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The cost of operational complexity: A causal assessment of pre-fire mitigation and wildfire suppression

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ABSTRACT

Pre-fire mitigation efforts that include the installation and maintenance of fuel breaks are integral to wildfire suppression in Southern California. Fuel breaks alter fire behavior and assist in fire suppression at strategic locations on the landscape. However, the combined effectiveness of fuel breaks and wildfire suppression is not well studied. Using daily firefighting personnel to proxy the quantity and diversity of potential fire suppression operations (i.e., operational complexity), we examined 15 wildfires from 2017 to 2020 in the Los Padres, Angeles, San Bernardino, and Cleveland National Forests to assess how weather and site-specific fuel break characteristics influenced wildfire containment when leveraged during suppression operations. After removing effects of fuel treatments, wildfire and aerial firefighting, we estimated that expanding fuel break width in grass-dominant systems from 10 to 100 m increased the average success rate against a heading fire from 31 % to 41 %. Likewise, recently cleared fuel breaks had higher success rates compared to poorly maintained fuel breaks in both grass (25 % to 45 %) and shrub systems (20 % to 45 %). Combined, grass and shrub systems exhibited an estimated success rate of 80 % under mild weather conditions (20th percentile) and 19 % under severe weather (80th percentile). Other significant determinants included forb and grass production, adjacent tree canopy cover and terrain. Consistent with complexity theory and previous suppression effectiveness research, our analysis showed signs of suppression effectiveness declining as firefighter personnel increased. Future work could better account for the role of suppression with improved data on firefighting resource types, actions, locations, and timing.

1. Introduction

As fire seasons in the United States become longer and drier (Abatzoglou and Williams, 2016; Dong et al., 2022; King et al., 2024), large wildfires have grown increasingly complex, impacting multiple aspects of society (Nowell et al., 2022; Essen et al., 2023) and leading to an emphasis on pre-fire mitigation efforts to improve response outcomes (USDAFS, 2022; Infrastructure Investment and Jobs Act, 117–58 U.S.C. § Section 40806, 2021). However, the combined effectiveness of pre-fire mitigation efforts that directly support fire management needs (herein, installation and maintenance of fuel breaks) and wildfire suppression (herein, the staffing and reinforcement of fuel breaks) is understudied. Though components of linear fuel breaks (Agee et al., 2000; Syphard et al., 2011a, 2011b; Gannon et al., 2023; Ortega et al., 2024) and wildfire suppression (Thompson et al., 2018; Plucinski, 2019b; Plucinski, 2019a; Gannon et al., 2020; Lemons et al., 2023; Ortega et al., 2024) have been analyzed, their combined effectiveness under varying fire weather and fuels conditions has not been explored in a causal framework. The historical use (Murphy et al., 1967; Green, 1977) and continued investments into fuel breaks make Southern California a

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prime location for investigating causal factors influencing the effectiveness of fuel breaks when staffed and reinforced during suppression operations (herein, leveraged fuel breaks).

Linear fuel breaks are strips of land, typically ranging from 20 to 300 m in width, where vegetation has been intentionally modified or removed to lower fire intensity and reduce the rate of spread (Byram, 1959; van Wagtendonk, 1996; FAO, 2002; Baijnath-Rodino et al., 2023). Many fuel breaks are co-located along natural barriers (i.e., ridgetops) or roadways, improving accessibility for ground crews and decreasing efforts necessary for direct suppression actions, or for the safe anchoring of backfire or burnout ignitions before the firefront arrives (Green, 1977; Thompson et al., 2021). Likewise, the limited tree canopy and favorable terrain associated with many fuel breaks makes them optimal locations to reach surface fuels with the aerial applications of water or fire-retardant, in turn reducing fire spread (Agee et al., 2000; Stonesifer et al., 2021). However, fuel breaks require regular maintenance to prevent undesirable revegetation and fuel accumulation (Ingalsbee, 2005). They can also facilitate the invasion of flammable, nonnative annual grasses (e.g., *Bromus tectorum*) (Merriam et al., 2006; Kerns et al., 2020). Degraded or invaded fuel breaks can create a false sense of security among the public and fire suppression personnel without providing direct benefits (Dennis, 2005). Also, perfectly maintained fuel breaks are unlikely to contain extreme fire behavior (due to spotting or running crown fires) regardless of adjacent fuel reduction treatments or suppression effort (Omi, 1996; Caggiano et al., 2021). Even under more favorable conditions, fuel breaks are not intended to passively stop fire progression, but rather meant to facilitate fire containment using suppression tactics, including the installation of firelines (Murphy et al., 1967).

Tactics such as fireline creation, burnout operations and aerial retardant drops are used by fire managers to stop fire progression (Dunn et al., 2017). Direct fireline tactics include removing vegetation with hand tools or heavy equipment (e.g., bulldozers, plows) to expose bare mineral soil directly adjacent to a flaming front. During periods of low to moderate fire behavior (generally lower than 1.2 m flame lengths) direct tactics are commonly applied, often aided by aerial delivery of water or retardant (Andrews et al., 2011; Stonesifer et al., 2021; Duncombe, 2023; Ortega et al., 2024). When precluded by fire behavior, access or safety concerns, indirect fireline tactics spatially separated from the fires edge are often used (Pietruszka et al., 2023). Depending on weather conditions, indirect tactics may include burnout operations along pre-existing features, fuel breaks, newly constructed fireline, or some combination thereof (Gannon et al., 2020; Simpson et al., 2021; Thompson et al., 2021; Thompson et al., 2022). However, direct or indirect fireline constructed at locations with longer evacuation times, inadequate safety zones, or limited lookout locations present more risk to firefighters (Fryer et al., 2013; Campbell et al., 2019, 2022b; Mistick et al., 2022), and therefore may not be staffed as robustly as areas with fewer concerns. This, in turn, can extend the duration of an individual wildfire, thereby increasing uncertainty for fire managers. This tradeoff exemplifies one source of latent inefficiencies that manifest as a 'cost of operational complexity' in a dynamic and uncertain system (Jaafari, 2003; Rosser and Rosser, 2014; Oh et al., 2017; Bayham et al., 2022).

Wildfire response exhibits all the components of operational complexity (i.e., complexity theory) including interconnected systems (e.g., human resources, equipment, technology and logistics), dynamic environments (e.g., fire weather, terrain), multiple cooperators, and external factors such as drought and public sentiment (Nowell and Steelman, 2019; Steelman and Nowell, 2019; Essen et al., 2023; Kirschner et al., 2023). Complicating matters further, fire responders face uncertain risk factors that are interconnected including fire growth and behavior (Scott, 1999; Finney, 2006; Juang et al., 2022) and environmental hazards such as steep terrain with rolling rocks, overhead snags and extreme heat (Dunn et al., 2019; Riley et al., 2022). This is in addition to the safe evacuation of the public and fellow fire responders (McCaffrey et al., 2018; Campbell et al., 2019; McLennan et al., 2019; Wei et al., 2023). Operationally complex and uncertain systems create latent inefficiencies (i.e., complexity costs) that need to be considered when determining causal assessment methods (Walton, 2014). Unlike fixed or variable costs associated with fireline construction, complexity costs can emerge at the interface between various scales and components of wildfire response, posing challenges to using traditional measurement methods (Gingrich and Metz, 1990; Hu et al., 2011). Examples include decision delays when weighing tradeoffs in a state of information overload, and the use of bounded rationality or heuristics as a means to deal with operational complexity, which can result in systematic errors in judgment, i.e., representativeness, availability, and anchoring biases (Kahneman, 2003; Rosser and Rosser, 2014; Rapp and Nelson, 2024). We use personnel available for ground-based construction of fireline as a proxy for operational complexity (i.e., quantity and diversity of potential fireline).

Previous research has examined various factors influencing wildfire containment and fireline operations. Studies in Southern California (Syphard et al., 2011b; Syphard et al., 2011a) evaluated fuel break effectiveness considering fuel break condition, accessibility and firefighting resources. Research from central Washington (Narayanaraj and Wimberly, 2011) identified roadways as significant indicators of fire perimeters. A broader regional analysis of the Western United States (Holsinger et al., 2016) assessed the relative importance of weather, fuels and topography in impeding fire spread, emphasizing recent wildfires, valleys and ridgelines as key factors. A predictive model for fire perimeters in the Northern Great Basin of the Western United States (O'Connor et al., 2017) incorporated metrics that captured resistance to control, travel costs, fire spread rates, and suppression difficulty (Rodríguez et al., 2020). In California, Povak et al. (2018) examined topographic controls at fire boundaries compared to interiors, identifying fire size and ecoregions as important determinants. Research in Spain expanded these findings, linking airborne support and travel costs to fire perimeters (Rodrigues et al., 2020), and linking fuel break effectiveness to suppression activities, flame length, and the encounter angle between fuel breaks and approaching fire (Ortega et al., 2024). Recent fuel break effectiveness research in Southern California (Gannon et al., 2023) highlighted the importance of suppression operations and weather, and in the Great Basin lower fuel break effectiveness was observed in degraded sagebrush ecoregions, on steep slopes, and during high temperatures (Weise et al., 2023). In Washington it was determined that fireline effectiveness declined during high severity fires (Lemons et al., 2023), while recent research in California has shown shaded fuel breaks to lower fire severity (Baijnath-Rodino et al., 2023; Low et al., 2023).

Guided by previous research and mindful of the historical and continued reliance on aggressive fire suppression in Southern California (Murphy et al., 1967; Green, 1977; Young et al., 2020), we seek to estimate the causal effects of fire weather and fuel break characteristics on the probability of fireline stopping fire progression, while also considering site-specific characteristics that contribute to fire behavior, and fire-wide costs of complex suppression operations. In doing so, we consider the operational complexity associated with fire response, alongside focal exposures and other competing and confounding covariates that contribute to fuel break effectiveness. Our primary objective is to inform the maintenance and implementation of fuel breaks to strategically aid with pre-season planning and active fire containment. Therefore, to work towards the isolation of a single data generating process, we focus on fuel breaks that co-occurred with fireline actions using hand tools, heavy equipment or burnout operations (i.e, leveraged fuel breaks) and exclude all other wildfire encounters.

2. Methods

2.1. Study area

We use the Los Padres, Angeles, San Bernardino, and Cleveland

National Forests in Southern California as our study area (Fig. 1). Southern California has a Mediterranean climate characterized by cool, wet winters and dry, warm summers. Fire regimes in the study area exhibit considerable variation, reflecting the ecological diversity including chaparral shrublands, coastal sage scrub shrublands, grasslands, oak woodlands, and montane coniferous forests. Vegetation distributions are influenced by an elevational gradient that spans from sea level to an excess of 3500 m (Wells et al., 2004). Linear fuels breaks have long been established across the study area to modify fire behavior and aid in suppression operations by removing trees and shrubs (Green, 1977). We use the study period to 2017 through 2020 to leverage spatial datasets of suppression operations not available prior to 2017 (NIFC, 2021a; NIFC, 2021b; Stonesifer et al., 2021).

2.2. *Fuel break, wildfire, and fireline data*

Data documenting the fuel break network used in our analysis was initially established by Brennan and Keeley (2011) for use in fuel break effectiveness research (Syphard et al., 2011a, 2011b) and then was adjusted by National Forest staff for a fuel break evaluation project (Chris Clervi, personal communication). Later, Gannon et al. (2023) incorporated fuel break width and an ordinal measure of overall condition into the dataset. In total, we considered an estimated 5150 km of fuel breaks across four National Forests of Southern California.

We compiled perimeter data for wildfires larger than 200 ha between 2017 and 2020, resulting in 15 wildfires that interacted with constructed fireline that leveraged preexisting fuel breaks (Table 1). We chose the 200-ha minimum to focus on wildfires that escaped initial attack and that were mapped with sufficient accuracy to evaluate if fuel breaks held or breached. Wildfire data sources included Monitoring Trends in Burn Severity (MTBS, 2021), the Geospatial Multi-Agency Coordination Group (GeoMAC, 2021), the Wildland Fire Decision Support System Interagency Fire History (WFDSS, 2021), and Wildland Fire Interagency Geospatial Services (WFIGS, 2021). We use wildfire perimeters from GeoMAC or WFDSS because they best captured the burned area boundary observed in post-fire aerial photography (NAIP, 2021). Final fire perimeters in GeoMAC and WFDSS typically rely on high-resolution aerial infrared mapping or field-based mapping conducted by local managers. To account for spatial coregistration errors and

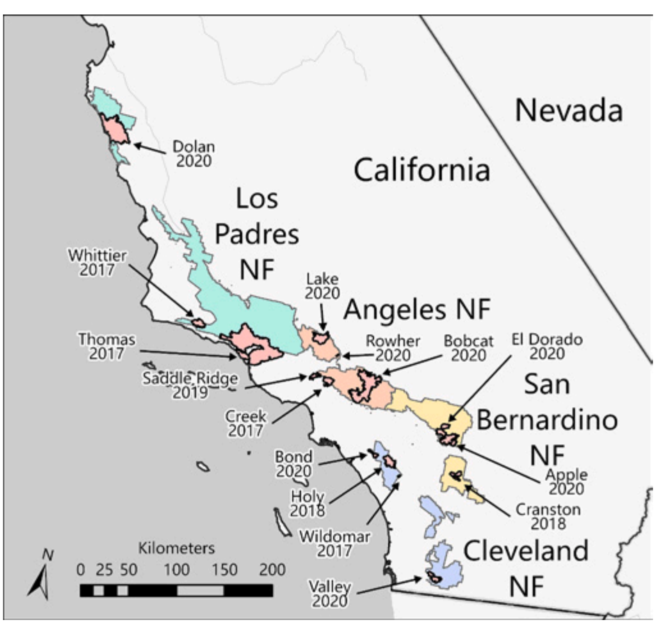

Fig. 1.. The study area includes the Angeles, Cleveland, Los Padres, and San Bernardino National Forests (NFs) in Southern California. Also depicted are the wildfires used in our analysis.

adjacent operational use of fuel breaks to assist in fire containment, we retained fuel breaks for our analysis if a wildfire was within 100 m of a fuel break's edge. In total, we retained 830 km of fuel breaks (16 % of 5150 km) that interacted with 15 wildfires.

We obtained constructed fireline data from the National Incident Feature Service (NIFC, 2021a) and incident-level data from the National Interagency Fire Center for 2017 only (NIFC, 2021b). We filtered the line event data to only include categories indicating fireline construction or use during an active incident to identify where fire suppression leveraged fuel breaks (Gannon et al., 2023). This included fireline feature categories such as 'completed dozer line', 'completed hand line', and 'road as completed line' (see Appendix A, Table A1 for a complete list). Though we acknowledge there were likely unrecorded fireline, we made no attempts to reconstruct missing records, nor do we assess unique fireline tactics (bulldozer, hand tools, burnout operations, etc.), or the intensity or extent of application. Roads without additional fuel break improvements were removed from our statistical analysis. We removed fuel breaks from our record if the fireline was more than 100 m away from the fuel break's edge. Of the 830 km of fuel break-wildfire interactions in our study period, 130 km (16 %) were known to be leveraged for fireline construction (Table 1).

2.3. *Sampling design*

We used a rasterization approach at 30-m resolution, consistent with the scale and projection of LANDFIRE spatial products (LANDFIRE, 2016), where the center of each pixel containing the centerline of a leveraged fuel break was converted to a sample point to develop our data frame. We then overlaid these sample points with final fire perimeter to determine if each point successfully stopped fire progression or had burned over as a failure (Fig. 2). Sample points were a success if the edge of the fuel break fell within 100-m of the final fire perimeter (Fig. 2, blue points), and sample points within the interior of the final fire perimeter were a failure (Fig. 2, red points). Our complete data frame had 4996 successes and 4813 failures on 130 km of leveraged fuel breaks across 15 fires (Table 1).

2.4. *Day-of-burning*

We compiled start and end dates for each fire from fire perimeter data sources (section 2.2.2), incident status summary reports (ICS-209, 2021), and the Spatial Wildfire Occurrence Data (Short, 2021). We used these dates in combination with a day-of-burning algorithm developed by Parks (2014). This algorithm utilized fire MODIS and VIIRS satellite detections points that occurred within a range of 1000 m from the reported ignition point and within 5 days of the reported date range to reconstruct day-of-burning for each sample point. See Gannon et al. (2023) for additional details.

2.5. *Operational objectives*

We conducted an exploratory analysis of fire weather associations with success and failure to elucidate possible operational objectives other than stopping wildfire progression, which we then validated with independent sources. Site-specific operational objectives are not readily recorded but are known to respond to changing weather conditions, in some instances exploiting favorable or docile weather to increase the area burned (Young et al., 2020) by leveraging previous fire scars, fuel treatments or other features identified during pre-season planning (Brugger, 2017; Welsh, 2017). That is, observed breaches of leveraged fuel breaks under docile weather conditions (i.e., WIND $\leq$1.75 m s^{-1}; WIND $\leq$2.00 m s^{-1} and VPD $\leq$ 2.4 kPa) may be related to tactical decisions made on the ground to allow fire spread to other control locations rather than a failure of the fuel break to support suppression efforts. We identified four wildfires where such instances were tagged for additional scrutiny. For example, on the western end of the 2017

Table 1
Number of observations for grass and shrub surface fuels.

		Grass			Shrub			Dataset		
Fire name - Year	Area (ha)	Success	Failure	Success rate	Success	Failure	Success rate	1	2	3
Balanced										
Apple - 2020	13,450	48	53	48 %	27	32	46 %	X	X	X
Bobcat - 2020	46,943	565	212	73 %	923	476	66 %	X	X	X
Bond - 2020	2703	–	–	–	41	33	55 %	X	X	X
Creek - 2017	6321	95	286	25 %	55	153	26 %	X	X	X
Dolan - 2020	50,395	66	36	65 %	65	82	44 %	X	X	X
El Dorado - 2020	9204	94	43	69 %	188	371	34 %	X	X	X
Holy - 2018	9318	26	16	62 %	199	64	76 %	X	X	X
Lake - 2020	12,545	278	164	63 %	707	643	52 %	X	X	X
Saddle Ridge - 2019	3561	5	5	50 %	–	–	–	X	X	X
Thomas - 2017	114,079	377	431	47 %	509	1158	31 %	X	X	X
Valley - 2020	6633	39	24	62 %	10	3	77 %	X	X	X
Subtotal		1593	1270	56 %	2724	3015	47 %			
Unbalanced										
Bond - 2020	2703	2	78	3 %	–	–	–	X	X	
Cranston - 2018	5395	144	4	97 %	156	21	88 %	X	X	
Rowher - 2020	262	97	15	87 %	49	0	100 %	X	X	
Saddle Ridge - 2019	3561	–	–	–	48	7	87 %	X	X	
Whittier - 2017	7451	24	0	100 %	118	0	100 %	X	X	
Wildomar –2017	351	17	0	100 %	24	0	100 %	X	X	
Subtotal		284	97	75 %	395	28	93 %			
Docile failures										
Bobcat - 2020	46,943	0	1	0 %	0	120	0 %	X		
Dolan - 2020	50,395	0	7	0 %	0	112	0 %	X		
Thomas - 2017	114,079	0	24	0 %	0	49	0 %	X		
Whittier - 2017	7451	0	7	0 %	0	83	0 %	X		
Subtotal		0	39	0 %	0	364	0 %			
Total		1877	1406	57 %	3119	3407	48 %			

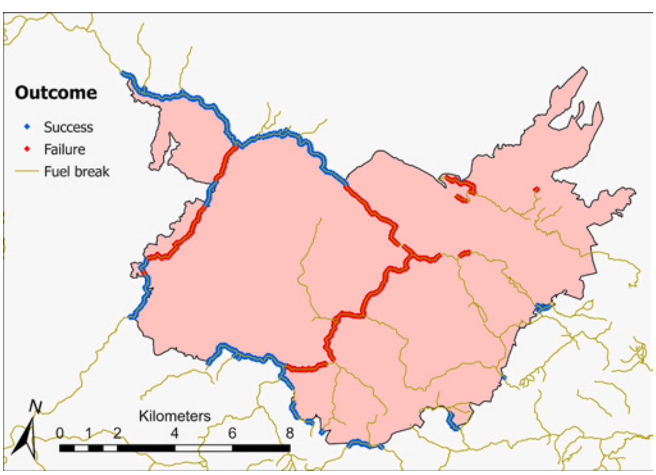

Fig. 2.. Fuel break sample points for the 2020 Lake fire, California. Leveraged fuel break sample points are displayed as either a success (blue) or failure (red). Samples were a success if the edge of the fuel break fell within 100 m of the final fire perimeter. Fuel breaks without reported fireline data were not considered in our analysis.

Thomas Fire, we observed fire progression during docile weather conditions that connected the active fire perimeter to the 2008 Tea and 2009 Jesusita fires (Inciweb, 2017). In total, 403 docile weather failure samples were identified for further considerations within our analysis (Table 1, docile failures). We do not attempt to disentangle the objective of slowing fire spread from stopping fire progression during moderate to extreme weather conditions.

2.6. Class balance

We also examined the balance between success and failure across two distinct surface fuel types for each fire: grass (T1, T2) and shrub (T4, T6, T7) as defined by Anderson (1982) and assessed by LANDFIRE (2016) (Table 1). Timber surface fuel models (T8 [n = 257], T9 [n = 329], T10 [n = 451]) and non-burnable fuel models (T99 [n = 111]) had limited observations and were not analyzed further. Improving the balance of success and failure reduces representation bias, which improves estimator consistency and model performance as assessed by the area under the receiver operating curve (AUC) (Zou et al., 2007; Salas-Eljatib et al., 2018). Using natural breaks in the distribution of success rates we defined a wildfire-fuel type combination as being adequately balanced if the success rate was between 20 % and 80 %. Accounting for the removal of docile weather failures led to the Whittier fire being classified as unbalanced for both the grass and shrub surface fuel types. The balanced sample seen in Table 1 was used to determine our model specifications (e.g., variable selection, model fit).

2.7. Variable selection

Variables attributing our data frame captured theoretical connections to the probability of stopping fire progression. From 38 potential variables (Appendix A, Table A2), we selected 13 using guidance from a least absolute shrinkage and selection operator (lasso) procedure and a causal Directed Acyclic Graph (cDAG) (Table 2). Lasso techniques fit a series of normalized models that can assist in the elimination of irrelevant variables through the utilization of penalty coefficients (Tibshirani, 1996). Causal DAGs are mathematically grounded flow charts that depict causal pathways and help visualize the interplay between potential variables and the model outcome to evaluate sources of bias when assessing how to best estimate least bias causal effects (Pearl, 1996; Greenland and Pearl, 2006; Lübke et al., 2020).

We categorized our selected variables into focal exposures, competing covariates, or confounding covariates as depicted in Fig. 3A through 3C and Fig. 4. Focal exposures represent the primary variables of interest (Fig. 3A) and are assumed to have no causal relationships among themselves or with competing covariates, with variable groupings in Figs. 3 and 4 acknowledging constrained or weak causal relationships. We included two focal exposures that captured 24-h average

Table 2
A list of variables used in our analysis, units, temporal and spatial scales, and data source.

Covariates	Units	Scale		Source
		Temporal	Spatial	
Focal exposures				
Vapor pressure deficit (VPD)	kPa	Daily average	4 km	gridMet (Abatzoglou, 2013)
10-m WIND speed	m s^{-1}	Daily average	4 km	gridMet (Abatzoglou, 2013)
Fuel break WIDTH	m	N/A	30 m	(Gannon et al., 2023)
Fuel break CONDITION	1 to 5 1 = barely noticeable to 5 = freshly maintained	N/A	30 m	(Gannon et al., 2023)
Competing covariates				
ANNUAL forb and grass production in the fuel break	kg ha^{-1}	Yearly average	30 m	Rangeland Analysis Platform (Jones et al., 2018)
PERENNIAL forb and grass production in the fuel break	kg ha^{-1}	Yearly average	30 m	Rangeland Analysis Platform (Jones et al., 2018)
Tree CANOPY COVER within 100 m radius	%	Circa 2016	30 m	(LANDFIRE, 2016)
Ground-based PERSONNEL	persons	Daily sum	Wildfire	(ROSS, 2021)
ENCOUNTER TYPE of 100 m fuel break segments	1 = BACKING; 2 = FLANKING; 3 = HEADING	Daily	4 km 30 m	gridMet (Abatzoglou, 2013) (Gannon et al., 2023)
AERIAL drop(s) within 100 m of the fuel break	0 = no; 1 = yes	N/A		(Stonesifer et al., 2021)
Confounding covariates				
Topographic position index (TPI) of fuel break with 200 m radius	N/A	N/A	30 m	(Gallant and Wilson, 2000; Weiss, 2001)
TREATMENT within 100 m of the fuel break	0 = no; 1 = yes	Previous 10 years	30 m	Forest Service Activity Tracking System (USDAFS, 2021)
WILDFIRE intersected the fuel break	0 = no; 1 = yes	Previous 10 years	30 m	Interagency fire history

fire weather on a daily time step: vapor pressure deficit (VPD) and 10-m WIND speed (Table 2; Fig. 4) (Mesinger et al., 2006; Srock et al., 2018). Other focal exposures captured pre-ignition planning and policies: fuel break WIDTH and CONDITION class (Table 2, Fig. 4). We assessed both covariates using pre-fire imagery from the National Agriculture Imagery Program (see Gannon et al., 2023 for additional details). Fuel break WIDTH was assigned in 5 m increments from 5 m to 50 m and in 10 m increments thereafter. Fuel break CONDITION was assigned a value from 1 to 5 with 1 being barely discernable from the surrounding vegetation, and 5 appearing freshly cut or maintained. If either fuel break WIDTH or CONDITION diverged for 800 m in length, we reassessed fuel break WIDTH and CONDITION.

Like focal exposures, competing covariates in our models (Fig. 3B) are assumed to have no causal relationships among themselves or with focal exposures, with variable groupings acknowledging constrained or weak causal relationships (Figs. 3 and 4). Competing covariates describing fuels included annual estimates of ANNUAL and PERENNIAL forb and grass production to capture the composition and structure of surface fuels (Jones et al., 2018) and tree CANOPY COVER to capture the connectivity of canopy fuels within and surrounding the fuel break (Table 2, Fig. 4). To ensure endogeneity stemming from reverse causality was not introduced by including an outcome of recent fire activity (e.g., expansion of invasive grasses following a wildfire) rather than a driver (e.g., high loading of invasive grasses prior to the fire), measures of ANNUAL and PERENNIAL production were included for the year prior to the observed wildfire (Gunasekara et al., 2008; Spiegler, 2022). Other competing covariates include ENCOUNTER TYPE (i.e., BACKING, FLANKING, HEADING), the application of AERIAL retardant or water drops by federal resources, and number of ground-based PERSONNEL assigned to a wildfire daily. We estimated ground-based PERSONNEL as the combined number of firefighters assigned to equipment (e.g., dozers) or crews (e.g., hand crew) according to the Resource Ordering and Status System (ROSS, 2021) for each day-of-burning. Days early in a fire incident without ROSS records were assigned five personnel to account for local resources. Daily PERSONNEL serve as a proxy for fire-wide operational complexity (defined as the quantity and diversity of potential fireline operations) that corresponds to wildfire-fuel break interactions. As operational complexity increases, latent inefficiencies (i.e., complexity costs) that are hard to measure using traditional techniques may emerge at the interface between various components of wildfire response (Gingrich and Metz, 1990; Hu et al., 2011; Oh et al., 2017). We seek to account for these inefficiencies but make no attempt to disentangle contributing factors.

Other selected variables accounted for confounding fixed effects (i.e., confounding exposures, Fig. 3C) that originate from a covariate being a common driver of one or more other covariates or exposures and the outcome of interest (Fig. 3C) (Babyak, 2009). For example, we used topographic position index (TPI) as an indicator of topographic setting (Table 2, Fig. 4), which could be confounding the effects of surface and canopy fuels, as well as the effects of fire weather through factors such as *meso* and topoclimate characteristics associated with valleys and ridgetops (Ackerly et al., 2010; Holden and Jolly, 2011). We fit TPI using a quadratic specification (i.e., *Pr(success) = f(TPI, TPI x TPI)*) to help distinguish between ridges (high TPI values) and valleys (low TPI values), both of which are often co-located with fuel breaks in Southern California (Murphy et al., 1967; Morandini et al., 2018; Gannon et al., 2023) and have been shown to coincide with fire perimeters (Holsinger et al., 2016). Other confounding exposures that were selected included indicator covariates for fuels TREATMENTS or WILDFIRES occurring within 10 years prior to the year-of-burning to account for recent reductions or manipulations in fuels adjacent to the fuel break (Table 2; Fig. 4). Excluding a confounder intermixes its effect with that of other focal or competing variables resulting in omitted variable bias (Babyak, 2009). See Fig. 4 for expected associations and Appendix B for additional information about variable development.

During variable selection we also sought to avoid four common causal pitfalls likely to introduce bias – mediator and collider variables, simultaneity (Fig. 3E through 3H), and selection bias. Mediators (e.g., observed fire behavior) reside on the pathway between an explanatory variable and the outcome, decomposing direct and indirect effects (Fig. 3E) (Pearl, 2001). To illustrate, the exploratory addition of fire radiative power diminished the effects of fire weather in our analysis, resulting in over-adjustment bias since the intent, in part, is to isolate the effects of fire weather (Etminan et al., 2021). Fire radiative power and other observed fire behavior metrics are also collider variables. In other words, fire radiative power is the common outcome of two of more drivers, such as fire weather and forest fuels (Lipsky and Greenland, 2022). The inclusion of observed fire behavior (*fb*) alongside weather (*fw*) and fuels (*f*) opens a backdoor pathway (Fig. 3F, dashed line) leading to an over specification bias (i.e., if $fw + f = fb$, then *fb* is already known). Extending this example, the inclusion of a covariate capturing

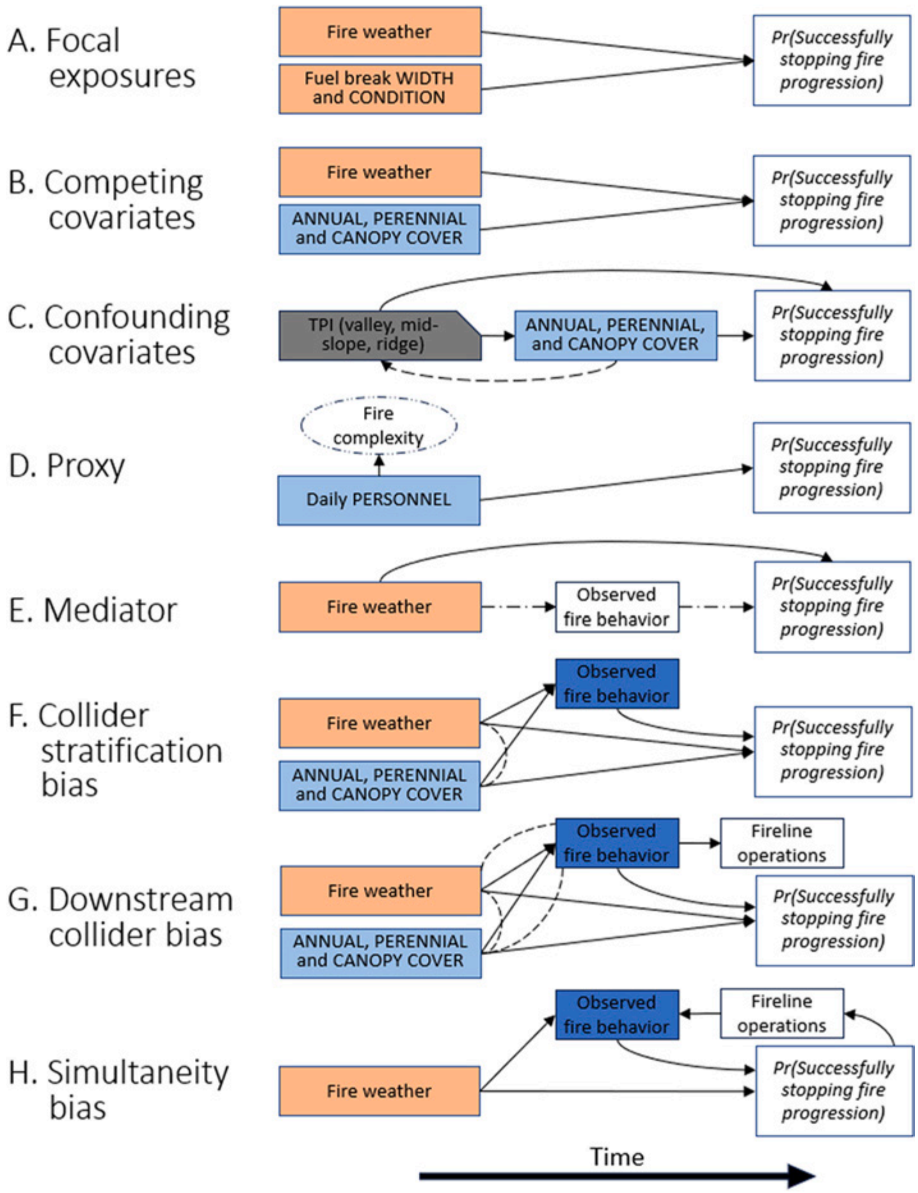

Fig. 3.. Individual components of a causal directed acyclic graph (DAG). **A** Focal exposures are the primary variables of interest. Black arrows (i.e., edges) represent causal pathways (variable X causes Y if Y depends on X for its value). **B** Competing covariates have a causal relationship with the outcome but are not causally related to focal exposures or competing covariates. **C** Confounding covariates are associated with other variable(s) of interest and the outcome, while assumed not to be the causal consequence of the predictor (i.e., fuels do not drive topography, black dashed arrow). **D** Proxy covariates represent variables that are not easily measured (dashed-dot-dot oval), necessitating the use of a proxy to adjust for the effect. **E** Mediator covariates reside on the causal pathway between an explanatory variable and the outcome, decomposing the total effects of an explanatory variables into direct (black arrow) and indirect effects (dash-dot black arrows). **F** Collider stratification bias introduced by an explanatory variable that is the common effect of two or more covariates that in turn affect the outcome, resulting in a back door pathway (dashed gray line). **G** Downstream collider bias introduced by a covariate that is downstream of a collider covariate (i.e., observed fire behavior informs fireline operations), resulting in an additional backdoor pathway (added dashed gray lines). **H** Simultaneity bias (circular arrows) introduced by an explanatory variable that is both a determinant and determined by the outcome.

fireline operations, which are in response to observed fire behavior, introduces downstream collider bias and opens an additional backdoor pathway (Fig. 3G, dashed lines). Additionally, observed fire behavior is a potential source of simultaneity bias (Fig. 3H) as it is both a determinant-of and determined-by the outcome (Wooldridge, 2019). While observed fire behavior affects the probability of successfully stopping fire progression, the probability of stopping fire progression also informs fire suppression, which affects observed fire behavior that in turn affects the probability of successfully stopping fire progressions. We also chose fireline construction as a condition for sample inclusion instead of as a covariate because the latter has the potential to introduce selection bias (Rohrer, 2018; Cummiskey et al., 2020). Due to the recent nascence of recording operational fireline data (circa 2017) we have low confidence it contains an accurate accounting of all constructed fireline, potentially biasing any counterfactual analysis that uses fireline as a covariate.

2.8. Statistical methods

Model specifications were determined with our balanced sample (Table 1). To address unwanted variation, we divided our fuel break dataset into two surface fuel model categories based on a 100 m circular neighborhood: grass (T1, T2) and shrub (T4, T6, T7) as defined by Anderson (1982). We used a multiplicative heteroskedastic probit

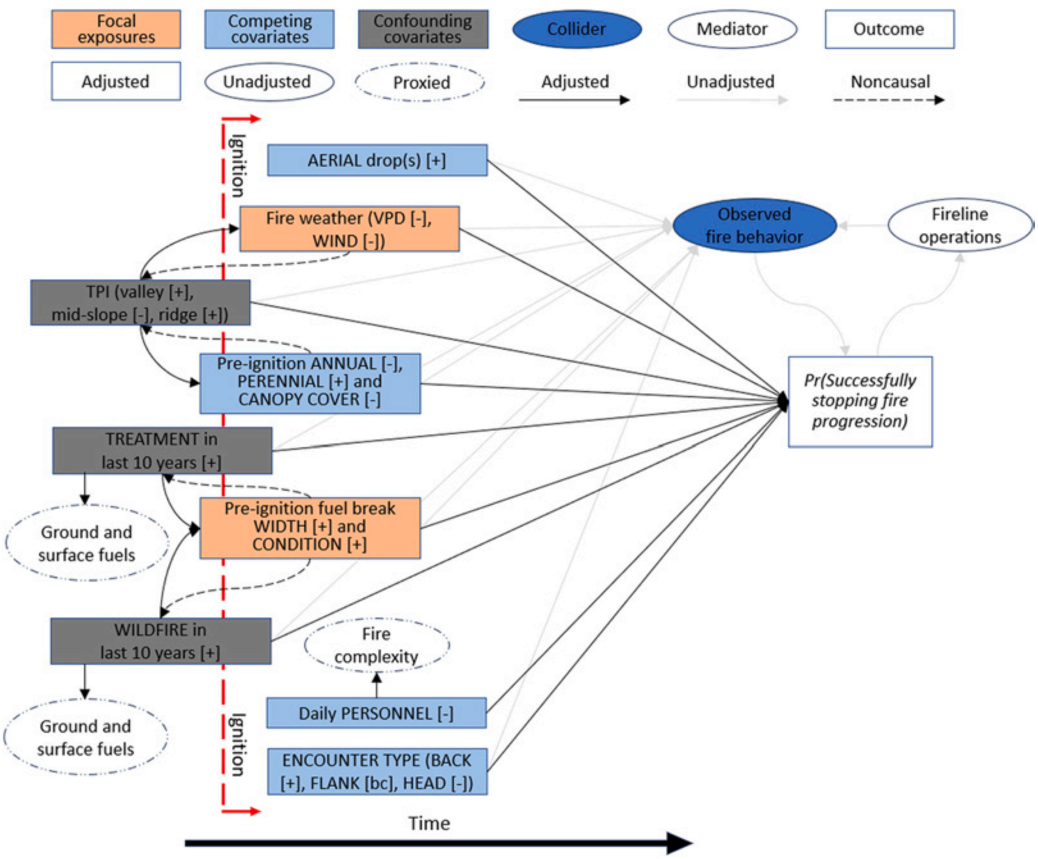

Fig. 4.. Causal directed acyclic graph (DAG) depicting assumed causal relationships among focal exposures, competing and confounding covariates, and the outcome (probability of leveraged fuel breaks successfully stopping fire progression). Square objects and black lines depict adjustments used in our analysis. Round objects and gray arrows were not adjusted for (i.e., unadjusted). Arrows represent assumed causal pathways. The gray broken arrow depicts a causal pathway that is assumed to be noncausal, a criterion of confounders (See Fig. 3 for additional details). Bracketed negative [-] and positive signs [+] represent expected associations with the outcome. Variable groupings acknowledge constrained or weak causal relationships.

model, which is a generalization of the maximum-likelihood probit model that allows the unexplained variance to depend on covariates to account for unequal variance in estimated outcomes. As such the probability that an observational outcome y_i takes on the value 1 is modeled as a nonlinear function of a linear combination of k independent variables $x_j = (x_{1j}, x_{2j}, \ldots, x_{kj})$ such that:

$$Pr\left(y_j = 1\right) = \Phi\{x_j b / exp(z_j \gamma)\}$$

where $\Phi()$ is the cumulative distribution function of a Gaussian distributed random variable with a mean of 0 and a variance that is a multiplicative function of m variables $z_j = (z_{1j}, z_{2j}, \ldots, z_{mj})$ (StataCorp, 2017). To model the outcome variance of the grass and shrub models, we used WIND and PERENNIAL herbaceous production, respectively (Harvey, 1976; Alvarez and Brehm, 1995). Sample points were clustered by their wildfire of origin to correct for non-independence originating from pseudoreplication, and geospatial locations (i.e., latitude and longitude) were included to account for spatial autocorrelation of sample points. Model fit was guided by accuracy assessments, with a particular focus on specificity and false positive rates, followed by an examination of AUC. Quadratic terms (i.e., $y = f[x, x^2]$) 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. When examining accuracy assessments during model fitting, false positive rates can be elevated when control covariates and effect modifiers are erroneously used to enhance variable significance through suppression effects (Brodeur et al., 2020). This principle helps guide the subversion of parameter significance as the primary metric used to determine model specifications (Diemer et al., 2021). Additional robustness checks were performed using a random subset of observations with consistent results using as few as 10 % of the balanced sample. See section 2.9 for additional details on AUC and accuracy assessments.

We fit three models with each of our nested datasets (Table 1): a complete model containing balanced, unbalanced, and docile failure samples (Model 1); a model including balanced and unbalanced samples (Model 2); and a model only including the balanced samples (Model 3). Statistical analysis was carried out using the hetprobit command in Stata 15 (StataCorp, 2017a). See summary statistics of model data in Appendix A, Table A3 and the variance inflation factor of each variable included in Appendix A, Table A4.

2.9. 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 heteroskedastic probit regression with model estimates ($\hat{y}$) and squared estimates ($\hat{y}^2$) as predictors of the outcome (i.e., success vs. failure). In each instance, model estimates ($\hat{y}$) were statistically significant predictors (*p-value* ≤ 0.05), while squared estimates ($\hat{y}^2$) were not (*p-value* > 0.05). This signifies a failure to reject the null hypothesis of no signs of incorrect specification of the link function.

Additionally, we evaluated each model's performance with 1) an in-sample assessment of the area under the receiver operator curve (AUC), and 2) an accuracy assessment (e.g., sensitivity, specificity, etc.)

Table 3
Accuracy assessment and area under the receiver operator curve (AUC) for multiplicative heteroskedastic probit models across the grass and shrub observations using three nested datasets.

	Grass			Shrub		
	Balanced Unbalanced Docile failures	Balanced Unbalanced	Balanced	Balanced Unbalanced Docile failures	Balanced Unbalanced	Balanced
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Sensitivity	0.838	0.841	0.855[†]	0.724	0.761[†]	0.728
Specificity	0.726	0.735	0.766[††]	0.759	0.781	0.795[††]
Positive predictive rate	0.803	0.813	0.821[†]	0.734	0.781[†]	0.762
Negative predictive rate	0.771	0.770	0.808[†]	0.750	0.761	0.764[†]
False positive rate	0.274	0.266	0.234[††]	0.241	0.219	0.205[††]
False negative rate	0.162	0.159	0.145[†]	0.276	0.240[†]	0.273
Accuracy	0.790	0.796	0.816[†]	0.742	0.771[†]	0.763
AUC	0.874	0.878	0.897[†]	0.829	0.859[†]	0.857
N	3283	3244	2863	6526	6162	5739

[†] Preferred model based on each criterion.
[††] Primary criteria used to select preferred model.

(Table 3). The AUC metric assesses how well model estimates are ranked across a range of classification thresholds (Salas-Eljatib et al., 2018; Zou et al., 2007). Across both surface fuel types, AUC showed modest variation among the three models, with the largest improvements resulting from the removal of unbalanced samples in the grass system and the removal of docile failures from the shrub system. Our accuracy assessments compared observed outcomes to model classifications based on a single classification threshold (i.e., if $Pr(success) \geq 0.5$ then outcome = success; otherwise, outcome = failure) (Parikh et al., 2008). The overall accuracy and sensitivity among the models reflected that displayed in AUC (Table 3). On the other hand, the removal of docile failures and unbalanced samples increased (i.e., improved) model specificity for both surface fuel types. We assessed model diagnostics and performance with Stata 15 (StataCorp, 2017a) using the linktest command to execute the Pregibon test, the roctab command to assess AUC, and confusion matrices to perform accuracy assessments.

3. Results

Across the nested datasets, our analysis suggests that increasing operational complexity of fire management (i.e., quantity and diversity proxied by PERSONNEL) reduced fire-wide effectiveness of leveraged fuel breaks with diminishing effects (e.g., Table 4, PERSONNEL *p-value* = 0.004, P x P *p-value* = 0.008). Likewise, directionality of coefficients did not vary across the nested datasets. When examining marginal effects of VPD and WIND, the central determinant used to examine model results (Fig. 5), we observed that the removal of docile failures did not substantially affect the estimated success rate in grass surface fuels, while in shrub surface fuels the average estimated success rate increased. We also observed that an increase in WIND decreased the estimated variance of the model error in grass surface fuels (Table 4, Model 3, *p-value* = 0.001), while an increase in PERENNIAL production increased the estimated variance of the model error in shrub surface fuels (Model 3, *p-value* < 0.001). In general, the balanced sample (Model 3) had the highest model specificity (Table 3, 0.766, 0.795), identifying the model with the greatest emphasis on firefighter safety. For this reason, we used Model 3 to examine marginal success rates of leveraged fuel breaks. Though probit models are commonly interpreted using marginal probabilities of success, we use the term "estimated success rate" to avoid the misapplication of our results. Our results should be considered alongside additional site-specific hazards to responder health and safety to avoid any misrepresentation of unique operational settings not captured within our model design.

Low model specificity (i.e., low ability to identify failures) or a correspondingly high false positive rate represents the largest threat to firefighter safety among our accuracy assessment metrics. Roughly 1-in-5 observed fuel break failures in our balanced dataset was falsely classified as a success in our model (i.e., false positive) (Table 3, grass 0.234; shrub = 0.205). In practical terms, some false positive classifications may represent locations with long evacuation times and, therefore, an elevated risk profile prohibiting continued staffing regardless of other considerations. Conversely, roughly 1-in-6 observed successes in the grass surface fuel type (Table 3, 0.145), and 1-in-4 in the shrub surface fuel type (Table 3, 0.273) were falsely classified by our model as failures (i.e., false negative), signifying potential missed opportunities for containment.

3.1. Focal exposures

Across both grass and shrub surface fuels, we observed that an increase in VPD (Table 4, grass *p-value* = 0.001; shrub *p-value* = 0.003) and WIND (grass *p-value* < 0.001; shrub *p-value* < 0.001) significantly decreased the estimated success rate, *ceteris paribus* (Fig. 5). Under the 50th percentile fire weather conditions represented in our sample, grass surface fuels had an estimated success rate (50 %) that was higher than shrub surface fuels (42 %) and more resilient to higher average wind conditions (Fig. 5, comparatively shallow contour slope). Referencing our sample, shrub surface fuels burned at higher VPD levels on average (grass = 2.1 kPa; shrub = 2.5 kPa), while grass surface fuels burned at higher WIND speeds on average (grass = 4.0 m s^{-1}; shrub = 3.3 m s^{-1}); both potentially contributed to grass fuel breaks appearing more resilient to higher WINDs. Further expanding the wildfire sample could reveal additional insights about influential conditions required to enable fire spread. In our sample, high VPD and WIND values rarely coincide (Fig. 5).

We observed effects unique to each surface fuel type when examining pre-ignition fuel break characteristics (Fig. 6). In grass surface fuels, increasing fuel break WIDTH (Fig. 6, left to right) significantly increased the estimated success rate (Table 4, *p-value* = 0.019), while an improvement in fuel break CONDITION (Fig. 6, top to bottom) only suggestively increased the success rate (Table 4, *p-value* = 0.086). Conversely, in shrub surface fuels we observed that an increase in fuel break WIDTH had no detectable effect (*p-value* = 0.957), while an improvement in its CONDITION significantly increased the estimated success rate (*p-value* = 0.006).

3.2. Competing covariates

Across both grass- and shrub-dominant fuel breaks, we observed that an increase in ANNUAL forb and grass production (Table 4, grass

Table 4

Coefficients for multiplicative heteroskedastic probit models for the grass and shrub surface fuels using three nested datasets. WIND and PERENNIAL were used to model the variance of the outcome for the grass and shrub models, respectively. *p*-values in parentheses.

	Grass						Shrub					
	Balanced Unbalanced Docile failures		Balanced Unbalanced		Balanced		Balanced Unbalanced Docile failures		Balanced Unbalanced		Balanced	
Outcome	Model 1		Model 2		Model 3		Model 1		Model 2		Model 3	
VPD	−0.428	***	−0.459	***	−0.572	***	−0.616	*	−0.834	**	−0.910	**
	(<0.001)		(<0.001)		(0.001)		(0.048)		(0.006)		(0.003)	
WIND	−0.226	***	−0.260	***	−0.248	***	−0.252	*	−0.426	***	−0.476	***
	(<0.001)		(<0.001)		(<0.001)		(0.027)		(<0.001)		(<0.001)	
WIDTH	0.00236	**	0.00235	**	0.00214	*	0.00144		6.55E-04		0.00014	
	(0.005)		(0.006)		(0.019)		(0.499)		(0.771)		(0.957)	
CONDITION	0.151	*	0.162	*	0.0978	#	0.294	**	0.329	**	0.289	**
	(0.014)		(0.017)		(0.086)		(0.001)		(0.003)		(0.006)	
ANNUAL (A)	−4.31E-04	**	−5.10E-04	**	−5.33E-04	**	−7.16E-04	***	−9.21E-04	***	−8.89E-04	***
	(0.004)		(0.006)		(0.008)		(<0.001)		(<0.001)		(<0.001)	
A x A	3.14E-08		5.59E-08		9.86E-08							
	(0.608)		(0.388)		(0.117)							
PERENNIAL	1.22E-05		-1E-05		−8.4E-05	*	1.08E-04		1.65E-04		2.52E-04	
	(0.834)		(0.868)		(0.045)		(0.640)		(0.534)		(0.420)	
CANOPY COVER (CC)	−0.0154	*	−0.0142	#	−0.0121	#	0.00122		0.0132		0.0182	
	(0.050)		(0.060)		(0.081)		(0.928)		(0.273)		(0.138)	
CC x CC							−6.77E-04	**	−0.00101	***	−0.00104	***
							(0.007)		(<0.001)		(<0.001)	
PERSONNEL (P)	−1.85E-04		−2.39E-04		−0.00048	**	−8.83E-04	**	−0.00130	*	−0.00138	#
	(0.144)		(0.119)		(0.004)		(0.007)		(0.014)		(0.057)	
P x P	1.52E-08		2.35E-08		4.74E-08	**	1.03E-07	*	1.36E-07	*	1.45E-07	#
	(0.277)		(0.180)		(0.008)		(0.012)		(0.028)		(0.064)	
FLANKING	0.178		0.190		0.172		−0.323		−0.430		−0.350	
	(0.186)		(0.218)		(0.113)		(0.381)		(0.525)		(0.686)	
HEADING	0.269	*	0.293		0.249	*	−0.293		−0.460		−0.409	
	(0.030)		(0.054)		(0.035)		(0.428)		(0.504)		(0.642)	
AERIAL	0.363	**	0.387	**	0.291	*	0.875	*	0.729	*	0.741	*
	(0.008)		(0.007)		(0.013)		(0.011)		(0.019)		(0.020)	
TPI	−0.0183	**	−0.0211	**	−0.0135	#	−0.0139		−0.0169	#	−0.0135	
	(0.002)		(0.003)		(0.052)		(0.166)		(0.100)		(0.205)	
TPI x TPI	4.78E-04	***	5.48E-04	***	4.28E-04	*	2.13E-04		2.37E-04		2.45E-04	
	(<0.001)		(<0.001)		(0.031)		(0.329)		(0.264)		(0.272)	
TREATMENT	0.366	**	0.348	*	0.257	*	0.713	**	0.828	***	0.832	***
	(0.009)		(0.020)		(0.034)		(0.006)		(<0.001)		(<0.001)	
WILDFIRE	0.726	**	0.829	**	0.646	*	0.961	*	1.172	*	1.351	*
	(0.003)		(0.008)		(0.037)		(0.046)		(0.036)		(0.021)	
LATITUDE	6.09E-06	*	6.13E-06	*	3.2E-06	#	4.96E-06		−9.7E-07		3.12E-07	
	(0.041)		(0.044)		(0.085)		(0.336)		(0.898)		(0.977)	
LONGITUDE	4.72E-06	#	4.84E-06		2.83E-06		−5.7E-07		−4.1E-06		−1.5E-07	
	(0.066)		(0.069)		(0.171)		(0.909)		(0.592)		(0.988)	
constant	6.739	*	6.848	*	4.674	**	13.64	**	8.868		5.842	
	(0.018)		(0.018)		(0.002)		(0.009)		(0.181)		(0.529)	
Outcome variance												
WIND	−0.183	***	−0.169	***	−0.226	***						
	(<0.001)		(<0.001)		(0.001)							
PERENNIAL							2.59E-04		4.01E-04	*	5.33E-04	***
							(0.106)		(0.015)		(<0.001)	
N	3283		3244		2863		6526		6162		5739	

# $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

ANNUAL *p-value* = 0.008, A x A *p-value* = 0.117; shrub *p-value* < 0.001) significantly decreased the estimated success rate. In grass-dominant fuel breaks, we also observed that an increase in PERENNIAL forb and grass production was associated with a significant decline in the estimated success rate (*p-value* = 0.045), though with limited practical importance (Fig. 7, top to bottom). Conversely, in shrub-dominant fuel breaks an increase in PERENNIAL forb and grass production was associated with an insignificant increase in estimated success rates (*p-value* = 0.420). However, these gains were quickly overwhelmed when tree CANOPY COVER exceeded 20 % and estimated success rates began to significantly decline (CANOPY COVER *p-value* = 0.138, CC x CC *p-value* < 0.001), capturing a nonlinear effect (Fig. 7, left to right). In grass fuel breaks we observed that an increase in tree CANOPY COVER suggestively decreased estimated success rates linearly (*p-value* = 0.081).

In grass surface fuels, we observed that an increase in ground-based PERSONNEL significantly decreased the estimated success rate (Table 4, PERSONNEL *p-value* = 0.004), with a diminishing rate of decline as PERSONNEL increased (P x P *p-value* = 0.008). There was only suggestive evidence of this diminishing decline in shrub surface fuels (PERSONNEL *p-value* = 0.057, P x P *p-value* = 0.064). We estimate fuel break success at 75 %, 61 %, and 49 % in grass surface fuels and 70 %, 53 %, and 39 % in shrub surface fuels for 500, 1000, and 1500 PERSONNEL under 50th percentile weather, respectively (Fig. 8, left to right).

We found diverging effects of ENCOUNTER TYPE when comparing surface fuel types. Unexpectedly, we found that the success rate in grass surface fuels was significantly lower when a wildfire was BACKING compared to when it was HEADING (Table 4, *p-value* = 0.035). In the shrub surface fuels, there were no detectable signs of significance in ENCOUNTER TYPE, though success improved during BACKING fires

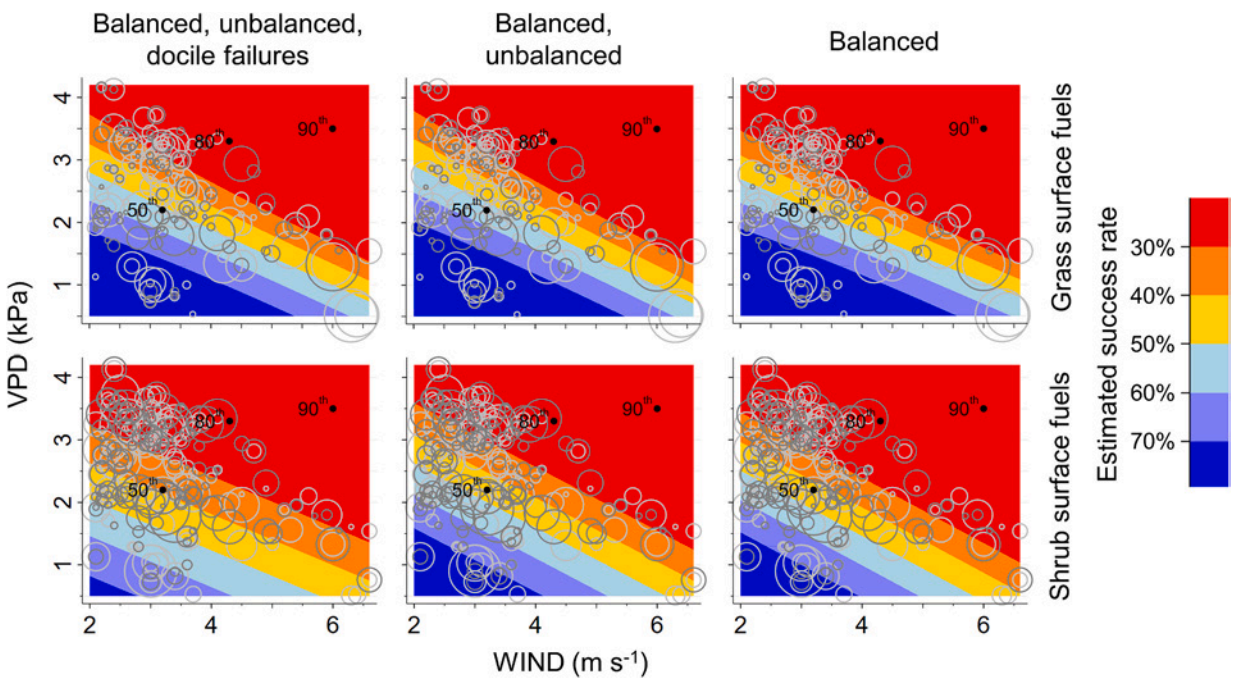

Fig. 5.. Estimated marginal success rates for grass (top) and shrub (bottom) surface fuels over a range of vapor pressure deficit (VPD) and WIND values using our nested datasets (Table 1). We observed that an increase in VPD and WIND decreased the success rate across datasets and surface fuel types. Bubble plots represent the distribution of weather across the complete datasets where the size of the bubble corresponds to the relative amount of data co-occupying that space. Light gray bubbles represent success, and dark gray bubbles represent failure. 50th, 80th and 90th point locations represent percentile weather conditions in our sample. Estimated success rates were assessed for HEADING fire with the effects of WILDFIRE, TREATMENT and AERIAL removed.

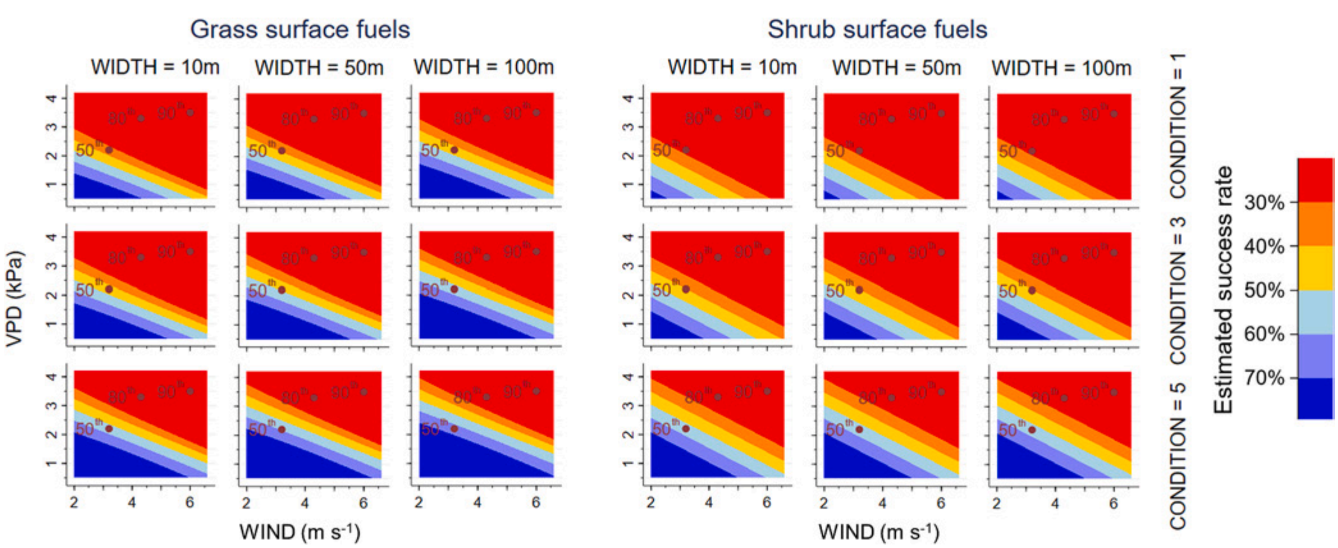

Fig. 6.. Estimated marginal success rates for grass (left) and shrub (right) surface fuels over a range of vapor pressure deficit (VPD), WIND, WIDTH and CONDITION using our balanced dataset (Table 1). We observed that an increase in WIDTH (left to right) increased the success rate in grass surface fuels, while an increase in CONDITION (top to bottom) increased the success rate across both surface fuel types. 50th, 80th and 90th point locations represent percentile weather conditions in our sample. Estimated success rates were assessed for HEADING fire with the effects of WILDFIRE, TREATMENT and AERIAL removed.

compared to FLANKING and HEADING fires (Appendix A, Fig. A1).

We observed that AERIAL retardant or water drops significantly increased the estimated success rate of fuel breaks across surface fuel types (Table 4, grass *p-value* = 0.013; shrub *p-value* = 0.020). We estimate the success rate increases from 48 % to 63 % in grass surface fuels and from 42 % to 60 % in shrub surface fuels when AERIAL drops occurred at our 50th percentile weather conditions for both WIND and VPD (Appendix A, Fig. A2). This effect has little to no practical significance at our 80th percentile weather conditions with estimated success rates increasing from 7 % to 17 % in grass surface fuels and from 13 % to 25 % in shrub surface fuels. Examining summary data, 73 % of AERIAL drops were performed when WIND was below the 50th percentile, and 72 % were performed when VPD was above the 50th percentile, signifying a higher relative use of AERIAL drops during arid conditions when winds are relatively calm.

3.3. Confounding covariates

Our estimated rate of success was higher in valleys and ridgetops. In grass and shrub surface fuels, respectively, our estimated success rate

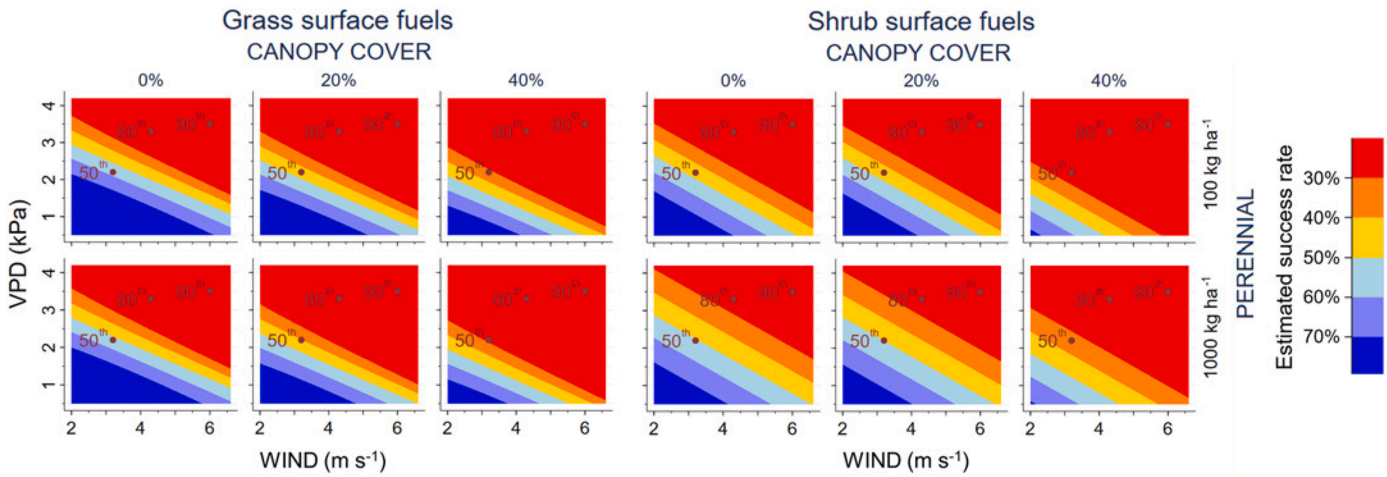

Fig. 7.. Marginal estimated success rates for grass (left) and shrub (right) surface fuels over a range of vapor pressure deficit (VPD), WIND, CANOPY COVER, and PERENNIAL forb and grass production using our balanced dataset (Table 1). We observed that an increase in CANOPY COVER (left to right) decreased the success rate across both surface fuel types, while an increase in PERENNIAL (top to bottom) increased the success rate in shrub surface fuels. Estimated success rates were assessed for HEADING fire with the effects of WILDFIRE, TREATMENT and AERIAL removed.

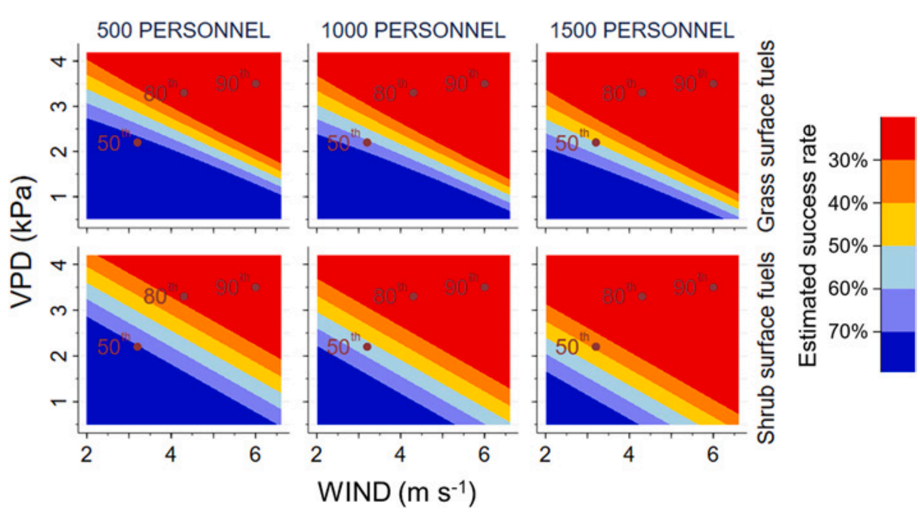

Fig. 8.. Marginal estimated success rates for grass (top) and shrub (bottom) surface fuels over a range of vapor pressure deficit (VPD), WIND, and PERSONNEL using our balanced dataset (Table 1). We observed that an increase in PERSONNEL (left to right) decreased the success rate across both surface fuel types, with the rate of decline slowing at PERSONNEL increased. 50^{th}, 80^{th} and 90^{th} point locations represent percentile weather conditions in our sample. Estimated success rates were assessed for HEADING fire with the effects of WILDFIRE, TREATMENT and AERIAL removed.

declined from 59 % and 45 % to 45 % and 42 % when comparing valleys (TPI = −8) to hilltops and slopes (TPI = 19) (Appendix A, Fig. A3), which are commonly represented within the data (50th percentile TPI: grass = 19; shrub = 25). However, estimated success rates recovered on ridgetops (TPI = 40) with grass surface fuels, reaching levels equivalent to those observed in valleys (Table 4, TPI *p-value* = 0.052; TPI x TPI *p-value* = 0.031).

Lastly, we found that the estimated success rate increased significantly when fuel breaks were adjacent to a fuels TREATMENT (Table 4, grass *p-value* = 0.034; shrub *p-value* < 0.001) or interacted with a WILDFIRE (grass *p-value* = 0.037; shrub *p-value* = 0.021) that had occurred within the previous 10-years. Under our 50th percentile weather conditions, estimated success rates in grass surface fuels increased from 50 % to 61 % following TREATMENT, and to 80 % following WILDFIRE (Appendix A, Fig. A4). Similarly, estimated success rates in shrub surface fuels increased from 42 % to 61 % following TREATMENT, and to 72 % following WILDFIRE.

4. Discussion

The development and implementation of fuel break networks remains a priority in Southern California where they have a history of supporting fire suppression efforts (Murphy et al., 1967; Green, 1977) and continue to be a focus of investment. Of note, we found evidence of fire-wide fuel break effectiveness diminishing when suppression operations were complex. When compared to previous research in our study area, our observed fuel break success rates were relatively high, ranging from 26 % to 100 % for individual fires (e.g., 22 to 47 % [Syphard et al., 2011a], 8 % to 82 % [Gannon et al., 2023]), likely due to our focus on leveraged fuel breaks (i.e., 84 % of fuel breaks that interacted with wildfire did not have constructed fireline reported and were removed from our analysis). Consistent with previous research, we found that daily weather metrics helped delineate conditions conducive to fuel break success from dry, windy conditions when fuel breaks often fail (e.g., Gannon et al., 2023; Ortega et al., 2024). Likewise, fuels break design, maintenance, and topographic location have been found to be important components of fire containment in prior research (e.g., Holsinger et al., 2016; Gannon et al., 2023). For example, ridgelines have been shown to act as natural fuel breaks where fire progression slows as it transitions downhill (Povak et al., 2018), and fire line constructed in valleys have been shown to benefit from road access and other natural barriers such as rivers (Narayanaraj and Wimberly, 2011; Holsinger et al., 2016; O'Connor et al., 2017). Prior research has also shown fuels composition and structure (e.g., Holsinger et al., 2016; Gannon et al., 2023), and site-specific components of operational complexity to be important indicators of success (e.g., suppression difficulty index; O'Connor et al., 2017; Rodríguez et al., 2020). In addition to our findings being consistent with prior research, the tracking of fire suppression operations allowed us to assess how often fuel breaks were leveraged during fireline construction in Southern California and under what conditions these efforts can be expected to successfully stop fire progression.

We found that on an annual basis, approximately 4 % of the fuel break network in our sample interacted with large wildfires between 2017 and 2020. Of those interactions, approximately 16 % were leveraged during fireline construction. In other words, it was reported that 0.6 % of the network was leveraged annually across the Southern California National Forests with a 56 % success rate. From these observations, our model estimates that fuel breaks are successful 50 % of the time (i.e., model adjusted), with a standard deviation of 32 %, suggests considerable variation based on unique circumstances. For instance, the estimated success rate for a 10-m wide fuel break against a HEADING fire with the effects of TREATMENTS (=0), WILDFIRES (=0), and AERIAL drops (=0) removed averaged 22 % and 20 % for grass and shrub surface fuels, *ceteris paribus*. Using this as a reference point, increasing fuel break WIDTH to 100 m would improve the success rate to 30 % in grass fuels, while having no effect in shrub fuels. On the other hand, improving the CONDITION of a 10-m wide fuel break from 1 (barely noticeable) to 5 (freshly maintained) would increase the estimated success rates to 40 % and 45 % in grass and shrub surface fuels. This reinforces the importance of leveraging recent fuel break maintenance when constructing fireline (Gannon et al., 2023). However, at elevated fire weather conditions (80th percentile of our sample: VPD = 3.3, WIND = 4.3), fire suppression operations deployed on freshly maintained, 100-m wide fuel breaks would have estimated success rates of 16 % and 20 % for grass and shrub surface fuels, while at docile weather conditions (20th percentile: VPD = 1.5, WIND = 2.5) estimated success rates would increase to 85 % and 76 %. Under these docile weather conditions, a tree CANOPY COVER of 50 % and an annual forb and grass production of 1000 kg ha^{-1} would reduce estimated success rates to 64 % and 46 % in grass and shrub surface fuels. These scenarios highlight the importance of undertaking a careful accounting of fuel break performance alongside forest restoration programs designed to reduce fire intensity and improve post-fire conditions (Prichard et al., 2020; Baijnath-Rodino et al., 2023; Lemons et al., 2023), particularly in a changing climate that has increased fire danger (Abatzoglou et al., 2021; King et al., 2024).

When analyzing the outcome of complex operations like wildfire management, the practical differences between success and failure should be acknowledged. In retrospect, and because we are only analyzing leveraged fuel breaks, successes have a higher likelihood of being staffed during wildfire interactions. Conversely, leveraged fuel break that failed have a higher likelihood of not being staffed during wildfire interactions due to a high potential for firefighter entrapment (Lahaye et al., 2018; Page et al., 2019) that could result from the unavailability of escape routes (Fryer et al., 2013; Campbell et al., 2017; Campbell et al., 2019), safety zones (Butler and Cohen, 1998; Dennison et al., 2014; Campbell et al., 2017; Campbell et al., 2022a), and lookout locations for fire management personnel to warn of an approaching wildfire or the intensification of local fire weather (Mistick et al., 2022). Other potential reasons for failures not being staffed include an *in situ* probability of success being too low to justify continued effort (Alexander et al., 2015), fire behavior modeling demonstrating a high likelihood of fire overcoming suppression activities (McDaniel, 2007), or the intentional hardening of fuel breaks to slow fire spread in advance of a wind driven fire (i.e., a failure in stopping progression by design). Each of these components can be further complicated by an extended and complex fire front (e.g., high perimeter to area ratio) capable of exponential fire growth (Juang et al., 2022) across multiple jurisdictions and ecoregions (Nowell et al., 2022; Jones et al., 2024). A greater incorporation of firefighter evacuation and safety metrics, as well as site-specific components of operational complexity (O'Connor et al., 2017), could result in meaningful gains in future modeling efforts by accounting for dynamic and complex conditions that inform *in situ* fire suppression decisions.

Under our current model specification, we account for fire-wide operational complexity with the daily PERSONNEL available for fireline construction, where we observed a negative association with the estimated success rate. One possible explanation for this decline are the emergent costs associated with operationally complex systems (Hu et al., 2011). An increase in personnel not only signifies a forecasted intensification of fire weather and risk induced resource ordering (Bayham et al., 2020), but also the emergence of complexity costs that materialize at the interface between various scales and components of potential fireline construction that are increasingly diverse and uncertain (Steelman and Nowell, 2019; Bayham et al., 2022; Essen et al., 2023; Jones et al., 2024). These circumstances may result in inefficiencies stemming from decision delays when weighing tradeoffs in a state of information overload, or from bounded rationality or heuristics as a means to deal with operational complexity, where the goal is to asses alternative strategies and tactics until arriving at a satisfactory set of actions that meet or exceed minimal criteria thresholds (Kahneman, 2003; Rosser and Rosser, 2014; Rapp and Nelson, 2024). From our model results, it may also be inferred that real time mitigation of operational complexities combined with sufficient or ample resource availability on large fires results in excess fireline productive capacity (Hand et al., 2017; Katuwal et al., 2017), inherently leading to an inefficient or unwarranted use of resources as supply exceeds demand (Thompson et al., 2023). In other instances personnel may not have the heavy equipment (e.g., engines and dozers) needed to efficiently construct firelines (Katuwal et al., 2016). Herein, an increase in PERSONNEL (i.e., operational complexity) led to a diminishing decline in the rate of successfully stopping fire progression (Fig. 8, Table 4), meaning complexity costs increased at a greater pace when complexity was low and slowed when complexity was high. Future research should prioritize exploring both site-specific and broader fire-wide operational complexities to advance our understanding of wildfire management.

In addition to considering operational complexity and associated complexity costs to improve model inference, we also examined site-specific management objectives (i.e., screening for docile failures) and class balance to improve model performance. The largest improvements in AUC, overall accuracy and model sensitivity occurred when removing unbalanced samples from our grass surface fuels and docile failures from shrub surface fuels (Table 3). Additionally, these removals improved model specificity and therefor firefighter safety considerations in both surface fuel systems, suggesting removed observations may have originated from a different data-generating process than the one under investigation in this study. In the case of docile failures, firefighters may be allowing a wildfire to pass through a fireline until reaching more favorable control locations, potentially facilitated with firing operations. Illuminating an additional data-generating process still embedded in our grass model, we also see personnel taking advantage of prevailing winds during cool, humid periods to harden the holding capacity on the heal of the fire, which manifests as a high relative proportion of backing fire failures (Appendix A, Fig. A1; median BACKING failure: VPD = 1.3 kPA; WIND = 6.0 m s^{-1}; median BACKING success: VPD = 2.2 kPA; WIND = 2.3 m s^{-1}). Alternatively, some of these failures may result from shifting Santa Anna winds reversing fire growth directionality. However this is unlikely given low VPD values coinciding with backing fire failures (median VPD = 1.3 kPa), and high VPD values that commonly coincide with Santa Ann winds resulting from cool, dry desert air compressing and subsequently warming as winds moves downslope towards the Pacific Coast (Westerling et al., 2004).

Though our models perform well and offer several insights, we also acknowledge several data constraints that if alleviated, could improve model performance and field application (Abdelraouf et al., 2024). Future efforts can seek to optimize the spatial and temporal scales of input data needed to capture underlying mechanisms of fire behavior and suppression. Improved tracking of invasive annual grass production and other fine fuels (Dahal et al., 2022) alongside the delineation of diurnal and nocturnal fire growth periods would capture unique components of fire weather and corresponding fire management operations (Mandel et al., 2011; Chen et al., 2022; Cardil et al., 2023; Shamsaei et al., 2023). Accounting for downslope wind events (e.g., sundowner winds of Santa Barabara area) and other mesoscale wind dynamics would help capture extreme fire behavior (Zigner et al., 2020; Carvalho et al., 2024). Standardizing spatiotemporal tracking of fire management personnel and equipment across agencies would enable an examination of marginal gains from additional resources across a wide variety of tasks and procedures (Sullivan et al., 2020). Standing up a data warehouse of aerial drops from both federal and state aircraft would allow for a better accounting of air resources supporting ground-based fireline operations (Stonesifer et al., 2021; Duncombe, 2023; Ortega et al., 2023). And finally, a careful accounting of fireline tactics inclusive of *in situ* fuel break construction and a daily accounting of fire management objectives would strengthen counterfactual modeling efforts including the use of structural equation modeling and regression discontinuity designs (Pearl, 2011; Cattaneo and Titiunik, 2022; Thompson and Carriger, 2023).

Despite these suggestions to improve our understanding of fuel break and fireline effectiveness, a limited focus on existing linear features does not address fire behavior and suppression challenges associated with spotting or running crown fires. Nor does it comprehensively inform the optimization of fuel break implementation or maintenance across the landscape (Massada et al., 2011; Aparício et al., 2022; Ager et al., 2023; Carrasco et al., 2023). Fuel break networks should be part of a holistic land management strategy focused on reducing unwanted fire behavior and effects (Beyers and Wakeman, 1997; Hersey and Barros, 2022; Fernández-Guisuraga and Fernandes, 2024), while also enabling the strategic application of fire suppression activities inclusive of allowing low- to moderate- severity wildfire to reduce fuels in tactically advantageous locations that can be leveraged during future fire suppression efforts. Long term strategic reductions in hazardous fuels should become an increasingly useful tool in advance of synchronous wildfire events that are currently rare (Fig. 5, 80th and 90th percentiles), but projected to increase in the future (Abatzoglou et al., 2021). Like fuel breaks, potential operational delineations (PODs) advanced by the USDA Forest Service represent an adaptive framework that can be used to foster fire-induced risk reductions through an integration of fire and fuels planning on a landscape scale (Thompson et al., 2022; Buettner et al., 2023; Neukirich et al., 2023). If socially and politically accepted, advancements in landscape planning have the potential to foster proactive land management approaches intended to reduce negative effects of future wildfires (Dunn et al., 2020).

Continued investments in the expansion, maintenance, and evaluation of fuel break networks should be coupled with proactive policies that promote a sustained reduction in fire risk. The national debate over the value of fuel breaks is likely to intensify as climate change continues to drive longer, more severe fire seasons with an increased frequency of severe fire weather conditions (Abatzoglou et al., 2021; Higuera and Abatzoglou, 2021; King et al., 2024). As agencies consider investing in fuels breaks as part of a comprehensive fire management strategy, it is also crucial to recognize fuel breaks have many roles beyond reducing hazardous fuels and provided access for suppression operations. Fuel breaks can function as supply drop zones, staging areas, evacuation routes, and strategic anchor points for planned ignitions. While this study focuses on their traditional role, exploring additional benefits of fuel breaks would provide a more complete understanding of their value.

5. Conclusions

We developed a fuel break effectiveness framework to help assess the historic and ongoing use of fuel breaks in Southern California. Our analysis suggests the operational complexity of fire management significantly effects fire-wide effectiveness of leveraged fuel breaks. After removing the effects of past treatments, wildfires, and aerial applications, we estimated a 32 % increase in success rates for grass-dominant systems when comparing 10 m to 100 m widths. Likewise, when comparing barely noticeable to freshly maintained fuel breaks success rates increased by 80 % and 125 % for grass and shrub systems. Furthermore, when analyzing the combined effectiveness of a freshly maintained 100-m wide fuel breaks, we estimated a 400 % increase in the success rate during docile weather condtions (20th percentile: VPD = 1.5, WIND = 2.5) when compared to elevated weather (80th percentile: VPD = 3.3, WIND = 4.3). Additionally, we observed that limiting canopy cover encroachment on linear fuel breaks, and the reduction or prevention of annual forbs and grasses increased estimated success rates. Though our results could help with the efficient allocation of scarce fire management resources, a narrow focus on individual fuel breaks is insufficient for addressing complex wildfire challenges. Instead, a holistic land management approach is necessary to effectively reduce wildfire risk, considering factors like fuel loading and structure, fire behavior, suppression tactics, and the potential for increased fire activity in the future. Enhanced tracking of wildfire data could help catalyze the development of predictive models to inform fire management strategies and tactics.

CRediT authorship contribution statement

Jesse D. Young: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Erin Belval:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Funding acquisition, Data curation, Conceptualization. **Benjamin Gannon:** Writing – review & editing, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Yu Wei:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization. **Christopher Dunn:** Writing – review & editing, Funding acquisition, Conceptualization. **Bradley M. Pietruszka:** Writing – review & editing, Writing – original draft. **David Calkin:** Writing – review & editing, Supervision, Resources, Conceptualization. **Matthew Thompson:** Writing – review & editing, Conceptualization.

Declaration of competing interest

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Data availability

Data availability from the United States Forest Service, Forest Service Research Data Archive: https://doi.org/10.2737/RDS-2024-0058

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.forpol.2024.103351.

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