ADVANCING EARTH AND SPACE SCIENCES

Geophysical Research Letters

RESEARCH LETTER
10.1029/2025GL116248

Soil Moisture is a Stronger Predictor of Forest Fire Spread Potential Than Weather in the U.S. Northern Rocky Mountains

Zachary A. Holden[1], Alan K. Swanson[2], Mojtaba Sadegh[3], Charles H. Luce[4], Erin Noonan-Wright[5], and Russell A. Parsons[1]

[1]USDA Forest Service, Rocky Mountain Research Station, Missoula, MT, USA, [2]Department of Community and Public Health, University of Montana, Missoula, MT, USA, [3]Department of Civil Engineering, Boise State University, Boise, ID, USA, [4]USDA Forest Service, Rocky Mountain Research Station, Boise, ID, USA, [5]USDA Forest Service, Northern Region Fire & Aviation Management, Missoula, MT, USA

Key Points:

- Fire management systems rely on short-term weather indicators of fire danger and spread
- We analyzed the effects of weather, fuels and soil moisture models on daily fire spread in recent U.S. Northern Rocky Mountain wildfires
- Hydrology-based variables are the dominant predictors on large fire spread in this region

Supporting Information:

Supporting Information may be found in the online version of this article.

Correspondence to:

Z. A. Holden,
zachary.holden@usda.gov

Citation:

Holden, Z. A., Swanson, A. K., Sadegh, M., Luce, C. H., Noonan-Wright, E., & Parsons, R. A. (2025). Soil moisture is a stronger predictor of forest fire spread potential than weather in the U.S. Northern Rocky Mountains. *Geophysical Research Letters*, *52*, e2025GL116248. https://doi.org/10.1029/2025GL116248

Received 29 MAR 2025
Accepted 24 JUL 2025

Author Contributions:

Conceptualization: Zachary A. Holden, Alan K. Swanson, Mojtaba Sadegh, Charles H. Luce, Russell A. Parsons
Formal analysis: Zachary A. Holden, Alan K. Swanson
Methodology: Zachary A. Holden, Alan K. Swanson, Russell A. Parsons
Supervision: Zachary A. Holden
Validation: Erin Noonan-Wright
Writing – original draft: Zachary A. Holden, Alan K. Swanson, Mojtaba Sadegh, Charles H. Luce, Erin Noonan-Wright, Russell A. Parsons
Writing – review & editing: Mojtaba Sadegh

Abstract Accurate prediction of forest fire spread is a critical management and scientific challenge as the world adapts to rapidly changing fire regimes. We reconstructed 5,400 daily burned area progression maps for 196 U.S. Northern Rocky Mountain wildfires (2012–2021) and used machine learning to estimate daily fire growth given local weather, hydroclimate, fuels and topography. Optimized models explained 36% of the variation in daily fire growth, increasing to 56% when an index of fire activity the previous day was included. Soil moisture and plant hydraulic stress were the dominant predictors of fire spread, increasing accuracy by 8%–9% over models with only fuel and weather. Wildfire danger forecasts and fire spread models in the U.S. use short-term weather indices and don't consider longer-term drought. Our findings suggest that soil moisture and vegetation stress are critical indicators of fire spread potential in this region, with implications for fire modeling and prescribed burn planning.

Plain Language Summary Forest fires have been increasingly affecting the western United States and many other regions worldwide. To support wildfire planning, mitigation and response efforts, researchers have developed a range of physics-based and data-driven models to simulate fire propagation. The majority of these models rely on weather conditions and fire danger indices for their predictions, without directly considering soil moisture and its influence on live fuel moisture. We mapped daily fire perimeters for 196 large forest fires from 2012 to 2021 using VIIRS satellite fire detections and statistical interpolation and used boosted regression tree models to estimate the effects of weather, fire danger, soil moisture and fuels on daily fire growth. Our results suggest that soil moisture-related variables strongly influence daily fire growth and potential for large fire growth days. Additionally, our models indicated that inclusion of previous day active pixel counts—that is, adding memory to the fire propagation model—can markedly enhance model performance. Our findings highlight the crucial role of soil moisture in influencing forest fire spread, with significant implications for future mitigation and response efforts.

1. Introduction

Wildfire activity has increased across much of the world (Senande-Rivera et al., 2022). In the western United States, connections between wildfires, weather and climate are well established (Abatzoglou & Kolden, 2013; Littell et al., 2009), pointing to increased atmospheric aridity (Park Williams et al., 2013), lengthening dry periods (Jolly et al., 2015) and warm-season precipitation declines (Holden et al., 2018) as drivers of increased wildfire area burned. Decades of fire exclusion in this region have changed the trajectory of forest structure and increased fuel loads (Boisramé et al., 2022), which coupled with prolonged drought and increasing atmospheric aridity have contributed to fires of unprecedented size and intensity (Alizadeh et al., 2021; Collins et al., 2011). Global climate models project increasing temperatures and further decreases in summer precipitation in some regions of the west, suggesting more frequent, and more extreme wildfires seasons are likely in the coming decades (Abatzoglou et al., 2021; Abatzoglou & Williams, 2016).

Planned prescribed burns are a critical tool for managing fuels and wildfires in the west (Pritchard et al., 2021). However, increased aridity has reduced the frequency of weather and moisture windows conducive to safe use of planned ignitions (Swain et al., 2023), resulting in increased risks for managers and reduced application of this

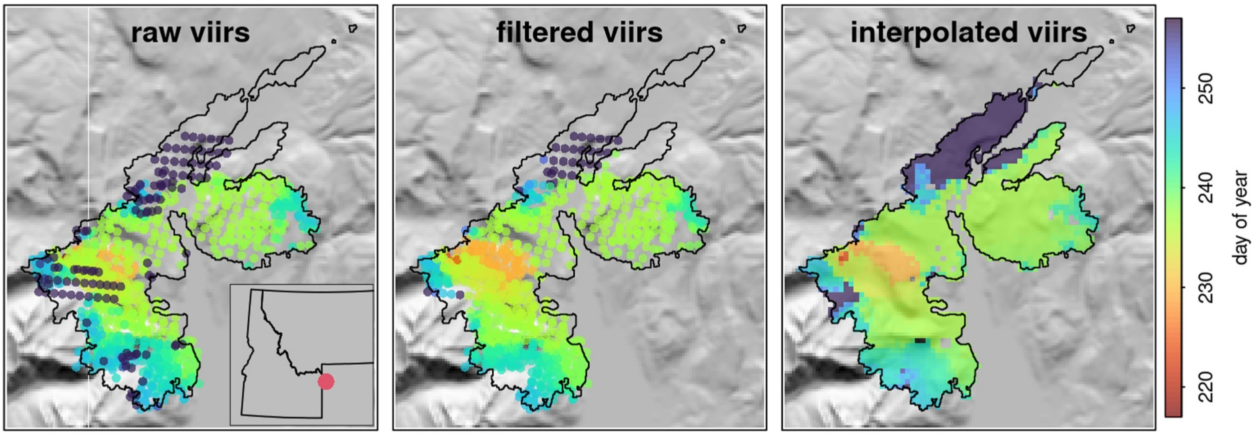

Figure 1. Day of burn mapping for the 2016 Berry fire in Wyoming. The left panel shows raw VIIRS active fire detection points colored by day of year. The middle panel shows these points after filtering early and delayed pixels and the right panel shows gridded day of burn estimated with nearest natural neighbor interpolation.

important land-management tool. The intersection of overstocked, stressed vegetation and increasingly extreme fire danger, coupled with increasing exposure of people and homes in the expanding wildland-urban interface (Modaresi Rad et al., 2023; Radeloff et al., 2018) broadly frame the challenges associated with the wildfire crisis. As a case in point, escaped prescribed fires in 2020 and 2021 led to a pause in planned ignitions on Federal land. A review of those incidents implicated long antecedent drought as a potential contributing factor, highlighting a need to better understand how evolving hydrologic conditions influence fire spread (USFS, 2022). Soil moisture is increasingly acknowledged as an important predictor of wildfire danger (Krueger et al., 2023). However, U.S. fire management strategies are designed around surface fuel moisture content and weather-based indicators with no explicit consideration of soil hydrology and its direct effects on live fuel moisture (Jolly et al., 2024).

In this study, we analyze how weather and hydroclimate influenced daily fire growth during recent large forest fires in the U.S. Northern Rocky Mountains. We estimate the day and location of a burned footprint within each fire, extract coincident weather and moisture variables for the burned area, and analyze the drivers of daily fire growth using machine learning. We focus on two main questions: (a) How predictable is daily fire spread? and (b) What are the dominant predictors of daily fire growth, considering a broad range of fuel, weather and hydrologic indicators?

2. Data and Methods

We used active fire data from the Visible Infrared Imaging Radiometer Suite (VIIRS; Schroeder et al., 2014) to estimate daily fire growth at 196 fires that occurred in the U.S. Northern Rocky Mountains from 2012 to 2021. We chose fires for which Monitoring Trends in Burn Severity perimeters and burn severity raster data were available (MTBS; Eidenshink et al., 2007). We screened fires in our geographic domain, excluding those smaller than 400 ha, with fewer than 10 active fire days, or where VIIRS detection points covered <50% of the burned area, where coverage was calculated as the proportion of 350 m grid cells that intesect >10% DNBR burned area perimeter (dnbr value ≥1) that also contained at least one VIIRS point. Finally, we extracted pre-fire forest cover data from the Rangeland Analysis Platform (RAP; Allred et al., 2021) and excluded fires with <30% forest cover, leaving approximately 5,400 fire spread days from 196 unique fires. Figure 1 shows VIIRS active fire points and interpolated outputs for the 2015 Berry fire in Wyoming as an example.

2.1. Daily Fire Progression Mapping

We compared several methods for mapping daily fire progression, including geographically weighted quantile regression (GWQR; Chen, 2012) kriging, and natural neighbor interpolation (NN; Scaduto et al., 2020; Sibson, 1981). We tested these methods by comparing daily fire perimeters from each model with estimates from more than 800 pairs of aerial fire perimeter maps from geoMAC. NN was previously shown to have high relative

Table 1
Weather, Hydrologic and Vegetation Variables Evaluated as Predictors of Daily Wildfire Spread

Variable name	Description	Units	Resolution
Soil water supply variables (5)			
soil, soil_anom	raw soil moisture; 14-day std. anom	mm/S.D.	250 m; daily
Prcp	GridMET precipitation day of burn	mm/day	4 km daily
ech2o_soil, plc	ech2o simulated daily soil moisture (%) and loss of hydraulic conductance	percent	250 m; 3-hourly
Fire danger variables (3)			
FM100/1000	100 and 1,000 hr dead fuel moisture	% dry wt	4 km; daily
ERC	energy release component	BTU/ft2	4 km; daily
Atmospheric demand variables (10)			
rh (min, max)	min. and max. relative humidity	percent	250 m daily
vpd (avg, min, max)	daily vapor pressure deficit	Kpa	250 m daily
pet, aet, def	Potential and actual ET, and water balance deficit (PET-AET)	mm	250 m daily
tmin, tmax, tdew	Daily min/max temperature and average daily dewpoint temperature	°C	250 m daily
Tskin	Ech2o simulated daily maximum surface temperature	°C	250 m,3-hourly
wind (5)			
wind (mean, max)	climate forecast system reanalysis (CFSR) mean, max daily wind speed	m/s	0.25 deg. hourly
maxwindPM, maxwindAM, meanwind	RTMA 95th percentile 1–8pm and 12–7am wind speed	m/s	2.5 km hourly
hgt700; hgt700_z	CFSR 700 mbar geopotential height (raw and standard z-score)	MPa	0.5 deg. hourly
pre-fire vegetation (37)			
grass, shrub, forest, bare, litter	pre-fire RAP cover fractions and anomalies from 1992 to 2021	percent	30 m annual
NPP	pre-fire RAP net primary productivity for shrub, grass and forest layers and anomalies from 1992 to 2021 data.	percent	30 m annual

Note. A full list of individual indices is provided in Table S1 of Supporting Information S1. The variables soil and soil_anom, pet, aet and def were extracted from daily 250-m historical Topofire soil water balance grids. Soil is the daily soil moisture value (millimeters) and soil_anom is the standardized daily value relative to the 1992–2021 period (units of standard deviation). Ech2o_soil and plc were simulated using the ech2o ecohydrology model.

skill for mapping wildfire perimeters in California (Scaduto et al., 2020), but we found its predictions were degraded by detections reoccurring in previously burned areas. Therefore we modified the NN approach by calculating quantiles of natural neighbors rather than weighted means. Finding it performed best; we used this method to develop daily 8 arc-second (∼250-m) resolution grids estimating the day of burn for each of our study fires. Additional details describing this analysis are provided in the Text S1.1, Figures S1–S4 and Table S1 in Supporting Information S1 lists the methods tested and their agreement with mapped perimeters.

2.2. Weather, Moisture and Fuel Predictors

We evaluated 57 predictor variables, including 37 pre-fire vegetation indices and 19 hydroclimatic indices concurrent with the day of burn, and a single static terrain index; average slope (Table 1). Temperature, humidity, and soil water balance data were extracted from 250-m resolution Topofire grids (Holden et al., 2019), and fuel moisture fire danger indices from 4 km GridMET data (Abatzoglou, 2013) using the mean value for the estimated spatial footprint of each burn day within a fire. For days with no active spread, we extracted weather indices from the previously burned pixels, going back in time until at least 10 pixels were found. Pre-fire fuel and vegetation data were extracted from the Rangeland Analysis Platform (RAP) vegetation cover fraction and Net Primary Productivity data (Allred et al., 2021). These provide annual (1986–2023) 30-m resolution estimates of fractional cover and biomass for annual and perennial grass, shrub, litter and forest cover types. For each layer, we extracted both raw and standardized values (z-scores relative to 1992–2021) within each daily burn footprint for a total of 37 pre-fire vegetation indices. Average slope was extracted for each daily burn footprint from a 30-m digital elevation model. Finally, we used the ecohydrology model ech2o (version 5.7.4-SPAC; Maneta &

Table 2
Performance of Boosted Regression Tree Models Estimating Daily Fire Growth for a Continuous Response (Log-Transformed Hectares Burned) and a Binary Response (Fire Spread Days > 400 ha)

Model type and selected variables	Accuracy statistics				
Continuous log (hectares)	nvar	R^2	MAE	R^2-PF	MAE-PF
plc, rmin, soil_ech2o, wind, annual_grass, perennial_grass, avg_30m_slope, fm100, npp_grass_anomaly	9	0.36	0.50	0.56	0.40
ech2o variables excluded					
rmin, fm100, annual_grass, npp_shrub, slope, perennial_grass, soil_anom, npp_nonforest_z, wind, maxwindPM	10	0.27	0.54		
binary—growth > 400 ha	nvar	AUC	PCC	AUC-PF	PCC-PF
plc, soil_ech2o, rmin, def, annual_grass, perennial_grass, slope + fm100, wind	8	0.85	0.80	0.91	0.92
ech2o variables excluded					
annual_grass, rmin, slope soil_anom, def, perennial_grass, maxwindPM, vpd, npp_shrub, pet, maxwindAM	11	0.80	0.75		

Note. The selected variables for each model are shown in order of importance. Accuracy is reported as variance explained (r-squared) and Mean Absolute Error (MAE) and AUC/PCC for the binary response. PF shows accuracy for each model with the number of active VIIRS pixels the previous day added as a predictor and retrained. R^2 and MAE are the model variance explained and mean absolute error. R^2-PF and MAE-PF are for models that include active pre-fire pixels.

Silverman, 2013) calibrated for Ponderosa pine seedlings (Simeone et al., 2019) to simulate daily minimum soil moisture, maximum soil surface temperature and percent loss of hydraulic conductance (PLC) for the extent of each fire, at 3-hourly time step and 250-m spatial resolution. More detail on data extraction and preparation methods can be found in Text S1.2 of Supporting Information S1.

2.3. Statistical Models and Data

2.3.1. Boosted Regression Tree Models

We trained boosted regression tree models (BRT; Friedman1999) to estimate daily fire spread and potential for large growth days. Our continuous response variable, daily area burned per fire in hectares, was base 10 log-transformed using an offset of 7. We also consider a classification model (binary response) with growth days ≥400 ha as a threshold for large fire growth.

We screened candidate predictors using spatial subsets of the data for training and testing (i.e., spatial cross-validation (CV)) and forward feature selection (FFS; Meyer et al., 2018), with CV folds constructed using random subsets of fire-level data. We extend this approach using multi-scale spatial cross-validation (MSCV; Erickson et al., 2023), running FFS multiple times on subsets of the data, each time varying the number of CV folds from $K = 5$–20 groups (approximately 5%–20% of data per fold) and tracking how often each predictor was selected. These methods are detailed in Text S1.3 of Supporting Information S1 and variable selection results are provided in Tables S2 and S3 of Supporting Information S1. We use the H statistic (Friedman & Popescu, 2008) to identify potential 2- and 3-way interactions and we visualize and interpret these effects using partial dependence plots. Finally, we refit these models with an additional predictor variable; the number of VIIRS detections that were active in the previous day. This indicator of nearby fire activity is included to provide additional context for models trained with only weather and hydroclimate. Tabulated variable interactions are shown in Table S4 of Supporting Information S1.

3. Results

3.1. How Predictable is Daily Wildfire Spread?

Table 2 shows model accuracy results for continuous (daily fire growth) and binary (large fire growth) response models. Optimized BRT model with 10 predictors explains 36% of the variability in daily area burned. Including the number of previously active fire pixels (PF) as a model predictor increased the accuracy to 56%. Area under the receiver-operator curve (AUC) scores for a binary response estimating spread days >400 ha were 0.86 and 0.91 without and with PF, respectively. Figure 2 shows linear correlations between observed and estimated daily spread

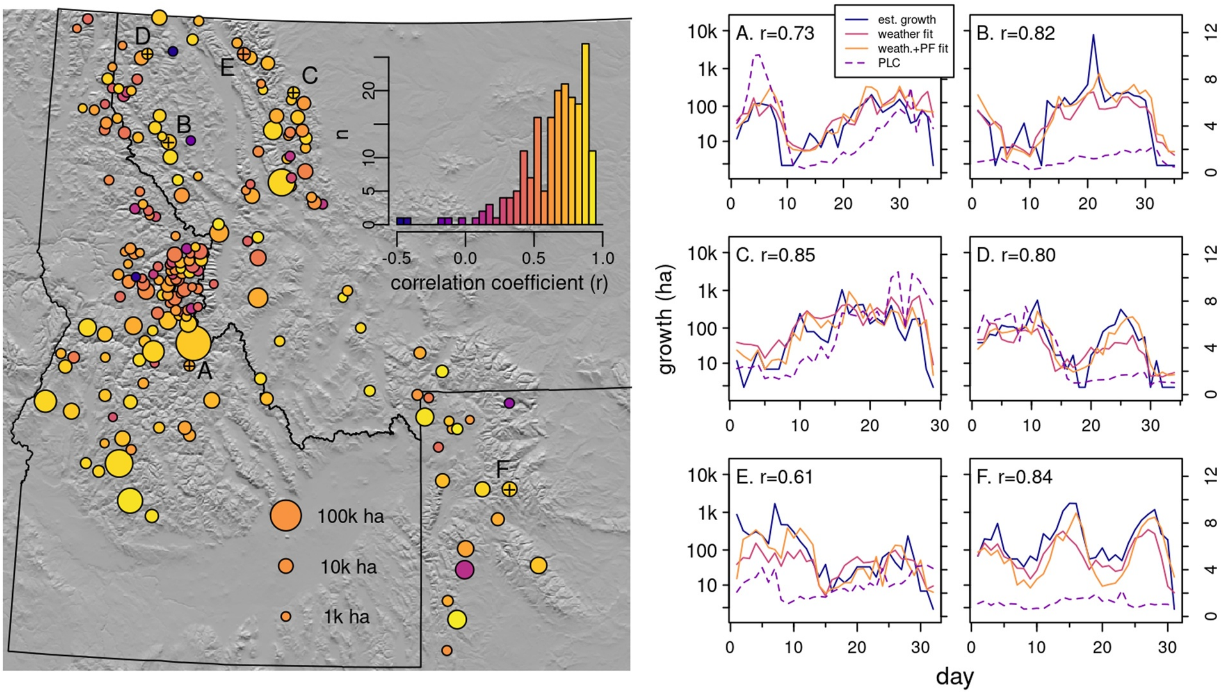

Figure 2. Relationships between daily fire growth estimated from VIIRS and predicted daily growth from a boosted regression tree model. The left panel shows correlations (Pearsons r) for 196 fires used in the analysis with circle color and size indicating correlation strength and fire size respectively. The right panel shows daily growth patterns for selected fires with line traces for models fit with and without the previous day active fire pixels (PF) included as a predictor. Letters in the right panel are referenced in the locator map by a letter and "+". Figure S7 in Supporting Information S1 shows variation in per-fire errors relative to fire size, duration and season.

for all 196 fires, and line traces of daily growth patterns for selected fires. Despite relatively low absolute accuracy, predictions based on weather and hydroclimate track day-to-day variations in daily growth reasonably well, with Pearson's $r > 0.7$ for 50 fires. Per-fire accuracy was slightly lower for early season fires and higher for larger, longer duration fires (Figure S7 in Supporting Information S1). The addition of PF substantially improves the agreement, suggesting that without the spatial context of actively burning area or fire line length, models based solely on weather and hydroclimatic conditions struggle to predict large growth days when actively burning area is high. The overall skill of these models, particularly the large growth day model, suggest there is potential for forecasting active fire spread by combining near real-time fire detection and mapping (e.g., Chen, 2022) and weather forecasts.

3.2. What Are the Strongest Predictors of Daily Fire Growth?

Soil moisture and percent loss of hydraulic conductance (PLC) were the dominant predictors for both continuous and binary models, with a strong interaction (Friedmans H = 0.26) and a weak 3-way interaction with minimum relative humidity (H = 0.03). Visualizing the marginal effects of these variables under warm dry conditions (<20% RH) suggests a threshold-like response in fire spread potential to the onset of hydraulic stress (Figure 3; Figure S8 in Supporting Information S1) with atmospheric aridity mediating the growth response. Wind variables were important predictors in all models and while their overall influence is small, an interaction between 100-hr fuel moisture and wind speed (H = 0.12) shows its effect is conditional on dry surface fuels (Figure 3c). Three pre-fire vegetation variables were retained in our final models, all related to grass cover. A strong interaction between annual and perennial grass cover (H = 0.29) shows higher spread potential where combined pre-fire grass cover was high. This result is consistent with our mechanistic understanding of fire behavior. However, the RAP vegetation cover product used here is derived from Landsat imagery and estimates under dense forest canopy may not be reliable (Allred et al., 2021). A list of all variable interactions encountered during multiple CV iterations is provided in Table S4 of Supporting Information S1.

Models without simulated soil moisture and PLC had significantly lower accuracy ($R^2 = 0.27$; MAE = 0.54) than the full model ($R^2 = 0.36$; MAE = 0.50). Although a simple soil moisture model and water balance variables become significant in their absence, their reduced skill suggests that the mechanistic detail enabled by an

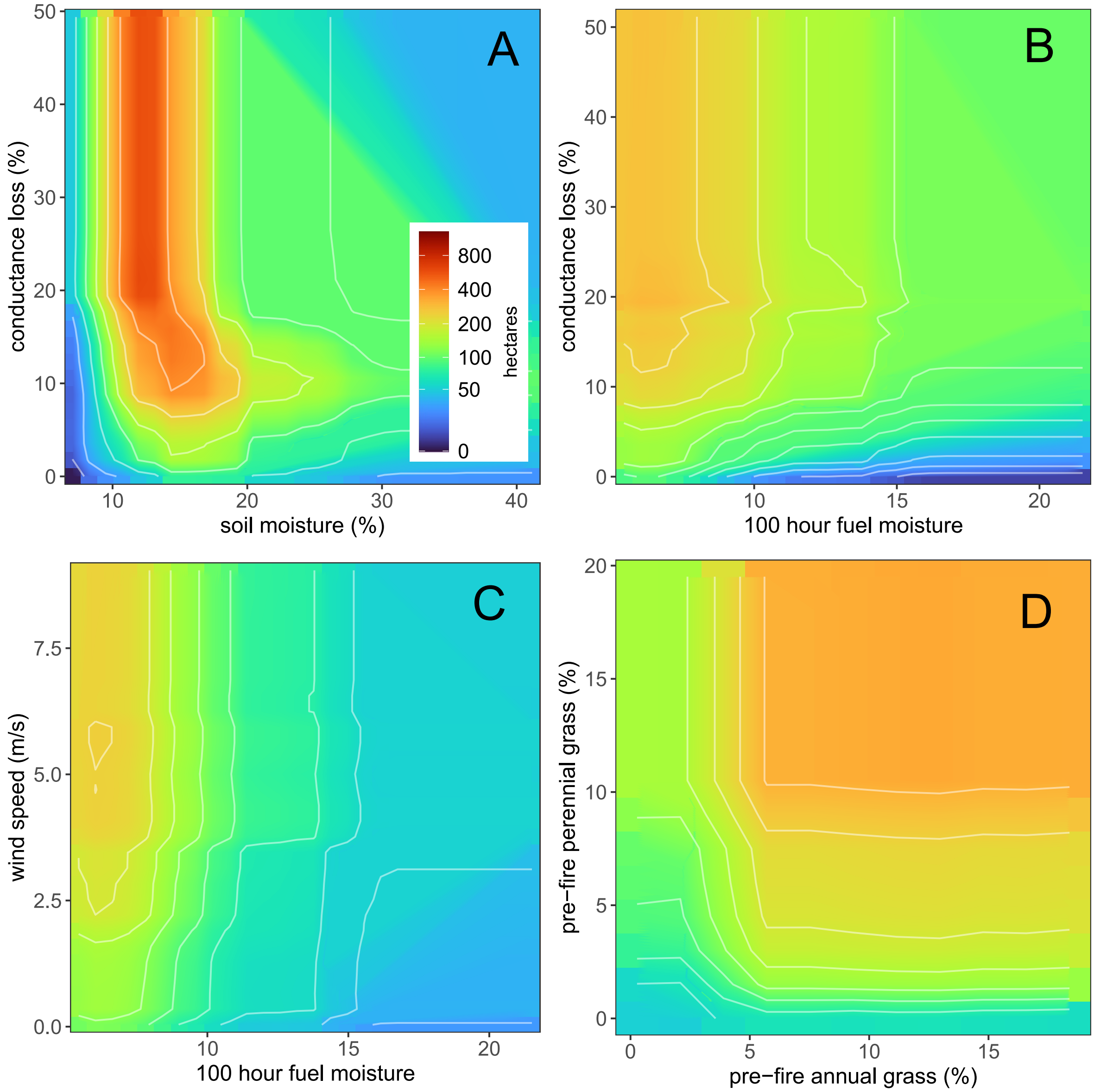

Figure 3. Partial dependence plots for six predictor variables and their interactions from a boosted regression tree model estimating log10-scale daily fire growth. (a) 3-way interaction between soil-moisture, percent loss of hydraulic conductance (PLC) and minimum relative humidity, shown for dry (RH < 20%) conditions. (b) PLC–-100-hr fuel moisture; (c) Mean climate forecast system reanalysis daily surface wind speed-100 hr fuel moisture; (d) Pre-fire annual–perennial grass cover. The plots share a common scale where color indicates the magnitude of the response. Plots and legend are shown in log-scaled units with legend label back-transformed from log-scale to hectares. Figure S8 in Supporting Information S1 shows the PLC-soil moisture interaction from panel A under low (<20%) and high (>40%) relatively humidity.

ecohydrology model captures important information relevant to fire behavior. There are several key differences between the soil moisture models that could explain this. Ech2o is an energy balance model, and unlike the water balance model where vegetation is uniform, includes spatially explicit pre-fire canopy cover and leaf area index inputs for each fire that influence variability in soil water loss from evapotranspiration and surface temperature variations below the canopy (i.e., microclimate). Furthermore, ech2o considers lateral and vertical moisture distribution, resulting in spatial patterns of soil moisture in valley bottoms not represented by the water balance model. Disentangling these effects will require further study. We see a small additional loss in accuracy for models trained after dropping water balance variables and using only traditional weather and fire danger indices ($r2 = 0.26$; MAE = 0.61). Tables S2 and S3 in Supporting Information S1 shows the feature selection results for all 57 predictors, and Figure S5 in Supporting Information S1 shows accuracy results for models constructed with different subsets of variables.

4. Discussion

Our results support a hypothesis that soil moisture plays a dominant role in controlling fire spread potential in the U.S. Northern Rocky Mountains, likely by mediating hydraulic stress and moisture content in live vegetation. This is consistent with recent combustion research (Boving et al., 2023; Brown et al., 2022; Scarff et al., 2021) simulation studies (Ruffault et al., 2023) and a growing body of research linking fire behavior and effects with plant ecophysiology (Dickman et al., 2023; Jolly et al., 2024). Although drought, and its effects on fuel abundance and moisture has long been conceptually applied to fire risk assessment at seasonal to daily time scales across regions using a variety of indices, quantification of the storage and lags associated with soil moisture effects in those indices has been missing or merely approximate (Littell et al., 2016). The strong roles of quantitatively estimated soil moisture and vegetation moisture status in this study have implications for wildland fire management in the U.S., where the use of longer time lag drought indices has historically been limited to the Keetch-Byram Drought Index (KBDI; Keetch & Byram, 1968), a simplified soil moisture index that is not a reliable indicator of drought in the western U.S. In the U.S. central plains investments in relatively dense networks of soil moisture monitors have proven effective for wildfire danger monitoring and mapping (; Krueger et al., 2015). However, such observations are sparse in the western U.S., where fire managers use longer time lag (1,000 hr) fuel moisture indices like the Energy Release Component (ERC; Deeming et al., 1977) as indicators of fire danger with only qualitative consideration for long-term drought conditions. These indices do not consider hydrology or snowmelt and require local knowledge and calibration using location-specific climate data to set fire danger levels (Risk & James, 2022). At present, analysis supporting incident response for larger fires is carried out through integrated systems like the Wildland Fire Decision Support System (WFDSS, Noonan-Wright et al., 2011) which connects spatial data and predictive fire models such as FARSITE (Finney, 1998), FLAMMAP (Finney, 2006) and FSPRO (Finney et al., 2011). However, predictability of these systems can be highly variable (Cruz & Alexander, 2013), and underlying treatment of surface moisture is relatively simple, with a 2-week fuel moisture conditioning routine that ignores antecedent drought conditions. Our study suggest that soil moisture and the onset of vegetation stress play a more important role in regulating large fire growth in U.S. Northern Rocky Mountain forests than previously recognized. This finding is in accordance with recent literature showing that increased nighttime fire activity is strongly influenced by both drought (Luo et al., 2024) and warmer nighttime temperatures (Balch et al., 2022; Freeborn et al., 2022). Incorporation of longer-term drought influences in fire management data systems and related applications could help managers better anticipate conditions under which prescribed fires could be successful (Majumder et al., 2025), better target suppression activities, and refine risk assessment analyses.

Resolving the connections between soil moisture deficits, vegetation water content and simulated fire behavior has been acknowledged as a key challenge in fire behavior modeling (Dickman et al., 2023). These linkages have been simulated at the leaf and plant scale (Ruffault et al., 2023) and measured in combustion studies (Boving et al., 2023; Scarf et al., 2021), but are not represented in current fire behavior models. Here, we simulated hydraulic stress (loss of hydraulic conductance; PLC) at landscape-scales using an ecohydrology model, with vegetation parameters calibrated for Ponderosa pine seedlings (Simeone et al., 2019). PLC is derived from leaf water potential, which varies widely by species. Because our studied fires span large vegetation gradients with no size or age-specific adjustments, we consider PLC a generalized index of stress in our analysis. Laboratory studies suggest that relative water content in leaves is a better measure of plant hydraulic stress (Sapes & Sala, 2021) and a stronger predictor of flammability (Boving et al., 2023). Nevertheless, the performance of these variables relative to an array of other predictors suggests soil moisture and reduced hydraulic function in live vegetation are important indicators of potential for large forest fire spread that have potential to improve seasonal wildfire danger assessments in this region. Because we restricted our analysis to fires in forested settings, we suggest care in generalizing these results to other regions, and there would be benefit from replication to assess how strong of a role soil hydrology plays elsewhere. Recent analyses of large fire growth potential have emphasized temperature and surface weather as factors contributing to large fire spread, with limited consideration given to drought (Brown et al., 2023; Potter & McEvoy, 2021; Whitman et al., 2024). Large-scale satellite studies suggest that soil moisture may be a stronger control on relative water content than atmospheric vapor pressure in western forests, but those effects are stronger in the Northwestern US (Lyons et al., 2021). In more arid, fuel limited regions like the Southwest, other factors like fuel availability or more recent weather could play a more significant role. Comparative analyses are needed to elucidate the role of soil moisture on fire spread in other regions.

5. Conclusion

Unique among other natural disasters like hurricanes and floods, the timing and intensity of some fires can be predicted, and even influenced. There is general agreement that more fire is needed in many western landscapes to mitigate even greater fire risk in the future. However, more proactive use of fire entails significant risk, and will require reliable weather and fire spread forecasting systems. This study demonstrates that soil moisture, simulated using an ecohydrology model, can significantly improve estimates of forest fire spread potential in the US Northern Rocky Mountains. While current fire management systems in much of the world rely primarily on short-term weather-based indicators, our results suggest that evolving wildfire monitoring, management and mapping systems should place greater emphasis on monitoring soil moisture conditions in addition to fuels and weather.

Data Availability Statement

Datasets used in this study are from publicly available data sources. Vegetation cover fraction data were extracted from Rangeland Analysis Platform data (version 3) downloaded from http://rangeland.ntsg.umt.edu/data/rap/rap-vegetation-cover/v3/. Gridded fuel moisture indices were accessed through the University of Idaho Northwest Knowledge Network: https://www.northwestknowledge.net/metdata/data/. Daily 250 m historical Topofire weather and soil water balance grids can be downloaded from the University of Montana: https://topofire.dbs.umt.edu/public_data/topofire_weather/. Historical hourly Realtime-Mesoscale Analysis data is available through the Google Earth Engine platform (https://developers.google.com/earth-engine/datasets/catalog/NOAA_NWS_RTMA). The Climate Forecast System Reanalysis data (CFSR) is provided by the National Oceanographic and Atmospheric Administration (NOAA). https://www.ncei.noaa.gov/data/climate-forecast-system/access/operational-analysis/time-series/. R software version 4.4.2 was used for all analysis and figures. Code and tabular data are archived in an Open Science Framework repository (Holden & Swanson, 2025).

Acknowledgments

We appreciate constructive comments and feedback from the editors and three anonymous reviewers. Computational resources from the University of Montana's Computational Ecology Lab and the Griz Shared Computing Cluster contributed to this research (NSF award numbers 2018112 and 1925267). This work was partially funded by the NOAA Climate Program Office National Integrated Drought Information System (ROR https://ror.org/00mmmy130) through an interagency transfer with the USDA Forest Service Rocky Mountain Research Station.

References

Abatzoglou, J. T. (2013). Development of gridded surface meteorological data for ecological applications and modelling. *International Journal of Climatology*, *33*(1), 121–131. https://doi.org/10.1002/joc.3413

Abatzoglou, J. T., Battisti, D. S., Williams, A. P., Hansen, W. D., Harvey, B. J., & Kolden, C. A. (2021). Projected increases in Western US forest fire despite growing fuel constraints. *Communications Earth and Environment*, *2*(1), 227. https://doi.org/10.1038/s43247-021-00299-0

Abatzoglou, J. T., & Kolden, C. A. (2013). Relationships between climate and macroscale area burned in the Western United States. *International Journal of Wildland Fire*, *22*(7), 1003–1020. https://doi.org/10.1071/wf13019

Abatzoglou, J. T., & Williams, A. P. (2016). Impact of anthropogenic climate change on wildfire across Western US forests. *Proceedings of the national academy of sciences* (Vol. 113(42), pp. 11770–11775). https://doi.org/10.1073/pnas.1607171113

Alizadeh, M. R., Abatzoglou, J. T., Luce, C. H., Adamowski, J. F., Farid, A., & Sadegh, M. (2021). Warming enabled upslope advance in Western US forest fires. *Proceedings of the national academy of sciences* (Vol. 118(22), e2009717118). https://doi.org/10.1073/pnas.2009717118

Allred, B. W., Bestelmeyer, B. T., Boyd, C. S., Brown, C., Davies, K. W., Duniway, M. C., et al. (2021). Improving Landsat predictions of rangeland fractional cover with multitask learning and uncertainty. *Methods in Ecology and Evolution*, *12*(5), 841–849. https://doi.org/10.1111/2041-210X.13564

Balch, J. K., Abatzoglou, J. T., Joseph, M. B., Koontz, M. J., Mahood, A. L., McGlinchy, J., et al. (2022). Warming weakens the night-time barrier to global fire. *Nature*, *602*(7897), 442–448. https://doi.org/10.1038/s41586-021-04325-1

Boisramé, G. F. S., Brown, T. J., & Bachelet, D. M. (2022). Trends in Western USA fire fuels using historical data and modeling. *Fire Ecology*, *18*(1), 8. https://doi.org/10.1186/s42408-022-00129-4

Boving, I., Celebrezze, J., Salladay, R., Ramirez, A., Anderegg, L. D. L., & Moritz, M. (2023). Live fuel moisture and water potential exhibit differing relationships with leaf-level flammability thresholds. *Functional Ecology*, *37*(11), 2770–2785. https://doi.org/10.1111/1365-2435.14423

Brown, P. T., Hanley, H., Mahesh, A., Reed, C., Strenfel, S. J., Davis, S. J., et al. (2023). Climate warming increases extreme daily wildfire growth risk in California. *Nature*, *621*(7980), 760–766. https://doi.org/10.1038/s41586-023-06444-3

Brown, T. P., Hoylman, Z. H., Conrad, E., Holden, Z., Jencso, K., & Jolly, W. M. (2022). Decoupling between soil moisture and biomass drives seasonal variations in live fuel moisture across co-occurring plant functional types. *Fire Ecology*, *18*(1), 14. https://doi.org/10.1186/s42408-022-00136-5

Chen, V. Y.-J., Deng, W.-S., Yang, T.-C., & Matthews, S. A. (2012). Geographically Weighted Quantile Regression (GWQR): An application to U.S. mortality data. *Geographical Analysis*, *44*(2), 134–150. https://doi.org/10.1111/j.1538-4632.2012.00841.x

Chen, Y., Hantson, S., Andela, N., Coffield, S. R., Graff, C. A., Morton, D. C., et al. (2022). California wildfire spread derived using VIIRS satellite observations and an object-based tracking system. *Scientific Data*, *9*(1), 249. https://doi.org/10.1038/s41597-022-01343-0

Collins, B. M., Everett, R. G., & Stephens, S. L. (2011). Impacts of fire exclusion and recent managed fire on forest structure in old growth Sierra Nevada mixed-conifer forests. *Ecosphere*, *2*(4), art51. https://doi.org/10.1890/ES11-00026.1

Cruz, M. G., & Alexander, M. E. (2013). Uncertainty associated with model predictions of surface and crown fire rates of spread. *Environmental Modelling and Software*, *47*, 16–28. https://doi.org/10.1016/j.envsoft.2013.04.004

Deeming, J. E., Burgan, R. E., & Cohen, J. D. (1977). *The national fire-danger rating system—1978. Gen. Tech. Rep. INT-GTR-39. Ogden, UT* (p. 63). U.S. Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station.

Dickman, L. T., Jonko, A. K., Linn, R. R., Altintas, I., Atchley, A. L., Bär, A., et al. (2023). Integrating plant physiology into simulation of fire behavior and effects. *New Phytologist*, *238*(3), 952–970. https://doi.org/10.1111/nph.18770

Eidenshink, J., Schwind, B., Brewer, K., Zhu, Z.-L., Quayle, B., & Howard, S. (2007). A project for monitoring trends in burn severity. *Fire Ecology*, *3*(1), 3–21. https://doi.org/10.4996/fireecology.0301003

Erickson, J. L., Holden, Z. A., & Efta, J. A. (2023). Modeling the distribution of headwater streams using topoclimatic indices, remote sensing and machine learning. *Journal of Hydrology X*, *21*, 100165. https://doi.org/10.1016/j.hydroa.2023.100165

Finney, M. A. (1998). *FARSITE: Fire area Simulator-model development and evaluation. Res. Pap. RMRS-RP-4, revised 2004, Ogden, UT* (p. 47). U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station.

Finney, M. A. (2006). An overview of FlamMap fire modeling capabilities. In P. L. Andres & B. W. C. Butler (Eds.), *Fuels management-how to measure success* (pp. 213–220). U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station.

Finney, M. A., Grenfell, I. C., McHugh, C. W., Seli, R. C., Trethewey, D., Stratton, R. D., & Brittain, S. (2011). A method for ensemble wildland fire simulation. *Environmental Modeling and Assessment*, *16*(2), 153–167. https://doi.org/10.1007/s10666-010-9241-3

Freeborn, P. H., Jolly, W. M., Cochrane, M. A., & Roberts, G. (2022). Large wildfire driven increases in nighttime fire activity observed across CONUS from 2003–2020. *Remote Sensing of Environment*, *268*, 112777. https://doi.org/10.1016/j.rse.2021.112777

Friedman, J. H., & Popescu, B. E. (2008). Predictive learning via rule ensembles. *Annals of Applied Statistics*, *2*(3), 916–954. https://doi.org/10.1214/07-AOAS148

Holden, Z. A., Jolly, W. M., Swanson, A., Warren, D. A., Jencso, K., Maneta, M., et al. (2019). TOPOFIRE: A topographically resolved wildfire danger and drought monitoring system for the conterminous United States. *Bulletin of the American Meteorological Society*, *100*(9), 1607–1613. https://doi.org/10.1175/BAMS-D-18-0178.1

Holden, Z. A., & Swanson, A. (2025). Data_code [collection]. *Open Science Framework*. https://doi.org/10.17605/OSF.IO/BKR4F

Holden, Z. A., Swanson, A., Luce, C. H., Jolly, W. M., Maneta, M., Oyler, J. W., et al. (2018). Decreasing fire season precipitation increased recent Western US forest wildfire activity. *Proceedings of the national academy of sciences* (Vol. 115(36), pp. E8349–E8357). https://doi.org/10.1073/pnas.1802316115

Jolly, W. M., Cochrane, M. A., Freeborn, P. H., Holden, Z. A., Brown, T. J., Williamson, G. J., & Bowman, D. M. J. S. (2015). Climate-induced variations in global wildfire danger from 1979 to 2013. *Nature Communications*, *6*(1), 7537. https://doi.org/10.1038/ncomms8537

Jolly, W. M., Freeborn, P. H., Bradshaw, L. S., Wallace, J., & Brittain, S. (2024). Modernizing the US National Fire Danger Rating System (version 4): Simplified fuel models and improved live and dead fuel moisture calculations. *Environmental Modelling and Software*, *181*, 106181. https://doi.org/10.1016/j.envsoft.2024.106181

Keetch, J., & Byram, G. (1968). A drought index for forest fire control. *Forest Service Research Paper SO. S-38*.

Krueger, E. S., Levi, M. R., Achieng, K. O., Bolten, J. D., Carlson, J. D., Coops, N. C., et al. (2023). Using soil moisture information to better understand and predict wildfire danger: A review of recent developments and outstanding questions. *International Journal of Wildland Fire*, *32*(2), 111–132. https://doi.org/10.1071/wf22056

Krueger, E. S., Ochsner, T. E., Engle, D. M., Carlson, J. D., Twidwell, D., & Fuhlendorf, S. D. (2015). Soil moisture affects growing-season wildfire size in the southern Great Plains. *Soil Science Society of America Journal*, *79*(6), 1567–1576. https://doi.org/10.2136/sssaj2015.01.0041

Littell, J. S., McKenzie, D., Peterson, D. L., & Westerling, A. L. (2009). Climate and wildfire area burned in Western U.S. ecoprovinces, 1916–2003. *Ecological Applications*, *19*(4), 1003–1021. https://doi.org/10.1890/07-1183.1

Littell, J. S., Peterson, D. L., Riley, K. L., Liu, Y., & Luce, C. H. (2016). A review of the relationships between drought and forest fire in the United States. *Global Change Biology*, *22*(7), 2353–2369. https://doi.org/10.1111/gcb.13275

Luo, K., Wang, X., de Jong, M., & Flannigan, M. (2024). Drought triggers and sustains overnight fires in North America. *Nature*, *627*(8003), 321–327. https://doi.org/10.1038/s41586-024-07028-5

Lyons, D. S., Dobrowski, S. Z., Holden, Z. A., Maneta, M. P., & Sala, A. (2021). Soil moisture variation drives canopy water content dynamics across the Western U.S. *Remote Sensing of Environment*, *253*, 112233. https://doi.org/10.1016/j.rse.2020.112233

Majumder, R., Terando, A. J., Hiers, J. K., Collazo, J. A., & Reich, B. J. (2025). A spatiotemporal optimization engine for prescribed burning in the southeast US. *Ecological Informatics*, *85*, 102956. https://doi.org/10.1016/j.ecoinf.2024.102956

Maneta, M. P., & Silverman, N. L. (2013). A spatially distributed model to simulate water, energy, and vegetation dynamics using information from regional climate models. *Earth Interactions*, *17*(11), 1–44. https://doi.org/10.1175/2012EI000472.1

Meyer, H., Reudenbach, C., Hengl, T., Katurji, M., & Nauss, T. (2018). Improving performance of spatio-temporal machine learning models using forward feature selection and target-oriented validation. *Environmental Modelling and Software*, *101*, 1–9. https://doi.org/10.1016/j.envsoft.2017.12.001

Modaresi Rad, A., Abatzoglou, J. T., Fleishman, E., Mockrin, M. H., Radeloff, V. C., Pourmohamad, Y., et al. (2023). Social vulnerability of the people exposed to wildfires in U.S. West Coast states. *Science Advances*, *9*(38), eadh4615. https://doi.org/10.1126/sciadv.adh4615

Noonan-Wright, E. K., Opperman, T. S., Finney, M. A., Zimmerman, G. T., Seli, R. C., Elenz, L. M., et al. (2011). Developing the US wildland fire decision support system. *Journal of Combustion*, *2011*(1), 168473. https://doi.org/10.1155/2011/168473

Park Williams, A., Allen, C. D., Macalady, A. K., Griffin, D., Woodhouse, C. A., Meko, D. M., et al. (2013). Temperature as a potent driver of regional forest drought stress and tree mortality. *Nature Climate Change*, *3*(3), 292–297. https://doi.org/10.1038/nclimate1693

Potter, B. E., & McEvoy, D. (2021). Weather factors associated with extremely large fires and fire growth days. *Earth Interactions*, *25*(1), 160–176. https://doi.org/10.1175/ei-d-21-0008.1

Prichard, S. J., Hessburg, P. F., Hagmann, R. K., Povak, N. A., Dobrowski, S. Z., Hurteau, M. D., et al. (2021). Adapting Western North American forests to climate change and wildfires: 10 common questions. *Ecological Applications*, *31*(8), e02433. https://doi.org/10.1002/eap.2433

Radeloff, V. C., Helmers, D. P., Kramer, H. A., Mockrin, M. H., Alexandre, P. M., Bar-Massada, A., et al. (2018). Rapid growth of the US wildland-urban interface raises wildfire risk. *Proceedings of the National Academy of Sciences* (Vol. 115(13), 3314–3319). https://doi.org/10.1073/pnas.1718850115

Risk, C., & James, P. M. A. (2022). Optimal cross-validation strategies for selection of spatial interpolation models for the Canadian forest fire weather index system. *Earth and Space Science*, *9*(2), e2021EA002019. https://doi.org/10.1029/2021EA002019

Ruffault, J., Limousin, J.-M., Pimont, F., Dupuy, J.-L., De Càceres, M., Cochard, H., et al. (2023). Plant hydraulic modelling of leaf and canopy fuel moisture content reveals increasing vulnerability of a Mediterranean forest to wildfires under extreme drought. *New Phytologist*, *237*(4), 1256–1269. https://doi.org/10.1111/nph.18614

Sapes, G., & Sala, A. (2021). Relative water content consistently predicts drought mortality risk in seedling populations with different morphology, physiology and times to death. *Plant, Cell and Environment*, *44*(10), 3322–3335. Epub 2021 Aug 23. PMID: 34251033. https://doi.org/10.1111/pce.14149

Scaduto, E., Chen, B., & Jin, Y. (2020). Satellite-based fire progression mapping: A comprehensive assessment for large fires in northern California. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *13*, 5102–5114. https://doi.org/10.1109/jstars.2020.3019261

Scarff, F. R., Lenz, T., Richards, A. E., Zanne, A. E., Wright, I. J., & Westoby, M. (2021). Effects of plant hydraulic traits on the flammability of live fine canopy fuels. *Functional Ecology*, *35*(4), 835–846. https://doi.org/10.1111/1365-2435.13771

Schroeder, W., Oliva, P., Giglio, L., & Csiszar, I. A. (2014). The new VIIRS 375m active fire detection data product: Algorithm description and initial assessment. *Remote Sensing of Environment*, *143*, 85–96. https://doi.org/10.1016/j.rse.2013.12.008

Senande-Rivera, M., Insua-Costa, D., & Miguez-Macho, G. (2022). Spatial and temporal expansion of global wildland fire activity in response to climate change. *Nature Communications*, *13*(1), 1208. https://doi.org/10.1038/s41467-022-28835-2

Sibson, R. (1981). A brief description of natural neighbor interpolation. In *Interpreting multivariate data* (pp. 21–36). John Wiley and Sons.

Simeone, C., Maneta, M. P., Holden, Z. A., Sapes, G., Sala, A., & Dobrowski, S. Z. (2019). Coupled ecohydrology and plant hydraulics modeling predicts ponderosa pine seedling mortality and lower treeline in the US northern Rocky Mountains. *New Phytologist*, *221*(4), 1814–1830. https://doi.org/10.1111/nph.15499

Swain, D. L., Abatzoglou, J. T., Kolden, C., Shive, K., Kalashnikov, D. A., Singh, D., & Smith, E. (2023). Climate change is narrowing and shifting prescribed fire windows in Western United States. *Communications Earth and Environment*, *4*(1), 340. https://doi.org/10.1038/s43247-023-00993-1

USDA Forest Service. (2022). National prescribed fire program review (p. 107).

Whitman, E., Barber, Q. E., Jain, P., Parks, S. A., Guindon, L., Thompson, D. K., & Parisien, M.-A. (2024). A modest increase in fire weather overcomes resistance to fire spread in recently burned boreal forests. *Global Change Biology*, *30*(6), e17363. https://doi.org/10.1111/gcb.17363

References From the Supporting Information

De Pondeca, M. S. F. V., Manikin, G. S., DiMego, G., Benjamin, S. G., Parrish, D. F., Purser, R. J., et al. (2011). The real-time mesoscale analysis at NOAA's national centers for environmental prediction: Current status and development. *Weather and Forecasting*, *26*(5), 593–612. https://doi.org/10.1175/WAF-D-10-05037.1

Friedman, J. H. (2001). Greedy function approximation: A gradient boosting machine. *Annals of Statistics*, *29*(5), 1189–1232. https://doi.org/10.1214/aos/1013203451

Hoylman, Z. H., Holden, Z., Bocinsky, R. K., Ketchum, D., Swanson, A., & Jencso, K. (2024). Optimizing drought assessment for soil moisture deficits. *Water Resources Research*, *60*(6), e2023WR036087. https://doi.org/10.1029/2023WR036087

McKee, T., Doesken, N. J., & Kleist, J. (1993). Relationship of drought frequency and duration to time scale. In *8th conference on applied climatology*.

Ramcharan, A., Hengl, T., Nauman, T., Brungard, C., Waltman, S., Wills, S., & Thompson, J. (2018). Soil property and class maps of the conterminous United States at 100-Meter spatial resolution. *Soil Science Society of America Journal*, *82*(1), 186–201. https://doi.org/10.2136/sssaj2017.04.0122

Roberts, D. R., Bahn, V., Ciuti, S., Boyce, M. S., Elith, J., Guillera-Arroita, G., et al. (2017). Cross-validation strategies for data with temporal, spatial, hierarchical, or phylogenetic structure. *Ecography*, *40*(8), 913–929. https://doi.org/10.1111/ecog.02881

Saha, S., Moorthi, S., Pan, H.-L., Wu, X., Wang, J., Nadiga, S., et al. (2010). The NCEP climate forecast system reanalysis. *Bulletin of the American Meteorological Society*, *91*(8), 1015–1058. https://doi.org/10.1175/2010BAMS3001.1

Veraverbeke, S., Sedano, F., Hook, S. J., Randerson, J. T., Jin, Y., & Rogers, B. M. (2014). Mapping the daily progression of large wildland fires using MODIS active fire data. *International Journal of Wildland Fire*, *23*(5), 655–667. https://doi.org/10.1071/wf13015