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Containment lines, PODs and suppression success: a case study of the 2021 Schneider Springs Fire

Jesse D. Young[A,*], Christopher D. O'Connor[B], Alexander Arkowitz[C,D], Elijah Orland[E,F], Scott Ritter[G], David Calkin[B], Rahul Wadhwani[B,H] and C. Alina Cansler[I]

For full list of author affiliations and declarations see end of paper

***Correspondence to:**
Jesse D. Young
USDA Forest Service Rocky Mountain Research Station, Human Dimensions, 240 W Prospect Road, Fort Collins, CO 80526, USA
Email: jesse.young@usda.gov

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ABSTRACT

Background. Wildfire suppression is shaped by a complex interplay of environmental conditions, resource allocation and management strategies. **Aims.** Examining the containment of the 2021 Schneider Springs Fire in the Eastern Cascades of Washington State, USA, we emphasise critical roles of variable selection, representative sampling and suppression-specific factors. **Methods.** Using descriptive, predictive and causal models, we assessed the influence of weather conditions, terrain features, personnel availability, tree canopy cover, fire containment lines, and previously identified 'best available' containment features. **Key results.** High vapour pressure deficit and strong winds were consistently associated with declining containment success. Terrain features such as valleys and ridges facilitated suppression operations, while steep slopes posed challenges. Additional personnel improved containment outcomes, though with diminishing returns in descriptive and predictive models. Tree canopy cover breaks enhanced suppression effectiveness, but with declining utility during windy conditions. Containment lines played a pivotal role, whereas the role of pre-identified containment features was context-dependent, likely influenced by broader strategic decisions. **Conclusions.** Wildfire containment wasinfluenced by multiple variables, and suppression strategies were situationally determined. Causal models provided valuable insights by isolating total effects of primary variables. **Implications.** Findings underscore adaptive fire management strategies that incorporate context-specific information. Future research should integrate fine-scale weather metrics and additional fire behaviour drivers that guide effective decision-making during dynamic operations.

Keywords: containment line, fire containment, fire personnel, fire suppression, fire weather, fireline, operational complexity, potential operational delineations.

Introduction

Potential Operational Delineations (PODs) are spatial fire planning units bounded on all sides by fire containment features such as roads, mountain ridges, non-burnable fuels or other features that facilitate fire containment (O'Connor *et al.* 2016; Thompson *et al.* 2016). POD networks are developed through a collaborative process that combines modelled fire containment (O'Connor *et al.* 2017) and suppression effort analytics (Rodriguez y Silva *et al.* 2020) with local expertise and experience (O'Connor and Calkin 2019). The first generation of PODs was developed to translate wildfire risk into operational fire management planning by leveraging networks of pre-identified containment features to compartmentalise landscape-scale wildfire risk (Thompson *et al.* 2016). POD networks represent a summary of 'best available' fire containment features under 90th percentile fire weather conditions but are not designed to be an exhaustive list of all possible containment features under all conditions. Assessing POD effectiveness is challenging due to the variability in fire weather and suppression operations over the duration of a large wildland fire event. A comprehensiveassessment would require accurate maps of fire progression and suppression actions (Thompson *et al.* 2022), which have not always been available. However, advancements in fire progression mapping and in the tracking of suppression actions have broadened research applications (Chen *et al.* 2022*b*; Arkowitz *et al.* 2025), allowing research to link fire behaviour drivers and mediators with POD holding capacity. Leveraging these advances, we analyse the role of PODs in the 2021 Schneider Springs Fire (a fire that escaped initial suppression actions) using descriptive, predictive and causal inference frameworks (Hernán *et al.* 2019; Lübke *et al.* 2020).

Fire progression mapping has advanced significantly with developments in remote sensing, geographic information systems and computational modelling (Lentile *et al.* 2006; Parks 2014; Scaduto *et al.* 2020). Initially documented through ground observations and post-fire analysis, fire progression is now mapped in near real-time using thermal infrared sensors and imagery from manned and unmanned aerial systems (UAS) and satellite-based instruments such as the Visible Infrared Imaging Radiometer Suite (VIIRS) (Kang *et al.* 2021; Chen *et al.* 2022*a*, 2022*b*; Cardil *et al.* 2023). These technologies enhance situational awareness during fire management (Andrade and Hulse 2022), inform evacuation planning (McCaffrey *et al.* 2018; McLennan *et al.* 2019; Boroujeni *et al.* 2024) and improve retrospective analyses of fire behavior (Hart and Preston 2020). Additionally, fire progression modelling supports predictive assessments of fire intensity, severity (Chamberlain *et al.* 2024) and containment effectiveness (Gannon *et al.* 2023; Young *et al.* 2024). Emerging applications include machine learning-enhanced fire modeling for predictive capabilities (Boroujeni *et al.* 2024; Shadrin *et al.* 2024) and climate change projections to assess long-term wildfire risk (Abatzoglou *et al.* 2021).

The integration of wildfire progression mapping and historical weather records also plays an important role in gaining insights from prior wildfire containment operations. The alignment of fire spread data with meteorological observations allows researchers to infer localised weather patterns, and in turn refine fire behaviour analysis (Wagenbrenner *et al.* 2016; Gale and Cary 2025). Spatially gridded weather data, initially developed for climate modelling, interpolates weather station, remote sensing and numerical models to create continuous, high-resolution atmospheric data over broad geographic areas (Knapp *et al.* 2011; Abatzoglou 2013; Mankin *et al.* 2025). Widely used in climate monitoring and disaster preparedness (Camatti *et al.* 2024; Rahat *et al.* 2024), these datasets improve observational wildfire data science by correlating fire spread with factors like wind, humidity and temperature (Young *et al.* 2024), allowing fire managers to anticipate how evolving weather conditions may influence fire growth and containment. Reconstructed weather data from past wildfires also contribute to long-term climatology studies (Marlon *et al.* 2012), in turn improving risk assessments and informing suppression strategies for fire-prone regions. These technological advances have not only improved real-time operational capabilities but also significantly enhanced post-fire analytical research potential.

Building on these advancements, recent progress in fire suppression research has significantly enhanced strategic decision-making in wildfire management. For example, in 2017 U.S. agencies began to systematically track wildfire suppression actions such as creation of hand line, bulldozer line, mastication, thinning and burnout operations (Arkowitz *et al.* 2025), leading to the development of fireline effectiveness metrics that evaluate suppression success on a fire-by-fire basis (Thompson *et al.* 2018; Gannon *et al.* 2020). These metrics have also facilitated the spatially explicit assessment of fuel break effectiveness, offering insights into how constructed barriers influence fire containment under varying conditions (Gannon *et al.* 2023; Lemons *et al.* 2023; Nguyen *et al.* 2024; Young *et al* 2024). Furthermore, the creation of suppression algorithms for wildfire simulations has enriched the ability of forest landscape models to incorporate wildfire management decisions (Young *et al.* 2019; Finney *et al.* 2009, 2025), enabling fire managers to assess long-term consequences of suppression strategies in virtual environments before implementation (Young *et al.* 2022; Furniss *et al.* 2024; Young and Ager 2024). By incorporating variables such as fire behaviour, resource allocation and terrain constraints, simulation models can help optimise suppression efforts and improve containment outcomes.

The integration of fire progression modelling, gridded weather data and fire suppression research has the potential to significantly advance wildfire management by improving predictive capabilities and strategic decision-making. This study leverages recent advances to examine how PODs influenced containment of the 2021 Schieder Springs Fire in the Eastern Cascades of Washington State, USA, using descriptive, predictive and causal inference frameworks, respectively, to inform data-driven wildfire management (Hernán *et al.* 2019). Our study addresses three research questions with increasing levels of analytical scrutiny:

(1) Where did fire progression halt in relation to POD boundaries, suppression actions and other operational conditions? (Descriptive);
(2) How do POD boundaries, suppression actions and operational conditions impact the probability of stopping fire progression? (Predictive);
(3) How does the probability of stopping fire progression change when conditioned on fire suppression actions occurring either on POD boundaries or in relation to other operational and influential factors? (Causal).

Through these questions, we examined containment outcomes on a single fire using a directed acyclic graph (DAG) to represent and analyse causal relationships and isolate total effects. The descriptive model considers the full fire area as observed, while the predictive model defines a factual population for forecasting. In contrast, the causal model's scope is deliberately restricted to observations with established containment line activity. This focused approach constructs a counterfactual population aimed at isolating covariate effects on the success of containment line operations in stopping fire progression, while carefully mitigating selection biases within this subset.

Methods

Study area

The 2021 Schneider Springs Fire (Fig. 1) was ignited by a lightning strike on National Forest Lands in central Washington's Yakima County on August 4, 2021, with fire containment on September 26 (Fig. 2) and fire control on October 21 (USDA FS 2021). The fire burned 46,008 ha of the Okanogan-Wenatchee National Forest and William O. Douglas Wilderness, impacting a mosaic of ponderosa pine, mixed-conifer and spruce–fir forests, interspersed with shrublands and grasslands. The region's rugged terrain, featuring steep ridges, deep valleys and dense stands of ponderosa pine (*Pinus ponderosa*), Douglas fir (*Pseudotsuga menziesii*) and grand fir (*Abies grandis*) complicated containment efforts (Fig. 1*a*). Furthermore, persistent drought conditions had left the vegetation highly flammable (White *et al.* 2023; King *et al.* 2024), contributing to extreme fire behaviour, including rapid runs, spotting and torching.

Weather played a critical role in both fire spread and suppression challenges (WADNR 2022). Low humidity and high temperatures during August and early September allowed the fire to expand significantly before containment lines could be effectively established. Strong winds frequently pushed flames across containment lines, forcing firefighters to adjust strategies and redeploy resources. Smoke from the fire also reduced air quality and visibility, limiting the use of aerial firefighting operations at times (NWCC 2021; Smith 2021). However, by mid-September, cooler temperatures, increased humidity and occasional precipitation aided firefighting efforts, allowing crews to strengthen containment lines and slow fire growth. Ultimately, improved weather conditions and extensive suppression operations helped contain the fire, though it remained a significant threat to natural resources and nearby communities until the winter season.

Prior fuels treatments and ungulate activity also played a role in the management of the 2021 Schneider Springs Fire (Fig. 1*b*). Sites treated with both forest thinning and prescribed fire in the decades preceding the fire had reduced fire behaviour compared with adjacent sites of thinning and piling or no treatment activity (Flatt 2022; Chamberlain *et al.* 2024). This was observed in the Angel Underburn project area in the southeastern extent of the fire, where a large, unburned island persisted (Fig. 1) in an area thinned approximately 15 years prior to the fire, followed by prescribed fire 5–10 years later (Smith 2022). In the same area, reports of ungulate browsing decreasing fuel loads and impacting vertical structure of vegetation may have played a role in reducing fire behaviour and limiting spread (Pillar and Overbeck 2025).

Fire progression and weather data

Fire growth data for this analysis (Fig. 2*a*) were derived from VIIRS. Combined, the VIIRS satellite deployments in 2011 and 2018 provide high-resolution (approximately 375 m) thermal imaging of the Schneider Springs Fire at 12-h intervals, roughly 01:30 and 13:30 in local time (i.e. UTC-8), enabling near real-time monitoring and mapping of active fire detections (Schroeder *et al.* 2014). Building on these advancements, Chen *et al.* (2022*a*) introduced the Fire Event Data Suite (FEDS) algorithm for California, which utilises an event-based system that clusters active fire detections to track wildfire progression in near real-time, and has since been expanded to the western US (Orland *et al.* 2025*a*, 2025*b*). Using FEDS data for the Schneider Springs Fire, we developed a geospatial algorithm used to align the final fire perimeter with that reported by the National Interagency Fire Center (NIFC) via the wildland fire interagency geospatial service group using aerial infrared data (NIFC-WFIGS 2024). After clipping FEDS data to the NIFC perimeter, burned areas only present in the NIFC data were identified and then re-integrated into the time-ordered FEDS progression data based on proximity. The final product is a combined shapefile of reconciled, cumulative fire progression data that were then time-order differenced to arrive at individual growth periods for each day over the course of the fire.

Using our refined fire growth data, we then determined the day-of-burning across the fire footprint, allowing us to align corresponding weather conditions with the approximate time of fire spread (Table 1). For our analysis, we used 24-h averages of vapour pressure deficit (VPD) and 10-m wind speed obtained from GridMet (Mesinger *et al.* 2006; Abatzoglou 2013; Srock *et al.* 2018). Our approach is supported by 24-h averages corresponding with 24-h fire spread events, with VPD providing critical seasonal and environmental context and wind speed directly influencing fire growth, thus obviating the need for more granular hourly data that could introduce unnecessary noise. Spatial polygon data capturing daily spread intervals and associated weather were converted into a series of raster datasets aligned with the spatial scale and projection of LandFire spatial products (LandFire 2022).

POD and containment lines

Beginning in 2016, pre-identified containment features already in common use around the western US were formally integrated into the POD framework to enhance wildfire containment and land management planning (Fig. 2*b*, Table 1). The first POD workshop on the Okanogan-Wenatchee National Forest was conducted in 2016, collating fire management strategies into a

Fig. 1. Location and overview of the 2021 Schneider Springs Fire in the Eastern Cascades of Washington State. (*a*) Facing west-southwest from Timberwolf Peak, high-severity fire burned dense forests on steep slopes. (*b*) Facing north, a fuels treatment implemented by the Washington State Department of Natural Resources was unsuccessfully leveraged during containment line construction. (*c*) Facing southwest, a POD boundary coincides with a rocky outcropping. (*d*) Facing west-northwest, the POD boundary was unable to contain severe fire behaviour. Photographs (*a*–*c*) depict conditions 1-year post fire in September. Photograph (*d*) depicts conditions 4-years post fire in June. Photographs by C. Alina Cansler.

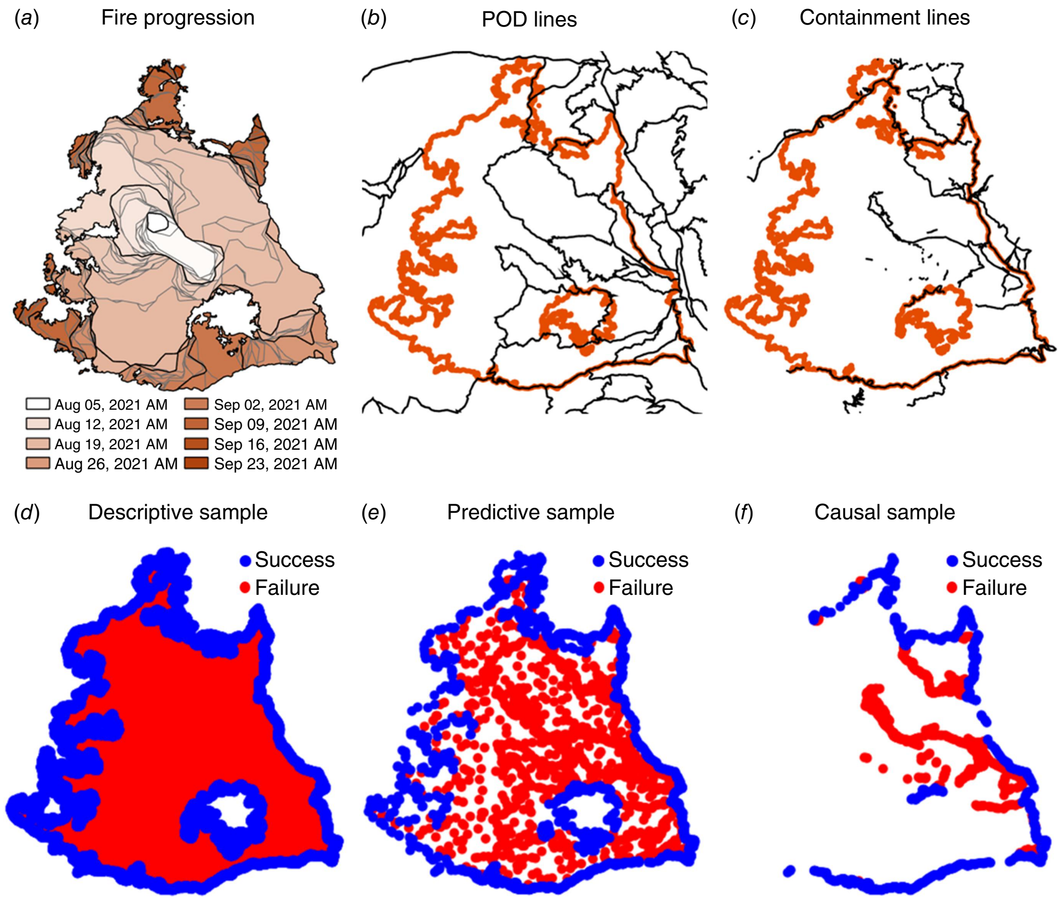

Fig. 2. (*a*) 12-h VIIRS derived fire progression data used to determine timing of fire weather, ground-personnel assigned to the fire and success and failures of suppression actions. (*b*) POD network used within our analysis. (*c*) Containment line activity signifying suppression operations that interacted with the 2021 Schneider Springs Fire. (*d*) Sample locations for Question 1 using a descriptive analysis, where all successes and failures were analyzed. (*e*) Sample locations for Question 2 using a predictive analysis with a balanced sample (across PODs/non-PODs, containment line/non-containment line and success/failure) evenly spread across covariate space. (*f*) Sample locations for Question 3 using a causal analysis that focused on containment line locations using a nested sample of the predictive sample.

structured, spatially explicit system with the assistance of a modelling approach designed to highlight potential containment locations (O'Connor *et al.* 2017). By incorporating historical fire records, topography and suppression feasibility, PODs guide strategic fire response (Calkin *et al.* 2021).

Formal digital collection of fire response data, including the construction and hardening of containment lines, began during the 2017 fire season within the NIFC (NIFC 2017), later being converted to the National Incident Feature Service during the 2018 fires season (NIFC-WFIGS 2024). Containment lines, also known as firelines (Fig. 2*c*, Table 1), subsequently underwent quality control procedures to ensure reliability (Arkowitz *et al.* 2025). Containment line feature categories include 'completed dozer line', 'completed hand line' and 'road as completed line' after fuels mitigations have occurred. Integrating POD boundaries with quality-controlled line data enabled a higher degree of precision when assessing the data generating process across wildfire incidents. Line features capturing POD lines and containment line activities were converted into raster datasets aligned with the spatial scale and projection of LandFire spatial products (LandFire 2022). Each raster then underwent a focal maximum analysis with a spread of seven pixels amounting to roughly a 105 m buffer (Fig. 3). The POD data layer was from the Risk Management Assistance Dashboard from 2022 with minimal additions in 2023 (RMA 2022), and within our analysis POD data are assumed to contain known information about pre-identified containment features during the 2021 wildfire season (Fig. 1*c*).

Topography and fuel conditions

We also incorporated topography and fuel conditions as covariates in our analysis (Table 1). Topography was

Table 1. Model covariates.

Covariates	Units	Scale	
		Temporal	Spatial
Vapour pressure deficit (VPD)	kPa	Daily average	4 km
Wind speed	m s^{-1}	Daily average	4 km
Containment line	0 = no; 1 = yes	*c.* 2021	30 m
POD line	0 = no; 1 = yes	*c.* 2022	30 m
Topographic position index (TPI)	N/A	N/A	30 m
Slope	Degrees	N/A	30 m
Ground-based personnel	Persons	Daily sum	Wildfire assigned
Tree canopy cover break	m	*c.* 2020	30 m
Latitude	m	N/A	NAD 1983 Contiguous USA Albers
Longitude	m	N/A	NAD 1983 Contiguous USA Albers

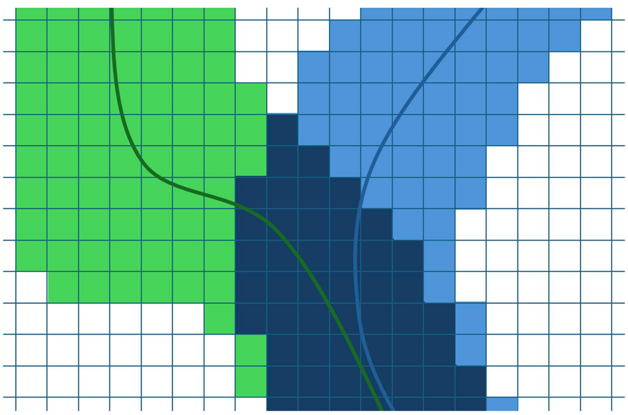

Fig. 3. Focal analysis depiction with a spread of seven 30 m pixels applied to POD and containment lines amounting to roughly a 105 m buffer on either side of linear features.

captured using the Topographic Position Index (TPI) and slope (Gallant and Wilson 2000). The TPI was derived with a 6000 m circular window applied to a 30 m LandFire elevation dataset (LandFire 2022), with high values indicating ridges and peaks, low values representing valley bottoms and values near zero indicating flat or mid-slope terrain. Slope of the terrain, measured in degrees and estimated with the LandFire elevation dataset, was included to further differentiate these features. Fuel conditions were captured using the 2020 LandFire data layer, specifically the percent tree canopy cover at a 30 m resolution (LandFire 2022). Tree canopy cover data underwent a series of focal analysis with increasing windows of three, five and seven pixels. Then using 30 m tree canopy cover data in conjunction with the layers derived from our focal analysis we developed an algorithm to determine the approximate tree canopy cover break (TCCB; i.e. tree canopy gap) as a continual surface across the study area (Supplementary Appendix S1). The TCCB captures current conditions of the tree canopy layer and associated contemporaneous effects of prior treatments during the Schneider Springs Fire.

Operational complexity

Another covariate used in our analysis was the day-to-day count of ground-based firefighting personnel (hand crews, engines and bulldozers) assigned to the 2021 Schneider Springs Fire (Fig. 4, Table 1). This information was obtained from the SIT-209-PLUS data (St. Denis *et al.* 2023), which compiles Incident Status Summaries (ICS-290) for wildfire in the US, including ground-based personnel assigned to either hand crews or heavy equipment (e.g. fire engines and bulldozers). Day-to-day count of ground-based personnel served as a proxy for operational complexity (i.e. operational decision space) in wildfire management, reflecting challenges posed by interconnected systems, dynamic environments and uncertain risks (Lahaye *et al.* 2018) that increase as additional fire personnel are assigned to an incident. For instance, planning containment operations becomes increasingly complex as the operational decision space expands to include locations with longer evacuation times, limited safety zones or inadequate lookout locations (Butler and Cohen 1998; Fryer *et al.* 2013; Dennison *et al.* 2014; Campbell *et al.* 2017, 2019, 2022; Mistick *et al.* 2022). This expansion occurs as additional personnel are assigned to an incident, in turn increasing firefighter risk and safety considerations for direct attack operations, which may result in the implementation of indirect tactics that extend the duration of the wildfire (Pietruszka *et al.* 2023). Complexity costs associated with complex decisions spaces are difficult to quantify with traditional methods, necessitating more nuanced approaches, such as using the day-to-day count of ground-based personnel as a proxy to

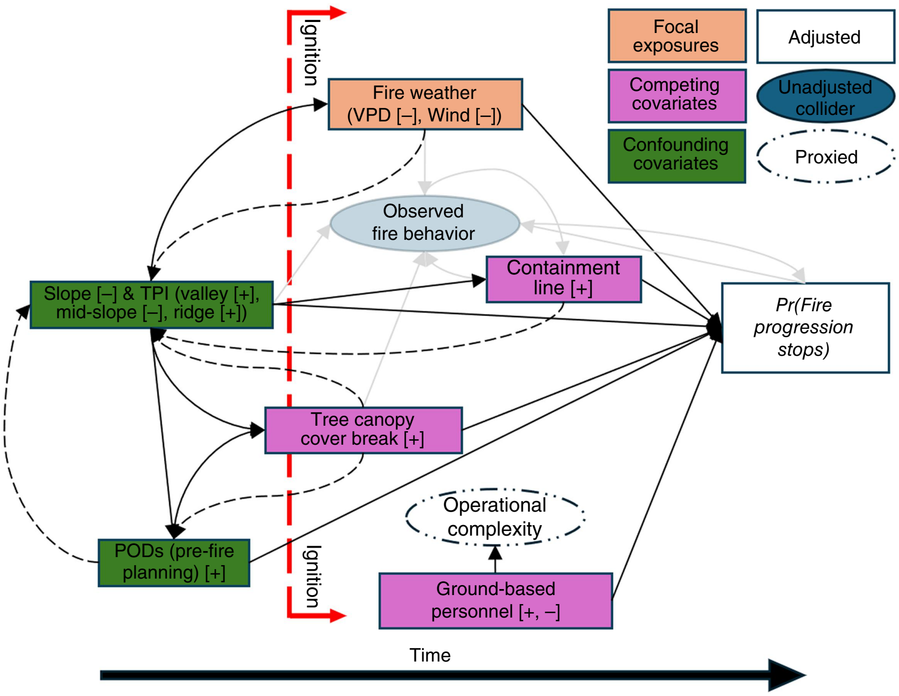

Fig. 4. Causal directed acyclic graph (DAG) depicting assumed causal relationships among focal exposures, competing and confounding covariates, and the outcome (probability of fire progression stopping). Square objects and black arrows (i.e. edges) depict adjustments in our analysis, with arrows representing assumed causal pathways. Solid round objects and grey arrows were not adjusted for (i.e. unadjusted). Broken round objects represent covariates that relied on a proxy for estimation. Broken black arrows depict pathways that are assumed to be non-causal, a criterion of confounders (see Young *et al.* (2024) for additional details). Bracketed negative [–] and positive signs [+] represent expected associations with the outcome. Variable groupings acknowledge constrained or weak causal relationships.

assess the impact of increasing complexity (Rosser and Rosser 2014). Though it is important to account for complexities when assessing operational outcomes, disentangling individual contributors is beyond the scope of this analysis.

Directed acyclic graph

Causal pathways between our input variables were examined using a causal DAG to focus on the core drivers of fire behaviour: fuels, weather, topography and fire management activity (Fig. 4). A DAG is used to represent and analyse causal relationships, with nodes representing variables and directed edges (arrows) indicating causal effects. Additionally, a DAG can help researchers reduce bias in estimated model coefficients by allowing them to identify mediators (that separate direct from indirect effects) and confounders. Variables in a DAG are categorised into focal exposures, and competing and confounding covariates to clarify their roles in the analysis. Focal exposures, which represent the primary variables of interest, were assumed to have no direct causal relationships among themselves or with competing covariates, as depicted in Fig. 4. Competing covariates were similarly assumed to be independent of each other, with only weak causal relationships among grouped variables or with other competing covariates. Confounding covariates were identified based on their potential to influence either focal or competing exposures and the outcome of interest, reflecting their role as common driver in the system. These categorisations helped structure the model to more accurately assess the relationships between key wildfire behaviour drivers and suppression outcomes.

Use of a DAG also helps avoid common pitfalls in causal evaluations by clarifying relationships among variables and preventing mediator and collider bias, simultaneity and selection bias. Mediator variables, such as observed fire behaviour, lie on the causal pathway between explanatory variables and the outcome (Pearl 2001; Babyak 2009), and their inclusion can lead to mediator bias by decomposing direct and indirect effects (Fig. 4). For example, incorporating fire radiative power in a similar model to the one presented here would likely diminish the influence of fire weather, in turn distorting the intended causal inference (Etminan 2021; Young 2024). Additionally, observed fire behaviour covariates act as collider variables (Lipsky and Greenland 2022), meaning they are influenced by multiple drivers already included in the model, such as fire weather and forest fuels (Fig. 4). Including a collider variable alongside its multiple drivers, results in over-adjustment bias (i.e. overfitting) by opening a backdoor pathway in the analysis. Furthermore, including containment line operations, which are a response to observed fire behaviour, alongside observed fire behaviour introduces downstream collider bias, opening an additional backdoor pathway (Young *et al.* 2024). The inclusion of observed fire behaviour alongside fire suppression efforts can also create simultaneity bias, as it both determines and is determined by fire suppression efforts and outcomes in terms of stopping fire progression (Wooldridge 2019). To mitigate backdoor and simultaneity biases (Rohrer 2018; Cummiskey *et al.* 2020), metrics capturing observed fire behaviour were not included in our analyses, and our causal model only included observations with containment operations to focus on a single data-generating-process. This later methodological choice and the observational nature of our data introduced two primary challenges for valid inference: confounding variation and potential selection biases within our subset (stemming from the inclusion criteria and missing critical fireline data). To account for these biases, model covariates (e.g. weather, topography, slope and fuels) known to be associated with both the decision to initiate fireline operations and the probability of containment were included. By structuring our analysis through a DAG, causal pitfalls were systematically addressed, in turn improving the reliability of causal inferences regarding fire suppression outcomes.

Sample design

Our analysis was structured around three inquiries designed to assess suppression operations and containment line effectiveness with increasing levels of analytical scrutiny. For each research question a rasterization approach at a 30-m resolution consistent with LandFire spatial products was used (LandFire 2022). Points within the sampling frame were generated by converting the center of each pixel that intersected with the fire perimeter to a point. These points were then overlaid with the final fire perimeter to determine success or failure in stopping fire progression (Fig. 2*d*). Points were considered successful if they were within 100 m of the final fire perimeter (blue points), while those within the fire perimeter were deemed failures (red points). Our complete sampling frame included 439,709 failures and 42,839 successes (Table 2). A 100-m threshold for success was used to account for spatial coregistration errors and adjacent operational use of POD lines to construct containment lines. Contingency lines outside of the 100 m buffer were not included in the analysis (Fig. 1).

The descriptive sample (Table 2, Fig. 2*d*) for the descriptive model used every sample point in the sampling frame to assess general fire containment. The predictive sample (Table 2, Fig. 2*e*) for the predictive model narrowed to a subset of sample points, using a balanced factorial design along the buffered delineations of POD line/non-POD line, containment line/non-containment line and success/failure locations, with each octant having a sample of 450 that was evenly distributed along the range of the octant's covariate space, ensuring covariate variability was maintained when the sample was reduced (see Table 1 for a list of covariates). A sample size of 450 was chosen to balance the need for a robust sample with limited observations in the octant representing successful POD lines without containment line operations (Table 2, n = 498). The causal sample (Table 2, Fig. 2*f*) for the causal model focused exclusively on locations with suppression operations (i.e. containment line data) that interacted with the wildfire, and thus reducing the octant space to a nested quadrant. Subsequently, this reduced the spatial representation of the sample to locations with fireline activity, which were focused along the northern, eastern and southern flanks of the fire. The western flank was burning in the William O. Douglas Wilderness area and did not receive ground-based fireline operations to aid in direct suppression efforts. The causal sample focused on containment line locations is nested within the predictive sample, which is nested within the descriptive sample. The causal sample also has a corresponding in-fire validation dataset. For an additional robustness check, we also repeated the sampling procedure for the predictive and causal samples to arrive at a reduced sample of 100 observations for each octant and nested quadrant, respectively.

Progressing our models from descriptive to predictive to causal provides a power framework for understanding past management while informing future decision making. Descriptive models establish a foundational understanding by summarising historical data on the drivers and mediators of fire behavior including terrain, weather, fuels and suppression operations. Building on this, predictive models forecast the probability of a fire stopping across the landscape under alternative conditions, enabling planners to anticipate risks and allocate resources more effectively across jurisdictions or synchronised wildfire events. Causal models take this a step further by honing the underlying mechanisms and relationships between suppression activities (i.e. containment lines) and factors such as fire weather or pre-fire planning (i.e. PODs). This progression provides a framework for increasingly informed decision making,

Table 2. Sample counts for each research question.

Group	Criteria	Descriptive sample		Predictive sample		Causal sample		Causal validation sample	
		Failure	Success	Failure	Success	Failure	Success	Failure	Success
1	Containment line = 0, POD line = 0	430,314	40,441	450	450	0	0	0	0
2	Containment line = 0, POD line = 1	5952	498	450	450	0	0	0	0
3	Containment line = 1, POD line = 0	2812	1200	450	450	450	450	2362	750
4	Containment line = 1, POD line = 1	631	700	450	450	450	450	181	250
	Total	439,709	42,839	1800	1800	900	900	2543	1000

The descriptive sample is the fire-wide population, while the predictive sample is evenly balanced (across POD/non-POD, containment line/non-containment line and success/failure) and evenly spread across covariate space. The causal sample contains locations from the predictive sample with suppression operations (i.e. presence of containment line).

allowing fire managers to anticipate events and design targeted interventions that alter the fire trajectory and improve suppression outcomes.

Statistical analysis

For each of our inquiries, we used a probit regression to estimate the probability of stopping fire progression such that:

$$\Pr(y_j = 1|x_j) = \Phi(x_j\beta)$$

where y_j is the binary outcome variable, x_j is a vector of independent variables, β is a vector of coefficients to be estimated and Φ is the cumulative Gaussian normal distribution function. In addition to reducing our sample and increasing the multi-dimensional space between sample points to the extent possible, spatial trends were accounted for by including latitude and longitude values for each sample point as covariates in the North American Datum of 1983 Contiguous USA Albers coordinate system (i.e. NAD 1983 Contiguous USA Albers). Statistical analyses were conducted using Stata 15 (StataCorp 2017*a*). Summary statistics, Pearson correlation matrices and variance inflation factors are provided in Supplementary Appendix S2, Tables S1–S3.

Model diagnostics and performance

We diagnosed the specification of each model with a Pregibon test (Pregibon 1980). After fitting the model, the Pregibon test fits a secondary probit regression with model estimates ($\hat{y}$) and squared estimates ($\hat{y}^2$) as predictors of the outcome (i.e. success vs failure). Only our causal assessment had a model estimate ($\hat{y}$) that was a statistically significant predictor ($P \le 0.05$), while also having a squared estimate ($\hat{y}^2$) that was not significant ($P > 0.05$). This signifies a failure to reject the null hypothesis of there being no sign of an incorrect specification of the link function. In other words, we can assume the underlying link function of our causal probit model (i.e. the inverse of the standard normal cumulative distribution function) was specified correctly.

Model fit was also guided by accuracy assessments, with a particular focus on high specificity and low false positive rates (i.e. false positives endanger firefighter safety), followed by an examination of AUC (area under the receiver operating characteristic curve). Our accuracy assessments compared observed outcomes to model classifications based on a single classification threshold (i.e. if $Pr(\text{success}) \ge 0.5$ then outcome = success; otherwise, outcome = failure) (Parikh *et al.* 2008). The AUC metric assessed how well model estimates were ranked across a range of classification thresholds (Zou *et al.* 2007; Salas-Eljatib *et al.* 2018). Quadratic (i.e. x^2 of $y = f[x, x^2]$) and interactive terms (i.e. x_1x_2 of $y = f[x_1, x_2, x_1x_2]$) that captured nonlinear effects and substantially improved model performance based on accuracy assessments and AUC measures were retained. Significant ($P < 0.05$) quadratic and interactive terms that did not substantially improve model performance were not retained. The subversion of parameter significance as the primary metric used to determine model specifications was guided by the known inflation of false positive rates caused by erroneous inclusion of control covariates and effect modifiers to enhance variable significance through suppression effects (Brodeur *et al.* 2020; Diemer *et al.* 2021). Higher cubic relationships were also explored and not retained. Each model was evaluated with an in-sample assessment, while the causal model was also evaluated with an out-of-sample assessment (validation Table 2; Table 3). An additional robustness check was performed by recasting the predictive and causal models with a reduced sample, with limited appreciable differences in model performance detected (Supplementary Appendix S2, Table S4). We assessed model diagnostics and performance with Stata 15 (StataCorp 2017*b*) using the linktest command to execute the Pregibon tests, the roctab command to estimate AUC metrics and confusion matrices to perform accuracy assessments.

Results

Descriptive model

Our descriptive inquiry revealed significant associations between several covariates and the probability of fire progression stopping. Average daily VPD had a strong negative association with success (Table 3, $\beta = -2.32^{***}$), indicating that higher atmospheric dryness reduced the probability of containment. However, the positive quadratic term ($\beta = 0.57^{***}$) suggested a nonlinear relationship with diminishing effects as VPD increased (Fig. 5). Daily average wind speed ($\beta = -0.40^{***}$) also negatively impacted fire suppression success, aligning with expectations that stronger winds promote fire spread, in turn reducing the probability of fire progression stopping. When contrasting suppression operations and the presence of PODs, the presence of containment lines ($\beta = 1.086^{***}$) had a stronger positive association, highlighting the importance of suppression operations in fire containment. However, POD line presence ($\beta = 0.18^{***}$) had a modest but significant association with fire progression stopping, suggesting that pre-identified containment features contribute to fire containment as well.

When interpreting topographic associations across the Schneider Springs footprint, ridges contributed to fire containment variability, evident by a significant TPI (Table 3, $\beta = 0.0011^{***}$) and its quadratic term (TPI × TPI, $\beta = 0.000002^{***}$), which is depicted with estimated marginal effects in Fig. 6. On the other hand, steep slopes ($\beta = -0.0041^{***}$) across the landscape and leading up to ridges reduced the probability of fire progression stopping, likely due to increased fire intensity and operational challenges. Operational complexity as proxied by personnel

Table 3. Probit regression coefficients (β), modeling diagnostics and performance assessment metrics.

	Descriptive model	Predictive model	Causal model	Causal model validation
Vapour pressure deficit (VPD)	-2.323623***	-4.907214***	-3.949030***	
VPD × VPD	0.571501***	1.270667***	0.237070	
Wind speed	-0.398042***	-0.789034***	-0.730986***	
Containment line	1.086128***	0.118889#		
POD line	0.181631***	-0.042377	-0.110597	
Topographic position index (TPI)	0.001080***	0.000365*	-0.000061	
TPI × TPI	0.000002***	0.000006***	0.000010***	
Slope	-0.004083***	-0.002477	-0.010970#	
Ground-based personnel	0.007078***	0.009159***	0.004485*	
Personnel × Personnel	-0.000010***	-0.000012***	-0.000003	
Tree canopy cover break (TCCB)	0.011174***	0.018208**	0.053157*	
TCCB × Wind speed	-0.001863***	-0.003410*	-0.011326*	
Latitude	0.000033***	0.000032***	0.000032**	
Longitude	-0.000030***	-0.000015**	0.000003	
Constant	1.53×10^2***	-1.16×10^2***	-8.05×10***	
Pregibon test				
$\hat{y}$ *P*-value	<0.001	<0.001	<0.001	
$\hat{y}^2$ *P*-value	<0.001	<0.001	0.064	
Sensitivity	0.078	0.808	0.868	0.845
Specificity	0.994	0.810	0.841	0.838
False positive	0.006	0.190	0.159	0.162
False negative	0.922	0.191	0.132	0.155
Accuracy	0.913	0.809	0.854	0.840
AUC	0.817	0.892	0.943	0.934
n	482,548	3600	1800	3543

#$P < 0.10$; *$P < 0.05$; **$P < 0.01$; ***$P < 0.001$.

($\beta = 0.0071$***) indicated a positive association, but its negative quadratic term ($\beta = -0.000010$***) and marginal effects suggested diminishing returns as operational complexity increased and eventual negative net gains when more than 350 personnel were assigned (Fig. 6). The width of TBBC also had a significant association with fire progression stopping ($\beta = 0.011$***), implying increasing containment success in areas where tree cover was reduced. Of importance though, the significance of the interactive term between TCCB and daily average wind ($\beta = -0.0019$***) indicated a declining association of wider TCCB aiding in fire progression stopping as wind increased (Fig. 6). Latitude ($\beta = 0.000033$***) and longitude ($\beta = -0.000030$***) were statistically significant, signifying holding features were spatially centered with high latitudes and low longitudes (northeast fire quadrant), but this had minimal practical impact on containment outcomes and speaks more to the progression and containment of the fire.

The descriptive model's performance showed high specificity (Table 3, 0.994) but low sensitivity (0.078), indicating it was better at identifying areas where the fire did not stop rather than predicting successful containment. The overall accuracy (0.913) was high, driven by the imbalance in fire progression outcomes, while the AUC (0.817) suggested good discriminatory ability. However, the high false negative rate (0.922) highlighted the challenge of predicting successful containment, reflecting the complexity and variability of fire behaviour and suppression efforts across the wildfire incident, and the importance of balancing outcomes (or the use of weighting) when deploying analytics.

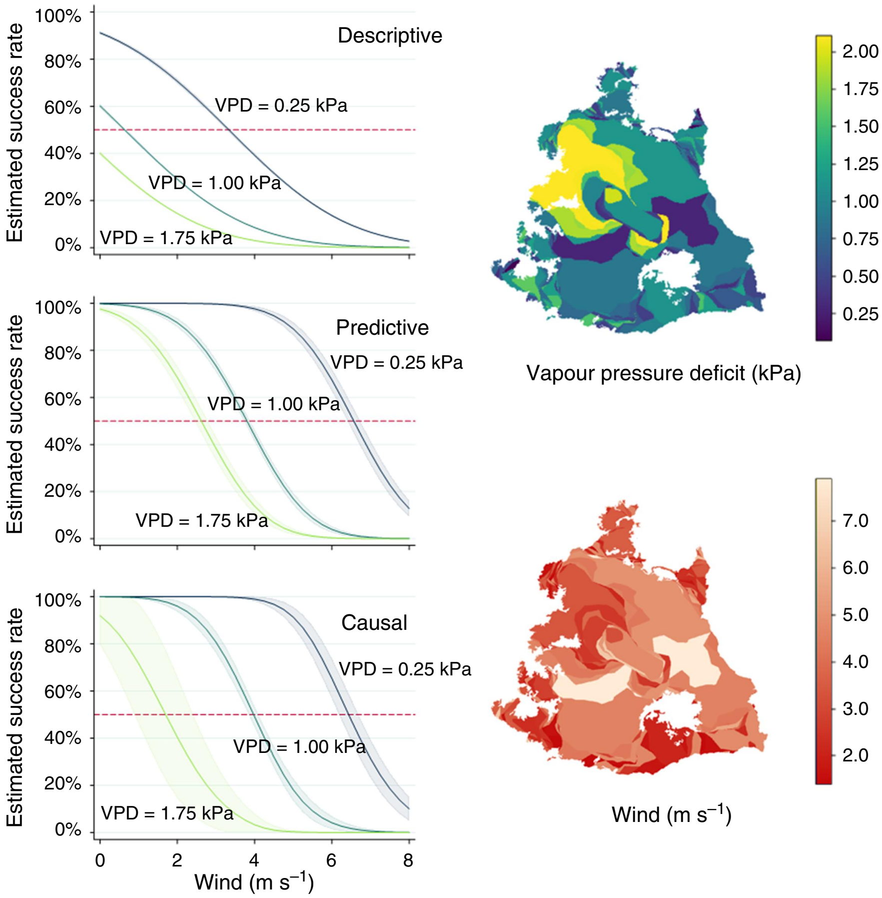

Fig. 5. Marginal effects across a range of daily averages of vapour pressure deficit (VPD [kPa]) and wind speed (m s^{-1}) alongside a reference map for each input variable. Reference maps display daily averages of *in situ* VPD and wind speed, which influenced fire progression during daily spread periods. These average values are assigned to sample points within the daily spread perimeter. Confidence intervals are bound at 95%.

Predictive model

Our predictive inquiry showed predictive effects similar to the descriptive associations with fire progression stopping but with some notable differences (Fig. 5). Average daily VPD was a strong negative predictor of fire containment (Table 3, $\beta = -4.91^{***}$) with a nonlinear relationship ($\beta = 1.27^{***}$). Likewise, daily average wind speed ($\beta = -0.79^{***}$) was a strong negative predictor. On the other hand, containment line presence ($\beta = 0.12^{\#}$, $P = 0.053$) was a positive predictor of containment, but with a much weaker effect than in the descriptive model, likely influenced by our balanced and representative sample (Table 2). The influence of POD line presence ($\beta = -0.042$) was negligible and no longer statistically significant, suggesting POD line effectiveness may depend on broader fire management strategies.

The TPI ($\beta = 0.00037^{*}$) and its quadratic term ($\beta = 0.000006^{***}$) remained significant, now indicating that both valley bottoms and ridges had a positive predictive role in fire containment (Fig. 6). Slope ($\beta = -0.0025$) retained a negative relationship with containment success but lost its predictive significance. The effect of personnel ($\beta = 0.0092^{***}$) was slightly stronger than in the descriptive model, again showing diminishing returns as operational complexity increased, indicated by the negative quadratic term ($\beta = -0.000012^{***}$). As before, the width of TCCB ($\beta = 0.018^{**}$) continued to show significant predictive capacity with fire containment, while the interactive term between TCCB and daily average wind ($\beta = -0.0034^{*}$) also remained significant, indicating a declining positive association of wider TCCB as winds increased (Fig. 6).

The predictive model showed substantial improvement in performance, with sensitivity (Table 3, 0.808) and specificity (0.810) having balance, in turn balancing marginal effects (Figs 5 and 6). When compared to the descriptive model, the false negative rate (0.191) was also significantly reduced, indicating improved accuracy in predicting successful fire containment. Overall accuracy (0.809) and AUC (0.892) suggest our predictive model is better at distinguishing between containment successes and failures than our descriptive model, likely due to the refined sampling scheme.

Causal model – containment line effectiveness

The causal model refined the analysis by focusing specifically on suppression operations, offering insights into cause-and-effect relationships when active firefighting efforts are applied. Average daily VPD had a strong negative effect (Table 3, $\beta = -3.95^{***}$), indicating that dry atmospheric conditions continued to reduce the likelihood of stopping

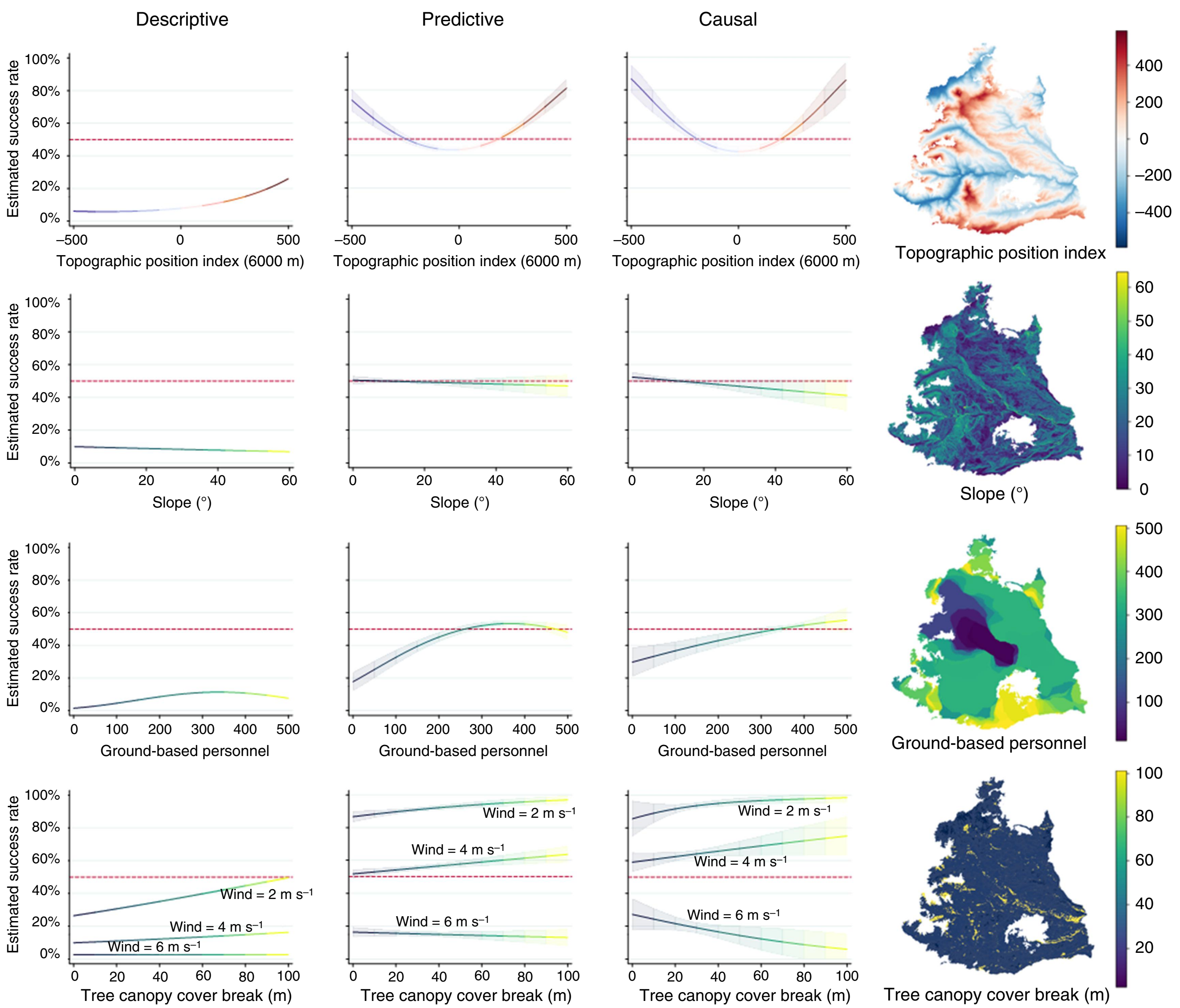

Fig. 6. Marginal effects across a range of topographic position index, slope, ground-based firefighting personnel and tree canopy cover breaks alongside a reference map for each input variable. Reference maps for firefighting personnel display the count of personnel assigned to the fire during daily spread periods. These values are assigned to sample points within the daily spread perimeter to capture the complexity of the operational decision space. Confidence intervals are bound at 95%.

fire progression. However, unlike previous models, the quadratic term ($\beta = 0.24$) was no longer significant, suggesting a linear relationship in the causal dataset (Fig. 5). Daily average wind speed ($\beta = -0.73$***) continued to show a strong negative effect, reinforcing the challenge of fire containment in high-wind conditions. Containment line presence was the criteria for inclusion in the causal model and therefore cannot be assessed within the causal model, while the presence of POD lines ($\beta = -0.11$) remained non-significant, suggesting limited direct influence when focusing on active suppression efforts.

The influence of terrain remained complex, with TPI showing a non-significant direct effect (Table 3, $\beta = -0.000061$) but a significant quadratic term ($\beta = 0.000010$***), suggesting non-linear influences on fire containment with both valleys and ridges having a positive effect (Fig. 6). Slope ($\beta = -0.011^{\#}$, $P = 0.062$) retained its negative effect, indicating that steeper landscapes hinder suppression efforts. Personnel availability ($\beta = 0.0045$*) remained positively associated with containment success, though diminishing returns observed in previous models were not significant, indicating continued benefits from additional staffing and an efficient use of fire management resources as operational complexity increased (Fig. 6). Notably, TCCB still had a positive effect on containment ($\beta = 0.053$*) with a larger impact. The interactive term between TCCB and daily average wind ($\beta = -0.011$*) also remained significant, indicating a negative effect of wider TCCB during high-wind conditions (Fig. 6).

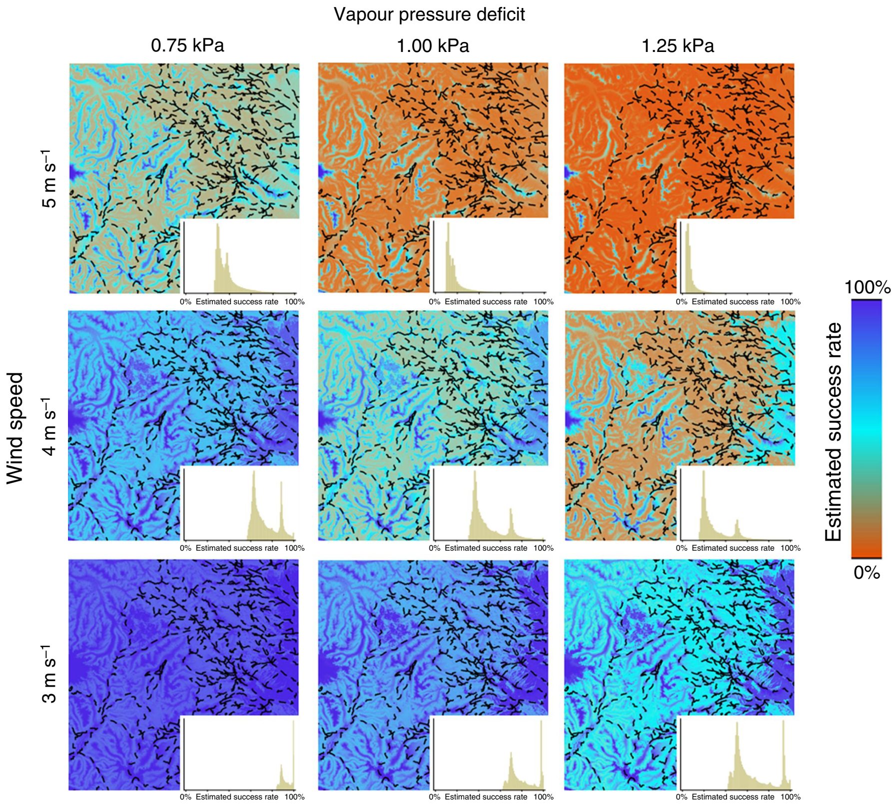

Fig. 7. Predictive model estimation maps and distributions of estimated success rates for the landscape surrounding the 2021 Schneider Springs Fire. Predictions are given over a range of daily averages of vapour pressure deficit (kPa) and wind speed (m s^{-1}). Dashed lines represent POD line locations. Effects of POD and containment lines are removed (i.e. models estimates were derived with POD and containment line rasters set to 0).

Our causal model was the only assessment to pass the Pregibon test (Table 3, $P = 0.064$), while also demonstrating a strong predictive performance. The causal model had the highest sensitivity (0.868) alongside high specificity (0.841), minimising both false positives (0.159) and false negatives (0.132). Overall accuracy (0.854) and AUC (0.943) indicated a highly effective classification model, likely due to its focus on direct suppression actions. The classification effectiveness of this model was also confirmed with a validation dataset that maintained a high AUC (0.934) and overall accuracy (0.840), while minimizing both false positives (0.162) and false negatives (0.155). These results suggest that when suppression operations are applied, environmental factors such as wind, terrain and dryness still play dominant roles, while the effectiveness of specific tactical interventions (e.g. reducing canopy cover) may depend on additional contextual factors including the potential fine fuels productions and wind intrusion in a wide TCCB.

Implementation

Integrating weather forecasts with our predictive and causal modelling results is crucial for identifying and evaluating potential containment features. By isolating and removing the effects of POD and containment lines, the predictive maps in Fig. 7 display a base case scenario that estimates the probability of natural containment without human intervention. These maps reveal a bimodal distribution with the first mode representing accessible areas with lower natural containment rates, while the second mode represents remote ridges with very little canopy cover and higher rates of natural containment. The causal maps in Fig. 8 provide a targeted framework for pre-fire planning and operational decisions. Our causal model specifically isolates the effects of fireline operations on fire containment outcomes under varying circumstances by constructing a counterfactual population solely from observations where these operations were initiated. This methodology and the observational nature of our data introduced two primary challenges for valid inference: confounding variation and potential selection biases within our subset (stemming from the inclusion criteria and missing critical fireline data). Both were addressed using model covariates (e.g. weather, topography, slope and fuels). By addressing these biases, our analysis offers robust insights into the effectiveness of initiated fireline operations in achieving desired containment outcomes along POD boundaries, thereby refining the causal effect within an operational context. Beyond this causal understanding, the predictive capacity of TCCB further enables assessment of weak points in POD networks, facilitating the prioritization and design of fuels treatments based on POD holding capacity under various weather scenarios. This empowers planners to strategically locate treatments to maximise expected gains in the probability of stopping fire progression, though ground and

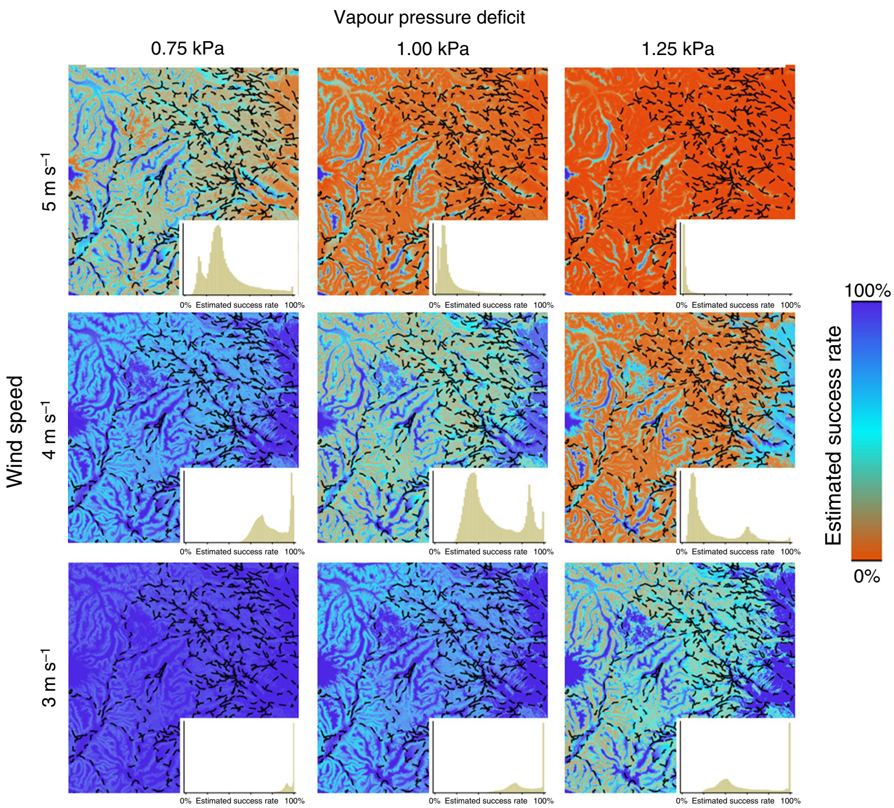

Fig. 8. Causal model estimation maps and distributions of estimated success rates for the landscape surrounding the 2021 Schneider Springs Fire. Causal estimations are given over a range of daily averages of vapour pressure deficit (kPa) and wind speed (m s^{-1}). Dashed lines represent POD line locations. Effects of POD lines are removed (i.e. models estimates were derived with the POD line raster set to 0).

surface fuel treatments warrant careful consideration during strategic planning.

Discussion

Our analysis demonstrated that fire suppression effectiveness is significantly influenced by environmental conditions, resource allocation and fire management strategies. Across all models, daily averages of VPD and wind speed consistently emerged as strong negative predictors of successful fire containment, reinforcing the well-established understanding that dry and windy conditions exacerbate fire spread thus reducing containment effectiveness (Srock *et al* 2018), particularly in dense forests (Fig. 1*d*) that burn with high severity (Chamberlain *et al.* 2024). The influence of terrain, as captured by the TPI and slope variables, highlighted the complex role of landscape features with valleys and ridges generally aiding containment efforts while steep slopes hinder suppression success (Holsinger *et al.* 2016; Povak *et al.* 2018; Young *et al.* 2024). Personnel availability was positively associated with fire suppression outcomes; however, diminishing returns were evident in the descriptive and predictive models, suggesting that beyond a certain threshold, additional personnel may not significantly improve containment and could even lead to operational inefficiencies as previously observed in southern California (Young *et al.* 2024). As operational complexity increases, fire suppression strategies may become less effective on average (Kahneman 2003; Rosser and Rosser 2014), particularly when the availability of personnel and potential interventions surpasses productive capacity or the availability of critical resources, such as heavy equipment (Hand *et al.* 2017; Katuwal *et al.* 2016, 2017). Additionally, our findings underscore the importance of TCCB in aiding fire suppression in areas where reduced tree cover reduced fire behaviour (Finney *et al.* 2009; Young *et al.* 2019; Chamberlain *et al.* 2024; Hakkenberg *et al.* 2024) and allowing for more effective firefighting interventions including air drops (Agee *et al.* 2000; Stonesifer *et al.* 2021). Importantly, the competitive edge of TCCB declined in windy conditions as wind intrusion increased and interacted with fine, flashy fuels within canopy gaps.

The comparison between the presence of containment and POD lines also provided insights into fire management strategies. The strong positive effect of containment lines in the descriptive model suggested that constructed fire barriers play a crucial role in fire progression stopping as previously identified (Gannon *et al.* 2023). However, in our predictive model, where a more balanced sample was used, the effect of containment lines was notably weaker, suggesting that representation bias in descriptive models may overestimate their impact. The limited statistical significance of POD lines in the predictive and causal models suggests that while POD lines provide a useful structured fire management framework, as seen in the descriptive model, their direct role in fire suppression success may be context-dependent, likely influenced by broader operational strategies such as road hardening and preemptive burning (Thompson *et al.* 2021).

Our causal model provides a refined assessment (Hernán *et al.* 2019), focusing specifically on suppression operations. Focusing on locations with containment line underscores the importance of disentangling direct suppression factors from broader containment strategies. Unlike the descriptive and predictive model, our causal model did not identify significant non-linear effects of VPD, suggesting a more straightforward relationship between atmospheric dryness and suppression success when accounting for operational factors. The continued negative impact of wind speed and steep slopes highlights persistent environmental challenges (Morandini *et al.* 2018). Personnel availability positively influenced containment success without statistical evidence of diminishing returns as observed in descriptive and predictive models, suggesting an efficient use of allocated resources, in part catalyzed by previous mechanical and prescribed fire treatments (Smith 2022). The TCCB was also significant in our causal model with a moderating effect of wind, implying that the effectiveness of reduced tree canopy cover may be contingent upon other factors, such as environmental conditions or the loading and spatial configuration of ground and surface fuels (Chamberlain *et al.* 2024).

From a modelling perspective, the progression from descriptive to predictive and causal approaches highlights the importance of carefully considering variable selection and sample representation. While our descriptive model exhibited high specificity, its low sensitivity suggests that descriptive models may be biased toward non-containment cases. Our predictive model improved sensitivity while maintaining strong predictive performance, and our causal model demonstrated the best balance of sensitivity and specificity, reinforcing its utility for causal inference. The improved classification accuracy in the causal model, particularly its strong AUC value (0.943), suggests that when suppression operations are explicitly considered, environmental factors remain primary determinants of success, while tactical interventions may depend on nuanced operational contexts not fully captured in our analysis.

Integrating these findings into operational decision-making could enhance wildfire response strategies. The strong performance of our predictive model can inform efficient allocation of resources by delineating locations with high probability of naturally stopping fire progression from locations where intervention is likely needed (Fig. 7). Similarly, our causal model suggests that incorporating real-time forecasted weather could help optimise suppression tactics dynamically. For instance, conditioned on an average daily wind speed of 4 m s^{-1} and a VPD of 1.00 kPa we estimate a landscape-wide success rate of 40%, which declines to 14% when VPD reaches 1.25 kPa, a 65% reduction. Additionally, examining stand-level attributes like TCCB under different weather scenarios can improve safety by strategically guiding fuel treatments designed to open the canopy as well as the deployment of firefighting personnel. This is particularly important under windy conditions (e.g. wind speeds reaching 5 m s^{-1} as depicted in Fig. 8) when wider TCCB may lose their effectiveness, likely driven by the increased production of fine fuels and wind intrusion. By coupling forecasted weather with topographic and fuel data within fire spread models (e.g. FSPro), fire managers can further refine average landscape-wide estimates to prioritise suppression efforts to locations most conducive to containment while also adjusting strategies in anticipation of changing conditions and expected fire growth. Furthermore, identifying terrain-driven suppression opportunities, such as leveraging valleys and ridges for containment (Holsinger *et al.* 2016; Povak *et al.* 2018; Young *et al.* 2024), could refine burnout operations and other tactical interventions (Narayanaraj and Wimberly 2011; Smith 2021; Thompson *et al.* 2021), in effect refining the timing of place-based interventions by leveraging the POD network rather than individual lines or locations. Ultimately, these findings highlight the need for a multifaceted approach to fire suppression, where environmental awareness, resource allocation and strategic planning are continuously integrated to improve wildfire containment outcomes.

While our study provides valuable insights into fire suppression effectiveness, several limitations should be acknowledged. First, our analysis is based on a single fire case study, which may limit the generalisability of our findings, though many of the results align with prior research on the effectiveness of fuel breaks (Young *et al.* 2024). Future studies should incorporate multiple incidents to better understand how POD and containment line effectiveness may differ across incidents and ecologies. Additionally, the fire spread data we used are inherently imperfect due to sampling windows limited to 12-h intervals in the early morning and early afternoon, as well as the risk of false positive or false negative detections due to heavy smoke or cloud cover. Our use of 24-h average weather metrics, while useful for broad analysis (Gannon *et al.* 2023; Young *et al.* 2024), could be refined by employing 12-h averages to better distinguish between day and night operations. Furthermore, forecasted weather conditions may not always align with observed fire weather data during critical operational windows, introducing potential discrepancies in predictive modelling that could be overcome with systems capable of dynamic forecasts or near real-time weather inputs. It is also likely that including heading, backing and flanking fire behavior metrics could help reduce false positives and negatives, providing a more nuanced understanding of suppression success. Lastly, though gaps in the canopy are often correlated with increased grass and forb production, our study does not explicitly account for ground and surface fuel layers, which play a crucial role in fire behaviour by providing fine, flashy fuels capable of spreading ground fire rapidly and ladder fuels that contribute to torching and crown fire activity (Hakkenberg *et al.* 2024). Additional insights can also be gained from distinguishing suppression operations by type (e.g. bulldozer, handline, aviation support and burnout operations). Addressing these limitations in future research could improve fire suppression modelling and enhance operational decision-making.

Conclusion

This study highlights the critical role of environmental conditions, resource allocation and fire management strategies in wildfire suppression. Average daily VPD and wind speed consistently reduced containment success, while terrain features, particularly valleys and ridges, aided suppression efforts. Personnel availability was positively associated with containment, though diminishing returns suggest that beyond a threshold, additional staffing may not yield proportional benefits. The TCCB also contributed to suppression effectiveness with a notably decline in windy conditions, emphasizing the importance of strategic vegetation management.

The comparison of containment and POD lines suggests that while containment lines play a crucial role in containment, their impact may be overestimated in descriptive models due to representation bias. The limited causal effect of POD lines indicates that their effectiveness depends on broader operational strategies. Though POD line placements are inherently biased toward locations perceived to be ideal, causal effects are better captured through other landscape variables in the model. The performance of our causal assessment reinforces the need for increased scrutiny applied to fire suppression research. Integrating real-time weather forecasts with fire spread and suppression models could enhance decision-making, allowing fire managers to prioritise containment efforts based on evolving conditions. A data-driven, adaptive approach that accounts for environmental factors and operational strategies will be key for improving wildfire containment outcomes.

Supplementary material

Supplementary material is available online.

References

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

Abatzoglou JT, Battisti DS, Williams AP, Hansen WD, Harvey BJ, Kolden CA (2021) Projected increases in western US forest fire despite growing fuel constraints. *Communications Earth and Environment* **2**, 227. doi:10.1038/s43247-021-00299-0

Agee JK, Bahro B, Finney MA, Omi PN, Sapsis DB, Skinner CN, van Wagtendonk JW, Weatherspoon CP (2000) The use of shaded fuelbreaks in landscape fire management. *Forest Ecology and Management* **127**, 55–66. doi:10.1016/s0378-1127(99)00116-4

Andrade SR, Hulse DE (2022) Evaluation and improvement of system-of-systems resilience in a simulation of wildfire emergency response. *IEEE Systems Journal* **17**, 1877–88.

Arkowitz A, Ritter SM, Thompson MP, Young JD, Pietruszka B, Calkin DE (2025) Quality assured spatial dataset of wildfire containment firelines and engagement outcomes 2017 to 2024. *Scientific Data* **12**, 897. doi:10.1038/s41597-025-05208-0

Babyak MA (2009) Understanding confounding and mediation. *Evidence-Based Mental Health* **12**, 68–71. doi:10.1136/ebmh.12.3.68

Boroujeni SPH, Razi A, Khoshdel S, Afghah F, Coen JL, O'Neill L, Fule P, Watts A, Kokolakis NM, Vamvoudakis KG (2024) A comprehensive survey of research towards AI-enabled unmanned aerial systems in pre-, active-, and post-wildfire management. *Information Fusion* **108**, 102369. doi:10.1016/j.inffus.2024.102369

Brodeur A, Cook N, Heyes A (2020) Methods matter: p-hacking and publication bias in causal analysis in economics: reply. *American Economic Review* **110**, 3634–3660. doi:10.1257/aer.20220277

Butler BW, Cohen JD (1998) Firefighter Safety Zones: a theoretical model based on radiative heating. *International Journal of Wildland Fire* **8**, 73–77. doi:10.1071/WF9980073

Calkin D, O'Connor CD, Thompson MP, Stratton R (2021) Strategic Wildfire Response Decision Support and the Risk Management Assistance Program. *Forests* **12**, 1407. doi:10.3390/f12101407

Camatti N, Essenfelder AH, Giove S (2024) Mapping the exposure of tourism to weather extremes: the need for a spatially-explicit gridded dataset for disaster risk reduction. *Environmental Research Letters* **19**, 64008. doi:10.1088/1748-9326/ad3e91

Campbell MJ, Dennison PE, Butler BW (2017) A LiDAR-based analysis of the effects of slope, vegetation density, and ground surface roughness on travel rates for wildland firefighter escape route mapping. *International Journal of Wildland Fire* **26**, 884–895. doi:10.1071/WF17031

Campbell MJ, Page WG, Dennison PE, Butler BW (2019) Escape route index: a spatially-explicit measure of wildland firefighter egress capacity. *Fire* **2**, 40. doi:10.3390/fire2030040

Campbell MJ, Dennison PE, Thompson MP, Butler BW (2022) Assessing potential safety zone suitability using a new online mapping tool. *Fire* **5**, 5. doi:10.3390/fire5010005

Cardil A, Tapia VM, Monedero S, Quiñones T, Little K, Stoof CR, Ramirez J, de-Miguel S (2023) Characterizing the rate of spread of large wildfires in emerging fire environments of northwestern Europe using visible infrared imaging radiometer suite active fire data. *Natural Hazards and Earth System Sciences* **23**, 361–373. doi:10.5194/nhess-23-361-2023

Chamberlain CP, Meigs GW, Churchill DJ, Kane JT, Sanna A, Begley JS, Prichard SJ, Kennedy MC, Bienz C, Haugo RD, Smith AC, Kane VR, Cansler CA (2024) Learning from wildfires: a scalable framework to evaluate treatment effects on burn severity. *Ecosphere* **15**, e70073. doi:10.1002/ecs2.70073

Chen Y, Hantson S, Andela N, Coffield SR, Graff CA, Morton DC, Ott LE, Foufoula-Georgiou E, Smyth P, Goulden ML, Randerson JT (2022*a*) California wildfire spread derived using VIIRS satellite observations and an object-based tracking system, scientific data. *Natural Resources Forum* **9**, 249. doi:10.1038/s41597-022-01343-0

Chen Y, Hopkins B, Wang H, O'Neill L, Afghah F, Razi A, Fule P, Coen J, Rowell E, Watts A (2022*b*) Wildland fire detection and monitoring using a drone-collected RGB/IR image dataset. *IEEE* **10**, 121301–121317.

Cummiskey K, Adams B, Pleuss J, Turner D, Clark N, Watts K (2020) Causal inference in introductory statistics courses. *Journal of Statistics Education* **28**, 2–8. doi:10.1080/10691898.2020.1713936

Dennison PE, Fryer GK, Cova TJ (2014) Identification of firefighter safety zones using lidar. *Environmental Modelling and Software* **59**, 91–97. doi:10.1016/j.envsoft.2014.05.017

Diemer EW, Hudson JI, Javaras KN (2021) More (adjustment) is not always better: how directed acyclic graphs can help researchers decide which covariates to include in models for the causal relationship between an exposure and an outcome in observational research. *Psychotherapy and Psychosomatics* **90**, 289–298. doi:10.1159/000517104

Etminan M, Brophy JM, Collins G, Nazemipour M, Mansournia MA (2021) To adjust or not to adjust: the role of different covariates in cardiovascular observational studies. *American Heart Journal* **237**, 62–67. doi:10.1016/j.ahj.2021.03.008

Finney M, Grenfell IC, McHugh CW (2009) Modeling containment of large wildfires using generalized linear mixed-model analysis. *Forest Science* **55**, 249–255. doi:10.1093/forestscience/55.3.249

Finney MA, Zimmer SN, Riley KL, Grenfell IC (2025) A generalized wildfire containment algorithm. *Ecological Modelling* **505**, 111134. doi:10.1016/j.ecolmodel.2025.111134

Flatt C (2022) Studies show prescribed burns key to forest resiliency. *NWNews*, 18 November.

Fryer GK, Dennison PE, Cova TJ (2013) Wildland firefighter entrapment avoidance: modelling evacuation triggers. *International Journal of Wildland Fire* **22**, 883–893. doi:10.1071/WF12160

Furniss TJ, Povak N, Hessburg PF, Salter RB, Duan Z, Wigmosta M (2024) Wildfire management decisions outweigh mechanical treatment as the keystone to forest landscape adaptation. *Fire Ecology* **20**, 105. doi:10.1186/s42408-024-00339-y

Gale MG, Cary GJ (2025) Evaluating Australian forest fire rate of spread models using VIIRS satellite observations. *Environmental Modelling and Software* **188**, 106436. doi:10.1016/j.envsoft.2025.106436

Gallant JC, Wilson JP (2000) Primary Topographic Attributes. Available at https://www.researchgate.net/publication/303543730

Gannon BM, Thompson MP, Deming KZ, Bayham J, Wei Y, O'Connor CD (2020) A geospatial framework to assess fireline effectiveness for large wildfires in the western USA. *Fire* **3**, 43. doi:10.3390/fire3030043

Gannon BM, Wei Yu, Belval E, Young J, Thompson M, O'Connor C, Calkin D, Dunn C (2023) A quantitative analysis of fuel break effectiveness drivers in Southern California National Forests. *Fire* **6**, 104. doi:10.3390/fire6030104

Hakkenberg CR, Clark ML, Bailey T, Burns P, Goetz SJ (2024) Ladder fuels rather than canopy volumes consistently predict wildfire severity even in extreme topographic-weather conditions. *Communications Earth & Environment* **5**, 721. doi:10.1038/s43247-024-01893-8

Hand M, Katuwal H, Calkin DE, Thompson MP (2017) The influence of incident management teams on the deployment of wildfire suppression resources. *International Journal of Wildland Fire* **26**, 615–629. doi:10.1071/WF16126

Hart SJ, Preston DL (2020) Fire weather drives daily area burned and observations of fire behavior in mountain pine beetle affected landscapes. *Environmental Research Letters* **15**, 54007. doi:10.1088/1748-9326/ab7953

Hernán MA, Hsu J, Healy B (2019) A second chance to get causal inference right: a classification of data science tasks. *Chance* **32**, 42–49. doi:10.1080/09332480.2019.1579578

Holsinger L, Parks SA, Miller C (2016) Weather, fuels, and topography impede wildland fire spread in western US landscapes. *Forest Ecology and Management* **380**, 59–69. doi:10.1016/j.foreco.2016.08.035

Kahneman D (2003) Maps of bounded rationality: psychology for behavioral economics. *American Economic Review* **93**, 1449–1475. Available at https://about.jstor. org/terms

Kang DK, Fischer E, Olsen MJ, Adams JA, O'Neil-Dunne J (2021) Optimizing disaster response: opportunities and challenges with Uncrewed Aircraft System (UAS) technology in response to the 2020 Labour Day wildfires in Oregon, USA.

Katuwal H, Calkin DE, Hand MS (2016) Production and efficiency of large wildland fire suppression effort: a stochastic frontier analysis. *Journal of Environmental Management* **166**, 227–36. doi:10.1016/j.jenvman.2015.10.030

Katuwal H, Dunn CJ, Calkin DE (2017) Characterizing resource use and potential inefficiencies during large-fire suppression in the western US. *International Journal of Wildland Fire* **26**, 604–614. doi:10.1071/WF17054

King KE, Cook ER, Anchukaitis KJ, Cook BI, Smerdon JE, Seager R, Harley GL, Spei B (2024) Increasing prevalence of hot drought across western North America since the 16th century. *Science Advances* **10**, eadj4289 Available at https://www.science. org

Knapp KR, Ansari S, Bain CL, Bourassa MA, Dickinson MJ, Funk C, Helms CN, Hennon CC, Holmes CD, Huffman GJ, Kossin JP, Lee HT, Loew A, Magnusdottir G (2011) Globally gridded satellite observations for climate studies. *American Meteorological Society* 893–907. doi:10.1175/2011BAMS3039.1

Lahaye S, Sharples J, Matthews S, Heemstra S, Price O, Badlan R (2018) How do weather and terrain contribute to firefighter entrapments in Australia? *International Journal of Wildland Fire* **27**, 85–98. doi:10.1071/WF17114

LandFire (2022) Homepage of the LandFire Project. (U.S. Department of Agriculture, Forest Service; U.S. Department of Interior).

Lemons RE, Prichard SJ, Kerns BK (2023) Evaluating fireline effectiveness across large wildfire events in north-central Washington State. *Fire Ecology* **19**, 8. doi:10.1186/s42408-023-00167-6

Lentile LB, Holden ZA, Smith AMS, Falkowski MJ, Hudak AT, Morgan P, Lewis SA, Gessler PE, Benson NC (2006) Remote sensing techniques to assess active fire characteristics and post-fire effects. *International Journal of Wildland Fire* **15**, 319–345. doi:10.1071/WF05097

Lipsky AM, Greenland S (2022) Causal directed acyclic graphs. *JAMA* **327**, 1083–1084. doi:10.1001/jama.2022.1816

Lübke K, Gehrke M, Horst J, Szepannek G (2020) Why we should teach causal inference: examples in linear regression with simulated data. *Journal of Statistics Education* **28**, 133–139. doi:10.1080/10691898.2020.1752859

Mankin KR, Mehan S, Green TR, Barnard DM (2025) Review of gridded climate products and their use in hydrological analyses reveals overlaps, gaps, and the need for a more objective approach to selecting model forcing datasets. *Hydrology and Earth System Sciences* **29**, 85–108. doi:10.5194/hess-29-85-2025

Marlon JR, Bartlein PJ, Gavin DG, Long CJ, Anderson RS, Briles CE, Brown KJ, Colombaroli D, Hallett DJ, Power MJ, Scharf EA, Walsh MK (2012) Long-term perspective on wildfires in the western USA. *Proceedings of the National Academy of Sciences* **109**, 535–43. doi:10.1073/pnas.1112839109

McCaffrey S, Wilson R, Konar A (2018) Should I stay or should I go now? Or should I wait and see? Influences on wildfire evacuation decisions. *Risk Analysis* **38**, 1390–1404. doi:10.1111/risa.12944

McLennan J, Ryan B, Bearman C, Toh K (2019) Should we leave now? Behavioral factors in evacuation under wildfire threat. *Fire Technology* **55**, 487–516. doi:10.1007/s10694-018-0753-8

Mesinger F, DiMego G, Kalnay E, Mitchell K, Shafran PC, Ebisuzaki W, Jović D, Woollen J, Rogers E, Berbery EH, Ek MB, Fan Y, Grumbine R, Higgins W, Li H, Lin Y, Manikin G, Parrish D, Shi W (2006) North American regional reanalysis. *Bulletin of the American Meteorological Society* **87**, 343–360. doi:10.1175/BAMS-87-3-343

Mistick KA, Dennison PE, Campbell MJ, Thompson MP (2022) Using geographic information to analyze wildland firefighter situational awareness: impacts of spatial resolution on visibility assessment. *Fire* **5**, 151. doi:10.3390/fire5050151

Morandini F, Silvani X, Dupuy JL, Susset A (2018) Fire spread across a sloping fuel bed: flame dynamics and heat transfers. *Combustion and Flame* **190**, 158–170. doi:10.1016/j.combustflame.2017.11.025

Narayanaraj G, Wimberly MC (2011) Influences of forest roads on the spatial pattern of wildfire boundaries. *International Journal of Wildland Fire* **20**, 792–803. doi:10.1071/WF10032

Nguyen D, Wei Y, Belval EJ, Thompson MP, Gannon BM, Young JD, O'Connor CD, Calkin DE (2024) An optimization model to prioritize fuel treatments within a landscape fuel break network. *PLoS One* **19**, e0313591. doi:10.1371/journal.pone.0313591

NIFC (2017) 2017, National Interagency Fire Center. NIFC FTP Server, Incident Specific Data, 2021. (National Interagency Fire Center: Boise, ID, USA). Available at https://ftp.wildfire.gov/ [accessed 15 September 2021]

NIFC-WFIGS (2024) 2017-2024, National Interagency Fire Center. National Incident Feature Service, Incident Firelines, 2021. (National Interagency Fire Center: Boise, ID, USA). Available at https://data-nifc.opendata.arcgis.com/ [accessed 15 September 2021]

NWCC (2021) Schneider Springs Fire Update, September 10, 2021. (Northwest Interagency Coordination Center). Available at https://nwccinfo.blogspot.com/2021/09/9102021-schneider-springs-fire-update.html

O'Connor CD, Calkin DE (2019) Engaging the fire before it starts: a case study from the 2017 Pinal Fire (Arizona). *Wildfire* **28**, 14–18.

O'Connor CD, Thompson MP, Rodríguez y Silva F (2016) Getting Ahead of the Wildfire Problem: Quantifying and Mapping Management Challenges and Opportunities. *Geosciences* **6**, 35. doi:10.3390/geosciences6030035

O'Connor CD, Calkin DE, Thompson MP (2017) An empirical machine learning method for predicting potential fire control locations for pre-fire planning and operational fire management. *International Journal of Wildland Fire* **26**, 587–597. doi:10.1071/WF16135

Orland E, McCabe TD, Becker Z, Chen Y, Scholten RC, Shiklomanov AN, Coffield SR, Liu T, Randerson J, Follette-Cook MB, Morton DC

(2025a) Fire Event Data Suite Data Western US Archive. Available at https://zenodo.org/records/15261836

Orland E, McCabe TD, Chen Y, Scholten RC, Becker Z, Loehman RA, Randerson JT, Coffield SR, Liu T, Shiklomanov AN, Nelson K, Peterson B, Follette-Cook MB, Morton DC (2025*b*) Near real-time indicators of burn severity in the Western U.S. from active fire tracking. *Fire Ecology* **21**(1), doi:10.1186/s42408-025-00407-x

Parikh R, Mathai A, Parikh S, Sekhar GC, Thomas R (2008) Understanding and using sensitivity, specificity and predictive values. *Indian Journal of Ophthalmology* **56**, 45–50. doi:10.4103/0301-4738.37595

Parks SA (2014) Mapping day-of-burning with coarse-resolution satellite fire-detection data. *International Journal of Wildland Fire* **23**, 215–223. doi:10.1071/WF13138

Pearl J (2001) Direct and Indirect Effects. In 'Proceedings of the Seventeenth Conference on Uncertainty in Artificial Intelligence'. UAI-P-2001-PG-411-420. doi:10.48550/arXiv.1301.2300

Pietruszka BM, Young JD, Short KC, St. Denis LA, Thompson MP, Calkin DE (2023) Consequential lightning-caused wildfires and the "let burn" narrative. *Fire Ecology* **19**, 50. doi:10.1186/s42408-023-00208-0

Pillar VD, Overbeck GE (2025) Grazing can reduce wildfire risk amid climate change. *Science* **387**, 7471. doi:10.1126/science.adu7471

Povak NA, Hessburg PF, Salter RB (2018) Evidence for scale-dependent topographic controls on wildfire spread. *Ecosphere* **9**, e02443. doi:10.1002/ecs2.2443

Pregibon D (1980) Goodness of link tests for generalized linear models. *Journal of the Royal Statistical Society* **29**, 15–23. doi:10.2307/2346405

Rahat SH, Saki S, Khaira U, Biswas NK, Dollan IJ, Wasti A, Miura Y, Bhuiyan MAE, Ray P (2024) Bracing for impact: how shifting precipitation extremes may influence physical climate risks in an uncertain future. *Scientific Reports* **14**, 17398. doi:10.1038/s41598-024-65618-9

RMA (2022) Risk Management Assistance (RMA) Dashboard. Potential Operational Delineations (PODs). Available at https://experience.arcgis.com/experience/f9d7f7f920494c3db43a23a8dffe4664 [accessed spring 2022]

Rohrer JM (2018) Thinking clearly about correlations and causation: graphical causal models for observational data. *Advances in Methods and Practices in Psychological Science* **1**, 27–42. doi:10.1177/2515245917745629

Rodríguez y Silva F, O'Connor CD, Thompson MP, Molina Martínez JR, Calkin DE (2020) Modelling suppression difficulty: current and future applications. *International Journal of Wildland Fire* **29**(8), 739–751. doi:10.1071/wf19042

Rosser JB, Rosser MV (2014) Complexity and Behavioral Economics. Available at https://www.lem.sssup.it/WPLem/documents/COMPLEXITY_AND_BEHAVIORAL_ECONOMICS_-_Rev_1.pdf

Salas-Eljatib C, Fuentes-Ramirez A, Gregoire TG, Altamirano A, Yaitul V (2018) A study on the effects of unbalanced data when fitting logistic regression models in ecology. *Ecological Indicators* **85**, 502–508. doi:10.1016/j.ecolind.2017.10.030

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. doi:10.1109/JSTARS.2020.3019261

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

Shadrin D, Illarionova S, Gubanov F, Evteeva K, Mironenko M, Levchunets I, Belousov R, Burnaev E (2024) Wildfire spreading prediction using multimodal data and deep neural network approach. *Scientific Reports* **14**, 2606. doi:10.1038/s41598-024-52821-x

Smith K (2021) Crews use fire to prevent growth of Schneider Springs Fire to the south. *Yakima Herald-Republic*, 26 August.

Smith K (2022) Scientists say thinning, prescribed burns helped forest during Schneider Springs fire in 2021. *Yakima Herald-Republic*, 6 November.

Srock AF, Charney JJ, Potter BE, Goodrick SL (2018) The hot-dry-windy index: a new fire weather index. *Atmosphere* **9**, 279. doi:10.3390/atmos9070279

StataCorp (2017*a*) Stata: Release 15. Statistical Software. (StataCorp LLC: College Station, TX, USA)

StataCorp (2017*b*) Stata Base Reference Manual: Release 15. (StataCorp LLC: College Station, TX, USA)

St. Denis LA, Short KC, McConnell K, Cook MC, Mietkiewicz NP, Buckland M, Balch JK (2023) All-hazards dataset mined from the US National Incident Management System 1999–2020. *Scientific Data* **10**, 112. doi:10.1038/s41597-023-01955-0

Stonesifer CS, Calkin DE, Thompson MP, Belval EJ (2021) Is this flight necessary? The aviation use summary (aus): a framework for strategic, risk-informed aviation decision support. *Forests* **12**, 1078. doi:10.3390/f12081078

Thompson MP, Bowden P, Brough A, Scott JH, Gilbertson-Day J, Taylor A, Anderson J, Haas JR (2016) Application of wildfire risk assessment results to wildfire response planning in the southern sierra nevada, california, USA. *Forests* **7**, 64. doi:10.3390/f7030064

Thompson MP, Lauer CJ, Calkin DE, Rieck JD, Stonesifer CS, Hand MS (2018) Wildfire response performance measurement: current and future directions. *Fire* **1**, 21. doi:10.3390/fire1020021

Thompson MP, Gannon BM, Caggiano MD (2021) Forest roads and operational wildfire response planning. *Forests* **12**, 110. doi:10.3390/f12020110

Thompson MP, O'Connor CD, Gannon BM, Caggiano MD, Dunn CJ, Schultz CA, Calkin DE, Pietruszka B, Greiner SM, Stratton R, Morisette JT (2022) Potential operational delineations: new horizons for proactive, risk-informed strategic land and fire management. *Fire Ecology* **18**, 17. doi:10.1186/s42408-022-00139-2

USDA FS (2021) United States Department of Agriculture, Forest Service, Okanogan-Wenatchee National Forest | November 2021 Schneider Springs Fire Burned Area Summary 2500-8 Burned Area Report. Available at https://www.fs.usda.gov/Internet/FSE_DOCUMENTS/fseprd1133791.pdf

WADNR (2022) Wildfire Season 2021 - Work of Wildfire Assessment. (Washington State Department of Natural Resources: Olympia, WA)

Wagenbrenner N, Forthofer JM, Brian KL, Shannon KS, Butler BW (2016) Downscaling surface wind predictions from numerical weather prediction models in complex terrain with WindNinja. *Atmospheric Chemistry and Physics* **16**, 5229–5241. doi:10.5194/acp-2015-761

White RH, Anderson S, Booth JF, Braich G, Draeger C, Fei C, Harley CD, Henderson SB, Jakob M, Lau CA, Mareshet Admasu L (2023) The unprecedented Pacific northwest heatwave of June 2021. *Nature Communications* **14**, 727. doi:10.1038/s41467-023-36289-3

Wooldridge JM (2019) 'Introductory Econometrics: A Modern Approach.' 7th edn. (Cengage Learning India). ISBN: 9355731078, 9789355731074

Young JD, Ager AA (2024) Resource objective wildfire leveraged to restore old growth forest structure while stabilizing carbon stocks in the southwestern United States. *Ecological Modelling* **488**, 110573. doi:10.1016/j.ecolmodel.2023.110573

Young JD, Thode AE, Huang CH, Ager AA, Fulé PZ (2019) Strategic application of wildland fire suppression in the southwestern United States. *Journal of Environmental Management* **245**, 504–518. doi:10.1016/j.jenvman.2019.01.003

Young JD, Ager AA, Thode AE (2022) Using wildfire as a management strategy to restore resiliency to ponderosa pine forests in the southwestern United States. *Ecosphere* **13**, e4040. doi:10.1002/ecs2.4040

Young JD, Belval E, Gannon B, Wei Y, O'Connor C, Dunn C, Pietruszka BM, Calkin D, Thompson M (2024) The cost of operational complexity: A causal assessment of pre-fire mitigation and wildfire suppression. *Forest Policy and Economics* **169**, 103351. doi:10.1016/j.forpol.2024.103351

Zou KH, O'Malley AJ, Mauri L (2007) Receiver-operating characteristic analysis for evaluating diagnostic tests and predictive models. *Circulation* **115**, 654–657. doi:10.1161/CIRCULATIONAHA.105.594929

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Author affiliations

[A]USDA Forest Service Rocky Mountain Research Station, Human Dimensions, 240 W Prospect Road, Fort Collins, CO 80526, USA.

[B]USDA Forest Service Rocky Mountain Research Station, Human Dimensions, Missoula, MT, USA.

[C]Colorado State University, Warner College of Natural Resources, Fort Collins, CO, USA.

[D]USDA Forest Service, Geospatial Wildfire Analytics – Contractor, Fort Collins, CO, USA.

[E]NASA Goddard Space Flight Center, Greenbelt, MD, USA.

[F]University of Maryland Baltimore County, GES-TAR II, Baltimore, MD, USA.

[G]Colorado State University, Forest and Rangeland Stewardship, Fort Collins, CO, USA.

[H]Oak Ridge Institute for Science and Education, Oak Ridge, TN, USA.

[I]University of Montana, W. A. Franke College of Forestry and Conservation, Missoula, MT, USA.