Project Notes:

Project Title: Modeling and Analysis of Wildfire Behavior in New England Using FARSITE
Name: Lu, Corey

Contents:

Knowledge Gaps:
This list provides a brief overview of the major knowledge gaps for this project, how they were resolved and where to find the information.

Knowledge Gap	Resolved By	Information is located	Date resolved
What external factors influence animal movement?	No longer relevant to project		
Prevention strategies / intervention effectiveness			
Cross boundary fire transmission & land ownership interaction			
Lightning-ignited fires under climate change, and human vs natural ignition interactions			
Regional model calibration	Found an article on calibrating FARSITE in a specific vegetation type	(Price & Germino, 2022)	11/20
Fuel model representation in eastern forests	Found article analyzing the effects of different fuels in eastern forests	(Ivey et al., 2024)	11/15
Seasonal drivers of fire spread	Found article analyzing wildfire occurrences in New England	(Pollina et al., 2013)	11/29
Urban-wildland interface effects			

Risk metrics beyond burn area			
Transferability of western fire assumptions			
Computational scalability			
Decision-relevant outputs for local planning			

Literature Search Parameters:

These searches were performed between 8/15/2025 and XX/XX/2019.
List of keywords and databases used during this project.

Database/search engine	Keywords	Summary of search
Science.org	Wildlife AND “human disturbance”	Found 2018 article on nocturnality shifts
WPI Library	“animal movement” AND GPS	
WPI Library	wildfire AND soil AND "organic carbon"	Found study on carbon material in soil after short and repeated wildfires
WPI Library	wildfire AND socioeconomic	
WPI Library	(wildfire OR “forest fire” OR “brush fire”) AND drought AND “New England”	
WPI Library	(wildfire OR “forest fire”) AND (drought OR aridity) AND (Massachusetts OR “northeast US”)	
WPI Library	“compound drought-wildfire” AND (“climate change” OR warming)	
WPI Library	(fire severity OR fire occurrence OR fire risk) AND (drought OR aridity) AND (climate change)	
WPI Library	(wildfire risk modeling OR fire hazard modeling) AND (drought OR soil moisture) AND (“northeast” OR “New England”)	

Tags:

#WildfireRisk
#HumanIgnitions
#ClimateChange
#SocioeconomicFactors
#FuelMoisture
#SoilChemistry
#FireModeling
#ExtremeEvents
#UrbanInterface
#Drought
#FireSuppression
#CarbonCycles
#MachineLearning
#RegionalFocus
#PolicyAndManagement

Article #1: The influence of human disturbance on wildlife nocturnality

Source Title	Science.org
Source citation (APA Format)	Gaynor, K. M., Hojnowski, C. E., Carter, N. H., & Brashares, J. S. (2018). The influence of human disturbance on wildlife nocturnality. *Science*, *360*(6394), 1232–1235. https://doi.org/10.1126/science.aar7121
Original URL	https://www.science.org/doi/10.1126/science.aar7121
Source type	Journal Article
Keywords	Wildlife behavior, human disturbance, nocturnality, meta-analysis, recreation ecology, global study
#Tags	#WildlifeEcology #HumanDisturbance #Nocturnality #ConservationBiology #MetaAnalysis #BehavioralAdaptation
Summary of key points + notes (include methodology)	**Core idea**: Humans are reshaping wildlife activity patterns, pushing animals to be more active at night. Methodology: - Conducted a meta-analysis of 76 peer-reviewed studies, covering 62 mammal species globally. - Compared activity patterns in low vs. high human disturbance contexts (hunting, recreation, agriculture, roads). - Quantified the proportion of nocturnal activity under different disturbance levels. **Findings**: On average, mammals increased nocturnal activity by 36% in areas with human presence. **Implication**: Temporal displacement may help wildlife avoid humans but could also disrupt predator-prey dynamics, energy budgets, and ecosystem functioning.
Research Question/Problem/ Need	How does human disturbance across different ecosystems influence the timing of wildlife activity?

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<td>Important Figures</td>
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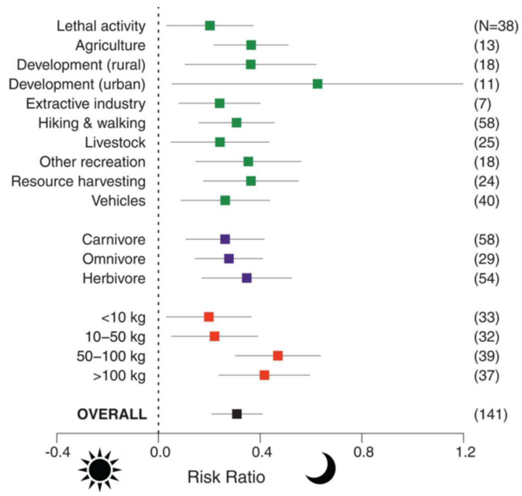

Fig. 2 Increase in large mammal nocturnality in relation to human activity types, trophic level, and body size.
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<tr>
<td>VOCAB: (w/definition)</td>
<td>Nocturnality: Activity pattern in which animals are primarily active during the night.
Meta-analysis: A statistical method that combines results from multiple independent studies to look for overall trends.
Diel Activity: The 24-hour cycle of activity (day vs night patterns).
Anthropogenic Disturbance: Environmental change or stress caused by human activity (recreation, development, hunting).</td>
</tr>
<tr>
<td>Cited references to follow up on</td>
<td>W. Viechtbauer, Conducting meta-analyses in R with the metafor package. J. Stat. Softw. 36, 1–48 (2010).</td>
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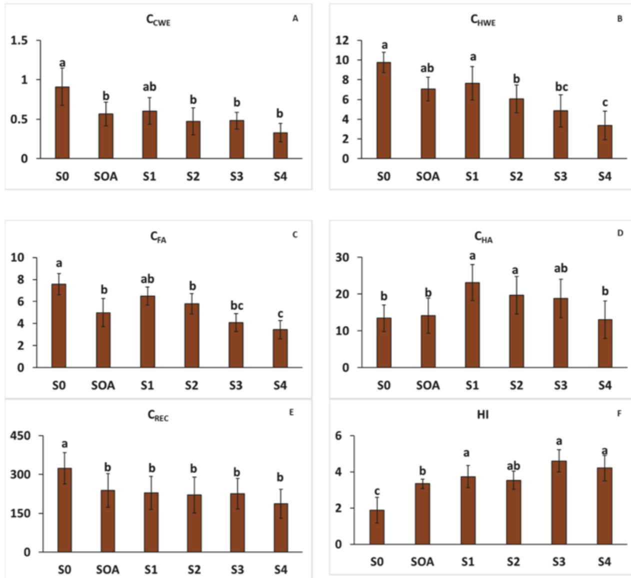
<tr>
<td>Follow up Questions</td>
<td>1. Do specific types of human activity cause different magnitudes or patterns of disturbance?
2. How do shifts toward nocturnality affect reproduction or survival rates?
3. Can real-time visitor and environmental data be used to predict the degree of this shift for small areas and/or short time periods?</td>
</tr>
</table>

Article #2: Impact of wildfire recurrence on soil properties and organic carbon fractions

Source Title	ScienceDirect
Source citation (APA Format)	Salgado, L., Alvarez, M. G., Díaz, A. M., Gallego, J. R., & Forján, R. (2024). Impact of wildfire recurrence on soil properties and organic carbon fractions. *Journal of Environmental Management*, *354*, 120293. https://doi.org/10.1016/j.jenvman.2024.120293
Original URL	https://www.sciencedirect.com/science/article/pii/S0301479724002792
Source type	Journal Article
Keywords	Soil organic carbon; Soil carbon fractions; Nitrogen; Soil properties; Wildfires
#Tags	#wildfire #soilChemistry #carbonCycles #nutrientLoss #fireFrequency
Summary of key points + notes (include methodology)	• Methods: Six plots in Allande, Asturias, with different fire recurrence histories (0–4 fires between 2005–2022) were sampled and analyzed. • Key Findings: ○ Soil texture: High sand content; more fire recurrence = less clay and silt due to erosion. ○ CEC: Declined with more fire recurrence; soils had lower base cations and higher aluminum saturation. ○ pH & EC: Remained acidic and unaffected by fire recurrence. ○ Nitrogen: All nitrogen forms (organic N, nitrate, ammonium) declined significantly with more fires. ○ Carbon fractions: ▪ Labile carbon (cold- & hot-water extractable) and fulvic acids decreased with fire recurrence. ▪ Humic acids stayed stable or increased, indicating a shift toward more recalcitrant (hard-to-decompose) carbon forms. ▪ Soils with more fires had higher humification index (HI). • Conclusion: Repeated wildfires degrade soil quality by reducing nutrients and labile carbon, altering carbon cycling, and lowering carbon sequestration potential.
Research Question/Problem/Need	How do recurrent wildfires affect soil organic carbon (SOC) fractions, nitrogen (N) fractions, pH, cation exchange capacity (CEC), and soil texture?

Important Figures	 This figure shows the concentrations of different organic carbon fractions in samples.
VOCAB: (w/definition)	• Soil Organic Carbon (SOC): Carbon stored in soil organic matter, crucial for fertility and carbon cycling. • Fractionation: Separation of SOC into different pools (labile, fulvic acids, humic acids, recalcitrant) based on stability and availability. • Labile Carbon: Easily decomposable carbon, readily available to microbes, sensitive to disturbances. • Fulvic Acids (FA): Water-soluble organic compounds that are part of soil organic matter, relatively labile. • Humic Acids (HA): More stable organic compounds that persist longer in soil after decomposition. • Recalcitrant Carbon: Very stable carbon resistant to microbial breakdown; persists for long timescales. • Cation Exchange Capacity (CEC): Soil's ability to hold and exchange positively charged ions (nutrients like Ca^{2+}, Mg^{2+}, K^{+}). • Humification Index (HI): A measure of the degree of organic matter decomposition and stabilization into humus. • Volatilization: Conversion of soil nutrients (like nitrogen) into gases during fire, leading to nutrient loss. • Denitrification: Microbial process converting nitrate into nitrogen gases, often leading to nitrogen loss from soil.
Cited references to follow up on	R. Sawyer, R. Bradstock, M. Bedward, R.J. Morrison Fire intensity drives post-fire temporal pattern of soil carbon accumulation in Australian fire-prone forests
Follow up Questions	1. Why might humic acids remain stable or even increase after fires, while fulvic acids decrease sharply? 2. Could different vegetation types (scrubland vs. forest) alter the resilience of soil carbon fractions to fire recurrence?

Article #3: The Influence of Socioeconomic Factors on Human Wildfire Ignitions in the Pacific Northwest, USA.

Source Title	The Influence of Socioeconomic Factors on Human Wildfire Ignitions in the Pacific Northwest, USA.
Source citation (APA Format)	Reilley, C., Crandall, M. S., Kline, J. D., Kim, J. B., & Diego, J. de. (2023). The Influence of Socioeconomic Factors on Human Wildfire Ignitions in the Pacific Northwest, USA. *Fire*, *6*(8), NA-NA. https://doi.org/10.3390/fire6080300
Original URL	https://go-gale-com.ezpv7-web-p-u01.wpi.edu/ps/i.do?p=AONE&u=mlin_c_worpoly&id=GALE%7CA762478309&v=2.1&it=r&aty=ip
Source type	Journal Article
Keywords	wildfire occurrence; human ignitions; pacific northwest; social-ecological systems; wildfire policy; regression analysis
#Tags	#Wildfire #IgnitionCauses #SocioeconomicFactors #HotspotAnalysis
Summary of key points + notes (include methodology)	Keypoints: - Caused by both natural and humans - Human ignitions dominate near communites - Biophyisical factors shape likelihood - Socioeconomic factors correlate with ignition rates ○ Poverty, income, unemployment, seasonal housing, education, and road desnisty - East vs west cascade differences - Hopspot anaylsis shows clusters of high human ignition near major population centers Methodology - Data included wildfire ignition records from USDA. - 24 socioeconomic and biophyiscal variables - Analysis included generalized linear models, hotspot analysis, and panel dataset.
Research Question/Problem/ Need	What are patterns of wildfire ignition causes across the Pacific Northwest? How do socioeconomic and biophysical factors influence wildfire ignitiosn in the region?

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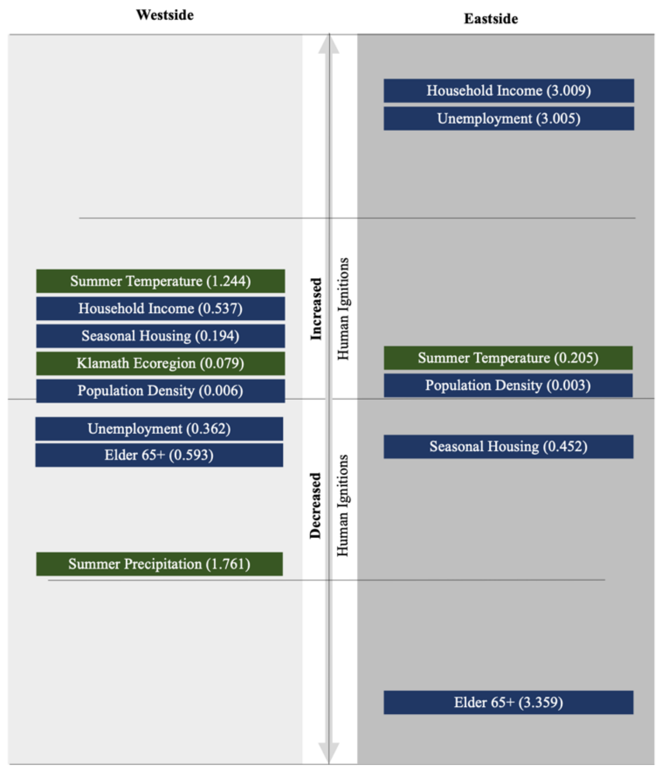
<tr><td>Important Figures</td><td>

Figure 8. Summary of regression and sensitivity analysis results illustrating the relationships between significant ($p < 0.10$) socioeconomic (blue) and biophysical (green) factors and human ignitions only. Significant factors are shown by magnitude of impact based on sensitivity analysis in Table 5 (noted in parenthesis). Note that significance is not absolute and the choice to use a different significance cutoff would have resulted in a different graphical representation of results.</td><td>Shows the varying effects of different factors based on their location/region. Some factors increase ignition likelihood while others decrease.</td></tr>
<tr><td>VOCAB:
(w/definition)</td><td colspan="2">Panel dataset: longitudinal dataset combing multiple variables across time and space
Klamath Ecoregion: A distinct ecological zone in SW Oregon with a unique fire regime.</td></tr>
<tr><td>Cited references to follow up on</td><td colspan="2">Pozo et al. (2022). Socio-Economic and Land-Cover Drivers of Wildfire in Chile</td></tr>
<tr><td>Follow up Questions</td><td colspan="2">1. How might future climate change amplify or alter these socioeconomic ignition patterns?
2. Could policy interventions (like road closures, recreational restrictions, or housing codes) significantly reduce ignition risk?
3. How transferable are these results to other fire-prone regions outside the Pacific Northwest?</td></tr>
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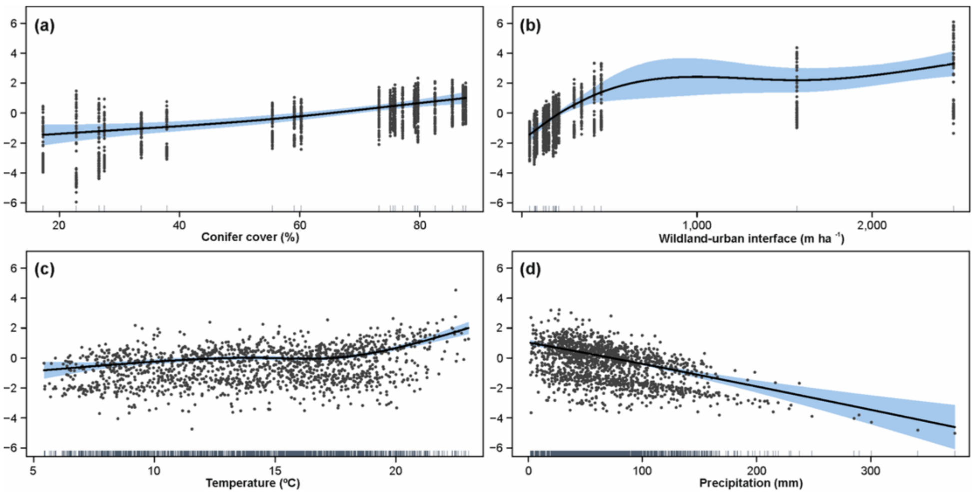
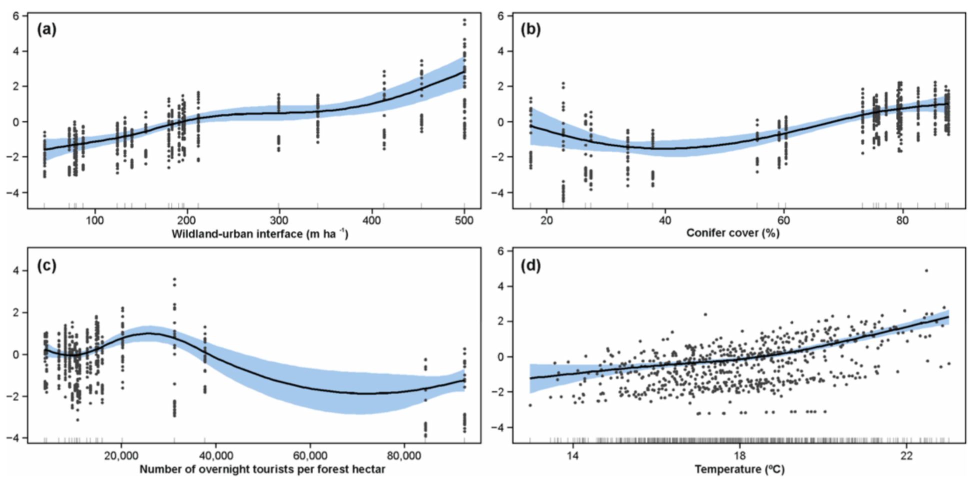
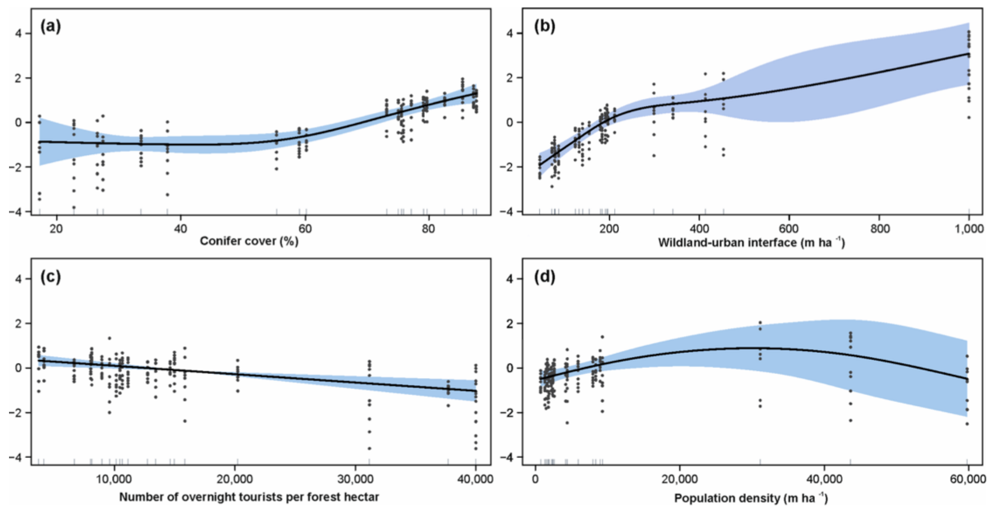
Article #4: A Combination of Human Activity and Climate Drives Forest Fire Occurrence in Central Europe: The Case of the Czech Republic

Source Title	A Combination of Human Activity and Climate Drives Forest Fire Occurrence in Central Europe: The Case of the Czech Republic
Source citation (APA Format)	Berčák, R., Holuša, J., Trombik, J., Resnerová, K., & Hlásny, T. (2024). A Combination of Human Activity and Climate Drives Forest Fire Occurrence in Central Europe: The Case of the Czech Republic. *Fire*, *7*(4), 109. https://doi.org/10.3390/fire7040109
Original URL	https://doi.org/10.3390/fire7040109
Source type	Journal article
Keywords	Central Europe; climate; fire risk; human activities; wildfires; Czech Republic; ignition drivers
#Tags	#Wildfires #ClimateChange #SocioeconomicFactors #CentralEurope #IgnitionRisk #HumanActivity #PredictiveModeling
Summary of key points + notes (include methodology)	• **Timeframe Studied**: 2006–2015 (10 years). Dataset included ~7,279 forest fires, averaging 728 per year. • **Methods**: ○ Used *Generalized Additive Models (GAM)* to assess the relationship between fire occurrence and multiple predictors (climate, forest structure, socioeconomic variables, landscape context). ○ Analyzed at three temporal scales: annual, monthly, and summer season (June–August). ○ Dependent variable: number of forest fires per forest hectare in 76 municipal districts. • **Main Findings**: ○ Fire occurrence showed **bi-modal seasonal peaks**: spring (April, linked to forestry operations & dry grass) and summer (July–August, linked to hot/dry conditions & recreation). ○ Also influenced by climate, human activity, and forest composition. • **Model performance**: ○ Explained variance in fire occurrence: 71.4% (annual), 48.7% (monthly), 53.9% (summer season). • **Conclusions**: ○ Fire risk in Central Europe results from combined **human activity + climate drivers**. ○ Need for better fire monitoring, public awareness campaigns, and fire-prone zone identification for resource allocation.

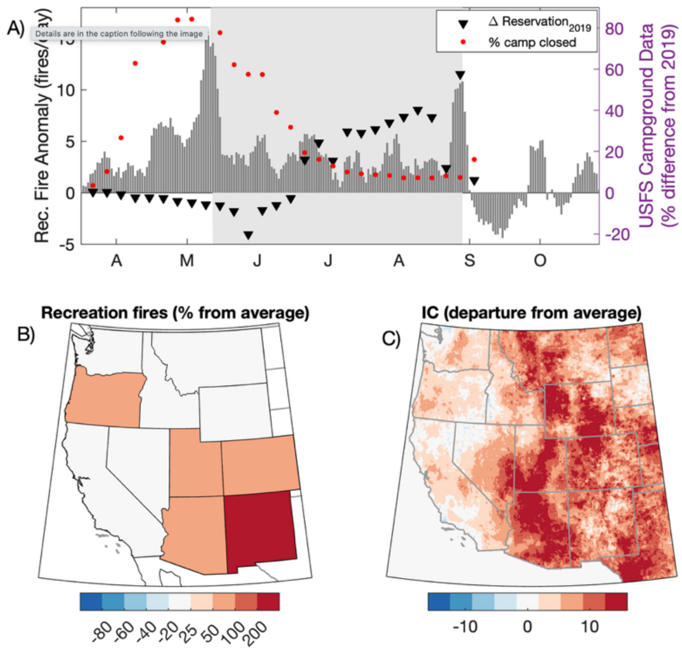
	○ Climate warming and changing forest structures (e.g., bark beetle mortality leading to more fuel) will exacerbate future risks.
Research Question/Problem/ Need	How do climate, forest composition, and human activity interact to drive forest fire occurrence in Central Europe, and what are the most significant predictors of ignition risk across different time scales?
Important Figures	Figures 4–6: GAM model results showing predictor effects (WUI, conifer cover, temperature, tourists, population).  

	
VOCAB: (w/definition)	Wildland–Urban Interface (WUI): The boundary zone where forests and human development meet; a key ignition risk factor. Generalized Additive Model (GAM): A statistical modeling approach that allows for flexible, nonlinear relationships between predictors and outcomes. Conifer cover: Proportion of coniferous trees (pine, spruce, etc.), often more flammable than deciduous trees. Unimodal response: A relationship where the effect increases up to a point, then decreases. Ignition drivers: Factors (climatic, biophysical, human) that influence the likelihood of wildfire ignition.
Cited references to follow up on	Mozny et al. (2021) – Climate change driven changes of vegetation fires in the Czech Republic ?.
Follow up Questions	Could integrating mobility data (GPS, cell phones) provide more precise proxies for human activity compared to population density or tourist counts? How do fire suppression response times alter the observed patterns, given that most fires studied were small? Would using higher-resolution spatial data (exact fire coordinates vs. district-level aggregates) improve predictive accuracy? How do bark beetle outbreaks and deadwood accumulation interact with ignition risk beyond the study's timeframe?

Article #5: COVID-19 Fueled an Elevated Number of Human-Caused Ignitions in the Western United States During the 2020 Wildfire Season

Source Title	COVID-19 Fueled an Elevated Number of Human-Caused Ignitions in the Western United States During the 2020 Wildfire Season
Source citation (APA Format)	Jorge, A. L., Abatzoglou, J. T., Fleishman, E., Williams, E. L., Rupp, D. E., Jenkins, J. S., Sadegh, M., Kolden, C. A., & Short, K. C. (2025). COVID-19 Fueled an Elevated Number of Human-Caused Ignitions in the Western United States During the 2020 Wildfire Season. *Earth's Future*, *13*(4), e2024EF005744. https://doi.org/10.1029/2024EF005744
Original URL	https://doi.org/10.1029/2024EF005744
Source type	Journal article
Keywords	Wildfire ignition, human-caused fires, COVID-19, recreation, debris burning, fireworks, socio-environmental systems, western United States.
#Tags	#Wildfire #COVID19 #HumanIgnitions #ClimateVsBehavior #Recreation #FireRisk

Summary of key points + notes (include methodology)	• Background: 2020 was the largest wildfire season in modern western US history. While climate conditions (hot/dry) enabled fire spread, they don't fully explain the surge in ignitions.
	• Main Argument: COVID-19 altered human mobility/behavior (stay-at-home orders, increased recreation, fireworks use), producing more opportunities for ignitions.
	• Key Findings:
	  ○ Human-caused fires in 2020 were ~20% higher than the 1992–2019 average.
	  ○ Recreation-related ignitions were 36% higher.
	  ○ Debris/open burning fires were 70% higher in spring 2020.
	  ○ Fireworks ignitions were 40% higher during July 4th week.
	  ○ Lightning-caused fires were at a 30-year low.
	• Methodology:
	  ○ Used Fire Program Analysis Fire-Occurrence Database (FPA FOD) (1992–2020, ~2.3M fires).
	  ○ Screened data for reporting biases (excluded some municipal/local data).
	  ○ Analyzed anomalies using 7-day rolling averages of ignition counts vs. 1992–2019 baseline.
	  ○ Linked ignition trends with climate (Ignition Component, gridMET dataset) and human activity datasets: Google Mobility reports, USFS campground reservations, and fireworks sales data.
	  ○ Compared observed ignitions with null climate model (linear regression on IC

	vs. ignitions) to separate climate vs. human behavior contributions. • Conclusions: COVID-19 social disruptions significantly elevated ignitions by altering human behavior in wildland–urban and recreation areas. Climate was a secondary driver of ignition frequency but a primary driver of fire spread.
Research Question/Problem/ Need	How did behavioral changes during COVID-19 influence the number and causes of wildfire ignitions in the western US, and how do these findings inform fire management in a warming climate?
Important Figures	 (a) Seven-day running average anomaly in wildfires from recreation and ceremony (black bars) during 2020 vs. 1992–2019. Black triangles show weekly differences in USFS campground reservations (2020 vs. 2019, thousands), and red dots show the percentage of campgrounds closed. Gray shading marks 25 May–8 Sept. (b) Percentage difference in recreation- and ceremony-caused fires during 25 May–8 Sept 2020 vs. 1992–2019 average. (c) Anomaly in ignition component during 25 May–8 Sept 2020 vs. 1992–2019.
VOCAB: (w/definition)	Ignition Component (IC): A US Fire Danger Rating System metric estimating fire start probability based on fuel moisture, weather, and spread potential. FPA FOD: Fire Program Analysis Fire-Occurrence Database, a nationwide wildfire ignition dataset. Null model: A baseline model predicting ignitions based only on climate variability, used to isolate behavioral effects.
Cited references to follow up on	Balch et al. (2017). Human-started wildfires expand the fire niche across the United States. PNAS.
Follow up Questions	How lasting are the COVID-related shifts in recreation and mobility—did they continue into 2021–2023, and do they suggest permanent changes in ignition risk?

Article #6: The Importance of small fires for wildfire hazard in urbanised landscapes of the northeastern US

Source Title	*The Importance of small fires for wildfire hazard in urbanised landscapes of the northeastern US*
Source citation (APA Format)	Amanda R. Carlson, Megan E. Sebasky, Matthew P. Peters, & Volker C. Radeloff. (n.d.). The importance of small fires for wildfire hazard in urbanised landscapes of the northeastern US. *International Journal of Wildland Fire.*, *30*(5), 307–321. https://doi.org/10.1071/WF20186
Original URL	https://doi.org/10.1071/WF20186
Source type	Journal article
Keywords	Wildfire hazard, small fires, wildland–urban interface (WUI), MaxEnt modeling, northeastern US, climate deficit, human ignitions
#Tags	#WildfireRisk #Northeast #UrbanInterface #ClimateChange #FireManagement
Summary of key points + notes (include methodology)	• **Objectives**: 1. Assess spatial and seasonal variations in small wildfire probability. 2. Compare small vs. large fires. 3. Explore how inconsistent fire definitions/reporting affect hazard models. • **Methods**: o Data: USFS fire occurrence database (2005–2017), focusing on fires >0.1 ha. o Modeling: Maximum entropy (MaxEnt) models to predict wildfire occurrence using environmental and human predictors (land cover, soil moisture, road density, topography, climate water deficit). o Scale: 20-state Northeast U.S., grouped into 4 sub-regions (New England, Mid-Atlantic, Upper Midwest, Lower Midwest). • **Findings**: o Majority of fires are small: 95% human-caused, 72% in spring. o Wildfire occurrence highest near low-density urban development and non-agricultural land cover. o Large fires were more linked to climatic water deficit, rugged topography, and intermediate development levels. o Small fires clustered near urban centers; large fires in more continuous wildlands (e.g., Pine Barrens, Appalachians). o Regional variation in reporting quality influenced hazard maps. • **Implications**: o Ignoring small fires underestimates wildfire risk in the Northeast. o Climate change (drought, warming) will increase hazard potential, especially in summer/fall.

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- ○ Consistent wildfire definitions and reporting standards are needed.
- ○ Management must account for small ignitions near WUI to reduce strain on suppression resources.

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<tr><td>Research Question/Problem/ Need</td><td>How do small wildfires contribute to overall wildfire hazard in urbanised landscapes of the northeastern U.S., and how can hazard models better capture their patterns and drivers?</td></tr>
<tr><td>Important Figures</td><td>

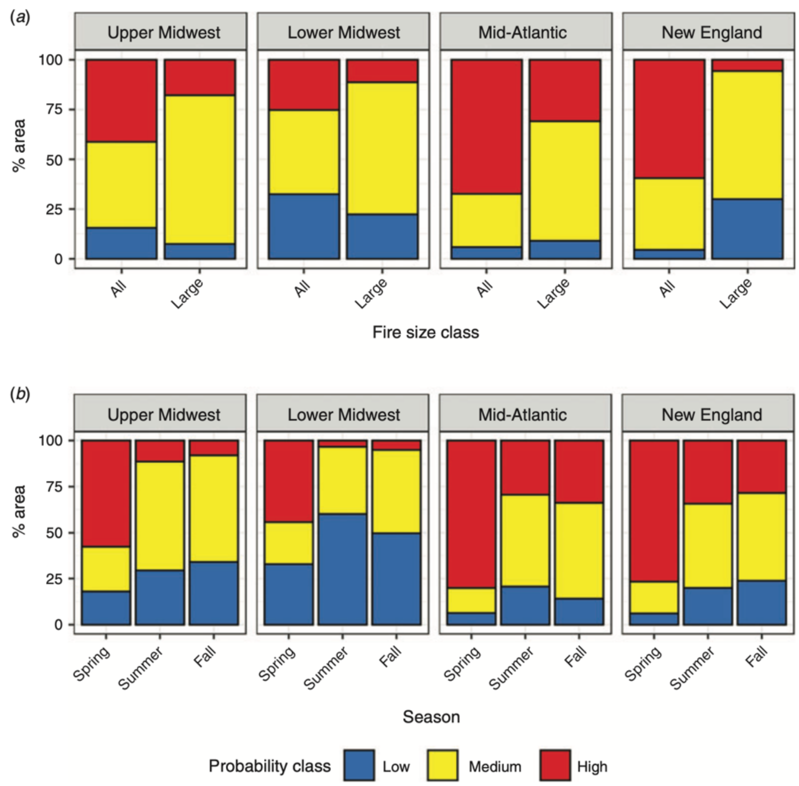

Fig. 6. Percentages of area classified as low, medium, and high occurrence probability for region-wide models predicting occurrences of (*a*) all fires and large fires only for all seasons; and (*b*) fires of all sizes by season, grouped by sub-region.

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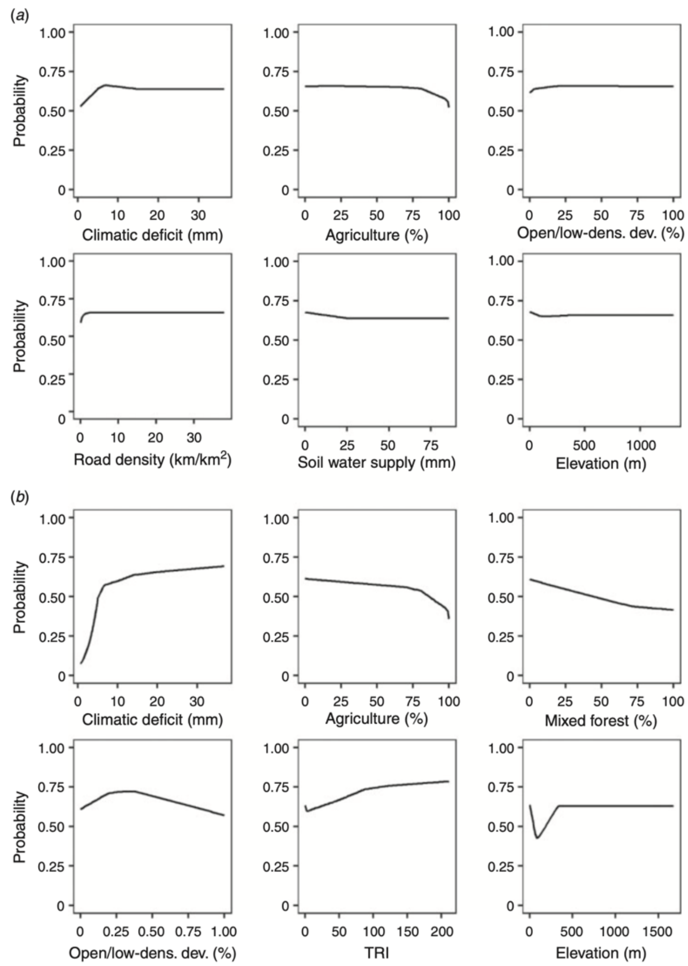

Fig. 8. Response curves for the six variables with the highest percentage contributions to the MaxEnt model predicting occurrence of (*a*) all wildfires; and (*b*) large fires (>4 ha) only for the Northeast region.

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<td>VOCAB:
(w/definition)</td>
<td>MaxEnt (Maximum Entropy Modeling): A machine learning method that estimates probability distributions based on presence-only data.
Intermix vs. Interface WUI: Intermix = housing intermingled with vegetation; Interface = housing adjacent to wildland.</td>
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<tr>
<td>Cited references to follow up on</td>
<td>Mietkiewicz et al. (2020) – Human ignitions and consequences to homes.</td>
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<td>Follow up Questions</td>
<td>How might incorporating future climate projections (drought/heat waves) alter the hazard maps?</td>
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Article #7: Towards predicting flammability of Sierra Nevada mixed conifer forests: drought stress and fuel moisture are strongly linked in angiosperms but decoupled in gymnosperms

Source Title	Towards predicting flammability of Sierra Nevada mixed conifer forests: drought stress and fuel moisture are strongly linked in angiosperms but decoupled in gymnosperms
Source citation (APA Format)	Boving, I., Celebrezze, J. V., Anderegg, L. D. L., & Moritz, M. (2025). Towards predicting flammability of Sierra Nevada mixed conifer forests: Drought stress and fuel moisture are strongly linked in angiosperms but decoupled in gymnosperms. *Fire Ecology*, *21*(1), 52. https://doi.org/10.1186/s42408-025-00396-x
Original URL	https://doi.org/10.1186/s42408-025-00396-x
Source type	Journal article
Keywords	Flammability, Live fuel moisture (LFM), Water potential, Turgor loss point (TLP), Angiosperms, Gymnosperms, Drought stress, Pyro-ecophysiology, Sierra Nevada
#Tags	#Drought #Wildfire #PlantPhysiology #FuelMoisture #California #FireRisk
Summary of key points + notes (include methodology)	**Background:** • Drought and wildfire are connected via plant hydration (water potential & live fuel moisture, LFM). • Plant water status influences both growth/mortality and wildfire ignition/spread. • Angiosperms (broadleaf species) and gymnosperms (conifers) may differ in how drought stress translates into flammability. **Research Questions:** 1. Do reductions in hydration (water potential, LFM) in the lab reflect seasonal field patterns? 2. Which hydration metric (water potential vs. LFM) better predicts flammability across species? 3. How does flammability change seasonally with shifts in hydration and phenology? **Methods:** • Study sites: Providence Creek Watershed, Sierra National Forest, CA (rain–snow transition zone, conifer–shrub mosaic). • Species: 3 gymnosperms (white fir, Jeffrey pine, incense cedar) and 3 angiosperms (California black oak, whitethorn ceanothus, greenleaf manzanita). • Field measures: Biweekly 2020–2021 summer drydowns of LFM & water potential.

	• Lab measures: Pressure–volume curves (TLP) + benchtop branch drydowns + flammability tests (hotplate device measuring ignition time, flame height, temp change, glow duration).
	• Analysis: Mixed-effects models, variance decomposition, PCA on flammability metrics.
	Results:
	• **Hydration relationships:**
	    o Angiosperms: Strong, consistent coupling of water potential and LFM (lab & field).
	    o Gymnosperms: Weak/inconsistent coupling; LFM changes not strongly tied to water potential.
	    o Tissue age mattered (new vs. old growth diverged early season).
	• **Flammability predictors:**
	    o LFM consistently predicted flammability better than water potential.
	    o Drier tissues → faster ignition, higher flame intensity.
	    o Species differences were significant:
	        ▪ *Q. kelloggii* (oak) = highest ignitability.
	        ▪ *Pinus jeffreyi* & *Calocedrus decurrens* = most combustible (greater heat release).
	        ▪ Gymnosperms ignited almost 100% of time; angiosperms less often.
	• **Seasonal dynamics:**
	    o New hydrated growth in early season reduced flammability.
	    o Later-season drying & phenology shifts increased flammability.
	    o Seasonal declines in LFM sometimes shifted species' rank order of ignitability.
	Conclusions:
	• **Angiosperms**: Drought stress strongly tied to LFM → better predictive link between drought and fire risk.
	• **Gymnosperms**: Decoupled relationship → flammability shaped more by morphology (leaf dry matter, VOCs) than by drought stress directly.
	• LFM is a stronger integrative predictor of flammability than water potential.
	• Understanding species-specific physiology and phenology is crucial for wildfire risk prediction in drought-prone forests.

Research Question/Problem/ Need	How do plant functional groups (angiosperms vs. gymnosperms) mediate the relationship between drought stress, live fuel moisture, and flammability, and what does this mean for predicting wildfire risk under climate change?

Lu 21

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<td>Important Figures</td>
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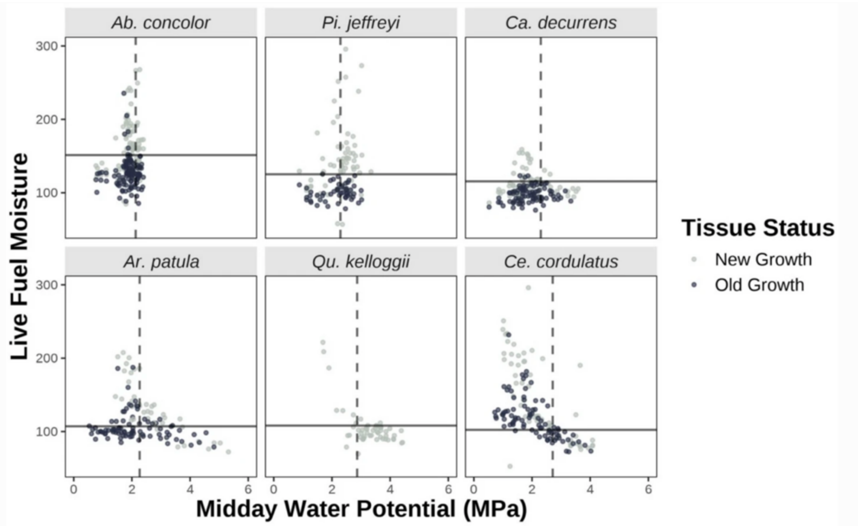
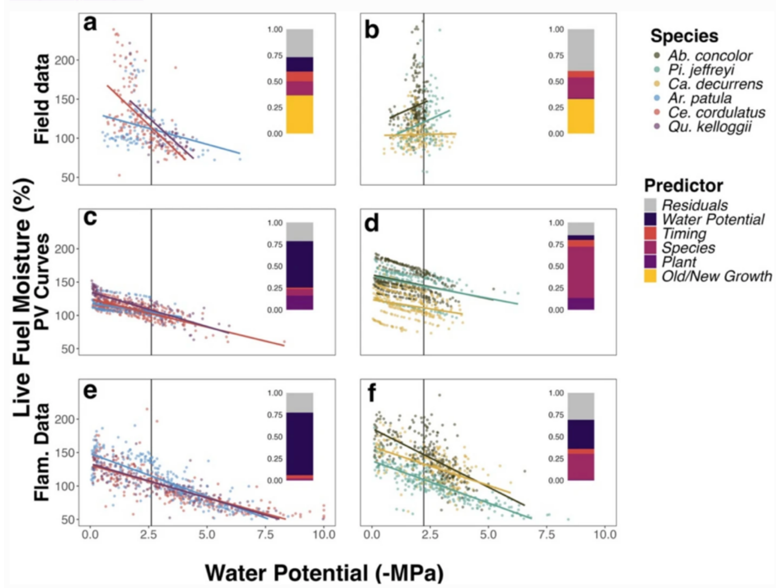


The relationship between live fuel moisture (LFM) and midday water potential for all species. Data collected between April and October in 2020 and 2021. LFM samples were split into already-developed tissue (previous year, dark gray) and newly developing tissue (current year, light gray). Vertical dotted lines indicate mean TLP for each species from PV Curves measured during fall 2020 and 2021; horizontal lines indicate the mean LFM at TLP (Table S1)

From: [Towards predicting flammability of Sierra Nevada mixed conifer forests: drought stress and fuel moisture are strongly linked in angiosperms but decoupled in gymnosperms]()



Relationship between live fuel moisture and water potential from three different dehydration methods for angiosperms (left panels) and gymnosperms (right panels), and variance decompositions showing the contribution of each predictor. **a–b** Field collected data for midday water potentials and LFM collected approximately fortnightly April–October in 2020 and 2021, with old and new growth combined for visualization of linear models but separated in variance decompositions. **c–d** PV Curve data measured on individual leaves. **e–f** Water potential and LFM relationships established during a benchtop drydown while building flammability curves ("Flam. Data"), in which separate branchlets were measured for each datapoint. Vertical lines show the mean TLP for each functional group

Fig. 2–3: Water potential vs. LFM across field, PV curves, and benchtop drydowns (stronger for angiosperms).

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<td>VOCAB:
(w/definition)</td>
<td>Pyro-ecophysiology: Study of how plant physiological traits (hydration, chemistry, morphology) influence fire behavior.
Turgor Loss Point (TLP): Threshold at which plant cells lose turgor pressure, leading to wilting and stomatal closure.</td>
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<td>Cited references to</td>
<td>Ma et al. (2021) – Climate change effects on LFM & fire risk.</td>
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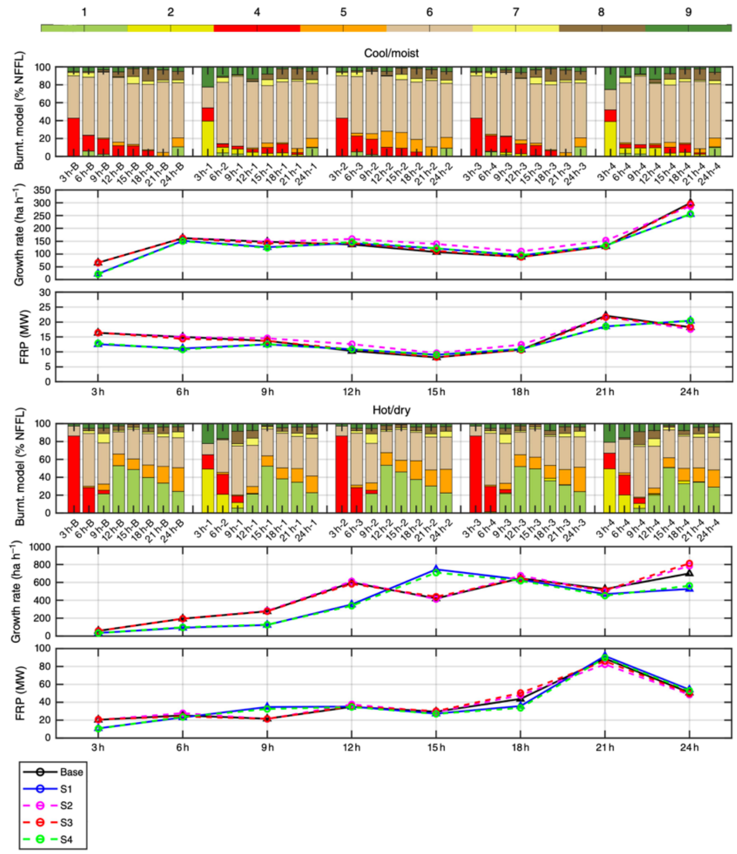
follow up on	
Follow up Questions	How might Massachusetts forests (oak–pine systems) align with these patterns?

Article #8: An integrated framework for habitat restoration in fire-prone areas. Part 2 – Fire hazard assessment of the different land management scenarios

Source Title	An integrated framework for habitat restoration in fire-prone areas. Part 2 – Fire hazard assessment of the different land management scenarios
Source citation (APA Format)	Vaz, R., Maia, P., Keizer, J., Fernandes, P., Pereira, S. C., & Carvalho, D. (2024). An integrated framework for habitat restoration in fire-prone areas. Part 2 – fire hazard assessment of the different land management scenarios. *International Journal of Wildland Fire*, *33*(11). https://doi.org/10.1071/WF24044
Original URL	https://doi.org/10.1071/WF24044
Source type	Journal Research Article
Keywords	Fire hazard; climate change; wildfire modeling; fuel treatment; WRF-SFIRE; fireline intensity; landscape management; Portugal; fire resilience; Mediterranean ecosystems
#Tags	#WildfireRisk #FireModeling #ClimateChange #WRF-SFIRE #FuelManagement #LandUseScenarios #Portugal #FireSuppression #ForestResilience

Summary of key points + notes (include methodology)	Study Area & Context:
	• Lombada Forest Intervention Region (ILMA), northeastern Portugal, within Montesinho Natural Park.
	• Mediterranean climate; increasing drought and fire frequency from climate change.
	
	Methods:
	• Used WRF-SFIRE, a coupled atmosphere–fire model, to simulate fire spread under future (2046–2065) SSP5-8.5 conditions.
	• Downscaled CMIP6 (MPI-ESM1.2-HR) data from 5 km → 1.2 km → 240 m resolution.
	• Identified two representative 2055 fire events using the Fire Weather Index (FWI):
	  ○ Cool/Moist: higher humidity, stronger winds.
	  ○ Hot/Dry: higher temperatures, lower humidity.
	• Converted landscape types into NFFL fuel models and compared five land-cover scenarios:
	• Base: current cover.
	  ○ S1: managed pine forest.
	  ○ S2: oak reforestation, unmanaged.
	  ○ S3: managed oak forest.
	  ○ S4: managed pine + managed oak (hybrid).
	• Evaluated burned area, fireline intensity, spread rate, and suppression difficulty (based

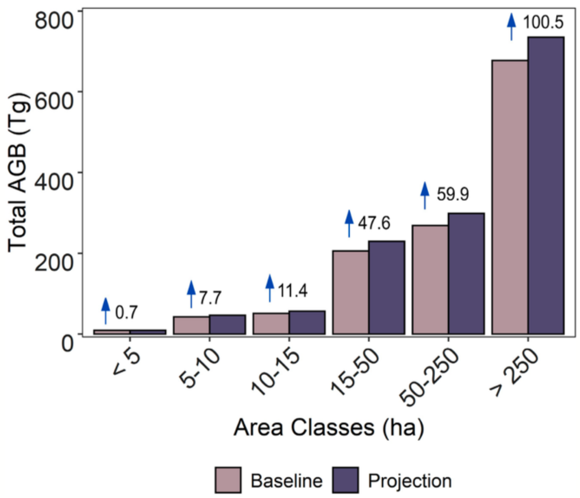
	on control class thresholds). Key Findings: • Managed pine (S1) most effectively reduced fire spread and intensity (up to 3× lower under dry conditions). • Hybrid management (S4) provided the best overall resilience but only slightly better than S1. • Unmanaged oak (S2) increased spread rate and intensity. • Agricultural/pasture areas served as fire barriers when moist but accelerated spread in dry conditions. • Managed scenarios (S1, S4) expanded "Fairly Easy to control" areas from ~50% to 70% and cut "Impossible to control" fires from ~40% to ~10%. Limitations: • Only two events and one ignition point due to computational limits. • Model slightly overestimated fuel moisture in cooler conditions. Conclusion: Targeted management—especially thinning and fuel reduction in pine forests—significantly improves wildfire resilience. Combining physics-based fire–atmosphere models like WRF-SFIRE with land-use planning offers a strong approach for climate-adapted fire management.
Research Question/Problem/ Need	How can different land management and reforestation strategies in Mediterranean fire-prone areas reduce fire hazard and improve suppression potential under projected future climate extremes?

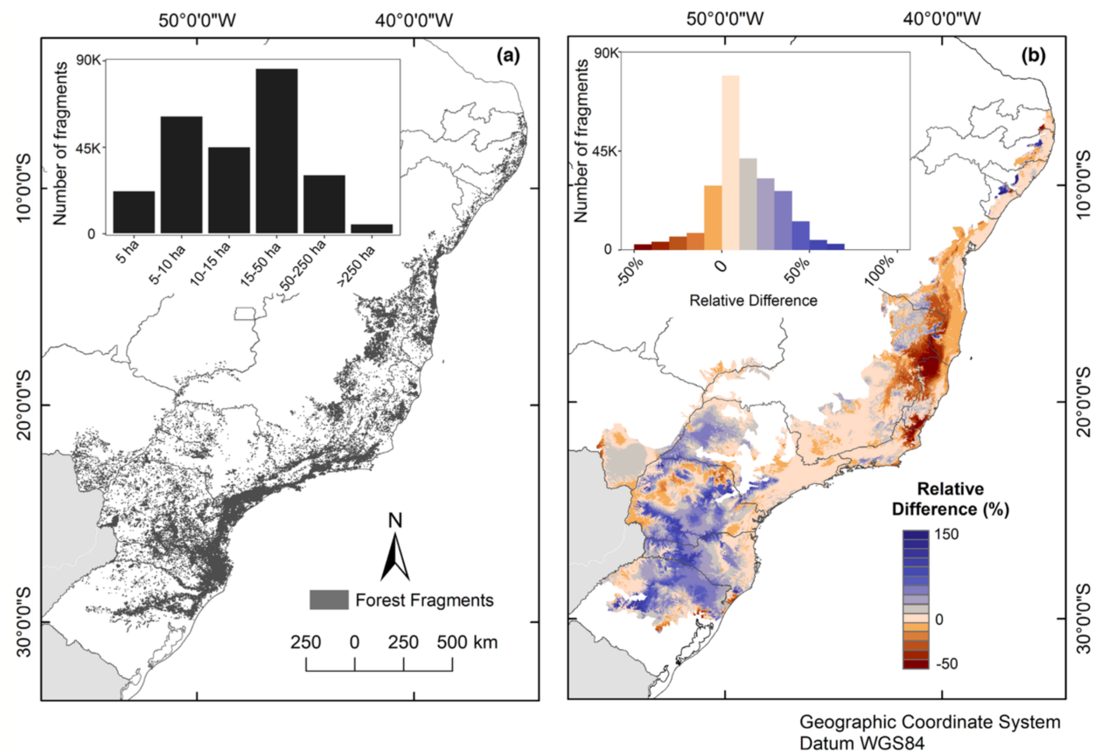
Important Figures	 Fig. 8. Burned categories as a percentage of the total burnt area every 3 h, mean 3 h fire Growth Rate (ha h^{-1}), and spatially integrated, mean 3 h Fire Radiative Power (FRP) for all burning points of the active fireline. Each 24- h block of Burned Categories represents a scenario per event, designated as: B, Base; 1–4, Scenarios 1–4. Fig. 4: Simulation domain and ignition point. Fig. 8–11: Fireline intensity, burned fuel composition, and suppression capability results.
VOCAB: (w/definition)	WRF-SFIRE: A coupled atmosphere–fire model integrating fire spread and atmospheric feedbacks. Fireline Intensity: Energy output per unit length of fire front, measured in kW/m, key to suppression difficulty. Fuel Model (NFFL): A standardized classification describing vegetation fuel characteristics influencing fire behavior. FWI (Fire Weather Index): Composite metric combining wind, temperature, humidity, and rainfall to assess fire danger. Fuel Moisture Content: Proportion of water in vegetation; higher values reduce ignition and spread. Suppression Capacity (Control Classes): Categorization of fire controllability based on intensity thresholds.
Cited references to follow up on	Lecina-Diaz et al. (2023) – Fire-smart agricultural policies.
Follow up Questions	Would integrating FlamMap or AutoGluon-based ML predictions complement WRF-SFIRE's physics-based modeling?

Article #9: Potential aboveground biomass increase in Brazilian Atlantic Forest fragments with climate change

Source Title	Potential aboveground biomass increase in Brazilian Atlantic Forest fragments with climate change
Source citation (APA Format)	Ferreira, I. J. M., Campanharo, W. A., Fonseca, M. G., Escada, M. I. S., Nascimento, M. T., Villela, D. M., Brancalion, P., Magnago, L. F. S., Anderson, L. O., Nagy, L., & Aragão, L. E. O. C. (2023). Potential aboveground biomass increase in Brazilian Atlantic Forest fragments with climate change. *Global Change Biology*, *29*(11), 3098–3113. https://doi.org/10.1111/gcb.16670
Original URL	https://doi.org/10.1111/gcb.16670
Source type	Journal article
Keywords	Atlantic Forest, aboveground biomass (AGB), climate change, fragmentation, carbon stock modeling, MaxEnt, ecosystem services, Brazil, restoration policy, RCP 4.5
#Tags	#ClimateChange #CarbonSequestration #RemoteSensing #Brazil #EcosystemModeling #ForestRestoration

Summary of key points + notes (include methodology)	• The study models future aboveground biomass (AGB) changes in Brazil's Atlantic Forest (AF) fragments under climate change (RCP 4.5 scenario to 2100).
	• **Method:** Used *maximum entropy modeling (MaxEnt)* with climatic predictors (WorldClim bioclimatic variables and elevation) and AGB baselines from *Baccini et al. (2012, 2017)* datasets.
	• **Results:**
	  ○ Models had high accuracy (AUC > 0.75).
	  ○ Projected 8.5% total carbon stock increase (~1800 Tg C) by 2100 if no deforestation occurs.
	  ○ 76.9% of the AF projected to have suitable climatic conditions for biomass gain.
	  ○ 34.7% of forest fragments projected to increase AGB; only 2.6% expected to lose AGB (mainly 13°–20°S latitude, i.e., Bahia–Espírito Santo).
	  ○ Larger forest fragments (>50 ha) will drive most biomass increase (~70% of total increment).
	  ○ Gains associated with higher precipitation and stable temperatures in southern AF; losses with drought and rising temperature in the northeast.
	• **Methodological strength:** Integration of remote sensing data with climate models using MaxEnt for probabilistic AGB mapping.
	• **Limitations:** Assumes static land cover (no deforestation/regrowth dynamics) and

	equilibrium between vegetation and climate. Uncertainties from model resolution, baseline data, and MaxEnt limitations. • **Policy Implications:** ○ Suggests that restoration and carbon offset projects (e.g., REDD+, Bonn Challenge, Brazilian AF Law) should prioritize southern and southeastern regions with favorable climate trends. ○ Northeast regions need drought-resistant native species and corridor restoration to maintain biodiversity.
Research Question/Problem/ Need	How will future climate change alter the spatial distribution and potential aboveground biomass density in fragmented Brazilian Atlantic Forest landscapes, and what are the implications for carbon storage and restoration policy?
Important Figures	Figure 6: Relative difference map of AGB (future vs. baseline) — identifies regions of biomass gain/loss and highlights vulnerable northeast zones. Figure 7: Biomass variation by forest fragment size — demonstrates that larger fragments (>50 ha) will drive most of the biomass increase.  FIGURE 7 Total estimated aboveground biomass (AGB) variations of Atlantic Forest remnants, Brazil per fragment area class between the baseline period and the 2070–2100 period under the Intergovernmental Panel on Climate Change Representative Concentration Pathway 4.5 scenario. All classes of fragment area were significantly different (*p*-value < .01). [Colour figure can be viewed at wileyonlinelibrary.com]

	 FIGURE 6 Relative difference (future aboveground biomass density [AGB] minus baseline value) of the estimated values of AGB. (a) Spatial distribution of forest fragments in the Atlantic Forest, and a histogram of fragments per area. (b) Spatial distribution of relative AGB difference for the entire study region, and a histogram of relative difference only for the forest fragments. Map lines delineate study areas and do not necessarily depict accepted national boundaries. [Colour figure can be viewed at wileyonlinelibrary.com]
VOCAB: (w/definition)	AGB (Aboveground Biomass): Total mass of living plant material above the ground; a key measure of forest carbon storage. MaxEnt (Maximum Entropy Model): A predictive modeling method that estimates probability distributions from environmental variables; used to map potential AGB. RCP 4.5: A moderate climate-change scenario from the IPCC indicating stabilization of greenhouse gas emissions and ~1.1–2.6 °C warming by 2100.
Cited references to follow up on	Baccini et al. (2012, 2017): Pioneering global forest carbon and biomass maps used as AGB baselines. Poorter et al. (2016): Study on biomass resilience in Neotropical secondary forests—key for restoration time scales. Pütz et al. (2014): Analysis of long-term carbon loss due to fragmentation in Neotropical forests.
Follow up Questions	How would the projected AGB outcomes differ under a high-emission RCP 8.5 scenario? Could incorporating satellite LiDAR or radar datasets reduce model uncertainty and improve AGB accuracy? How might species composition changes or biodiversity loss affect overall carbon storage trends in the Atlantic Forest?

Article #10: Spatiotemporal wildfire modeling through point processes with moderate and extreme marks

<table>
<tr><td>Source Title</td><td>Spatiotemporal wildfire modeling through point processes with moderate and extreme marks</td></tr>
<tr><td>Source citation (APA Format)</td><td>Koh, J., Pimont, F., Dupuy, J.-L., & Opitz, T. (2021). Spatiotemporal wildfire modeling through point processes with moderate and extreme marks (No. arXiv:2105.08004). arXiv. https://doi.org/10.48550/arXiv.2105.08004</td></tr>
<tr><td>Original URL</td><td>https://arXiv.org/abs/2105.08004</td></tr>
<tr><td>Source type</td><td>Research article</td></tr>
<tr><td>Keywords</td><td>wildfire modeling, point processes, Bayesian hierarchical, extreme-value theory, spatiotemporal modeling</td></tr>
<tr><td>#Tags</td><td>#WildfireModeling #IgnitionAndSize #ExtremeFires #Statistics #BayesianModels</td></tr>
<tr><td>Summary of key points + notes (include methodology)</td><td>Methods:

The study applies log-Gaussian Cox point processes to model the spatial and temporal distribution of wildfire ignition events.
Each ignition point is assigned a “mark” representing the burnt area (fire size). The size distribution is modeled using a mixture approach that separates moderate and extreme fires through extreme value theory.
Covariates such as the Fire Weather Index, forest cover, and seasonality are incorporated using smooth nonlinear functions that vary by season.
Shared random effects link the ignition occurrence and fire size components, capturing common underlying factors like unobserved spatial patterns.
The model accounts for zero-inflation (locations or times with no fires) by stratified subsampling of zero counts to improve computational efficiency.

Findings / Contributions:

The joint model predicts both the likelihood of ignition and final burnt area more accurately than separate models.
Predictor effects differ between moderate and extreme fires, showing that fire size influences which factors are most important.
Shared latent factors improve efficiency and reduce uncertainty by connecting occurrence and size models.
The framework is demonstrated using daily summer wildfire data (1995–2018) from the French Mediterranean region.

Implications / Strengths:

Establishes a comprehensive statistical framework that links fire ignition and spread in one model.
Improves understanding of drivers behind large or extreme fires, not just general
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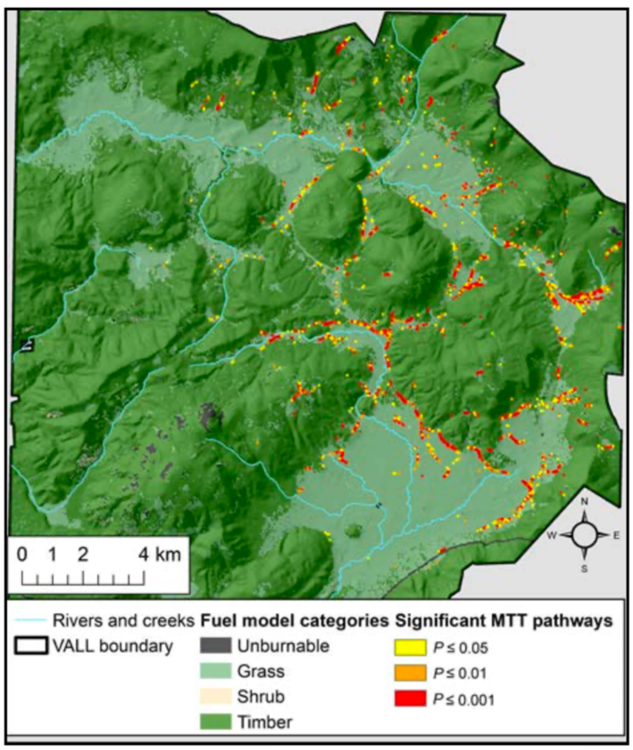
	ignition patterns. • Provides a flexible method that can be adapted for other regions or spatial scales. Limitations: • The approach was tested in a single region, so adaptation to other areas may require calibration. • As a preprint, it may not have undergone full peer review, and its practical application still needs validation. • The model is computationally demanding and relies on high-quality spatial and temporal data on weather, fuels, and land cover.
Research Question/Problem/ Need	To build a unified statistical model that handles both when/where wildfires ignite (the occurrence) and how large they grow (size/severity), capturing both moderate and extreme fires in a joint framework.
Important Figures	
VOCAB: (w/definition)	Point process: A statistical method for modeling random events (like ignitions) in space and time. Mark: An extra value attached to each event — here, the fire's size. Extreme Value Theory: A statistical approach for studying rare, large events (like huge wildfires). Log-Gaussian Cox Process (LGCP): A fancy way of saying "a model where the fire probability varies smoothly over space and time." Shared latent effect: A hidden variable that affects both ignition and fire size simultaneously.
Cited references to follow up on	1. Serra, L., & Opitz, T. (2018). Spatiotemporal models for fire counts and sizes using marked point processes. 2. Schoenberg, F. P. (2011). Point processes, spatial statistics, and wildfire modeling. 3. Warton, D. I., & Shepherd, L. C. (2010). Poisson point process models for species distribution data.
Follow up Questions	How could machine learning (like AutoGluon) replicate this approach using a hybrid data-driven model instead of a purely statistical one?

Article #11: Modeling Fire Pathways in Montane Grassland–Forest Ecotones

Source Title	*Modeling Fire Pathways in Montane Grassland–Forest Ecotones*
Source citation (APA Format)	Conver, J. L., Falk, D. A., Yool, S. R., & Parmenter, R. R. (2018). Modeling Fire Pathways in Montane Grassland-Forest Ecotones. *Fire Ecology*, *14*(1), 17–32. https://doi.org/10.4996/fireecology.140117031
Original URL	https://fireecology.springeropen.com/articles/10.4996/fireecology.140117031
Source type	Scientific journal article
Keywords	disturbance, fire regimes, fuel, New Mexico, Pinus ponderosa, ponderosa pine, resiliency, Valles Caldera, vegetation dynamics
#Tags	#WildfireModeling #EcotoneDynamics #FlamMap #FireSpread #VallesCaldera #LandscapeEcology #FireBehavior #FuelMoisture #Resilience
Summary of key points + notes (include methodology)	Overview: This study models fire movement in montane grassland–forest transition zones (ecotones) in the Valles Caldera National Preserve, New Mexico, to determine how fire spreads across mixed fuel landscapes. It focuses on identifying dominant fire pathways and understanding the ecological role of fire in maintaining grassland–forest balance. Methods: • The researchers used the Minimum Travel Time (MTT) algorithm in FlamMap v.4 to simulate 270 fire spread pathways across various weather and fuel scenarios. • Input data: • LANDFIRE rasters for slope, aspect, canopy, and elevation • Custom fuel models calibrated by VALL staff • Wind patterns derived from WindNinja simulations (three main wind directions and three speeds) • Historical weather data (1966–2009) from the Jemez RAWS station, modeling 50th, 90th, and 99th percentile fire weather conditions. • Fire season defined as when Energy Release Component (ERC) exceeded the 90th percentile. • Simulations included grass, timber, and ecotonal fuel types; each ignition point represented real historical fire starts. • A chi-squared test compared expected vs. observed frequencies of fire occurrence across fuel types to identify statistically significant fire corridors. Findings:

	• Fire spread pathways clustered along grassland–forest ecotones, indicating these transition zones act as primary fire corridors. • The wet interiors of grasslands (valle bottoms) were less flammable due to higher fuel moisture. • 84% of significant fire pathways were within 90 m of forest edges, confirming fires move efficiently along ecotones. • Ecotones maintain a dynamic stability, preventing forest encroachment into grasslands and promoting ecological balance. • Topography and wind strongly influence fire direction; fire moves faster along gentle slopes and around volcanic domes (cerros). • Management implication: prescribed burns should mimic natural fire vectors along ecotones to maintain ecosystem resilience.
Research Question/Problem/ Need	How do landscape features (topography, fuel composition, and weather conditions) influence the spread of fire in montane grassland–forest ecotones?
Important Figures	 **Figure 6.** Statistically significant fire spread pathways for three levels of significance in the VALL as calculated by the chi-squared test. A total of 2267 cells (0.3 % of the VALL) burned significantly more than expected at the $P < 0.05$ level, all of which were concentrated in the ecotone or dry fuels in some *valles.*
VOCAB: (w/definition)	Ecotone: A transition area between two ecological communities (e.g., forest and grassland). Minimum Travel Time (MTT): An algorithm that computes the fastest potential fire spread paths across a landscape. Fuel Model: Classification of vegetation types by fuel characteristics affecting fire behavior (Scott & Burgan, 2005). Energy Release Component (ERC): Index representing potential energy available to a fire; used to define fire season severity. Resilience: The ability of an ecosystem to recover after disturbance while maintaining

	structure and function.
Cited references to follow up on	Dewar (2011) – fire history and frequency in the same region.
Follow up Questions	Can the MTT modeling framework be applied effectively to eastern U.S. mixed forest-grassland ecotones?

Article #12: Increasing Large Wildfire in the Eastern United States

Source Title	*Increasing Large Wildfire in the Eastern United States*
Source citation (APA Format)	Donovan, V. M., Crandall, R., Fill, J., & Wonkka, C. L. (2023). Increasing Large Wildfire in the Eastern United States. *Geophysical Research Letters*, *50*(24), e2023GL107051. https://doi.org/10.1029/2023GL107051
Original URL	https://doi.org/10.1029/2023GL107051
Source type	Journal article
Keywords	Large wildfires, Eastern United States, fire regime, climate change, ecoregions, ignition sources, wildfire seasonality, MTBS dataset, spatio-temporal patterns, fire management.
#Tags	#WildfireRisk #EasternUS #ClimateChange #FuelLoads #FireEcology #GeospatialAnalysis #FireSeasonality #HumanIgnition

Summary of key points + notes (include methodology)	**Methodology:**
	• Data sources include:
	  ○ MTBS (Monitoring Trends in Burn Severity) dataset for wildfire perimeters
	  ○ USDA Fire Program Analysis Fire Occurrence Database (FPA-FOD) for ignition sources
	  ○ EPA Level III Ecoregions to subdivide into 35 regions
	• Sampled 2,433 wildfires ≥ ha (not prescribed or unknown)
	• Metrics analyzed include: fire size, number, total hectares burned, probability of occurrence, seasonality, ignition source
	• Statistical tests:
	  ○ Mann-Kendall Trend Test (nonparametric) for monotonic increases/decreases.
	  ○ Generalized Linear Models (binomial) for annual wildfire occurrence and ignition trends.
	  ○ Bray-Curtis Dissimilarity Index to compare fire seasonality between early (1984–1993) and late (2011–2020) decades.
	  ○ Kernel density estimation to visualize seasonality shifts.
	  ○ Analyses conducted in R statistical software (v4.2.2).
	Findings:
	• **Overall Increase:**
	  ○ Large wildfires (≥200 ha) are increasing in the *southern and eastern portions* of the Eastern Temperate Forests, particularly in the *Southern Coastal Plain, Central Appalachians, and Southeastern Plains.*
	  ○ *79%* of ecoregions showed an increase in large wildfire number; *84%* showed an increase in total hectares burned.
	• **Magnitude:**

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- Some regions saw wildfire frequency rise by over 2,000% (e.g., Arkansas Valley, Ouachita Mountains).
- Average wildfire size increased from hundreds to thousands of hectares in certain areas.

- **Seasonality:**
  - Spring fires dominate most ecoregions, but trends show shifting timing—some regions (e.g., Blue Ridge) show more fall/winter fires, while others (Southern Coastal Plain) show more spring/summer fires.
- **Ignition Sources:**
  - Human-caused wildfires dominate (>80% overall), though lightning accounts for most area burned in some regions (Southern Coastal Plain).
  - No significant change in the proportion of human vs. natural ignitions over time.
- **Spatial Variability:**
  - Northern ecoregions (e.g., North Central Hardwood Forests) show declines—possibly due to *mesophication* (shift to moisture-tolerant tree species) and higher precipitation.
- **Drivers:**
  - Likely climate (increasing heat/drought frequency), fuel accumulation (woody encroachment, invasive species like *Imperata cylindrica*), and limited prescribed burning opportunities.

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<td>Research Question/Problem/ Need</td>
<td>How are large wildfire characteristics (size, number, area burned, seasonality, ignition source) changing over time across the Eastern Temperate Forests, and what are the implications for wildfire risk and management in the eastern United States?</td>
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<td>Important Figures</td>
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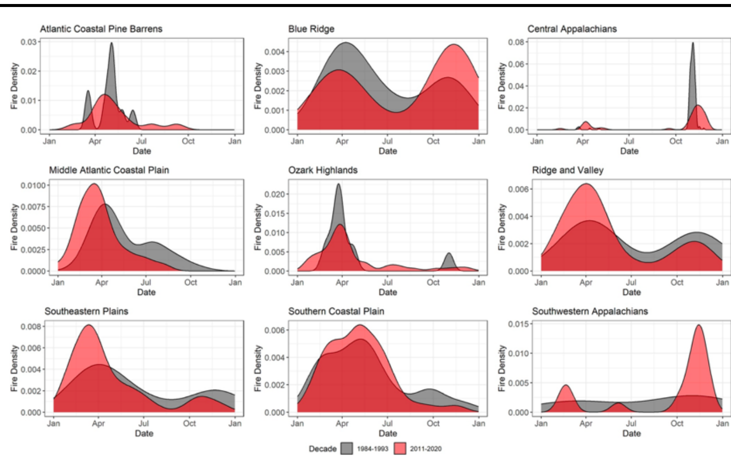

Figure 3. The seasonal distribution of large wildfires that occurred between the first, 1984–1993 (gray), and last, 2011–2020 (red), decades of assessment across ecoregions with ≥5 wildfires in each decade, represented using Gaussian kernel density estimates (Wickham, 2016).

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<td>VOCAB:
(w/definition)</td>
<td>Ecoregion: A geographically defined area with consistent ecosystem characteristics (climate, vegetation, soil).
Mesophication: Process where suppression of fire leads to more shade-tolerant, moisture-loving vegetation, reducing fire likelihood.
Mann-Kendall Trend Test: A statistical method to assess monotonic trends in time-series data without assuming normality.
Bray-Curtis Dissimilarity: A metric used to measure compositional dissimilarity between two sets (here, seasonal fire patterns).</td>
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	MTBS Dataset: Monitoring Trends in Burn Severity database providing nationwide burned-area boundaries from satellite imagery.
Cited references to follow up on	Iglesias, V. et al. (2022). U.S. fires became larger, more frequent, and more widespread in the 2000s. Science Advances, 8(11). Prestemon, J. et al. (2016). Projecting wildfire area burned in the southeastern U.S., 2011–60. Int. J. Wildland Fire.
Follow up Questions	How can satellite detection methods be improved to better capture small fires (<40 ha) in humid, forested environments?

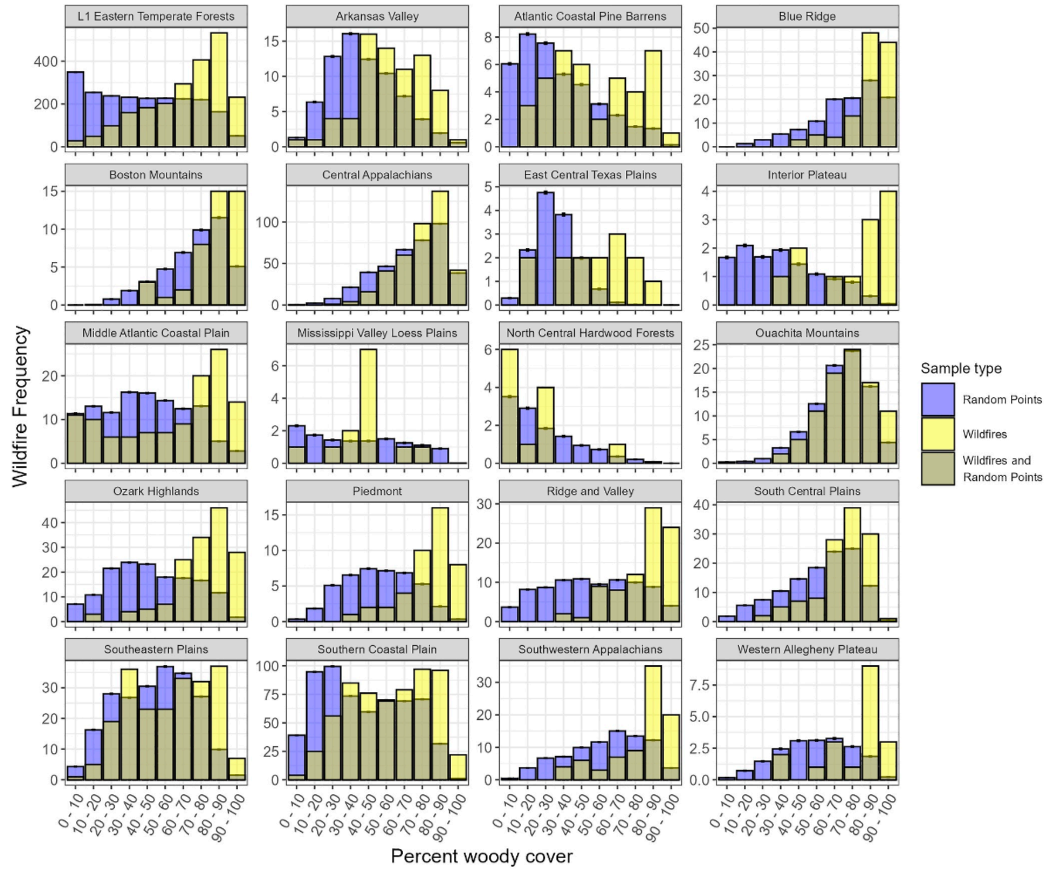
Article #13: An Overview of FlamMap Fire Modeling Capabilities

Source Title	An Overview of FlamMap Fire Modeling Capabilities
Source citation (APA Format)	Finney, M. A. (2006). An Overview of FlamMap Fire Modeling Capabilities. *In: Andrews, Patricia L.; Butler, Bret W., Comps. 2006. Fuels Management-How to Measure Success: Conference Proceedings. 28-30 March 2006; Portland, OR. Proceedings RMRS-P-41. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. p. 213-220, 041*. https://research.fs.usda.gov/treesearch/25948
Original URL	https://www.fs.usda.gov/rm/pubs/rmrs_p041/rmrs_p041_213_220.pdf
Source type	Technical Paper
Keywords	
#Tags	
Summary of key points + notes (include methodology)	• **Purpose:** To describe the modeling capabilities and applications of *FlamMap 3.0*, a software used for simulating wildfire behavior and evaluating fuel treatment strategies. • **Background:** Builds upon earlier 1D fire spread models (e.g., Rothermel 1972; Albini 1976) and integrates them into a GIS-based, landscape-level tool. • **Methodology / Model Components:** ○ **Inputs:** Eight GIS raster themes describing fuels and topography form a *Landscape (LCP) File*. ○ **Assumptions:** Fuel moisture, wind speed, and direction are constant in time. ○ **Calculation modes:** 1. **Basic Fire Behavior** – computes fire behavior characteristics (spread rate, flame length, intensity) for each cell under constant conditions. 2. **Minimum Travel Time (MTT)** – simulates fire growth using Finney's (2002) algorithm to find the minimum-time pathways across the landscape, producing outputs like fire arrival time, spread rate, and burn probability. 3. **Treatment Optimization Model (TOM)** – identifies optimal fuel treatment locations that reduce fire spread by blocking major MTT paths, under assumptions about fire size and extreme weather conditions. • **Applications:** ○ Used for assessing **fuel hazard**, **risk assessment**, and **fuel treatment design**.

	- Examples include the *Florida Risk Assessment* and *CRAFT* projects. - Provides raster and vector outputs (e.g., flame length, crown fire index, burn probabilities). - Can integrate with other GIS tools for verification and analysis of spatial fire data. • **Advantages:** - Allows consistent, spatially explicit comparisons of potential fire behavior. - Integrates empirical and theoretical models. - Supports management decisions for landscape fuel treatments. • **Limitations:** - Assumes constant environmental conditions—no temporal variability in weather or fuel moisture. - Independence among cells may overlook dynamic fire interactions.
Research Question/Problem/ Need	How can spatial fire modeling tools like FlamMap be used to evaluate and optimize fuel management strategies, simulate fire spread, and assess landscape-level wildfire risk under given environmental conditions?
Important Figures	
VOCAB: (w/definition)	Treatment Optimization Model (TOM): Procedure that identifies the best locations for fuel treatments to impede fire spread.
Cited references to follow up on	Finney, M.A. (2004). Landscape fire simulation and fuel treatment optimization.
Follow up Questions	How can models be tuned and validated using real fire data.

Article #14: Woody Cover Fuels Large Wildfire Risk in the Eastern US.

Source Title	Woody Cover Fuels Large Wildfire Risk in the Eastern US.
Source citation (APA Format)	Ivey, M. A., Wonkka, C. L., Weidig, N. C., & Donovan, V. M. (2024). Woody Cover Fuels Large Wildfire Risk in the Eastern US. *Geophysical Research Letters*, *51*(24), e2024GL110586. https://doi.org/10.1029/2024GL110586
Original URL	
Source type	Journal Article
Keywords	
#Tags	
Summary of key points + notes (include methodology)	This study shows that woody vegetation cover has increased by ~37% since 1990, and that higher woody cover strongly increases the probability of large wildfires across most ecoregions. Woody cover is increasing everywhere in the Eastern Temperate Forest ecoregion. Odds of wildfire increase significantly with woody cover. At the L1 ecoregion scale: 3.9% increase in wildfire odds per 1% increase in woody cover. Wildfires most likely when woody cover is 60-100%. • Wildfire data came from the MTBS dataset • Vegetation data came from Rangeland Analysis Platform ○ Shrubs and trees were combined into woody cover • Used Modified Mann–Kendall tests and Sen's Slope to measure trends • Compared woody cover of real wildfires vs. woody cover of "null fires" • Used. A logistic regression • Verified that wildfires occur disproportionately in heavily wooded areas • Fuel-heavy woody vegetation leads to harder suppresion.
Research Question/Problem/ Need	Does increasing woody cover drive increased probability of large (>200 ha) wildfires in the eastern United States, and how is woody cover changing over time across Eastern US ecoregions?

Important Figures	 **Figure 2.** The distribution of woody cover within verified wildfires (yellow) compared to a bootstrapped sample of random points used to represent the distribution of woody cover across the general landscape (blue) within the Level 1 and Level 3 ecoregions of the Eastern US between 1991 and 2021. Random points were sub-sampled in numbers equivalent to the total number of large wildfires within each ecoregion 999 times to generate 1,000 null frequency distributions and then averaged to create a single null distribution for each ecoregion (blue). Error bars represent standard error of the averaged values within each bin of the null distribution.
VOCAB: (w/definition)	• Woody Encroachment – Expansion of shrubs and trees into grasslands or open forests, increasing fuel loads. • Sen's Slope – A non-parametric estimator of the magnitude of a monotonic trend (e.g., % woody cover increase per year). • Mann-Kendall Trend Test – A statistical test for detecting monotonic trends in time series data. • Mesophication – Process by which fire-suppressed forests accumulate moisture-retaining shrubs and trees, reducing flammability except during drought. • Wildland–Urban Interface (WUI) – Zones where homes and wild vegetation intermix; high ignition risk. • Ladder Fuels – Vertical fuels (shrubs, small trees) that allow fire to climb from surface to canopy. • Odds Ratio (OR) – How much the odds of an event (wildfire) increase with each unit increase in a variable (1% woody cover).
Cited references to follow up on	Rothermel (1991) — Classic crown fire behavior modeling (relevant for FlamMap/FARSITE).

Follow up Questions	How would FlamMap consequence modeling change if high woody cover acts as a multiplier on extreme spread days?

Article #15: Fire suppression makes wildfires more severe and accentuates impacts of climate change and fuel accumulation.

Source Title	Fire suppression makes wildfires more severe and accentuates impacts of climate change and fuel accumulation.
Source citation (APA Format)	Kreider, M. R., Higuera, P. E., Parks, S. A., Rice, W. L., White, N., & Larson, A. J. (2024). Fire suppression makes wildfires more severe and accentuates impacts of climate change and fuel accumulation. *Nature Communications*, *15*(1), 1–11. https://doi.org/10.1038/s41467-024-46702-0
Original URL	https://doi.org/10.1038/s41467-024-46702-0
Source type	Journal article
Keywords	Wildfire suppression; suppression bias; climate change; fuel accumulation; wildfire severity; regressive vs. progressive suppression; simulation modeling; fire ecology; fire behavior
#Tags	#Wildfire #FireManagement #ClimateChange #FuelLoad #Ecology #RiskModeling #SuppressionBias #FireSeverity

Summary of key points + notes (include methodology)	Fire suppression dramatically increases wildfire severity, burned area, growth and ecological impact. Suppression bias (suppressing mild fires disproportionately, then fires skew toward extreme high-intensity fires) is a newly quantified concept)
	• Regressive suppression increases high-severity fire.
	• Area burned grows faster under suppression.
	• Regressive suppression decreases pyrodiversity.
	• Progressive suppression reduces severity
	• Social and ecological implications
	    ○ Ensures that the public mainly sees catastrophic fires, reinforcing fear and public pressure
	    ○ Reduces exposure to low-severity fires ecosystems depend on.
	    ○ Limits ecological adaptation to climate change
	    ○ Increases likelihood of regime shifts
	
	The researchers created a large-scale wildfire simulation model with:
	• 1000 ignitions × 25 fuel aridity levels × 25 fuel loading levels × 5 suppression scenarios × 40 replicates → ≈ 5 million simulated fires
	
	Model components
	• Weather & fuel moisture simulated daily

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- Ignition timing randomized
- Fire spread:
  - Elliptical growth (Huygens' principle)
  - Rothermel fire spread equations
  - Fireline intensity & flame length → Composite Burn Index (severity)
- Suppression modeled in two stages:
  - Initial attack success probability (based on Hirsch et al. 1998)
  - Suppression of escaped fires (Fig. 1b suppression curves)

Suppression scenarios

- Regressive: Maximum, High, Moderate
- Progressive: Preferentially suppress high-intensity fire
- No suppression

Climate change and fuel accumulation simulation

- VPD trend +0.00837 kPa per year (RCP 8.5)
- Fuel loading +0.036 Mg/ha/yr (based on Boisramé et al. 2022)

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<tr>
<td>Research Question/Problem/ Need</td>
<td>How does fire suppression influence wildfire behavior, severity, burned area, and ecological impact and what are the consequences of different suppression strategies?</td>
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<td>Important Figures</td>
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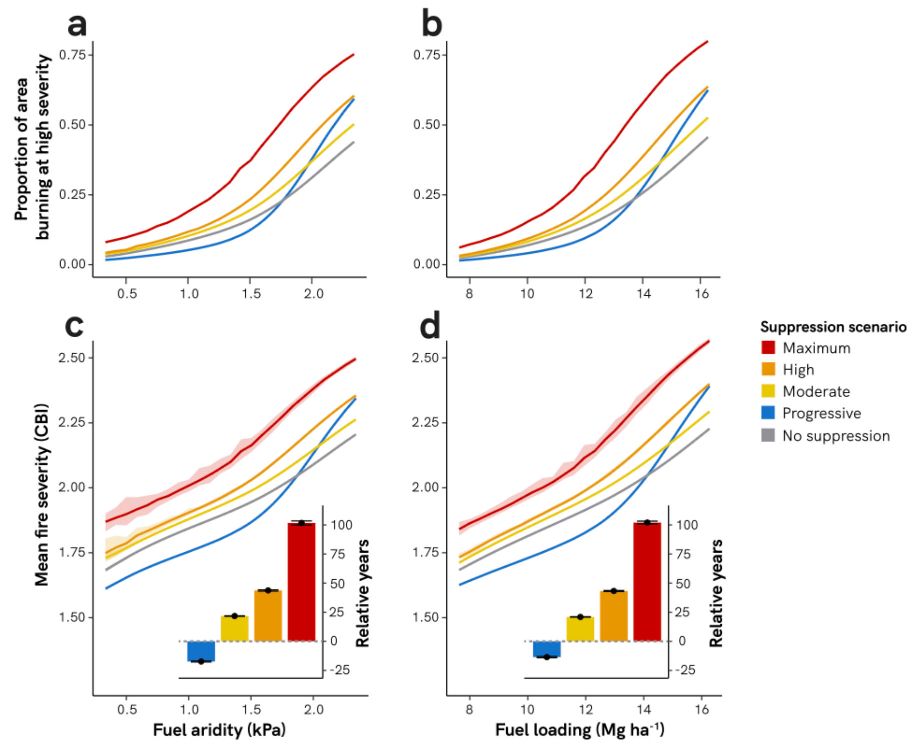

Fig. 2 | Effects of fire suppression on fire severity. Panels **a** and **b** show the proportion of high-severity fire (CBI > 2.25) across ranges of fuel aridity and fuel loading. Panels **c** and **d** show mean fire severity across ranges of fuel aridity and fuel loading. Insets show the average number of years of modeled climate change (vapor pressure deficit increase of 0.008 kPa yr^{-1}) or fuel accumulation (100-h fuel accumulation rate of 0.036 Mg ha^{-1} yr^{-1}) to yield the difference in fire severity between suppressed and unsuppressed fires. Variability across the 40 simulation replications is shown with 95% confidence intervals (too small to see for some) or error bars (insets on **c** and **d**). Fuel loading in panel **b** and **d** depicts 100-h surface fuel loading values. Simulations across the fuel aridity range were run at a constant 100-h surface fuel loading of 11.23 Mg ha^{-1}; simulations across the fuel loading range were run at constant mean fire season vapor pressure deficit of 1.17 kPa.

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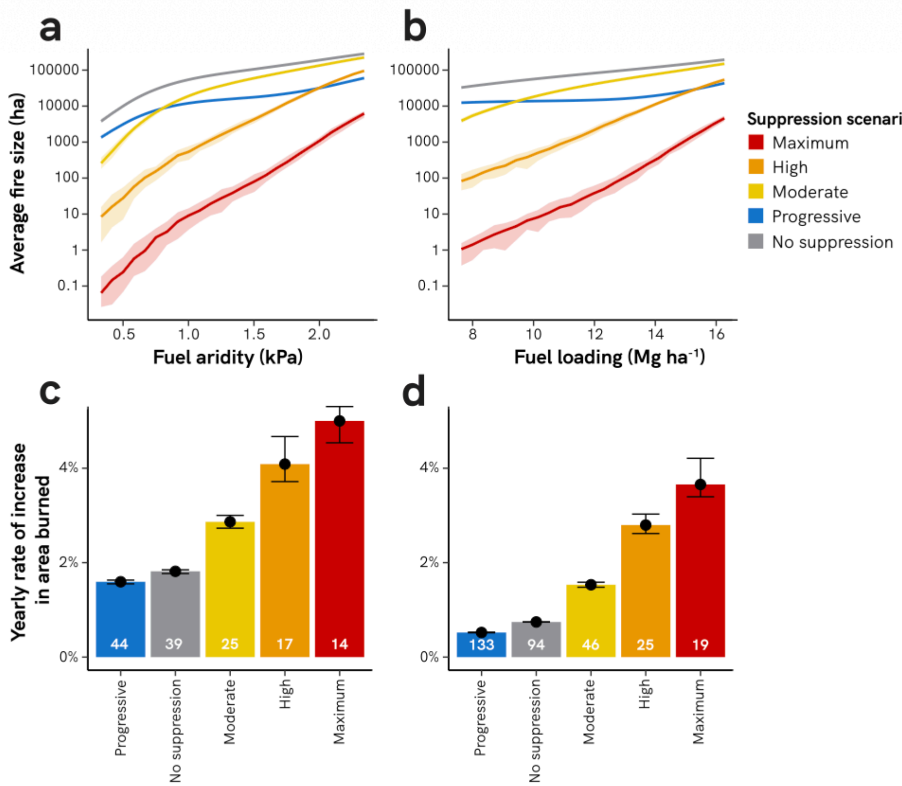
<tr><td></td><td>

Fig. 3 | Effects of fire suppression on burned area increase. Panels **a** and **b** show trends in average fire size across ranges of fuel aridity and fuel loading. Fuel loading in panel **b** depicts 100-h surface fuel loading values. Yearly rates of increase in panels **c** and **d** are calculated with a yearly increase in fuel aridity of 0.008 kPa yr^{-1} or a yearly increase in fuel accumulation (100-h fuel accumulation rate) of 0.036 Mg ha^{-1} yr^{-1}, respectively. White numbers at the base of bars are the doubling time, in years, of burned area. Variability across the 40 simulation replications is shown with 95% confidence intervals (**a** and **b**; too small to see on some curves) or error bars (**c** and **d**). Simulations across the fuel aridity range were run at a constant 100-h surface fuel loading of 11.23 Mg ha^{-1}; simulations across the fuel loading range were run at constant mean fire season vapor pressure deficit of 1.17 kPa.</td></tr>
<tr><td>VOCAB:
(w/definition)</td><td>

Suppression bias – Tendency for suppression to disproportionately remove low-intensity fires, leaving only high-intensity fires to burn.
Suppression paradox – Long-term effect where putting out fires increases fuel loads, making future fires bigger and harder to control.
Regressive suppression – Suppressing low-intensity fires more than high-intensity ones; common in current US management.
Progressive suppression – Opposite; suppress high-intensity fire more heavily.
VPD (Vapor Pressure Deficit) – Atmospheric dryness metric; higher VPD → more flammable conditions.
CBI (Composite Burn Index) – Standard measure of fire severity (0 = unburned, 3 = max severity).
Pyrodiversity – Diversity of fire effects (severity, patterns, intensity) across landscapes.

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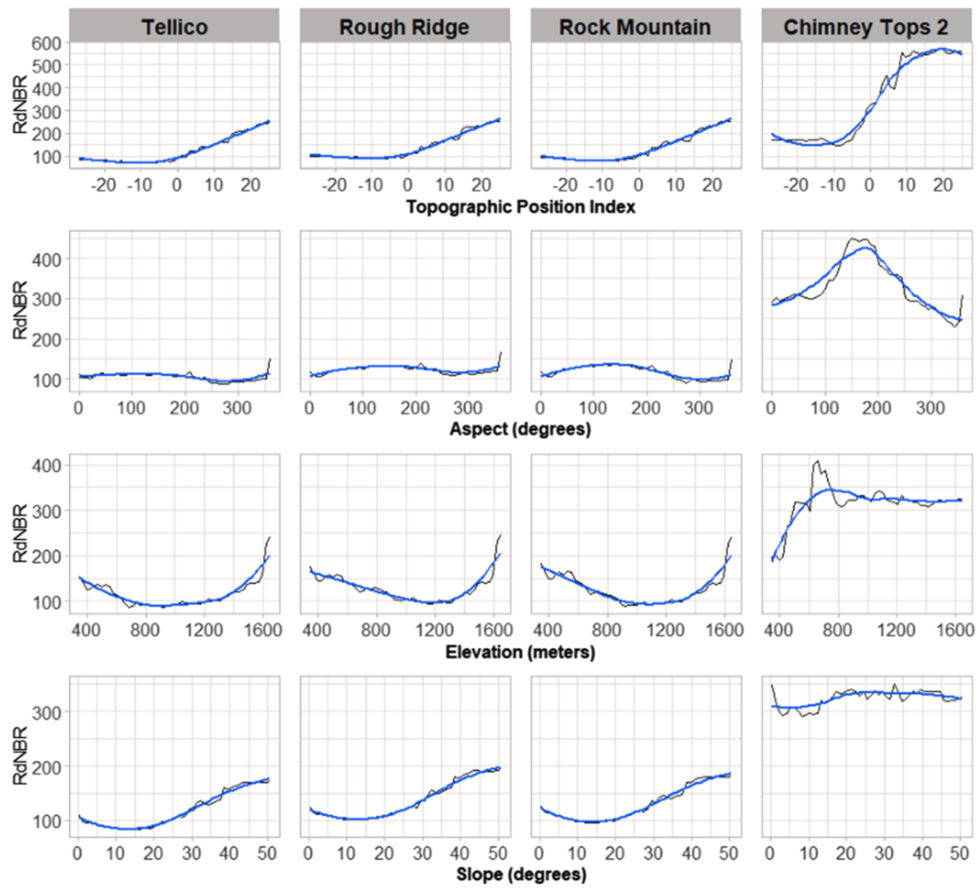
<tr><td>Cited references to follow up on</td><td>Boisramé et al. (2022) – fuel accumulation trends</td></tr>
<tr><td>Follow up Questions</td><td>How could progressive suppression be realistically implemented in the northeastern US?</td></tr>
</table>

Article #16: Drivers and ecological impacts of a wildfire outbreak in the southern Appalachian Mountains after decades of fire exclusion.

Source Title	Drivers and ecological impacts of a wildfire outbreak in the southern Appalachian Mountains after decades of fire exclusion.
Source citation (APA Format)	Reilly, M. J., Norman, S. P., O'Brien, J. J., & Loudermilk, E. L. (2022). Drivers and ecological impacts of a wildfire outbreak in the southern Appalachian Mountains after decades of fire exclusion. *Forest Ecology and Management*, *524*, 120500. https://doi.org/10.1016/j.foreco.2022.120500
Original URL	https://doi.org/10.1016/j.foreco.2022.120500
Source type	Journal article
Keywords	Southern Appalachians; wildfire; drought; burn severity; oak–pine forests; mesophication; topography; mountain wave wind; post-fire ecology
#Tags	#Wildfire #Climate #Forestry #Ecology #BurnSeverity #Appalachians #FireHistory #Mesophication #Drought #Management
Summary of key points + notes (include methodology)	Most severe drivers of the 2016 fires were drought combined with leaf fall, producing extremely dry, airy fuels. 10,000 ignitions occurred, and most were suppressed, but 8 fires excited 5,000 ha. Thousands of near-simultaneous ignitions overwhelmed suppression. Steep topography + dry deciduous litter + wind lead to rapid spread. **Burn Severity Patterns & Methodology** Method: • Used Landsat NBR composites to calculate RdNBR (relativized burn severity index). • Classified severity thresholds using 60 field plots of post-fire mortality (Appendix Fig A.1). • Created random forest model predicting severity from topographic variables: • elevation, slope, aspect, topographic position index (TPI). Findings: • Across all fires: 72.7% low-severity, 21.1% moderate, 6.2% high (p. 7). • Ridges and steep upper slopes = highest burn severity (Fig. 7). • Bottom-up topographic control dominated patterns except Chimney Tops 2 (wind-driven severity). • Model explained ~38% variance.
Research Question/Problem/	What historical, climatic, ecological, and topographic factors drove the unusually large 2016 wildfire outbreak?

Need	How do these fires impact long-term forest composition, biodiversity, regeneration, and management responses in a historically fire-frequent but recently fire-excluded region?
Important Figures	 **Fig. 7.** Partial dependence plots from a random forest model predicting burn severity as measured by the relativized change in the normalized burn index (RdNBR) in the four largest southern Appalachian fires. Low topographic position index valleys correspond with sheltered ravines and low slopes while higher values correspond with upper slopes and ridges.
VOCAB: (w/definition)	• Mesophication – Shift toward cool, moist, fire-sensitive forest conditions due to fire exclusion. • RdNBR (Relativized differenced Normalized Burn Ratio) – Satellite-based metric quantifying burn severity relative to pre-fire conditions. • Topographic Position Index (TPI) – Metric showing if a point is in a ridge, slope, or valley position. • Duff Layer (O-horizon) – Deep organic soil layer; when consumed, kills fine roots and can cause delayed tree mortality. • Mountain Wave Wind – Strong downslope wind caused by stable air crossing mountain ridges; lowers humidity and increases fire spread potential. • Serotinous Cones – Cones requiring heat from fire to open (e.g., Table Mountain pine).
Cited references to follow up on	Wimberly & Reilly (2007) – Using Landsat for fire severity in Appalachians.
Follow up Questions	How can FARSITE or FlamMap incorporate topography-severity relationships (like TPI and slope

	effects)?

Article #17: Climatology and Meteorological Evolution of Major Wildfire Episodes in the Northeastern United States

Source Title	Climatology and Meteorological Evolution of Major Wildfire Events over the Northeast United States
Source citation (APA Format)	Pollina, J. B., Colle, B. A., & Charney, J. J. (2013). Climatology and Meteorological Evolution of Major Wildfire Events over the Northeast United States. *Weather and Forecasting*, *28*(1), 175–193. https://doi.org/10.1175/WAF-D-12-00009.1
Original URL	https://journals.ametsoc.org/view/journals/wefo/28/1/waf-d-12-00009_1.xml
Source type	Peer-reviewed journal article (meteorology / fire weather climatology)
Keywords	Wildfire climatology, Northeast United States, fire weather, synoptic patterns, subsidence, relative humidity, FARSITE-relevant meteorology, Yarnal classification, PH/EH/BH patterns
#Tags	#WildfireModeling #FireWeather #Meterology #NewEngland #FARSITE

Summary of key points + notes (include methodology)	• The study develops the **first comprehensive climatology of major wildfires (>100 acres)** in the Northeast U.S. (NEUS) from **1999–2009**, identifying **155 major wildfire events**.
	• The NEUS is divided into two regions:
	  ○ **Region 1**: higher-elevation interior (Appalachians)
	  ○ **Region 2**: coastal plain and lee of the Appalachians
	• **Seasonality**:
	  ○ Peak wildfire activity occurs in **April–May**
	  ○ ~76% of Region 1 fires and ~53% of Region 2 fires occur in spring
	  ○ Summer fires are relatively rare due to higher fuel moisture
	• **Primary ignition source**: humans (~81% of fires), not lightning
	• **Synoptic patterns**:
	  ○ Most fires occur under **high-pressure–dominated patterns**
	  ○ Three dominant types:
	    ▪ **Extended High (EH)** – most common in Region 1
	    ▪ **Prehigh (PH)** – most common in Region 2
	    ▪ **Back of High (BH)**
	  ○ Together, PH + EH + BH account for ~77–78% of all fires
	• **Meteorological drivers**:
	  ○ Large-scale **subsidence**
	  ○ **Dry air aloft** mixed downward into the boundary layer
	  ○ **Downslope warming/drying** east of the Appalachians
	• **Reanalysis vs reality**:

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- ○ NARR **overestimates relative humidity by ~20–25%**
- ○ Actual observed RH during fire events often **30–40%**, higher than Red Flag thresholds but still fire-prone

- **Trajectory analysis (HYSPLIT)**:
  - Air parcels near **850 hPa** originate from **southern Canada or the Great Lakes**
  - PH patterns show the **strongest subsidence and RH decrease**
- **Operational relevance**:
  - Current **Red Flag Warning RH threshold (<30%) may be too strict** for NEUS
  - Authors suggest **~40% RH** may be more appropriate regionally

Methodology highlights:

- Fire occurrence data from NICC and state forestry agencies
- Synoptic classification using **modified Yarnal (1993) scheme**
- Meteorological composites using **NARR (32 km resolution)**
- Backward air-mass trajectories via **HYSPLIT**
- Bootstrap resampling to test synoptic-pattern significance

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<td>Research Question/Problem/ Need</td>
<td>How does wildfire occurrence in the NEUS vary seasonally and interannually?
Need: Improve regional fire weather forecasting and evaluate whether existing warning thresholds are appropriate for the Northeast.</td>
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<td>Important Figures</td>
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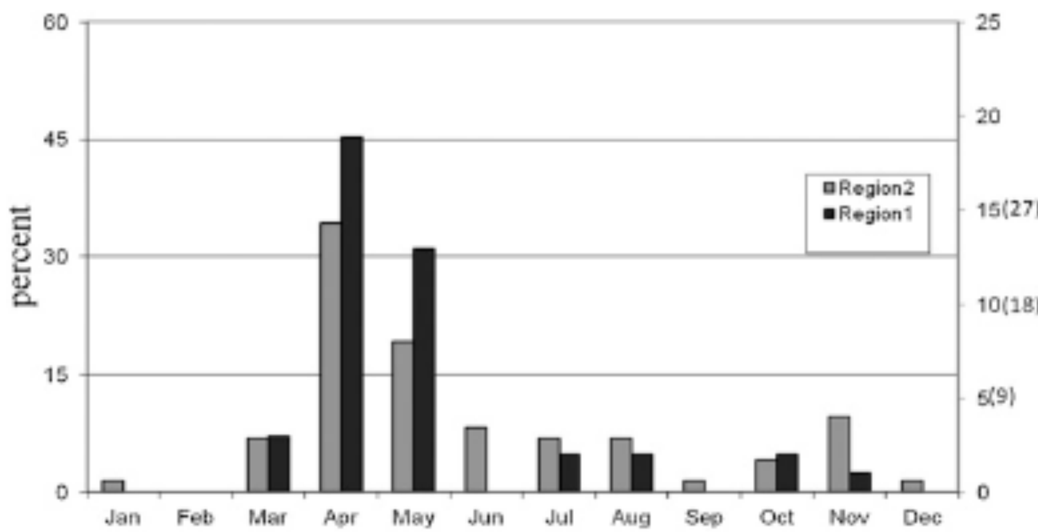

FIG. 4. Monthly climatology of NEUS wildfires for region 1 (black) and region 2 (gray). The left axis is the percentage of fires that occurred in a particular month and the right axis is the number of fires for region 1 (no parentheses) and region 2 (in parentheses).

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<td>VOCAB:</td>
<td>Prehigh (PH): A surface high-pressure system building in after a cold front, often producing dry,</td>
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(w/definition)	northwesterly flow. Extended High (EH): A large, slow-moving high-pressure system covering a broad area, allowing prolonged drying. Back of High (BH): Western side of a high-pressure system with southwesterly flow. Subsidence: Downward motion of air in the atmosphere, leading to warming and drying. Boundary Layer (PBL): Lowest part of the atmosphere where surface heating and mixing occur. NFDRS: National Fire Danger Rating System used to assess wildfire potential. HYSPLIT: Model used to compute air-mass trajectories. NARR: North American Regional Reanalysis dataset.
Cited references to follow up on	Charney & Keyser (2010) – Mesoscale modeling of NE wildfire events
Follow up Questions	How well do FARSITE simulations reproduce fire behavior under PH vs EH patterns? Should fuel moisture conditioning in FARSITE be tied to synoptic pattern duration?

Article #18: Modeling of fire spread in sagebrush steppe using FARSITE: An approach to improving input data and simulation accuracy.

Source Title	Modeling of fire spread in sagebrush steppe using FARSITE: an approach to improving input data and simulation accuracy
Source citation (APA Format)	Price, S. Jake, & Germino, M. J. (2022). Modeling of fire spread in sagebrush steppe using FARSITE: An approach to improving input data and simulation accuracy. *Fire Ecology*, *18*(1), 23. https://doi.org/10.1186/s42408-022-00147-2
Original URL	https://doi.org/10.1186/s42408-022-00147-2
Source type	Peer-reviewed journal article
Keywords	FARSITE, wildfire modeling, fuel models, LANDFIRE, Rangeland Analysis Platform (RAP), sagebrush steppe, fire spread simulation, Sorensen coefficient, Cohen's kappa
#Tags	#WildfireModeling #FARSITE #LANDFIRE #ModelValidation
Summary of key points + notes (include methodology)	• The study evaluates how accurately FARSITE can reproduce real wildfire perimeters in sagebrush steppe ecosystems, where fuels are spatially heterogeneous and pre-fire vegetation data are often missing. • Baseline simulations using LANDFIRE pre-mapped fuel behavior fuel models (FBFMs) performed poorly, with low agreement between simulated and observed fire perimeters (SC ≈ 0.32–0.38, K ≈ 0.30–0.36). • The authors developed an alternative fuel-mapping approach using Rangeland Analysis Platform (RAP) satellite-derived vegetation cover (percent shrub, perennial grass, annual grass, bare soil). • RAP vegetation layers were classified using unsupervised maximum likelihood classification into four land-cover types, which were then cross-walked to candidate Scott & Burgan (2005) fuel models. • MTT (Minimum Travel Time) was first used to test multiple fuel-model combinations efficiently, after which the best combinations were run in FARSITE for full multi-day simulations. • The best RAP-derived fuel configuration dramatically improved accuracy for the 2015 Soda Fire (SC = 0.70, K = 0.68). • The same fuel-model "crosswalk" was transferred to the nearby 2016 Cherry Road Fire, achieving even higher agreement (SC up to 0.80, K up to 0.79), demonstrating regional transferability. • Remaining errors were primarily due to overestimation of flanking and backing fires, attributed to FARSITE's assumption of homogeneous fuels within each pixel and lack of lateral fuel discontinuities.

Research Question/Problem/ Need	How can wildfire spread simulations using FARSITE be made more accurate in heterogeneous, semiarid ecosystems where standard fuel datasets (e.g., LANDFIRE) misrepresent fine-scale vegetation structure?
Important Figures	
VOCAB: (w/definition)	FARSITE: A spatially explicit wildfire growth model that simulates fire spread using time-varying weather, fuels, and topography. FBFM (Fire Behavior Fuel Model): A standardized set of fuel parameters used in Rothermel-based fire spread equations. LANDFIRE: A national U.S. dataset providing mapped fuels, vegetation, and canopy characteristics for wildfire modeling. RAP (Rangeland Analysis Platform): A satellite-based system providing annual, 30-m resolution estimates of vegetation cover by functional type. Sorensen's Coefficient (SC): A measure of spatial agreement between simulated and observed burned areas that does not account for chance agreement. Cohen's Kappa (K): A statistical metric of agreement that adjusts for agreement occurring by chance. MTT (Minimum Travel Time): A computationally efficient fire spread model assuming constant weather, used for rapid calibration.
Cited references to follow up on	Jahdi et al. (2015, 2016) – FARSITE calibration and validation
Follow up Questions	Would higher spatial resolution fuels (e.g., lidar-derived) further reduce flanking/backing fire overestimation? How sensitive are the improved results to fuel moisture assumptions, given that fuels were conditioned uniformly?

Article #19: Contemporary Wildfire Hazard Across the Eastern Region

Source Title	Contemporary Wildfire Hazard Across the Eastern Region
Source citation (APA Format)	Vogler, K. C., Brough, A., Moran, C. J., Scott, J. H., Gilbertson-Day, J. W., & Olszewski, J. H. (2021). *Wildfire Risk Across the Eastern Region* [Technical report]. Pyrologix LLC. https://pyrologix.com/wildfire-risk-across-the-eastern-region/
Original URL	https://pyrologix.com/wildfire-risk-across-the-eastern-region/
Source type	Government-commissioned technical report / wildfire hazard assessment
Keywords	Wildfire hazard, burn probability, FSim, FlamMap, WildEST, Eastern United States, LANDFIRE, wildfire modeling, suppression difficulty, wildfire risk
#Tags	#LANDFIRE #WildfireModeling #FSim
Summary of key points + notes (include methodology)	• This report documents the **wildfire hazard modeling** component of the Eastern Region All-Lands Wildfire Risk Assessment (ERRA), covering **20 northeastern U.S. states**. • Wildfire hazard is defined by **two components**: 1. **Burn probability (likelihood)** 2. **Fire intensity** (flame length, rate of spread, crown fire behavior) • **FSim** (Finney et al., 2011) was used to model **burn probability** at 120 m resolution using: ○ Historical wildfire occurrence (1992–2018 FPA FOD) ○ Historical weather (RAWS, ERC from gridded datasets) ○ Calibrated LANDFIRE fuelscapes • FSim simulations were run for **10,000–100,000 iterations per Fire Occurrence Area (FOA)** and calibrated to historical large-fire statistics (>100 acres). • Due to limitations of stochastic intensity outputs in low-fire regions, **fire behavior intensity was modeled separately using WildEST**, a **deterministic FlamMap-based framework**. • **WildEST**: ○ Runs 27 deterministic fire behavior simulations (wind × fuel moisture scenarios) ○ Uses **Weather Type Probability (WTP)** rasters derived from gridMET weather data (2000–2019) ○ Produces 30 m resolution outputs: flame length, rate of spread, fire type probabilities, and operational control probabilities • A **custom post-processing method** was required to address fragmented eastern fuels and excessive small simulated fires: ○ Used **Lorenz curves** to define FOA-specific large-fire thresholds ○ Removed small simulated fires that unrealistically inflated burn probability

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Burn probability was upsampled from 120 m to 30 m using spatial smoothing and thresholding to align with WildEST outputs.
Integrated hazard metrics produced:

Risk to Potential Structures (RPS)
Wildfire Hazard Potential (WHP)
Suppression Difficulty Index (SDI)

Agricultural fuels (cornfields) were modeled using a custom fuel model (AG9) with seasonal intensity reductions to avoid overestimation.

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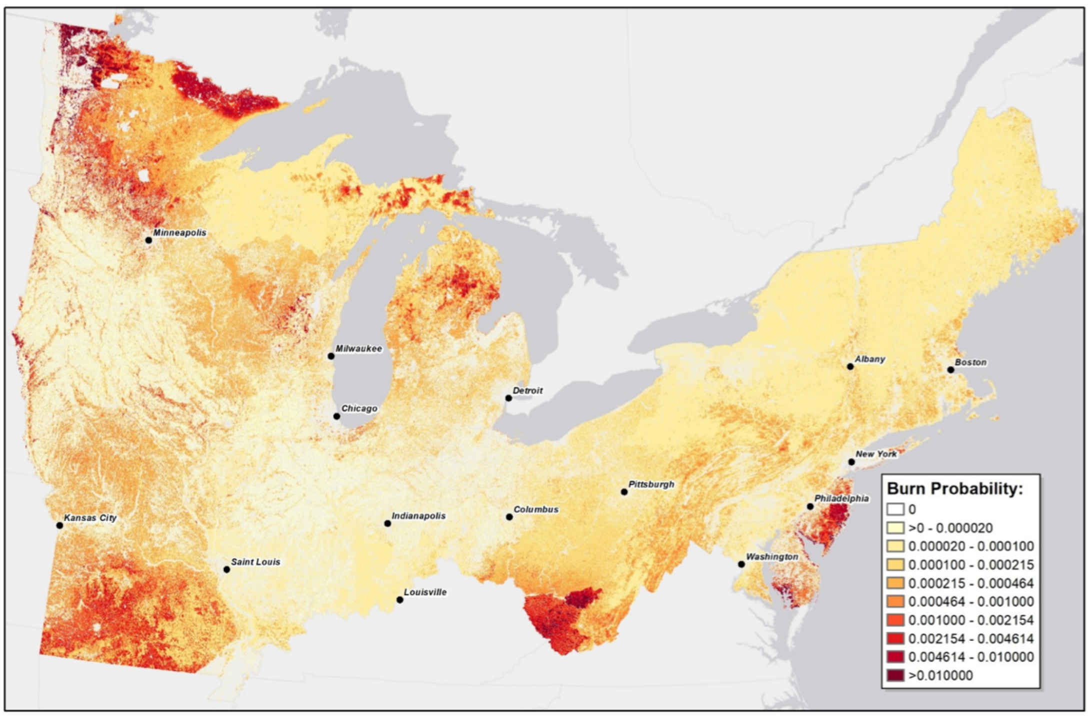
<tr><td>Research Question/Problem/ Need</td><td>How can wildfire hazard (likelihood + intensity) be accurately quantified across the fragmented, low-fire-frequency landscapes of the Eastern United States using physically based fire models?</td></tr>
<tr><td>Important Figures</td><td>


Figure 7. Map of integrated FSim burn probability results for the Eastern Region study area at 30-m resolution.
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<tr><td>VOCAB:
(w/definition)</td><td>Burn Probability (BP): The annual probability that a given pixel will burn, derived from thousands of simulated fire seasons.
FSim: A stochastic large-fire simulation model used to estimate wildfire likelihood.
WildEST: A deterministic, FlamMap-based modeling framework for estimating wildfire intensity using weather-type probabilities.
Weather Type Probability (WTP): Spatial probability of specific wind and fuel moisture scenarios weighted by potential area burned.
Lorenz Curve: A statistical tool used here to identify fire sizes responsible for most burned area.
Fire Occurrence Area (FOA): Subregions with similar fire-climate characteristics used for FSim calibration.</td></tr>
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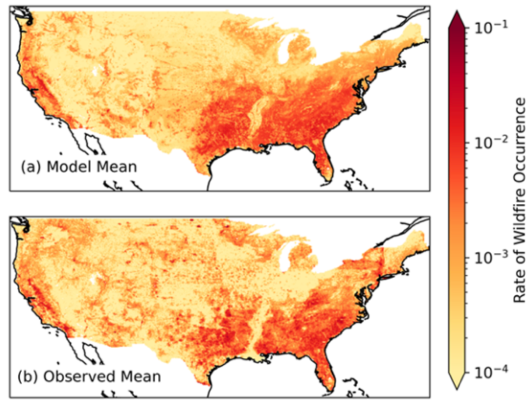
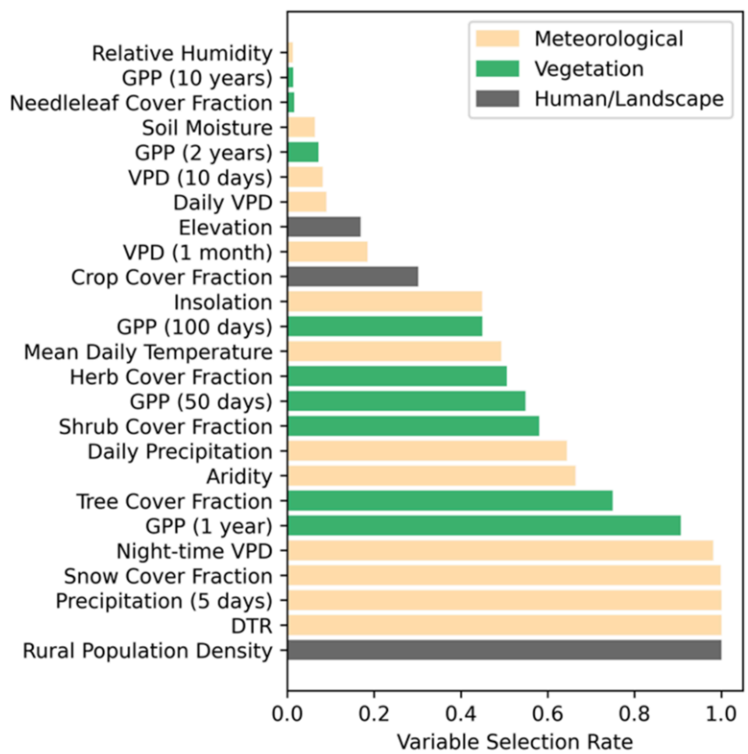
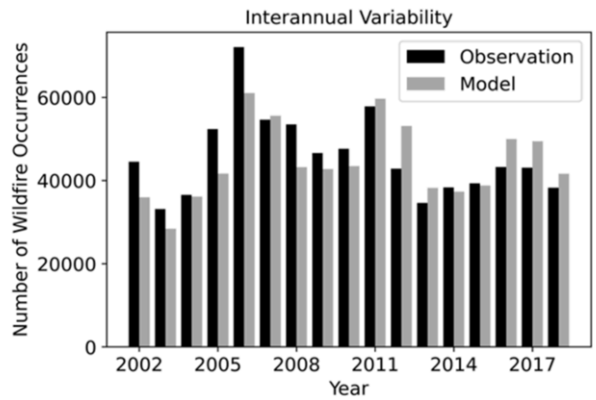
	Suppression Difficulty Index (SDI): A metric estimating how difficult a wildfire would be to control based on fuels, terrain, access, and fire behavior.
Cited references to follow up on	Charney & Keyser (2010) – Mesoscale modeling of NE wildfire events
Follow up Questions	How sensitive are burn probability results to FOA-specific large-fire thresholds?

Article #20: Modelling the daily probability of wildfire occurrence in the contiguous United States

Source Title	Modelling the daily probability of wildfire occurrence in the contiguous United States
Source citation (APA Format)	https://doi.org/10.1088/1748-9326/ad21b0
Original URL	https://doi.org/10.1088/1748-9326/ad21b0
Source type	Journal Article
Keywords	wildfire risk, wildfire occurrence modeling, natural hazards, contiguous United States, generalised linear models, social-ecological systems
#Tags	
Summary of key points + notes (include methodology)	• The paper develops a daily wildfire occurrence probability model at 0.1° (~10 km) spatial resolution for the contiguous U.S. • Uses an adapted Generalized Linear Model (GLM) framework rather than machine learning to: o Maintain interpretability o Reduce overfitting in a highly stochastic process • Three major methodological innovations: 1. Objective stepwise variable selection using AIC + VIF thresholds to handle 47 candidate predictors 2. Predictor domain optimization, identifying the range where each predictor is influential (e.g., aridity increases risk up to a point, then reduces it due to fuel limitation) 3. Compression correction using a power-law transformation to better represent extreme probabilities • Fire occurrence data sourced from FPA FOD (2002–2018); fires defined as unplanned events >0.25 acres • Predictors include: o Meteorology (precipitation, VPD, temperature, snow cover) o Vegetation (land cover fractions, GPP, antecedent growth) o Human factors (rural population density, roads, infrastructure) • Model implemented as a large ensemble (≈2100 members) to quantify uncertainty and robustness • Performance: o AUC = 0.85–0.88 (very good predictive power) o Accurately captures geographic patterns, seasonal timing, and interannual variability • Key insight: rural population density is a stronger predictor than total population density

Research Question/Problem/ Need	How can wildfire occurrence probability be accurately predicted at a daily timescale while remaining interpretable, robust, and globally scalable—especially given the complex interaction of human, vegetation, and meteorological drivers?
Important Figures	 **Figure 2.** Comparison of (a) modelled and (b) observed mean of daily modelled probability of wildfire occurrence over the period 2002–2018. The model results are the average across the Pareto superior set of ensemble members. Both maps are plotted on a logarithmic scale.  **Figure 5.** Rate of selection of individual predictor variables in the 2000-member ensemble from the stepwise variable selection algorithm. Only variables that were selected in more than 1% of the ensemble members are shown.

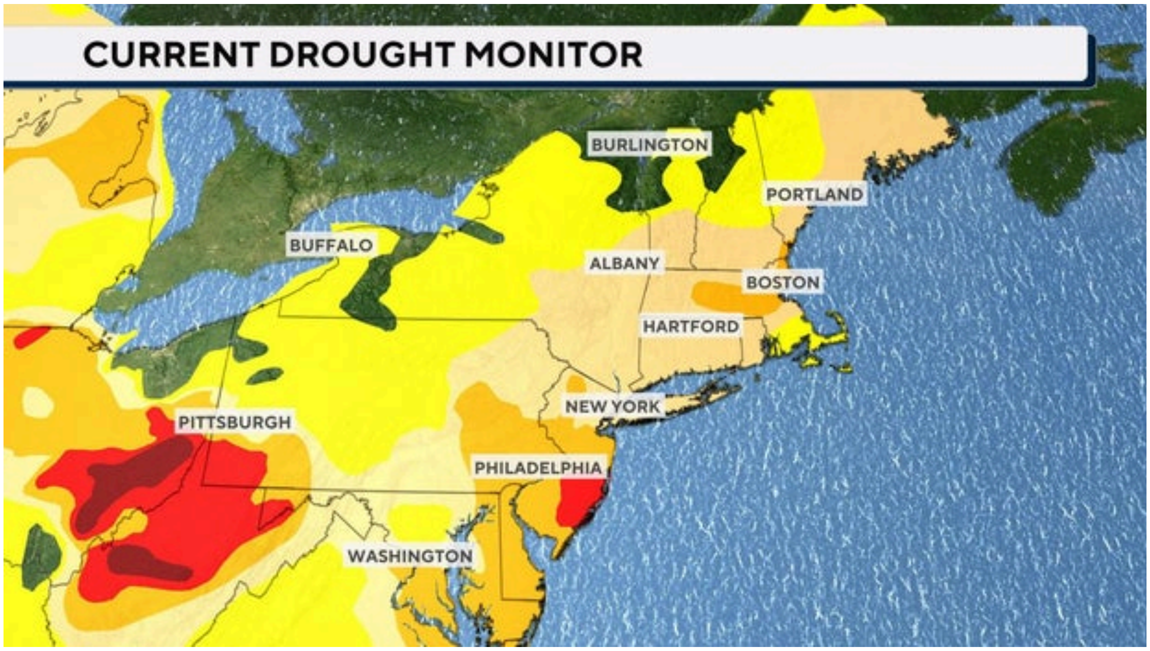
	 **Figure 4.** Annual total modelled and observed fire occurrences in the contiguous United States from 2002–2018.
VOCAB: (w/definition)	• Generalized Linear Model (GLM) – A statistical model extending linear regression to non-normal response variables (here, binomial fire/no-fire outcomes). • AUC (Area Under Curve) – Metric measuring a model's ability to distinguish between occurrence and non-occurrence. • Variance Inflation Factor (VIF) – Measure of multicollinearity among predictors. • Predictor Compression – Tendency of GLMs to underrepresent extreme probabilities. • Vapor Pressure Deficit (VPD) – Measure of atmospheric drying power affecting fuel moisture. • Pareto-optimal subset – Set of models that are not outperformed across multiple evaluation metrics.
Cited references to follow up on	Hantson et al. (2020) – Fire model intercomparison (FireMIP)
Follow up Questions	Can predictor domain optimization be adapted for regional calibration (e.g., New England vs Southwest)?

News Article: Maps show drought and fire conditions in Northeast states

Source Title	Maps show drought and fire conditions in Northeast states
Source citation (APA Format)	Maps show drought and fire conditions in Northeast states—CBS News. (2024, November 9). *CBS News*. https://www.cbsnews.com/news/maps-drought-fire-conditions-northeast/
Original URL	https://www.cbsnews.com/news/drought-fire-conditions-northeast-maps/
Source type	News Article
Keywords	
#Tags	

Summary of key points + notes (include methodology)	• The Northeastern United States is experiencing widespread drought conditions, contributing to elevated wildfire risk.
	• The National Weather Service Storm Prediction Center issued an elevated fire weather outlook spanning Massachusetts to northern Virginia and West Virginia.
	• Critical fire-weather drivers include:
	  ○ Sustained winds of 10–15 mph
	  ○ Wind gusts up to 25–35 mph
	  ○ Relative humidity as low as ~20% in some locations
	• Red Flag Warnings were issued across much of the Northeast and New England, signaling conditions favorable for rapid fire spread.
	• The U.S. Drought Monitor indicates:
	  ○ 57% of the NY–NJ–CT tri-state area under moderate drought
	  ○ Massachusetts experiencing moderate to severe drought, with multiple active wildfires reported.
	• State-level drought statistics are presented using percentage-of-area metrics (e.g., % of state in moderate, severe, or extreme drought), derived from weekly drought monitoring reports rather than original field experiments.
	• The article relies on observational meteorological datasets, drought indices, and official agency alerts rather than modeling or predictive simulation.

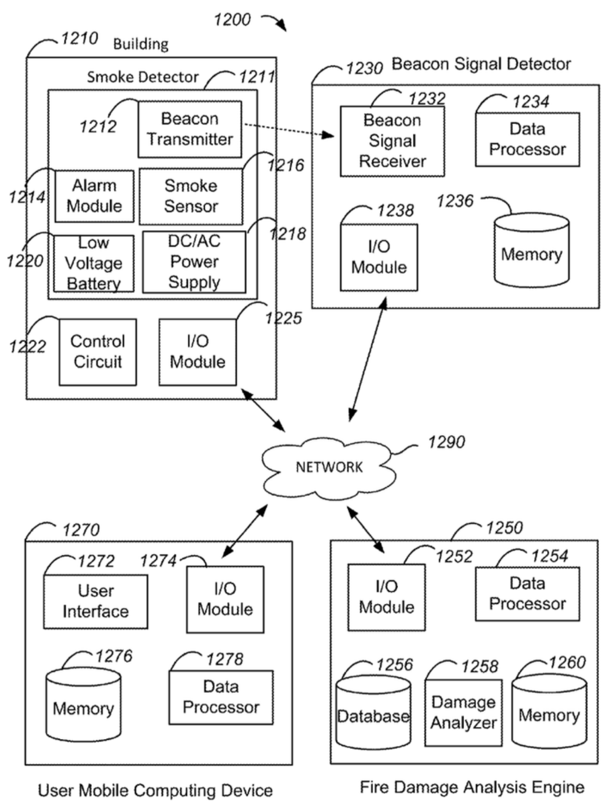
Research Question/Problem/ Need	How do short-term meteorological conditions (wind, humidity) interact with longer-term drought patterns to elevate wildfire risk in regions not traditionally associated with frequent large wildfires, such as the Northeastern United States?

Important Figures	
VOCAB: (w/definition)	None. This article was intended for a general audience.
Cited references to follow up on	None
Follow up Questions	

Patent #1: Wildfire Risk Assessment

Source Title	Wildfire Risk Assessment
Source citation (APA Format)	Billman, B. J., Hartman, W., Bhide, A., III, C. L. O., Rubin, E., Zuwala, M., Gray, E., & Sausman, S. (2014). *Wildfire risk assessment* (United States Patent No. US8760285B2). https://patents.google.com/patent/US8760285B2/en?oq=US%C2%A08760285%C2%A0B2
Original URL	https://patents.google.com/patent/US8760285B2
Source type	Patent
Keywords	Wildfire risk assessment; fire behavior simulation; mitigatable features; virtual wildfire; mobile application; insurance risk modeling; home ignition zone; wildfire mitigation; augmented reality; GIS visualization
#Tags	#WildfireModeling #FireRiskAssessment #Patents #FireBehaviorSimulation #WUI #InsuranceModeling #VirtualFire #GIS

Summary of key points + notes (include methodology)	This patent describes a system and method for assessing wildfire risk at the property level, primarily for homeowners and insurance providers, using a mobile computing device. Unlike physics-based wildfire spread models (e.g., FARSITE), the invention focuses on feature-driven risk scoring and interactive simulation.
	Core Components
	• Mobile application that:
	  ○ Presents users with a structured wildfire inspection checklist (vegetation, slope, materials, access, nearby structures).
	  ○ Requests photos of features when visual confirmation improves risk estimation.
	  ○ Uses augmented visual assistance to guide image capture.
	• Risk computation engine that:
	  ○ Determines wildfire risk based on answers + images.
	  ○ Identifies mitigatable features (e.g., firewood piles, propane tanks, unmanaged vegetation).
	  ○ Recalculates risk after mitigation actions are simulated.
	Virtual Wildfire Simulation
	• A virtual wildfire can be ignited on a map of the property.
	• Fire paths are computed based on identified features.
	• Fire spread is accelerated by hazardous (mitigatable) features.
	• Users can remove features and re-run the simulation to observe reduced fire spread.
	Important: the simulation is qualitative / heuristic, not physics-based (no Rothermel equations, fuel moisture modeling, or PDE fire fronts).
	Insurance Integration
	• Risk scores can:
	  ○ Adjust insurance premiums.

	◦ Flag properties as uninsurable. • Designed for underwriting workflows, not operational fire management. Additional System • A smoke-detector beacon system broadcasts building status during active fires. • Firefighters or mobile receivers collect signals to infer whether buildings are likely destroyed.
Research Question/Problem/ Need	How can wildfire risk to individual properties be rapidly assessed and reduced using user-collected local data, without relying on complex fire physics models?
Important Figures	 *FIG. 12*
VOCAB: (w/definition)	• **Mitigatable feature** – A property characteristic (e.g., vegetation, materials) that increases wildfire risk but can be modified or removed. • **Home Ignition Zone (HIZ)** – Area surrounding a structure where fuels most strongly influence ignition probability. • **Virtual wildfire** – A simulated fire visualization driven by hazard features rather than physical fire spread equations. • **Augmented visual assistance** – On-screen guidance to help users capture diagnostic images. • **Beacon signal** – Low-power radio transmission used to communicate building status during fires.

Cited references to follow up on	Collins et al., 2009 – Real-time building status during fires
Follow up Questions	How does this feature-based simulation compare quantitatively with physics-based models like FARSITE or FlamMap?

Patent #2: Wildfire Cone of Confidence Simulation System and Processes

Source Title	Wildfire Cone of Confidence Simulation System and Processes
Source citation (APA Format)	Brady, R. I. (2024). *Wildfire cone of confidence simulation system and processes* (United States Patent No. US11998783B1). https://patents.google.com/patent/US11998783B1/en
Original URL	https://patents.google.com/patent/US11998783B1
Source type	Patent
Keywords	Wildfire modeling; fire spread simulation; cone of confidence; uncertainty visualization; evacuation planning; decision support systems; GIS; fire history integration
#Tags	#wildfire #fireModeling #FARSITE #decisionSupport #riskVisualization #emergencyManagement #patent #uncertainty
Summary of key points + notes (include methodology)	This patent describes a “wildfire cone of confidence” system that overlays uncertainty-aware probabilistic information onto outputs from existing wildfire propagation models. The core innovation is a post-processing and iterative framework that integrates model outputs, historical fire data, and real-time fire progression data to communicate confidence bounds in predicted fire spread. Methodology: 1) Run a wildfire simulation 2) Compile simulation output into a predicted path and direction 3) Overlay historical fire data 4) Create a weighted overlay 5) Apply a statistical probability model 6) Identify regions where outputs align within two standard deviations of the mean 7) Generate a visual “cone of confidence” at future time intervals 8) Continuously update the model using real-time fire progression data 9) Apply a evacuation buffer to aid emergency responders.
Research Question/Problem/ Need	Existing wildfire models produce highly granular outputs (rate of spread, flame length, perimeters) that are difficult for non-experts—especially the public—to interpret for evacuation and safety decisions.

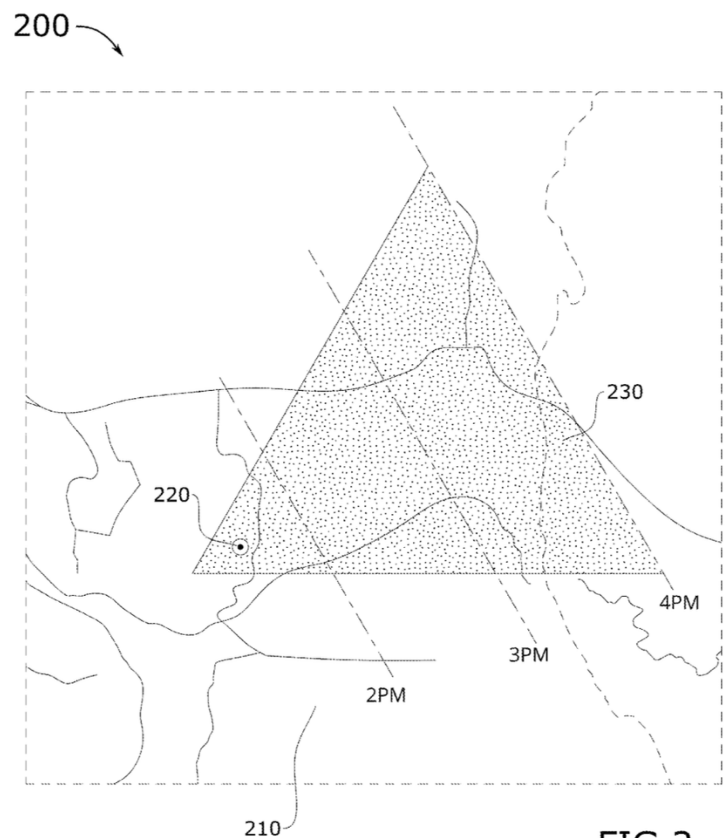
<table>
<tr><td>Important Figures</td><td>

FIG.2</td></tr>
<tr><td>VOCAB:
(w/definition)</td><td>Weighted Overlay: A GIS/statistical technique that combines multiple spatial datasets (e.g., model output + fire history) using assigned weights.
Fire Progression Data: Observed data describing how a fire actually spreads over time, used for real-time updating and validation.
Evacuation Buffer: An additional spatial margin added to predicted hazard zones to account for uncertainty and provide safety margins for evacuation planning</td></tr>
<tr><td>Cited references to follow up on</td><td>none</td></tr>
<tr><td>Follow up Questions</td><td>How sensitive is the cone of confidence to the choice of underlying wildfire model (e.g., FARSITE vs. cellular automata)?</td></tr>
</table>

Template

Source Title	
Source citation (APA Format)	
Original URL	
Source type	
Keywords	
#Tags	
Summary of key points + notes (include methodology)	
Research Question/Problem/ Need	
Important Figures	
VOCAB: (w/definition)	
Cited references to follow up on	
Follow up Questions	