	0.117***	0.103***	0.139***	0.125***
	(0.035)	(0.035)	(0.035)	(0.041)	(0.039)
Avg slope (%)	-0.004	-0.006	-0.001	-0.013	-0.018*
	(0.006)	(0.006)	(0.006)	(0.008)	(0.010)
Avg elevation (100 feet)	0.087***	0.090***	0.082***	0.065***	0.047***
	(0.026)	(0.027)	(0.027)	(0.017)	(0.013)
Share of family ownership	-0.443	-0.449	-0.324	-0.985***	-1.598***
	(0.565)	(0.565)	(0.555)	(0.376)	(0.301)
Forest types	Yes	Yes	Yes	Yes	No
county FEs	Yes	Yes	Yes	Yes	Yes
Observations	8,749	8,749	8,749	8,749	8,749
R^2	0.08504	0.07772	0.08213	0.07849	0.11124
F-test (1st stage), p-value, Log(2yr avg acres burned in prescribed fire)	1.34×10^{-37}	1.94×10^{-37}	1.27×10^{-37}	3.38×10^{-38}	2.33×10^{-89}
Wald (1st stage), p-value, Log(2yr avg acres burned in prescribed fire)	3.56×10^{-5}	4.02×10^{-5}	3.76×10^{-5}	7.51×10^{-6}	5.8×10^{-11}
Wu-Hausman, p-value	1.84×10^{-6}	1.01×10^{-6}	1.94×10^{-6}	8.78×10^{-7}	1.12×10^{-8}

Table 6: Effects of Prescribed Fires on Wildfire Extent: Wildfire Burned Area Instrumented by Naturally-Caused Fires and Prescribed Fire Instrumented by Forest Sector Wage and Deer Harvest

	Log(Acres burned in wildfire)				
	(1)	(2)	(3)	(4)	(5)
Fitted log(2yr avg acres burned in prescribed fire)	-0.178**	-0.192**	-0.164*	-0.208**	-0.145*
	(0.085)	(0.088)	(0.085)	(0.099)	(0.085)
Log(Avg max vapor pressure deficit)	1.946**	2.976***		4.338***	4.164***
	(0.792)	(0.640)		(1.085)	(1.112)
Avg annual temperature (C)	0.248*	0.192	0.339***		
	(0.140)	(0.130)	(0.129)		
Log(Avg annual precipitation)	-0.881**		-1.392***		
	(0.373)		(0.290)		
Saw timber volume MBF per acre	0.009	0.013	-0.003	0.000	-0.027
	(0.023)	(0.024)	(0.022)	(0.024)	(0.026)
Avg siteclass	0.836***	0.911***	0.754***	0.962***	0.986***
	(0.225)	(0.240)	(0.232)	(0.286)	(0.275)
Avg stand age (10 years)	0.099**	0.099**	0.089**	0.113**	0.085*
	(0.041)	(0.042)	(0.040)	(0.046)	(0.046)
Avg slope (%)	-0.007	-0.010	-0.003	-0.017	-0.017
	(0.009)	(0.009)	(0.008)	(0.012)	(0.015)
Avg elevation (100 feet)	0.063***	0.067***	0.056**	0.055***	0.042**
	(0.023)	(0.025)	(0.024)	(0.021)	(0.018)
Share of family ownership	-1.450**	-1.507**	-1.241*	-2.122***	-2.444***
	(0.678)	(0.677)	(0.648)	(0.509)	(0.424)
Forest types	Yes	Yes	Yes	Yes	No
county FEs	Yes	Yes	Yes	Yes	Yes
Observations	5,259	5,259	5,259	5,259	5,259
R^2	0.20264	0.19242	0.20625	0.17601	0.19596
F-test (1st stage), p-value, Log(2yr avg acres burned in prescribed fire)	4.61×10^{-50}	1.72×10^{-48}	3.21×10^{-51}	7.61×10^{-42}	8.51×10^{-74}
Wald (1st stage), p-value, Log(2yr avg acres burned in prescribed fire)	1.51×10^{-7}	1.84×10^{-7}	1.84×10^{-7}	3.98×10^{-7}	2.39×10^{-9}
Wu-Hausman, p-value	3.46×10^{-5}	1.33×10^{-5}	7.05×10^{-5}	7.27×10^{-6}	6.29×10^{-7}

Table 7: Effects of Prescribed Fires on Wildfire Incident: Wildfire Burned Area Instrumented by Naturally-Caused Fires and Prescribed Fire Instrumented by Forest Sector Wage and Deer Harvest

	Log(Wildfire count)				
	(1)	(2)	(3)	(4)	(5)
Fitted log(2yr avg acres burned in prescribed fire)	-0.031**	-0.033**	-0.029**	-0.036**	-0.025*
	(0.013)	(0.014)	(0.014)	(0.016)	(0.013)
Log(Avg max vapor pressure deficit)	0.244**	0.411***		0.663***	0.628***
	(0.115)	(0.086)		(0.169)	(0.173)
Avg annual temperature (C)	0.045**	0.036*	0.056***		
	(0.023)	(0.021)	(0.020)		
Log(Avg annual precipitation)	-0.143**		-0.207***		
	(0.058)		(0.043)		
Saw timber volume MBF per acre	0.001	0.002	0.000	-0.001	-0.004
	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)
Avg siteclass	0.124***	0.136***	0.113***	0.145***	0.144***
	(0.034)	(0.037)	(0.035)	(0.044)	(0.042)
Avg stand age (10 years)	0.013**	0.013**	0.012**	0.016**	0.011
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Avg slope (%)	-0.001	-0.002	-0.001	-0.003	-0.003
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Avg elevation (100 feet)	0.010***	0.011***	0.009**	0.009***	0.006**
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Share of family ownership	-0.168	-0.177*	-0.141	-0.291***	-0.330***
	(0.102)	(0.102)	(0.099)	(0.076)	(0.061)
Forest types	Yes	Yes	Yes	Yes	No
county FEs	Yes	Yes	Yes	Yes	Yes
Observations	5,259	5,259	5,259	5,259	5,259
R^2	0.18225	0.16891	0.18678	0.14293	0.17670
F-test (1st stage), p-value, Log(2yr avg acres burned in prescribed fire)	4.61×10^{-50}	1.72×10^{-48}	3.21×10^{-51}	7.61×10^{-42}	8.51×10^{-74}
Wald (1st stage), p-value, Log(2yr avg acres burned in prescribed fire)	1.51×10^{-7}	1.84×10^{-7}	1.84×10^{-7}	3.98×10^{-7}	2.39×10^{-9}
Wu-Hausman, p-value	1.78×10^{-6}	5.26×10^{-7}	3.43×10^{-6}	1.55×10^{-7}	1.06×10^{-8}

4.3 Simulation of Prescribed Fires and Wildfires

To better understand the extent to which climate adaptation by prescribed burning can mitigate wildfire acreage, we use our estimation results to simulate how prescribed fire acres and wildfire acres co-evolve when the climate gets warmer and drier. According to the RCP 8.5 climate projection, counties in the study areas expect to see a change in VPD in the range of -3 percent to +23 percent (average +6 percent) by 2030, and +2 percent to +32 percent (average +12 percent) by 2050. We simulate this projected warmer and drier climate change by increasing VPD according to the downscaled output from 20 Global Climate Models (GCMs) projection (Abatzoglou and Brown, 2018) for all 310 counties in the study area that had at least one wildfire occurrence in the last 20 years. We first project annual prescribed fire acreage as a function of only the projected change in VPD for the next 20 years. Using the elasticity estimates from our IV model results for prescribed fires (Table 3 Column 1) and wildfires (Table 6 Column 5), we simulate how prescribed fire acreage and wildfire 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 estimated elasticity 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_3 in equation (8), and wildfire responds directly to changes in VPD through our estimate of η_2 in equation (10). Importantly, our baseline projection does not let prescribed burning and wildfire affect each other in the simultaneous equations system - i.e., $W\widetilde{B_{cRAt-2}}$ is held fixed in equation (8) and $P\widetilde{B_{cRAt-2}}$ is held fixed in equation (10).

Next, we simulate the full simultaneous change between prescribed burning and wildfire, where increases in VPD raise both prescribed burning and wildfire, while prescribed burning increases in response to wildfire but wildfire decreases in response to prescribed burning i.e., $W\widetilde{B_{cRAt-2}}$ is not held fixed in equation (8) and $P\widetilde{B_{cRAt-2}}$ is not held fixed in equation (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 Figure 2. We also examine how changes in burn permit requirements affect the responsiveness of prescribed burns to wildfire acreage by presenting a simulation where no burn permits are required anywhere across the landscape.

We begin our presentation of simulation results by showing an illustrative example of how prescribed fire and wildfire evolve over time in our simulation using two representative counties. Here, we take Baker County and Collier County, both in Florida (Figure 4), which have experienced both wildfires and active prescribed fire practices.

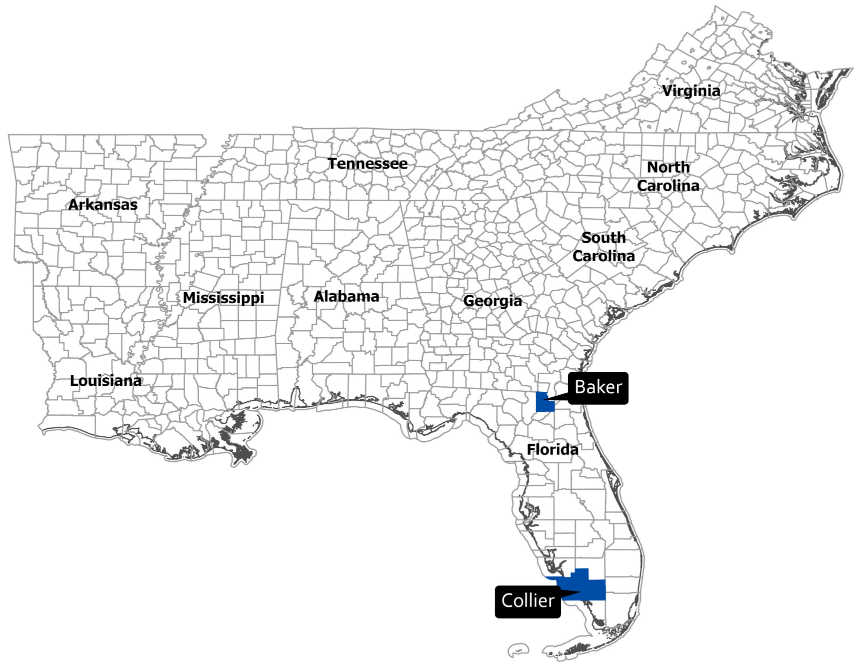
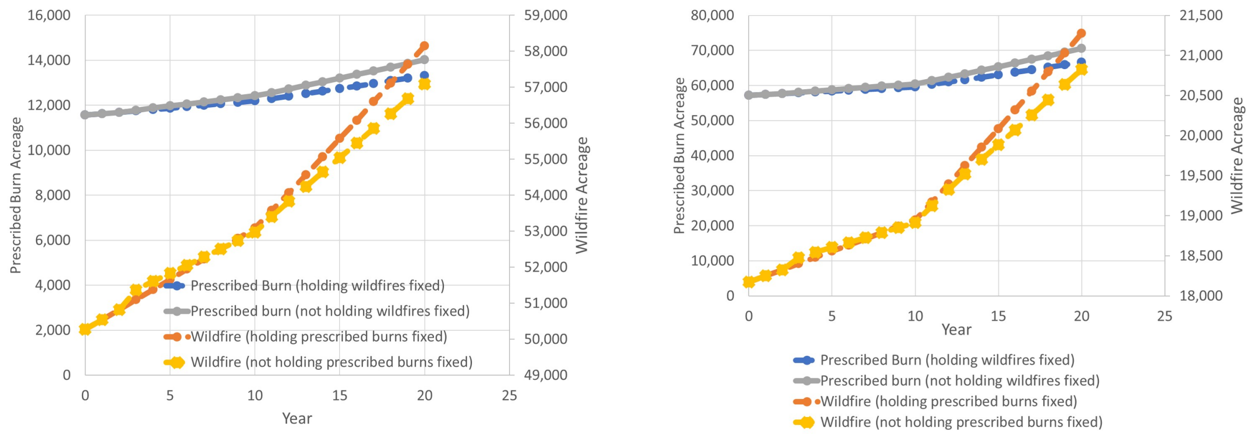


Figure 4: The locations of two representative counties used for illustration

In Figure 5, 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. On the other hand, the orange line shows wildfires when there is no climate adaptation through prescribed burning, and the yellow line shows wildfires when landowner-prescribed burns mitigate some of the wildfire increase as a climate adaptation response. The difference between the orange and yellow lines in any point in time is the wildfire mitigation benefits from the climate adaptation of prescribed burning.

The wildfire mitigation effect from climate adaptation is aggregated to the entire study area across counties that had wildfires in the past 20 years. Figure 6 is a distribution of the results, shown as a percentage reduction in growth of wildfire acreage due to growth in prescribed fires by 2040. The left histogram in Figure 6 is based on current burn permit requirements, and the right histogram in Figure 6 is based on a hypothetical scenario that no state requires a burn permit. The



(a) Baker County, FL

(b) Collier County, FL

Figure 5: Simulated change in prescribed fire and wildfire acreage. Parameter estimates used in the simulation are log (2-year avg acres burned in wildfire) and log (avg max VPD) in Table 3 column (1) for prescribed fire and log (2-year avg acres burned in prescribed fire) and log (avg max VPD) in Table 6 column (5) for wildfire.

blue dotted line is the average across the sample - so climate adaptation from prescribed burning lowered the growth in wildfire acreage by an average of 16 percent for the current permit scenario and 23 percent for no permit scenario.

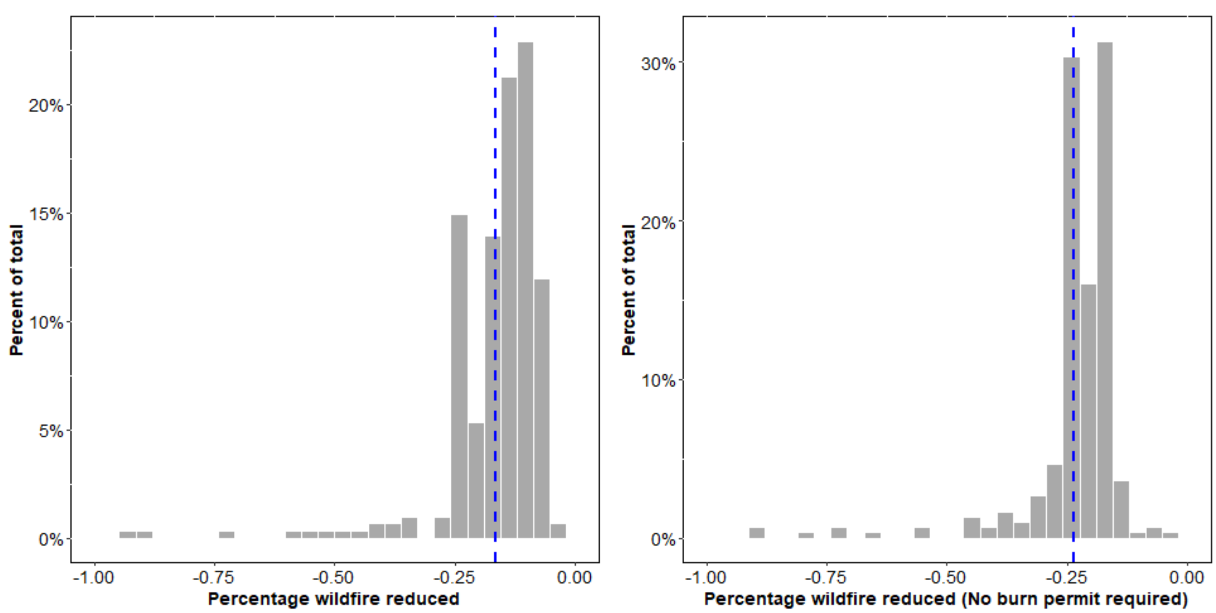


Figure 6: Histogram of wildfire acreage reduction percentage relative to baseline scenario, Current permit requirement (left) and no burn permit requirement scenario (right)

Figure 7 shows the spatial distribution of the results depicting how climate adaptation from prescribed burning mitigates growth in wildfires, calculated as the difference in wildfire acreage in 2040 between the baseline scenario and full scenario (i.e., wildfire mitigation due to prescribed fires) divided by the total increase in wildfire acreage by 2040.

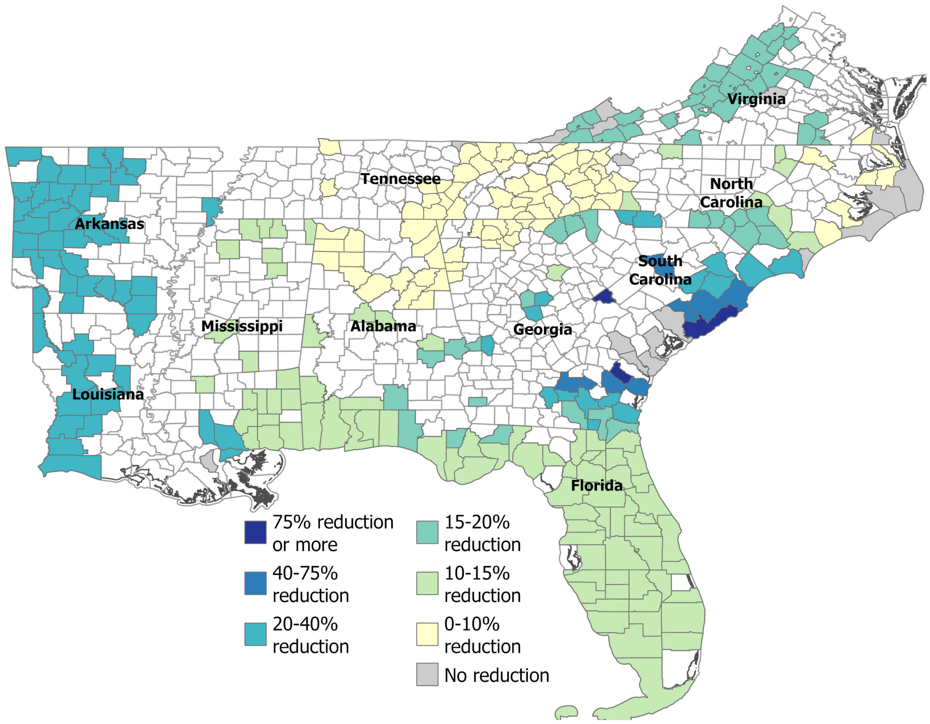


Figure 7: Reduction in wildfire acreage due to prescribed fires as percentage of total increase in wildfire acreage by 2040. Note: counties with no color had no large wildfires during the study period of 2010-2021 and are not included.

Table 8 summarizes the aggregate simulation results: (1) the difference in prescribed fire acreage between the baseline and full simultaneous case (i.e., impact of wildfires in inducing more prescribed burns), (2) the difference in wildfire acreage resulting from climate adaptation (i.e., impact of prescribed fires in reducing wildfires), and (3) the climate adaptation difference (column 2) expressed as a percentage of total increase in wildfire acreage over time (i.e., share of the wildfire acreage growth mitigated by prescribed fires). In aggregate, we project that prescribed fire acreage will increase by 23 percent in 20 years due to an increase in VPD alone in our baseline simulation, and by 43 percent if we account for the simultaneous relationship with wildfire acreage. The wildfire acreage will increase by 17 percent if we only account for a change in VPD, but the increase is mitigated by the increase in prescribed burns to 14 percent. By 2040, the increase in wildfire acreage would be reduced by about 18 percent in aggregate because of landowners adapting to climate change through more prescribed fires. In a hypothetical setup where all states don't require a burn permit, prescribed burns will increase by 60 percent from the current level by 2040, which leads to a 26 percent wildfire acreage mitigation rather than the 18 percent reduction under the current burn permit requirement.

We also see some heterogeneity across states, as shown in Table 8. One surprising result is a large increase in prescribed burning and a correspondingly large wildfire mitigation benefit in Arkansas. Arkansas is expected to see a 25 percent increase in VPD by 2050 (Table A6), a much larger increase than any other state, contributing to a substantial increase in wildfire acreage. The fact that the state does not have a burn permit requirement also contributes to a relatively large response from prescribed burns to the increase in wildfires.

Table 8: Simulation results by state

State	Delta prescribed burns (acres)	Delta wildfire acres (acres)	Delta as % of total wildfire increase
All	511,920	-13,435	-18.3%
AL	27,973	-133	-10.5%
AR	286,428	-2,548	-23.1%
FL	109,051	-3,930	-13.4%
GA	4,419	-2,916	-23.3%
LA	34,087	-892	-24.5%
MS	23,790	-315	-11.9%
NC	4,982	-365	-9.9%
SC	13,741	-86	-34.3%
TN	1,532	-217	-8.3%
VA	5,917	-2,033	-17.4%

Note: Column 1 shows the difference in prescribed fire acres between the baseline case (holding wildfire fixed) and full case (not holding wildfire fixed). Column 2 shows the difference in wildfire acres between the baseline case (holding prescribed fire fixed) and full case (not holding prescribed fire fixed). Column 3 shows the percentage of wildfire mitigation (column 2) relative to the overall increase in wildfire acreage by 2040.

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 percent 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 in timberlands 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 acreage and incidents to assess the wildfire mitigation benefits of prescribed fires.

By applying fixed effects and instrumental variables to this simultaneous equations system, 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. Recently burned wildfire acreage, a proxy for recent wildfire risk, is also found to increase prescribed fire use, while increasing regulatory stringency of prescribed burning reduces prescribed fire acreage. These findings suggest that the policy environment could 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.

We also find that prescribed fires reduce wildfire extent and, to a lesser degree, ignition of wildfires. The magnitude of the impact prescribed fires have on reducing wildfire extent could be considerable, averaging around 18 percent of the expected wildfire increase in the next 20 years. 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). It is worth noting, however, that our finding is specific to the study area and bound by the empirical data. We chose the U.S. Southeast for its most 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. Therefore, we cannot generalize our findings in other regions, 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. In California, liability laws related to cases when prescribed fire escapes used to be a strict liability, which places the burden of restitution for damages on the burner regardless of any actions taken by the burner to avoid damages. It 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).

Prescribed fires reduce the occurrence and extent of wildfires and will play an increasing role in climate change adaptation. They provide other ecological benefits, such as soil restoration and regeneration, 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.

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A Appendix Tables and Figures

Table A1: Summary of Key Requirements in Prescribed Fire Applications

States	Certified Burner	Written Prescription	Permit	Smoke Plan	Funding/Cost Share
AL	Y	Y	Y	N (voluntary)	Y
AR	N	N	N (notice only)	N (voluntary)	Y
FL	Y	Y	Y	Y	Y
GA	Y	N	Y	Y	Y
LA	Y	Y	N	N (voluntary)	Y
MS	Y	Y	Y	N (voluntary)	Y
NC	Y	Y	Y	Y	Y
SC	Y	Y	N (notice only)	Y	Y
TN	Y	Y	Y	N	Y
VA	Y	Y	N (notice only)	Y	Y

Table A2: Prescribed Burn Decision: Robustness check

	Log(Acres burned in prescribed fire)				
	(1)	(2)	(3)	(4)	(5)
Fitted permit x Log(2yr avg acres burned in wildfire)	-1.404**	-1.377***	-1.506***	-1.232**	-1.483**
	(0.560)	(0.503)	(0.523)	(0.513)	(0.573)
Fitted smoke plan x Log(2yr avg acres burned in wildfire)	0.722	-0.120	-0.075	-0.105	-0.266
	(0.514)	(0.360)	(0.373)	(0.373)	(0.405)
Fitted log(2yr avg acres burned in wildfire)	0.777***	1.594***	1.657***	1.574***	1.947***
	(0.223)	(0.287)	(0.301)	(0.287)	(0.355)
Permit required	2.746***				
	(0.401)				
Smoke plan required	1.300***				
	(0.310)				
Log(Avg max vapor pressure deficit)	2.836***	2.362**		3.047***	4.035***
	(0.954)	(1.060)		(0.931)	(1.023)
Avg annual temperature (C)	0.381***	0.391***	0.486***		
	(0.080)	(0.087)	(0.082)		
Log(Avg annual precipitation)	1.113***	1.326***	0.895***		
	(0.360)	(0.319)	(0.317)		
Saw timber volume MBF per acre	-0.132***	0.006	0.007	0.002	0.023
	(0.048)	(0.048)	(0.049)	(0.048)	(0.055)
Avg siteclass	0.261**	-0.086	-0.115	-0.125	-0.254**
	(0.129)	(0.101)	(0.101)	(0.105)	(0.115)
Avg stand age (10 years)	-0.043	0.013	-0.001	0.015	-0.129**
	(0.066)	(0.048)	(0.048)	(0.049)	(0.055)
Avg slope (%)	-0.001	-0.014	-0.012	-0.018	-0.023
	(0.013)	(0.015)	(0.015)	(0.014)	(0.017)
Avg elevation (100 feet)	0.083***	0.066**	0.057**	0.015	0.004
	(0.029)	(0.029)	(0.029)	(0.029)	(0.030)
Share of family ownership	2.062***	1.512***	1.685***	1.158**	1.262**
	(0.663)	(0.546)	(0.549)	(0.553)	(0.632)
Forest types	Yes	Yes	Yes	Yes	No
county FEs	Yes	Yes	Yes	Yes	Yes
state-year FEs	No	Yes	Yes	Yes	Yes
Observations	9,612	9,612	9,612	9,612	9,612
R^2	0.35345	0.50825	0.48265	0.49597	0.37756
Wald (1st stage), p-value, Log(2yr avg acres burned in wildfire)	1.88×10^{-14}	7.65×10^{-9}	1.09×10^{-8}	2.99×10^{-8}	1.41×10^{-11}
Wald (1st stage), p-value, Permit required x Log(2yr avg acres burned in wildfire)	4.27×10^{-5}	0.00011	6.39×10^{-5}	0.00014	4.77×10^{-6}
Wald (1st stage), p-value, Smoke plan required x Log(2yr avg acres burned in wildfire)	8.48×10^{-8}	4.24×10^{-5}	3.77×10^{-5}	1.26×10^{-5}	0.00023
Wu-Hausman, p-value	1.96×10^{-9}				

Table A3: Prescribed Burn Decision: Naive Model with Endogenous Wildfire Extent as Independent Variable

	Log(Acres burned in prescribed fire)				
	(1)	(2)	(3)	(4)	(5)
Permit required x Log(2yr avg acres burned in wildfire)	-0.141***	-0.195***	-0.196***	-0.177***	-0.181***
	(0.048)	(0.059)	(0.060)	(0.062)	(0.067)
Smoke plan required x Log(2yr avg acres burned in wildfire)	-0.143***	-0.176***	-0.175***	-0.171***	-0.208***
	(0.053)	(0.046)	(0.047)	(0.049)	(0.049)
Log(2yr avg acres burned in wildfire)	0.269***	0.352***	0.351***	0.355***	0.395***
	(0.054)	(0.078)	(0.079)	(0.080)	(0.086)
Permit required	2.019***				
	(0.216)				
Smoke plan required	1.797***				
	(0.192)				
Log(Avg max vapor pressure deficit)	2.880***	2.271**		3.603***	4.829***
	(0.695)	(0.964)		(0.857)	(0.923)
Avg annual temperature (C)	0.438***	0.495***	0.581***		
	(0.064)	(0.084)	(0.076)		
Log(Avg annual precipitation)	0.925***	1.093***	0.654**		
	(0.305)	(0.300)	(0.290)		
Saw timber volume MBF per acre	-0.173***	-0.032	-0.034	-0.041	-0.032
	(0.041)	(0.041)	(0.042)	(0.041)	(0.047)
Avg siteclass	0.331***	0.084	0.053	0.106	-0.010
	(0.102)	(0.073)	(0.071)	(0.078)	(0.084)
Avg stand age (10 years)	-0.013	0.096**	0.083**	0.114***	-0.037
	(0.049)	(0.042)	(0.042)	(0.042)	(0.044)
Avg slope (%)	0.008	0.002	0.005	-0.005	-0.005
	(0.012)	(0.012)	(0.012)	(0.011)	(0.012)
Avg elevation (100 feet)	0.089***	0.083***	0.073***	0.024	0.016
	(0.027)	(0.022)	(0.021)	(0.023)	(0.025)
Share of family ownership	1.475***	0.704*	0.848**	0.126	0.108
	(0.525)	(0.418)	(0.412)	(0.409)	(0.453)
Forest types	Yes	Yes	Yes	Yes	No
county FEs	Yes	Yes	Yes	Yes	Yes
state-year FEs	No	Yes	Yes	Yes	Yes
Observations	9,612	9,612	9,612	9,612	9,612
R^2	0.51711	0.69588	0.69456	0.68642	0.66092

Table A4: Effect of Prescribed Fire on Wildfire Extent: Naive Model with Endogenous Prescribed Fire as Independent Variable

	Log(Acres burned in wildfire)				
	(1)	(2)	(3)	(4)	(5)
Log(2yr avg acres burned in prescribed fire)	0.059***	0.102***	0.103***	0.115***	0.114***
	(0.016)	(0.026)	(0.026)	(0.029)	(0.024)
Log(Avg max vapor pressure deficit)	1.590**	0.520		1.550*	1.119
	(0.614)	(0.878)		(0.935)	(0.950)
Avg annual temperature (C)	0.070	0.226*	0.246*		
	(0.072)	(0.130)	(0.131)		
Log(Avg annual precipitation)	-0.448**	-0.259	-0.354		
	(0.214)	(0.309)	(0.250)		
Saw timber volume MBF per acre	-0.007	-0.014	-0.014	-0.018	-0.034
	(0.016)	(0.019)	(0.019)	(0.020)	(0.021)
Avg siteclass	0.418***	0.285***	0.278***	0.312***	0.355***
	(0.149)	(0.106)	(0.105)	(0.119)	(0.118)
Avg stand age (10 years)	0.134***	0.113***	0.110***	0.123***	0.133***
	(0.035)	(0.030)	(0.028)	(0.032)	(0.040)
Avg slope (%)	-0.003	-0.001	-0.001	-0.005	-0.006
	(0.006)	(0.005)	(0.005)	(0.006)	(0.007)
Avg elevation (100 feet)	0.037***	0.056**	0.054**	0.033**	0.025*
	(0.012)	(0.023)	(0.022)	(0.014)	(0.014)
Share of family ownership	-1.112***	-0.818**	-0.786**	-1.058***	-1.216***
	(0.366)	(0.395)	(0.390)	(0.329)	(0.335)
Forest types	Yes	Yes	Yes	Yes	No
county FEs	Yes	Yes	Yes	Yes	Yes
state-year FEs	No	Yes	Yes	Yes	Yes
Observations	8,749	8,749	8,749	8,749	8,749
R^2	0.19720	0.25068	0.25050	0.24646	0.23646

Table A5: Effect of Prescribed Fire on Wildfire Incident: Naive Model with Endogenous Prescribed Fire as Independent Variable

	Log(Wildfire count)				
	(1)	(2)	(3)	(4)	(5)
Log(2yr avg acres burned in prescribed fire)	0.008***	0.013***	0.013***	0.015***	0.015***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)
Log(Avg max vapor pressure deficit)	0.211**	0.053		0.215	0.162
	(0.094)	(0.135)		(0.141)	(0.143)
Avg annual temperature (C)	0.013	0.037*	0.039*		
	(0.011)	(0.020)	(0.020)		
Log(Avg annual precipitation)	-0.061*	-0.032	-0.042		
	(0.033)	(0.044)	(0.034)		
Saw timber volume MBF per acre	-0.001	-0.002	-0.002	-0.003	-0.005
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Avg siteclass	0.059***	0.037**	0.036**	0.041**	0.046***
	(0.022)	(0.015)	(0.014)	(0.017)	(0.017)
Avg stand age (10 years)	0.019***	0.016***	0.015***	0.017***	0.019***
	(0.005)	(0.004)	(0.004)	(0.005)	(0.006)
Avg slope (%)	-0.001	0.000	0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Avg elevation (100 feet)	0.005***	0.008***	0.008***	0.005**	0.004**
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Share of family ownership	-0.139**	-0.094	-0.091	-0.134***	-0.155***
	(0.054)	(0.061)	(0.059)	(0.050)	(0.050)
Forest types	Yes	Yes	Yes	Yes	No
county FEs	Yes	Yes	Yes	Yes	Yes
state-year FEs	No	Yes	Yes	Yes	Yes
Observations	8,749	8,749	8,749	8,749	8,749
R^2	0.19901	0.26240	0.26231	0.25674	0.24888

Table A6: Annual temperature, precipitation, maximum vapor pressure deficit, and projected future vapor pressure deficit by state

States	Variables	Mean	SD
AL	Average annual precipitation (mm)	1539.26	258.09
	Average annual temperature (C)	17.65	1.41
	Average max vapor pressure deficit (hPa)	16.70	2.15
	Projected change in vapor pressure deficit by 2050 (%)	0.09	0.03
AR	Average annual precipitation (mm)	1406.93	291.19
	Average annual temperature (C)	16.24	1.25
	Average max vapor pressure deficit (hPa)	15.67	2.25
	Projected change in vapor pressure deficit by 2050 (%)	0.25	0.04
FL	Average annual precipitation (mm)	1480.93	244.70
	Average annual temperature (C)	21.75	1.60
	Average max vapor pressure deficit (hPa)	17.85	1.76
	Projected change in vapor pressure deficit by 2050 (%)	0.08	0.02
GA	Average annual precipitation (mm)	1337.37	283.68
	Average annual temperature (C)	17.98	1.67
	Average max vapor pressure deficit (hPa)	17.26	2.30
	Projected change in vapor pressure deficit by 2050 (%)	0.05	0.02
LA	Average annual precipitation (mm)	1587.65	316.14
	Average annual temperature (C)	19.73	1.11
	Average max vapor pressure deficit (hPa)	16.87	2.12
	Projected change in vapor pressure deficit by 2050 (%)	0.12	0.03
MS	Average annual precipitation (mm)	1592.49	269.57
	Average annual temperature (C)	17.99	1.25
	Average max vapor pressure deficit (hPa)	16.55	1.71
	Projected change in vapor pressure deficit by 2050 (%)	0.14	0.04
NC	Average annual precipitation (mm)	1396.77	302.48
	Average annual temperature (C)	15.42	1.88
	Average max vapor pressure deficit (hPa)	14.44	2.26
	Projected change in vapor pressure deficit by 2050 (%)	0.12	0.02
SC	Average annual precipitation (mm)	1304.59	257.33
	Average annual temperature (C)	17.60	1.09
	Average max vapor pressure deficit (hPa)	17.10	1.71
	Projected change in vapor pressure deficit by 2050 (%)	0.07	0.02
TN	Average annual precipitation (mm)	1505.96	242.00
	Average annual temperature (C)	14.74	1.05
	Average max vapor pressure deficit (hPa)	14.12	1.60
	Projected change in vapor pressure deficit by 2050 (%)	0.18	0.04
VA	Average annual precipitation (mm)	1247.26	230.93
	Average annual temperature (C)	13.83	1.57
	Average max vapor pressure deficit (hPa)	13.37	1.77
	Projected change in vapor pressure deficit by 2050 (%)	0.17	0.03

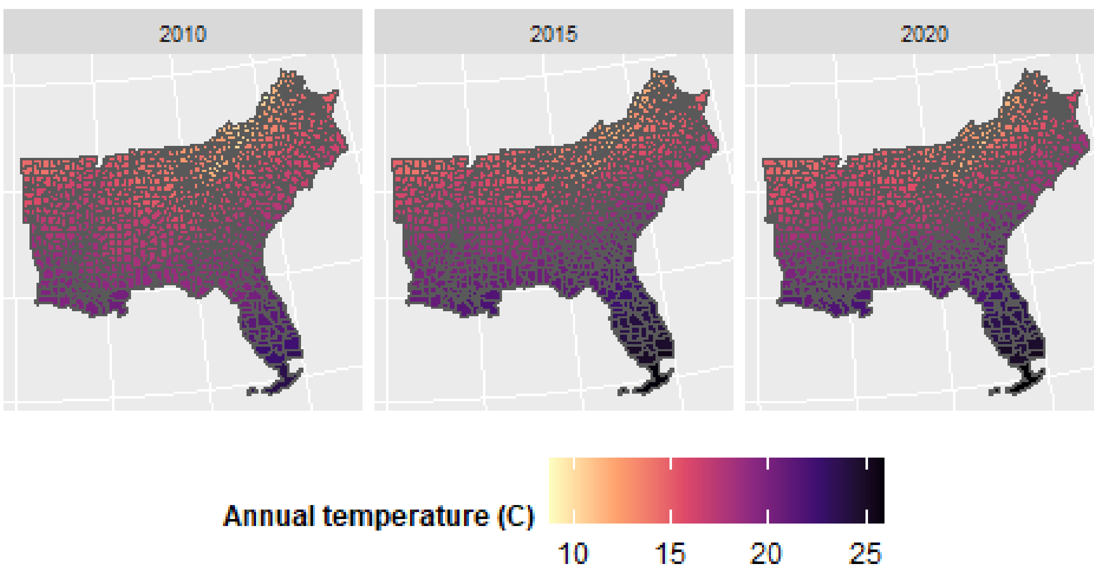

Figure A1: Annual average temperature in 2010, 2015, 2020

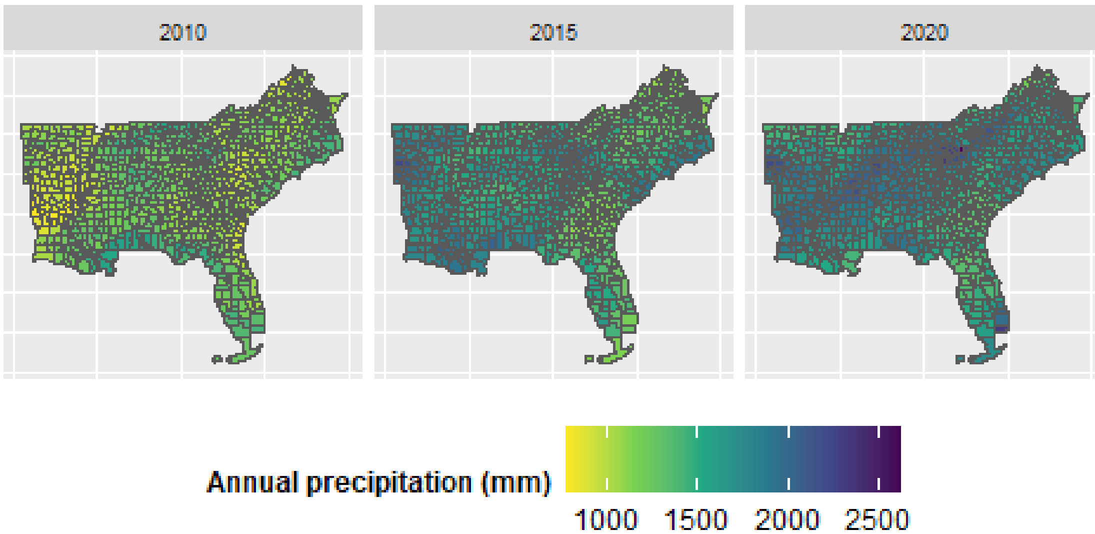

Figure A2: Annual average total precipitation in 2010, 2015, 2020

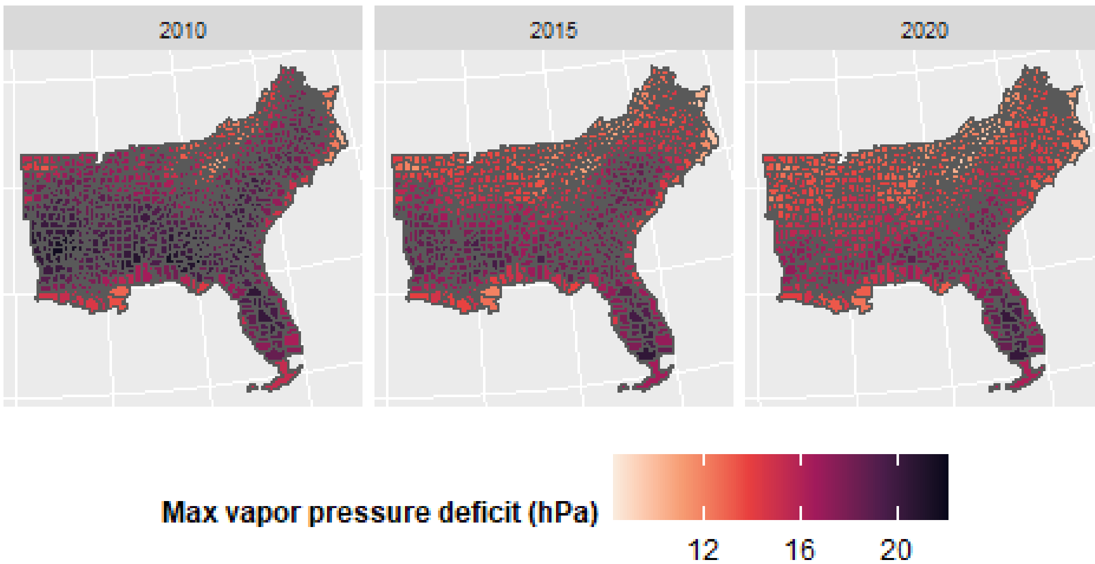

Figure A3: Annual average maximum vapor pressure deficit in 2010, 2015, 2020