A Appendix Tables and Figures

Table A1: Prescribed Burn Decision: Robustness check

Note. Significance denoted by $p<0.1$; ** $p<0.05$; *** $p<0.01$.

Table A2: Effect of Prescribed Fire on Probability of Wildfire Events: Main Probit Model Coefficient Results with Prescribed Fire Instrumented by Number of Establishments in Forestry Sector

Note. IHS: Inverse Hyperbolic Sine. Establish: The number of establishments in the forestry sector. Significance denoted by ${}^*p<0.1$; ${}^{**}p<0.05$; ${}^{***}p<0.01$.

Table A3: First Stage Results of Main Wildfire Probit Model

Note. IHS: Inverse Hyperbolic Sine. Establish: The number of establishments in the forestry sector. Significance denoted by ${}^*p<0.1$; ${}^{**}p<0.05$; ${}^{***}p<0.01$.

Table A4: Marginal Effect of Prescribed Fire on Probability of Wildfire Events: Robustness Results with Wildfire Suppression Efforts and Naturally Caused Wildfire Count Included as a Control

Note. Establish: The number of establishments in the forestry sector. Significance denoted by *p<0.1; ∗∗p<0.05; ∗∗∗p<0.01. We constructed wildfire suppression effort variable based on the Incident Management Situation Reports (IMSR) dataset (Nguyen et al. 2024), which documents daily wildland fire situations across ten geographical regions in the U.S. The data includes summaries for each reported day on wildfire activities and committed fire suppression resources (i.e., personnel and equipment). Since the data does not have geospatial identification (e.g., coordinates, counties), we matched the incidents to counties using another Incident Status Summary data, also known as ICS-209, which links each wildfire to the county (St. Denis et al. 2023). However, the process still leaves quite a few unmatched wildfires, so for these unmatched cases, we assigned counties that the local National Wildfire Coordinating Group (NWCG) unit the fire belonged to based on the National Interagency Fire Center unit ID database, available at https://unitid.nifc.gov/.

Table A5: Marginal Effect of Prescribed Fire on Probability of Wildfire Events: Robustness Check with County Fixed Effects

Note. Establish: The number of establishments in the forestry sector. Significance denoted by *p<0.1; **p<0.05; ***p<0.01.

Table A6: Annual temperature, precipitation, maximum vapor pressure deficit, and projected future vapor pressure deficit (RCP8.5) by state.

States		Mean	SD
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 2030-2040 (%)	6.35	0.66
	Projected change in vapor pressure deficit $2040-2050$ (%)	0.87	0.30
	Projected change in vapor pressure deficit 2030-2050 (%)	7.27	0.51

Table A7: Simulation results by state: RCP4.5 scenario

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.

Figure A1: Annual average maximum vapor pressure deficit in 2010, 2015, 2020

Figure A2: Projected change in vapor pressure deficit in 2030-2040

Figure A3: Projected change in vapor pressure deficit in 2040-2050

Figure A4: Simulation results: Projected mitigation benefits of wildfire reduction under RCP 4.5 scenario

B Appendix Example Numerical Calculations of Theory of Optimal Protection

The expected bare land value of a timber stand from Eq. (2) in the main text is expressed as:

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

where all parameters are defined in the main text. The landowner chooses length T and the amount of prescribed burning PB to maximize V. In this appendix, we use estimates of timber growth $F(T)$ along with stumpage prices (p) to illustrate how changes in climate (C) impact prescribed burning through altering wildfire arrival λ as described in Eq. (7) in the main text:

$$
\frac{\partial PB}{\partial C} > 0 \Longrightarrow \frac{\partial PB}{\partial \lambda_0} > 0 \tag{B.2}
$$

To develop numerical solutions that illustrate Eq. (7), shown here as Eq. B.2, we specify a specific functional form of the fire arrival rate as a logistic using Eq. (5) in the main text:

$$
\lambda = \lambda(C, PB) = \frac{1}{\left[1 + e^{(\alpha_0 + \alpha_1 C + \alpha_2 PB)}\right]}, \text{ where } \alpha_1 < 0, \alpha_2 > 0 \implies \frac{\partial \lambda}{\partial C} > 0 \text{ and } \frac{\partial \lambda}{\partial PB} < 0 \tag{B.3}
$$

In the absence of prescribed burning, the exogenous fire arrival rate depends only on C and is:

$$
\lambda_0 = \lambda(C, PB = 0) = \frac{1}{\left[1 + e^{(\alpha_0 + \alpha_1 C)}\right]}
$$
(B.4)

One additional assumed functional form is our use of the von Bertallanfy function for tree growth:

$$
F(T) = a(1 - e^{-bT})^3
$$
 (B.5)

To illustrate that ∂P B $\partial\lambda_0$ > 0 , we use data from Mihiar and Lewis (2021) on tree growth $F(T)$, stumpage prices (p) , and trees per acre for two widely managed pine species in two separate counties in our study region:

County Forest type $a \mid b$ Trees per acre p Escambia County, FL | Longleaf/Slash pine \vert 27.58 \vert 0.046 \vert 208 1.97 Berkeley County, SC | Loblolly/Shortleaf pine \vert 21.17 | 0.067 | 96 | 1.83

Table B1: Forestry revenue parameters for two representative counties

We have no information on the fire arrival rate parameters (α_0, α_1) or on the cost function for prescribed burning $c_1(PB)$, but we do have empirical knowledge of burning and climate that can be used to calibrate reasonable values for these parameters:

Table B2: Burning and climate data for two representative counties

County	annual Avg	Avg	annual Maximum an-	Pres- Vapor
	prescribed	wildfire $(\%$ of \vert	nual wildfire	Deficit sure
	burning $(\%$ of	forest)	$(\% \text{ of forest})$	(VPD)
	forest)			
Escambia	0.0326	0.00048	0.006	15.25
County, FL				
Berkeley	0.09	0.0014	0.006	16.81
County, SC				

Given the burning and climate data for these representative counties, and the logistic functional form for fire arrival (Eq. 5), the implicit value of $\alpha_0 + \alpha_1 C + \alpha_2 PB$ can be computed as approximately 5.1, such that $\lambda = \lambda(C, PB) =$ 1 $[1+e^{(5.1)}]$ = 0.006, which matches the largest proportion of forest burned by wildfire in these counties during our study time frame. We further assume that PB is measured as the fraction of land that is subject to prescribed burning, and the prescribed burning cost function is assumed to be of a quadratic form with increasing marginal costs:

$$
c_1(PB) = 46 + 1500PB + 150PB^2
$$
 (B.6)

With this function, a country with an average $PB = 0.03$ would have annual prescribed burning costs of approximately \$91/acre. Finally, we assume a post-fire salvage cost of $c_2 = $200/$ acre.

Given these assumptions, we numerically compute the optimal value of PB given exogenous changes in climate, which is reflected in changes in λ_0 . Since we have no information about what magnitude α_2 should be, we calibrate it for each county so as to get optimal prescribed burning proportions that are roughly consistent with the empirical data. Table B3 shows the key comparative static that ∂P B $\partial\lambda_0$ > 0 , which in turn determines the wildfire arrival $\lambda(C, PB)$.

Table B3: Optimal prescribed burning shares as a function of exogenous changes in wildfire arrival rate

	Escambia County, FL ($\alpha_2 = 5$)		Berkeley County, SC ($\alpha_2 = 15$)	
Exogenous	Optimal	Wildfire	Optimal	Wildfire
wildfire arrival	prescribed	arrival	prescribed	arrival
$\lambda_0 = \lambda(C,0)$	burning share	$\lambda(C, PB)$	burning share	$\lambda(C, PB)$
	PB		PB	
0.006	0.017	0.00505	0.022	0.00438
0.0067	0.047	0.00530	0.028	0.00441
0.011	0.13	0.00589	0.059	0.00457
0.018	0.21	0.00645	0.090	0.00473

References

Mihiar, Christopher, and David J Lewis. 2021. "Climate, adaptation, and the value of forestland: A national Ricardian analysis of the United States." Land Economics 97 (4): 911–932.

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St. Denis, Lise A, Karen C Short, Kathryn McConnell, Maxwell C Cook, Nathan P Mietkiewicz, Mollie Buckland, and Jennifer K Balch. 2023. "All-hazards dataset mined from the US National Incident Management System 1999–2020." Scientific data 10 (1): 112.