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Research article

Strategic application of wildland fire suppression in the southwestern United States

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ABSTRACT

Much of the western United States is experiencing longer fire seasons with an increased frequency of high-severity fires and fire risk. Fire managers in the southwestern United States have increased efforts to reduce fire risk by managing more fires to meet resource objectives (e.g. thin forests, reduce hazardous fuel loads, and restore the landscape). However, little is known about the situational circumstances and decision space that inform the strategic response to wildland fire. Using generalized and time-to-event modeling techniques, we examined how fire management decisions are reached in a context informed by weather, burning conditions, and subsequent fire behavior. Modeling results captured daily containment probabilities along a gradient from limiting natural conditions to suppression invoked containment. Results inform fire management decisions, future research efforts, and the simulation of wildland fires with resource objectives.

1. Introduction

The southwestern United States (Southwest) has a history of logging (Lang and Stewart, 1910), pulse germination (Pearson, 1950; Savage et al., 1996) and costly fire suppression that have contributed to abnormally dense forests (> 2000 trees ha^{-1} in some areas in northern Arizona) with high fuel loads (Covington and Moore, 1994). These hazardous fuels combined with an increased frequency of dry periods over longer, warmer fire seasons (IPCC, 2014; Jolly et al., 2015; Luce et al., 2016; Westerling et al., 2006; Westerling, 2016) have increased the aridity and fire risk of the landscape (Singleton et al., 2019; Williams et al., 2013, 2014). These conditions have played-out in such events as the 2002 Rodeo–Chediski Fire (200,000 ha (500,000 ac)), the 2011 Wallow Fire (220,000 ha (540,000 ac)), and the 2011 Las Conchas Fire (63,000 ha (156,000 ac)) (SIT-209, 2018).

In recent decades, wildland fire managers in the Southwest have increased their efforts to reduce fire risk by managing unplanned ignitions to achieve multiple resource objectives (henceforth managed fires). Allowing managed fires to thin forests, reduce hazardous fuel loads, and restore landscape resilience (Allen et al., 2002, 2011) can be an inexpensive management option that reduces future fire risk and size (Ager et al., 2017a, 2017b; Prichard et al., 2017; Riley et al., 2018; Thompson et al., 2016a, 2016b), while restoring frequent fire ecosystems (Huffman et al., 2017; Larson et al., 2013; North et al., 2012). Recent changes in wildland fire management that encourage incident commanders to use a wide range of strategies and tactics to achieve management objectives have facilitated the practice of managing unplanned ignitions (Thompson et al., 2016b). Specifically, the 2009 Guidance for Implementation of Federal Wildland Fire Management Policy (US DOI/USDA, 2009), divided fire management strategies into two subgroups; 1) protection objectives and 2) resource objectives. Fires dominated by protection objectives are commonly managed using a full suppression strategy, where the goal is to safely limit the spread of the fire (henceforth suppression fires). Managed fires dominated by resource objectives are often managed using the strategies of monitor, contain and confine, and point/zone protection.

A historic focus on suppressing fires to achieve protection objectives has led to a rich set of data on the circumstances that contribute to the containment of suppression fires (Finney et al., 2009; Flowers et al., 1983; O'Connor et al., 2017). These data were used by Finney et al. (2009) to develop a suppression containment model that is widely used as part of fire simulation systems (Finney et al., 2009, 2010) to prioritize fuel management investments (Ager et al., 2014; Wei et al., 2018), and assess wildland fire risk (Ager et al., 2017a, 2017b; Scott et al., 2013). However, there is less knowledge about the factors that influence the containment of fires that are being managed to meet resource objectives. For instance, what conditions trigger incident commanders to declare a managed fire versus a suppression fire and vice versa during a fire event? Understanding how suppression activities are used during managed fires would expand fire simulation capabilities for the full suite of fire management strategies, and enable additional studies of how managed fires can contribute to meeting a wide array of resource objectives (Barros et al., 2018; Riley et al., 2018).

To further inform wildland fire management policy and modeling,

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we studied suppression activities to disentangle strategic responses to daily fluctuations in fire risk and subsequent fire hazards in the Southwest. Fire hazard refers to the exceedance of an acceptable threshold of fire risk (Coder, 2013) driven by fire weather, topography (Scott et al., 2013), and hazardous fuels (Hardy, 2005). Specifically, we examined underlying factors of fire hazard that determine fire containment based on management objectives (i.e. protection v. resource) and corresponding strategic responses (i.e. full suppression v. monitor, contain and confine, and point/zone protection). Using samples of suppression fires managed for protection objectives, and managed fires managed for resource objectives, we:

1) Determined if the suppression containment model developed for suppression fires in the western United States (West) adequately explained the containment of suppression and managed fires in the Southwest.
2) Identified factors that affected the containment of managed fires and used this information to develop a probabilistic time-to-containment model for managed fires (henceforth the managed fire containment model).

We envision that this model can be incorporated into fire simulation software e.g. FSim, Finney et al. (2009, 2011) and used to study a wide range of issues concerning fire feedbacks and synergies between fuel management and fire suppression.

2. Data

2.1. Wildland fire data

To examine the underlying factors of wildland fire containment in the Southwest, we used publicly available SIT-209 reports to identify 323 fires in Arizona and New Mexico from 2002 to 2016[1] that could be classified as a suppression or managed fire based on management objectives (SIT-209, 2018). It is important to note that management objectives are not mutually exclusive. Protection and resource objectives can coexist on different zones of a fire, or on the same zone but on different days as managers respond to changing conditions. We acknowledge that suppression fires dominated by protection objectives may have zones where resource objectives can be achieved under the appropriate burning and weather conditions (Huffman et al., 2017), or may have zones where a full suppression strategy cannot be effectively deployed (O'Connor et al., 2017). Likewise, managed fires dominated by resource objectives may have zones or burning days where protection objectives are achieved with suppression strategies (such as the progression of a managed fire towards valuable resources).

To identify suppression and managed fires we developed a set of criteria. Suppression fires were defined as fires with a full suppression strategy used on at least 75% of fire management zones, on at least 75% of the fire's burning days as reported in the SIT-209 reports[2] (SIT-209, 2018). These criteria identified 146 suppression fires from 2002 to 2016 that were predominantly managed with protection objectives.

Fires with a full suppression strategy used on less than 25% of fire management zones, on less than 25% of the fire's burning days were identified as candidate managed fires. Of the candidate fires, 78 from 2002 to 2016 were identified as managed fires due to SIT-209 reports referencing resource objective terminology (Appendix A; Table A1). An additional 99 managed fires from 2009 to 2016 were identified by isolating candidate fires that were designated as fuel reducing treatments in the United States Forest Service, Accomplished Activities database (USDA Forest Service, 2018). In total we identified 177 managed fires predominantly managed with resource objectives.

Wildland fires were excluded if they burned for five days or less, and all but two suppression fires and three managed fires met the large fire threshold of 40.5 ha (100 ac). Additionally, fire complexes that contain multiple fires reported on the same SIT-209 report were excluded if classified as a suppression fire and retained if classified as a managed fire. When modeling the containment of suppression fires, the aggregation of variables generated by a fire complex could bias model estimations (e.g. fast fire spread; Finney et al., 2009). However, when modeling the containment of managed fires we hypothesized that variables external to the fire would largely affect the application of management strategies and subsequent containment. Therefore it was unlikely that the inclusion of 11 managed fire complexes would have appreciably affected containment. To account for possible sample bias, we ensured model estimations were robust to the removal of managed fire complexes, and fires < 40.5 ha.

2.2. Explanatory variables

We used SIT-209 reports (SIT-209, 2018) to obtain data on the explanatory variables used in the suppression containment model that was previously developed for the West by Finney et al. (2009) (Table 1). With these data we fit the suppression containment model with suppression and managed fires from the Southwest. The variable fast SPREAD captures intervals of high intensity that are known to have a negative association with the odds of successful fire containment (Hirsch and Martell, 1996). Additionally, if a high intensity surface fire is burning in dense TIMBER fuels, it is more likely to ignite and spread a crown fire (Van Wagner, 1977), which reduces the likelihood of successful containment (Stocks et al., 2004). On the other hand, as partial perimeter containment increases and site-specific fire management responses are refined, the odds of containment increase (Finney et al., 2009; Holmes and Calkin, 2013; Katuwal et al., 2016). This effect is captured in the number of previous spread intervals (NPI).

Explanatory variables used to develop the managed fire containment model were obtained from publicly available sources that include SIT-209 reports, and the Remote Automated Weather Station (RAWS) that was nearest to the wildland fire with similar elevation. Variables were grouped into *burning*, *weather*, and *risk metrics* (Table 2). *Burning metrics* captured the current and expected moisture content of hazardous fuels. These include the energy release component (ERC) and the average relative humidity (AvgRH). AvgRH is included, despite being a weather variable, due to its strong tie to dead fuel moistures through the time-lag principle, which describes how dead fuels adjust to the moisture in the local atmosphere (i.e. relative humidity) (Van Wagtendonk, 2006). Expected dead fuel moistures in future burn periods and the associated strategic response are captured in the interaction term between ERC and AvgRH. *Weather metrics* included PRECIPITATION and WIND, and their interaction term as a proxy for monsoon events. Limited PRECIPITATION associated with calm monsoon activity can be leveraged to allow managed fires to safely spread. On the other hand, heavy monsoons can deliver widespread PRECIPITATION that naturally contain and control fires, and can also be associated with windy events and dangerous outflows that may increase suppression activities prior to their arrival. The *risk metric* included is the number of HOUSES AT RISK of experiencing wildland fire effects. HOUSES AT RISK were assessed daily by wildland fire management personnel and reported in SIT-209 reports. We expected an increase in the number of HOUSES AT RISK to increase suppression activity. See Table 3 for a full set of expected signs for the managed fire containment model parameters. Summary statistics of explanatory variables can be found in Appendix A, Table A2.

In addition to the variables above, we explored the usefulness of daily temperature, spread component, and burning index, as well as the risk metrics of the cumulative number of houses destroyed by wildland

[1] 2015 data is not included. Key data is erroneously populated with 2014 records.

[2] Burning days without reports are assumed to be managed under prevailing strategies.

Table 1
Explanatory variables in the suppression containment model fit with suppression and managed fires in the Southwest. We used a dichotomous observational unit of a spread interval that is delineated by daily fire spread being above or below the average fire spread of each individual fire without interruption (Finney et al., 2009).

Explanatory Variable	Description	Unit	
TIMBER	Presence of timber burning in the spread interval[a]	Boolean:	0 = no timber 1 = timber
NDAYS	Number of days in the spread interval	Count	
NPI	Number of previous spread intervals	Count	
SPREAD	Presence of fast fire spread in the interval when compared to the average spread of each individual fire	Boolean:	0 = slow spread 1 = fast spread
TIMBER x NDAYS	Interaction between timber and the number of days in the spread interval		
SPREAD x NDAYS	Interaction between fast spread and the number of days in the spread interval		

Sources: SIT-209 reports (2002–2014, 2016) (SIT-209, 2018).
[a] Identified on SIT-209 reports using references to burning timber, or timber surface fuel models 8, 9, or 10 as described in Anderson (1982).

Table 2
Explanatory variables in the managed fire containment model fit with managed fires in the Southwest. The observational unit is a burning day.
Burning and *Weather metrics*: Remote Automated Weather Stations (RAWS) (2002–2014, 2016) (KCFAST, 2018). *Risk metric*: SIT-209 reports (2002–2014, 2016) (SIT-209, 2018). BTUs = British Thermal Units; mph = miles per hour.

Explanatory Variable	Description	Unit
Burning Metrics		
ERC	Energy release component is the energy released per unit area from the flaming front of a wildland fire.	10 BTUs/ft^2
AvgRH	Average relative humidity is the daily average amount of water vapor in the air relative to the point of saturation.	5% points
ERC x AvgRH	Proxy for expected dead fuel moisture	
Weather Metrics		
PRECIPITATION	Daily precipitation (rain and snow)	0.1 inch
WIND	Daily average wind speeds	1 mph
PRECIP x WIND	Proxy for monsoon and other storms	
Risk Metric		
HOUSES AT RISK	Primary houses (owner occupied/non-seasonal) at risk of experiencing wildland fire effects	10 houses

Table 3
Expected sign on coefficients in terms of the number of burning days decreasing (−) or increasing (+). Energy release component (ERC). Average relative humidity (AvgRH).

	Low AvgRH	High AvgRH
Low ERC	+/−	- (natural containment)
High ERC	- (suppression)	+/−
	Low WIND	High WIND
Low PRECIPITATION	+/−	- (suppression)
High PRECIPITATION	- (natural containment)	- (supp./nat. cont.)
Increased HOUSES AT RISK	- (suppression)	

fire, and the number of commercial buildings or outbuildings that were threatened or cumulatively destroyed. The aforementioned risk metrics had a high frequency of zeros, suggesting fires are not managed for resource objectives within their proximity or they are of limited concern when in proximity to the fire (i.e. outbuildings).

3. Statistical analysis

3.1. Suppression containment model

Using Finney et al. (2009) as guidance, we used a generalized linear mixed model (GLMM) with fixed and random fire effects to explore if the suppression containment model adequately explains the containment of suppression and managed fires in the study area (Fig. 1, A–C). Due to a lack of observable heterogeneity and insignificant random fire effects (Bolker et al., 2009), we also fit generalized linear models (GLM).

We defined containment for suppression fires like Finney et al. (2009) as the last SIT-209 report of an unbroken series that reported fire growth. The observational unit is a binary spread interval, defined as continuous days with fire spread (consumed hectares) that is above or below the average fire spread over the life of the individual fire (Finney et al., 2009). The sample of 146 suppression fires had 475 spread intervals with an average of 3.3 intervals per fire, while the 177 managed fires had 668 spread intervals with an average of 3.8 intervals per fire. The significance of model parameters was validated using a jackknife simulation procedure that systematically removed and re-estimated the containment of each fire.

3.2. Managed fire containment model

The managed fire containment model was developed with the managed fire sample (Fig. 1, D–I). We used time-to-event (i.e. survival model) modeling techniques (Cox, accelerated failure-time) with observations clustered by fire to examine the effects of *burning*, *weather*, and *risk metrics* on the containment of managed fires. We investigated the conditions that resulted in the natural containment of managed fires and deployment of suppression activities designed to limit fire growth.

The event of interest was the containment of managed fire defined as the last SIT-209 report with fire growth, where the number of days between reports was within two weeks. Containment dates were supported with SIT-209 report notes when possible, and fires were excluded if containment dates could not be reasonably determined. Though the definition of managed fire containment is not ideally replicating Finney et al. (2009), constraining the sample to only include fires with a series of uninterrupted SIT-209 reports would reduce and

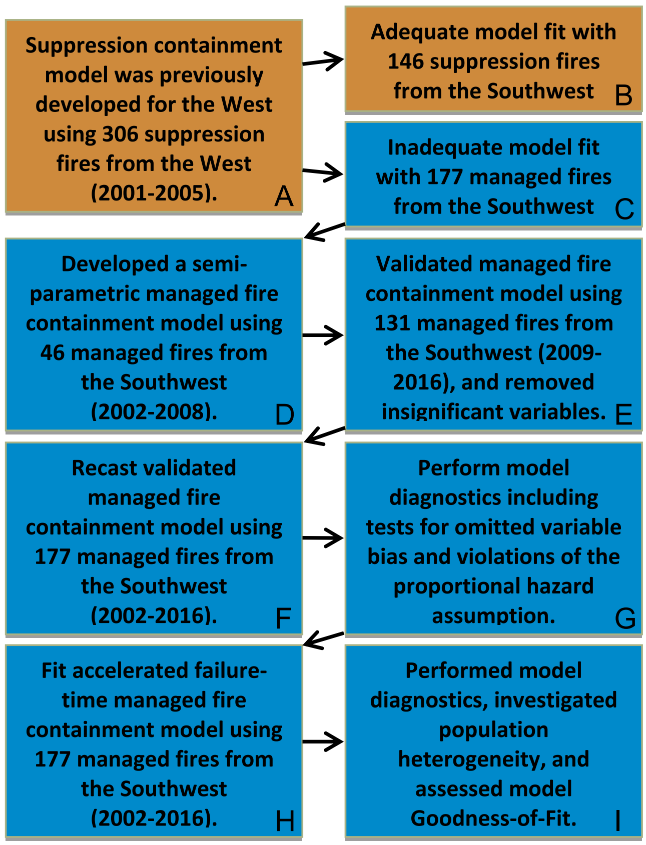

Fig. 1. Flowchart of methods used in our analyses. Orange (A–B) represent suppression fire data and methods. Blue (C–I) represent managed fire data and methods. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

bias the sample substantially. This is due to intermittent reporting that is commonly performed every 2 weeks as the supervision of a managed fire is transitioned to a new team. Our definition of managed fire containment was used in suppression and managed fire containment models.

The observational unit was a burning day defined as each day the managed fire is actively burning including the day of containment. Our sample of 46 managed fires from 2001 to 2008 had a total of 987 burning days with a median and mean of 15 and 21.5 burning days. Our sample of 131 managed fires from 2009 to 2016 had a total of 3219 burning days with a median and mean of 21 and 24.6 burning days.

3.2.1. Semi-parametric Cox model – development and diagnostics

To identify the appropriate explanatory variables, we fit a semi-parametric Cox model with 46 managed fires from 2002 to 2008 (*Wald* $\chi^2 = 46.38$, $p < 0.0001$) (Cleves et al., 2004 p. 157; Huebner et al., 2016) (Fig. 1, D). We then validated the parameters of our test model with an independent dataset of 131 managed fires from 2009 to 2016 (*Wald* $\chi^2 = 44.63$, $p < 0.0001$) (Fig. 1, E). Significance of *burning* and *weather metrics* were validated, while some *risk metrics* were not. *Risk metrics* that failed to validate included daily fire SPREAD and the interaction between SPREAD and the number of HOUSES AT RISK. While slow fire SPREAD significantly increased the odds of containment in the sample from 2002 to 2008 ($p = 0.041$), this effect was not seen from 2009 to 2016.

We recast a complete model with all 177 managed fires and performed model diagnostics (Fig. 1, F). Model diagnostics showed no appreciable signs of omitted variable bias (model specification), or violations of the proportional hazard assumption ("effects do not change with time except in ways that you have already parameterized" (Cleves et al., 2004, p. 176) (Fig. 1, G)). See Appendix B for additional details on Cox model diagnostics that were performed.

3.2.2. Parametric time-to-event model – development and diagnostics

To improve model efficiency (greater performance with fewer observations) we fit our sample of 177 managed fires with a parametric, accelerated failure-time model with an underlying daily hazard that follows a lognormal-distribution (Cleves et al., 2004, pp. 197–200) (Fig. 1, H). We defined the underlying functional form using multiple lines of evidence. Foremost, we examined the underlying hazard function (daily probability of containment) of the complete semi-parametric Cox model, which is not estimated and rather is generated as a model artifact that is capable of following a non-monotonic distribution (Cleves et al., 2004 p. 7, 121). This gave evidence towards a lognormal-distributed underlying hazard.

A lognormal-distributed hazard was further supported through model selection criteria, and conversations with wildland fire managers in the Southwest. Managers express that in the first days or weeks of a managed fire, the daily probability (hazard) of wildland fire containment generally increases as fire managers analyze the situational circumstances, and the availability of resources and personnel needed to manage the fire to meet resource objectives over a prolonged period of time. After managers have reached the decision that a fire will be a managed fire, the daily odds of containment decay over time as fire managers predominantly use the strategies of monitor, contain and confine, and point/zone protection.

Model diagnostics were performed on the lognormal-distributed model, and population heterogeneity (random fire effects) was investigated with a gamma-distributed frailty model with little evidence of support ($\theta = 0.01$: $\bar{\chi}^2 = 0.17$, $p = 0.34$) (Fig. 1, I). However, clustered standard errors were validated using jackknife simulation techniques, and were therefore retained. We assessed Goodness-of-Fit for the lognormal-distributed model with a comparison of the Cox-Snell residual and Nelson-Aalen cumulative hazard. Little divergence was found, supporting an adequate model fit. Refer to Appendix B for additional details regarding time-to-event modeling techniques, model selection, validation and diagnostics.

4. Results

Observed fire duration and size for our suppression and managed fires can be seen in Fig. 2. Suppression fires burned 6–74 days (median = 12 days), with a median size of 2031 ha (5018 ac), and a size range of 16–217,741 ha (40–538,049 ac). Managed fires burned 6–107 days (median = 20 days), with median size of 769 ha (1900 ac), and a size range of 24–38,437 ha (60–94,980 ac).

4.1. Suppression containment model – suppression fires

Overall the suppression containment model performed well when fit with suppression fires from the study area (Table 4; GLMM: *Wald* $\chi^2 = 96.14$, $p < 0.0001$; GLM: *LR* $\chi^2 = 218.25$, $p < 0.0001$). A likelihood ratio test of random fire effects showed no signs of significance (LRT: $\bar{\chi}^2 = 0.0032$; $p = 0.48$), and the inclusion of random effects showed no additional gains as assessed by Akaike (AIC) and Bayesian Information Criterion (BIC) (Table 4).

Covariate parameters in the suppression containment model are interpreted using odds ratios (OR = ê(coefficient)), which are a measure of an expected outcome given an exposure when compared to an unexposed analog (Szumilas, 2010). The directional effect of each odds ratio in the Southwest was in agreeance with the West, while the significance and effect size varied. The SPREAD ORs in the Southwest captured a decreased probability of containment during fast fire SPREAD intervals (OR = 0.1218), and an increased probability during slow fire SPREAD intervals (Table 4, note c, OR = 8.2105). This is similar to the West with ORs of 0.2961 and 3.3772 (=(1/0.2961)).

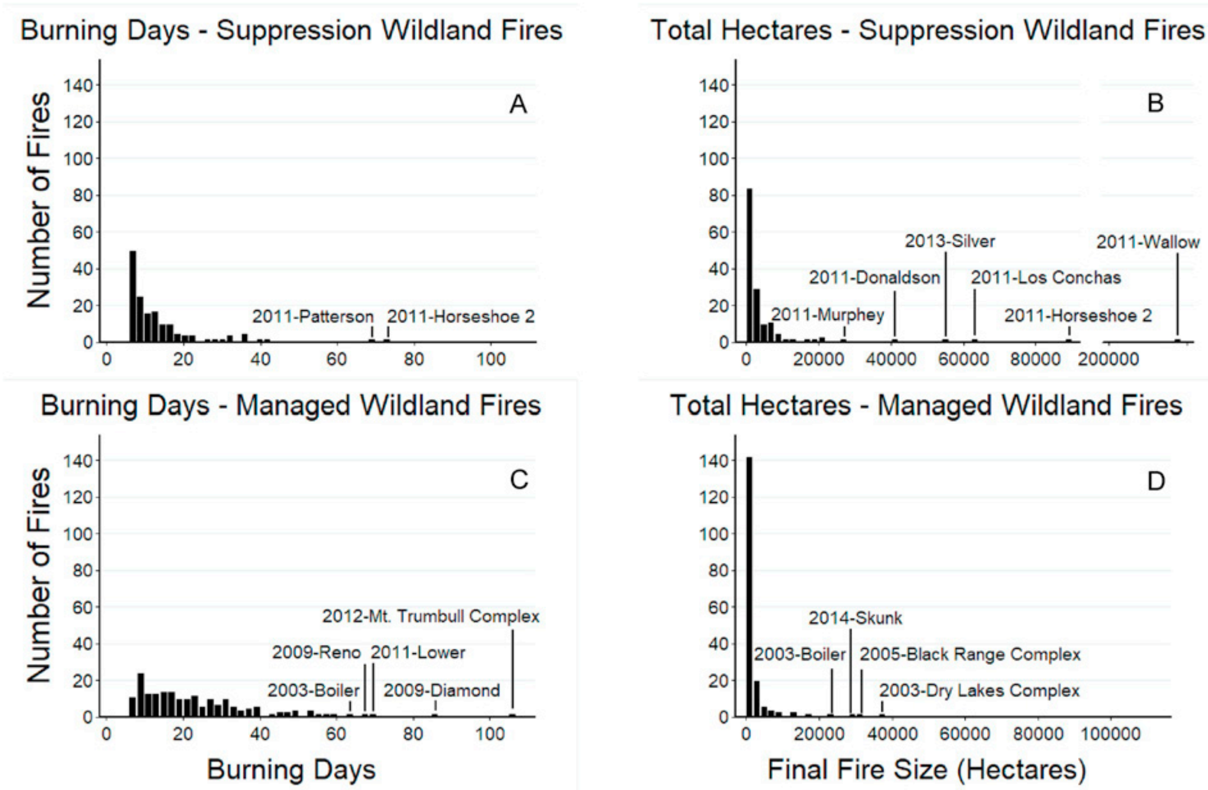

Fig. 2. Histogram of burning days and final fire size for 146 suppression fires (A, B), and 177 managed fires (C, D).

Table 4
Suppression containment model fit with suppression fires in the West (2001–2006) and Southwest (2002–2016) using Generalized Linear (Mixed) Models (GLM, GLMM). West suppression fire results are from Finney et al. (2009).

Explanatory Variables	West Suppression Fires		Southwest Suppression Fires					
	GLMM		GLMM[a]			GLM		
	Odds Ratio[b] (OR)	Standard Error	Odds Ratio (OR)	Standard Error	Jackknife Standard Error	Odds Ratio (OR)	Standard Error	Jackknife Standard Error
TIMBER = 1	2.2548	0.5556	1.0132	0.4684	0.7494	1.0090	0.4598	0.6949
NDAYS = 0	3.1376	0.1909***	1.4441	0.0821***	0.1879*	1.4432	0.0810***	0.1738**
NPI	1.1456	0.0267***	1.0849	0.1257	0.1341	1.0781	0.0591	0.0608
SPREAD = 1	0.2961	0.6462*	0.1209	0.6234***	0.8994**	0.1218[c]	0.6091***	0.8905**
TIMBER x NDAYS	0.4759	0.1935***	0.8775	0.1034	0.2175	0.8783	0.1022	0.2044
SPREAD x NDAYS	0.3830	0.3348***	0.6898	0.1606**	0.3888	0.6896	0.1599**	0.3762
AIC/BIC			383.88/417.19			381.88/411.02		

Southwest suppression fires = 146; spread intervals (n) = 475.
$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.
[a] Likelihood ratio test versus GLM: $\bar{\chi}^2 = 0.0032$; $p = 0.48$.
[b] Coefficient = ln (OR), e.g. timber coefficient = ln (2.2548) = 0.8131.
[c] SPREAD = 0 with jackknife standard error: SPREAD OR = 8.2105** (≈(1/0.1218)), NDAYS OR = 0.9953.

Conversely TIMBER occurrence was not a determinant of suppression fire containment in the Southwest.

4.2. Suppression containment model – managed fires

The suppression containment model was also fit with managed fires in the Southwest (Table 5; GLMM: *Wald* $\chi^2 = 28.86$, $p = 0.0001$; GLM: *LR* $\chi^2 = 39.81$, $p < 0.0001$). As before random fire effects were insignificant (LRT: $\bar{\chi}^2 = 0.34$; $p = 0.28$), likely due to limited fire heterogeneity in the sample. Additionally, both models indicated an insignificant TIMBER effect in the Southwest.

There were also a number of key differences. When examining managed fires, an addition of each NPI significantly increased the odds of containment by 10% (=(1.1044–1) *100) on average (Table 5; GLM). This effect was not seen with suppression fires in the Southwest. Furthermore, the odds of containment for managed fires in the Southwest increased during long intervals of above average SPREAD (SPREAD x NDAYS; Table 5, OR = 1.1673). Fourteen days of above average managed fire SPREAD led to a 107% increase in the odds of containment, while above average SPREAD for less than seven burning days significantly reduced the odds (Appendix A; Fig A1).

Table 5
Suppression containment model fit with managed fires in the Southwest (2002–2016) using Generalized Linear (Mixed) Models (GLM, GLMM).

Explanatory Variables	Southwest Managed Fires					
	GLMM[a]			GLM		
	Odds Ratio[b] (OR)	Standard Error	Jackknife Standard Error[c]	Odds Ratio (OR)	Standard Error	Jackknife Standard Error
TIMBER = 1	0.9265	0.2971	0.3103	0.9846	0.2676	0.2658
NDAYS = 0	0.9789	0.0264	0.0235	0.9826	0.0248	0.0214
NPI	1.1476	0.0743*	0.0787*	1.1044	0.0310***	0.0307***
SPREAD = 1	0.2322	0.2986***	0.3075***	0.2379	0.2914***	0.2957***
TIMBER x NDAYS	1.0224	0.0308	0.0295	1.0177	0.0290	0.0270
SPREAD x NDAYS	1.1688	0.0374***	0.0386***	1.1673	0.0368***	0.0377***
AIC/BIC	748.31/784.34			746.65/778.18		

Southwest managed fires = 177; spread intervals (n) = 668.
$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.
[a] Likelihood ratio test versus GLM: $\bar{\chi}^2 = 0.34$; $p = 0.28$.
[b] Coefficient = ln (OR), e.g. timber coefficient = ln (0.9265) = −0.0763.
[c] *F*-score and *p*-value failed to converge.

Table 6
Managed fire containment model fit with managed fires in the Southwest (2002–2016) using a lognormal time-to-event model.

Explanatory Variables	Southwest Managed Fires			
	Lognormal Time-to-Event			
	Time Ratio[a] (TR)	Standard Error	Clustered Std. Error	Jackknife Std. Error
Burning Metrics				
ERC = 0	0.8896	0.0372***	0.0329***	0.0348***
AvgRH = 0	0.9207	0.0260***	0.0260***	0.0272***
ERC x AvgRH	1.0129	0.0042***	0.0038***	0.0041***
Weather Metrics				
PRECIPITATION = 0	1.2165	0.0789**	0.0588***	0.0623***
WIND = 0	1.0014	0.0156	0.0154	0.0157
PRECIPITATION x WIND	0.9673	0.0115***	0.0087***	0.0092***
Risk Metric				
HOUSES AT RISK	0.7396	0.2245	0.0792***	0.1148***

Southwest managed fires = 177; burning days (n) = 4206. AIC = 309.51; BIC = 366.61.
$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.
[a] Coefficient = ln (TR), e.g. ERC coefficient = ln (0.8896) = −0.1170.

4.3. Managed fire containment model

The managed fire containment model performed well (*Wald* $\chi^2 = 38.73$, $p < 0.0001$) (Table 6).[3] The average daily probability of containment of managed fire experienced sigmoidal growth until peaking at 0.069 roughly 32 days after fire discovery (Fig. 3, A); then slowly decayed to reach 0.050 on day 100. The daily hazard cumulated to 1 on day 26, and 5.5 on day 100 (Fig. 3, B). In other words, the average managed fire was contained on burning day 26, and would be contained 5.5 times by burning day 100. The average managed fire had an 8 day survival probability of 0.95; a 21 day survival probability of 0.50 (median survival); and a 55 day survival probability of 0.05 (Fig. 3, C). In contrast, the average suppression fire in our sample had an observed 12 day median survival time.

Covariate parameters in our managed fire containment model are interpreted as time ratios (TR = ê(coefficient); Table 6) that accelerate or decelerate the average effect of time (burning days) on containment (daily and cumulative hazard function). Fig. 4 plots out TRs for *burning metrics* as the expected percent change in the number of burning days ((TR - 1) * 100) at varying levels of their interacting covariates.

4.3.1. Burning metrics

An increase of 10 British Thermal Units per ft^2 ($BTUs/ft^2$) in ERC was positively correlated with a conditional increase in average relative humidity (AvgRH) as illustrated in Fig. 4, A. When AvgRH was at 20% an increase in ERC of 10 $BTUs/ft^2$ resulted in a 6.3% reduction in burning days. Alternatively, when AvgRH was at 80% an increase of 10 $BTUs/ft^2$ in ERC resulted in a significant 9.3% increase in burning days. A positive correlation was also seen when examining an increase in AvgRH (Fig. 4, B). At very low levels of ERC (≤ 37 $BTUs/ft^2$), an increase in AvgRH significantly reduced the number of burning days, and increased the odds of natural containment. Conversely, at high levels of ERC (≥ 105 $BTUs/ft^2$) an increase in AvgRH significantly increased the number of burning days.

Interactive effects between ERC and AvgRH were also visualized using a series of daily hazard, cumulative hazard, and survival functions (Fig. 5) based on the interactive distribution of the variables (Appendix A; Fig A2, A). Each of three ERC ranges (low, moderate, high) had a negative association with AvgRH, with higher ranges being more elastic

[3] The test model fit with 46 managed fires initially included daily fire SPREAD ($p = 0.04$) and the interaction between daily fire SPREAD ($p = 0.01$) and the number of HOUSES AT RISK (*Wald* $\chi^2 = 54.90$, $p < 0.0001$).

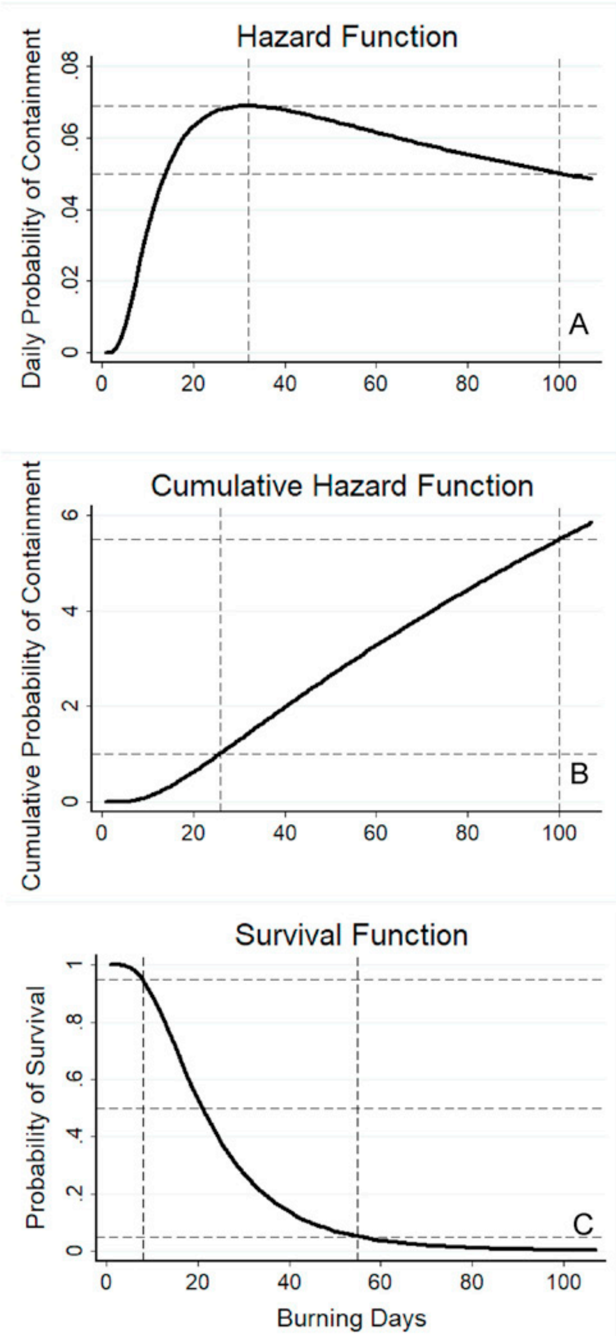

Fig. 3. A: The daily hazard function plots out the daily probability of containment for an average managed fire that peaked on burning day 32 at 0.069. B: The Cumulative hazard function aggregates daily hazards (probabilities) of containment over time with the average managed fire being contained on burning day 26. C: The survival function displays the probability that a managed fire will burn uncontained over time with a median survival time of 21 burning days, which contrasts with an observed survival time of 12 burning days for suppression fires.

to changes in AvgRH (Appendix A; Fig A2, A). Within the low range of ERC (7.5–27.5 BTUs/ft^2), an increase in ERC (shifts from blue to yellow line) reduced the daily probability of containment (Fig. 5, A), which reduced the accumulation rate of the cumulative probability of containment (Fig. 5, B, yellow line). A reduced rate in accumulation then decelerated the containment of the wildland fire as depicted by a slower decay of survival and an increased median survival time (Fig. 5, C). Within the high range of ERC (100–220 BTUs/ft^2), an opposite mechanism was depicted by a decrease in median survival time as the use of suppression activities became more likely (Fig. 5, G–I).

The moderate ERC range (10–90 BTUs/ft^2) spanned an inflection point (Fig. 5, D–F). Starting with ERC = 10 BTUs/ft^2 (blue line) an increase in ERC decreased the daily probability of containment as resource objective management increased (shift to red and green line). An inflection point was then reached in proximity to ERC = 50–70 BTUs/ft^2 and AvgRH = 30–50%, *ceteris paribus*. Further increases in ERC increased the likelihood of protection objectives and containment (yellow line).

4.3.2. Weather metrics

A tenth inch increase in PRECIPITATION was negatively correlated with a conditional increase in average WIND as illustrated in Fig. 6, A. When average WIND was 2 miles per hour (mph), an increase in PRECIPITATION of a tenth inch resulted in a 13.8% increase in the number of burning days. Alternatively when average WIND was 10 mph, a tenth inch increase in PRECIPITATION resulted in a 12.8% decrease in the number of burning days. A negative correlation was also seen when examining average WIND speeds in Fig. 6, B. At PRECIPITATION levels $\geq$0.915 tenths of an inch, an increase in average wind significantly decreased burning days, with this effect increasing as precipitation rose.

Interactive effects between PRECIPITATION and WIND were also visualized using a series of daily hazard, cumulative hazard, and survival functions (Fig. 7) with combinations based on the distribution of variable interactions (Appendix A; Fig A2, B). During a low average WIND speed (1 mph), an increase in PRECIPITATION (shift from blue to grey lines) reduced the daily probability of containment (Fig. 7, A), which reduced the accumulation rate of the cumulative probability of containment (Fig. 7, B). A reduced rate in accumulation then decelerated the containment of the fire as depicted by a slower decay of survival and increased median survival time (Fig. 7, C). During a high average WIND speed (11 mph), an opposite mechanism was depicted by a decrease in median survival time as widespread monsoon effects or the use of suppression activities became more likely (Fig. 7, G–I). A moderate WIND speed (5 mph) represented an inflection point between protection objective management and resource objective management, as evident in increasing PRECIPITATION having little effect.

4.3.3. Risk metric

HOUSES AT RISK also had a significant effect on the probability of containment. Under average *burning* and *weather* conditions, the median survival time of a managed fire was 21 burning days. This was significantly reduced to 16 days if there were 10 HOUSES AT RISK; 11.5 days if there were 20 HOUSES AT RISK; and 8.5 days if there were 30 HOUSES AT RISK.

4.3.4. Generalized managed wildland fire containment model

To generalize the managed fire containment model we found suitable proxies for variables that are not incorporated into or generated by current wildland fire simulation technologies (e.g. FSim). Proxied variables included AvgRH and PRECIPITATION. A suitable proxy for AvgRH was found to be the daily divergence of ERC from the average ERC over the span of a fire $(div(ERC_{ti}) = ERC_{ti} - (\sum_{t=0}^{T_i} ERC_t/Burning\ Days(T_i)))$. A decrease in ERC relative to the average ERC suggests a rise in AvgRH (Appendix A; Table A3). A suitable proxy for PRECIPITATION was found to be the daily change in ERC ($\Delta ERC_t = ERC_t - ERC_{t-1}$). Precipitation is associated with drops in ERC, and ERC is a proxy for fuel moisture in wildland fire simulators.

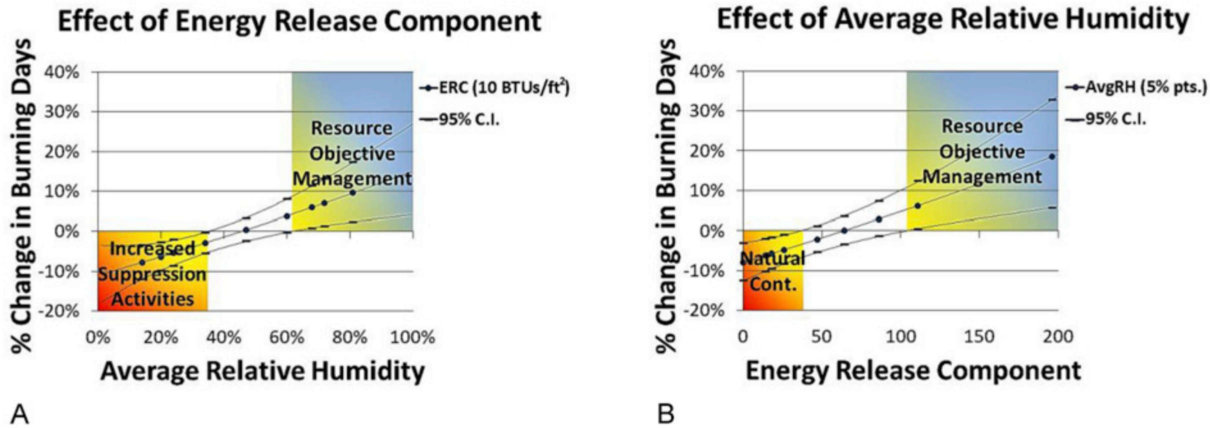

Fig. 4. Effects of a unit^{-1} increase for *burning metrics* over a range of values for their interacting covariate. Y-axis: % change in burning days ((TR -1) * 100). X-axis: range of the interacting covariate. (A) depicts how an increase in energy release component (ERC) effects fire duration, conditioned on AvgRH. For example, a 10 BTUs/ft^2 increase in ERC is expected to decrease a managed fire's burning days by 6.3%, given AvgRH is 20%. Points are evaluated at the 1st, 5th, 10th, 25th, 50th, 75th, 90th, 95th, and 99th percentile of the interacting covariate (x-axis). Colored boxes represent significant areas based on 95% confidence intervals using clustered standard errors (Table 6).

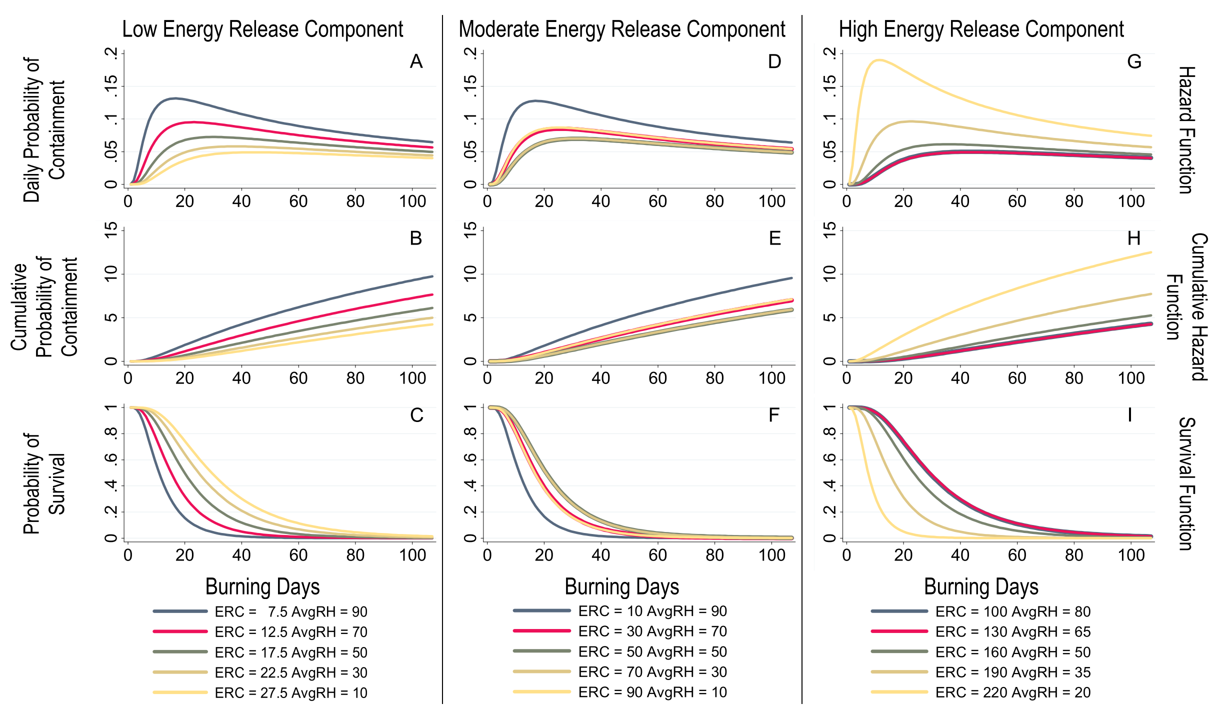

Fig. 5. Interactive effects between energy release component (ERC) and average relative humidity (AvgRH) in a series of daily hazard functions, cumulative hazard functions, and survival functions over low, moderate, and high ranges of ERC, *ceteris paribus*. Within the low ERC range (A–C), an increase in ERC concurrent with a decreasing AvgRH, increased fire duration. Within the high ERC range (G–I), an increase in ERC concurrent with a decreasing AvgRH, decreased fire duration.

The proxied model performed well (*Wald* $\chi^2 = 41.85, p < 0.0001$), and very little explanatory power was lost based on AIC and BIC (Table 6; Table A3). A 10 point increase in the divergence of ERC (div (ERC_{ti})) (proxy for decreasing AvgRH), resulted in a 17.4% increase in burning days conditioned on an ERC of 18 BTU/ft^2; and an 8.7% increase in burning days conditioned on an ERC of 86 BTU/ft^2 (Table A3, note b). A drop of 10 BTUs/ft^2 in ERC (ΔERC_t) (proxy for PRECIPITATION) resulted in a 26.4% (=((1/0.7911) - 1) * 100) increase in the number of burning days conditioned on still winds; and a 25.3% (=((1/1.3393) - 1) * 100) decrease in the number of burning days conditioned on winds of 16 mph (Table A3, note c). These proxies had effects and displayed trends over the range of their interactive covariates that were similar to those of the proxied variables. The probability of daily containment peaked at 0.071, with a median survival probability of 20.4 burning days.

5. Discussion

The suppression containment model adequately captured the containment of suppression fires in our study area. Extended periods of slow fire SPREAD significantly increased the probability of containment, while extended periods of fast fire SPREAD significantly

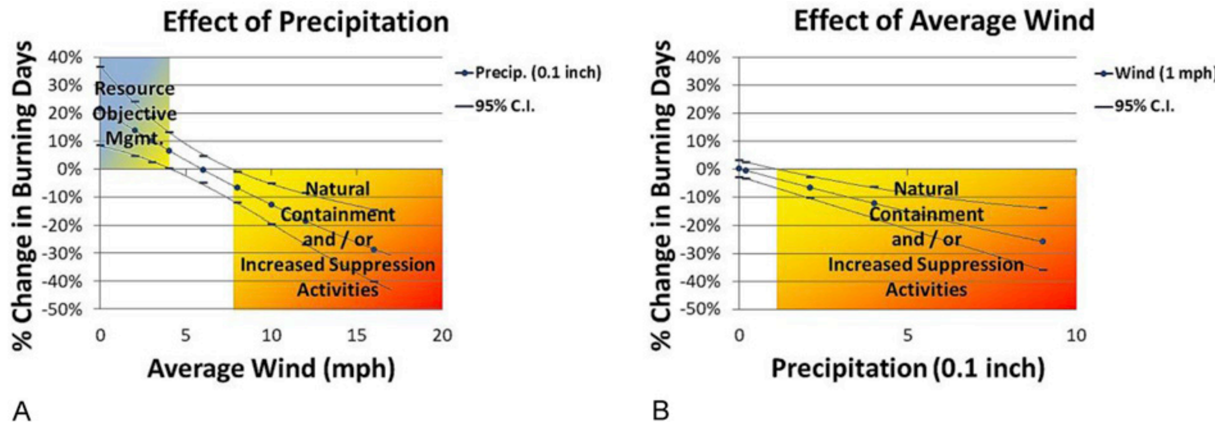

Fig. 6. Effects of a unit^{-1} increase for *weather metrics* over a range of values for their interacting covariate. Y-axis: % change in burning days ((TR -1) * 100). X-axis: range of the interacting covariate. (A) depicts how an increase in PRECIPITATION effects fire duration, conditioned on average WIND speed. For example, a 0.1 inch of PRECIPITATION is expected to decrease a fire's burning days by 19.7%, given a WIND speed of 10 mph. Points are evaluated at the 1st, 5th, 10th, 25th, 50th, 75th, 90th, 95th, and 99th percentile of the interacting covariate (x-axis). Colored boxes represent significant areas based on 95% confidence intervals using clustered standard errors (Table 6).

decreased the probability. This is in support of the major conclusion of Finney et al. (2009) and others that fires dominated by protection objectives are contained with successful suppression activities during extended periods of quiescent weather (Finney et al., 2009; Flowers et al., 1983).

When fitting the suppression containment model with managed fires, containment was more probable following long periods of fast fire SPREAD, and as NPI increased. We postulate this to be the combined effect of updated fire size on (final) reports, and containment being postponed until burn-out operations could be implemented to further reduce hazardous fuels during ideal burn windows. Based on our conversations with fire managers, the aforementioned explanations are more likely than containment induced by increased fire hazards.

The managed fire containment model developed for resource objectives effectively captured the containment of managed fires in the Southwest. Additionally, splitting our sample temporally for model development (2002–2008) and validation (2009–2016) allowed us to validate the criteria used to identify managed fires since the retirement of the term Wildland Fire Use after 2008. Furthermore, model validation resulted in a loss of predictive power of fire SPREAD after 2008, lending additional evidence to an increased use of burn-out operations prior to containment.

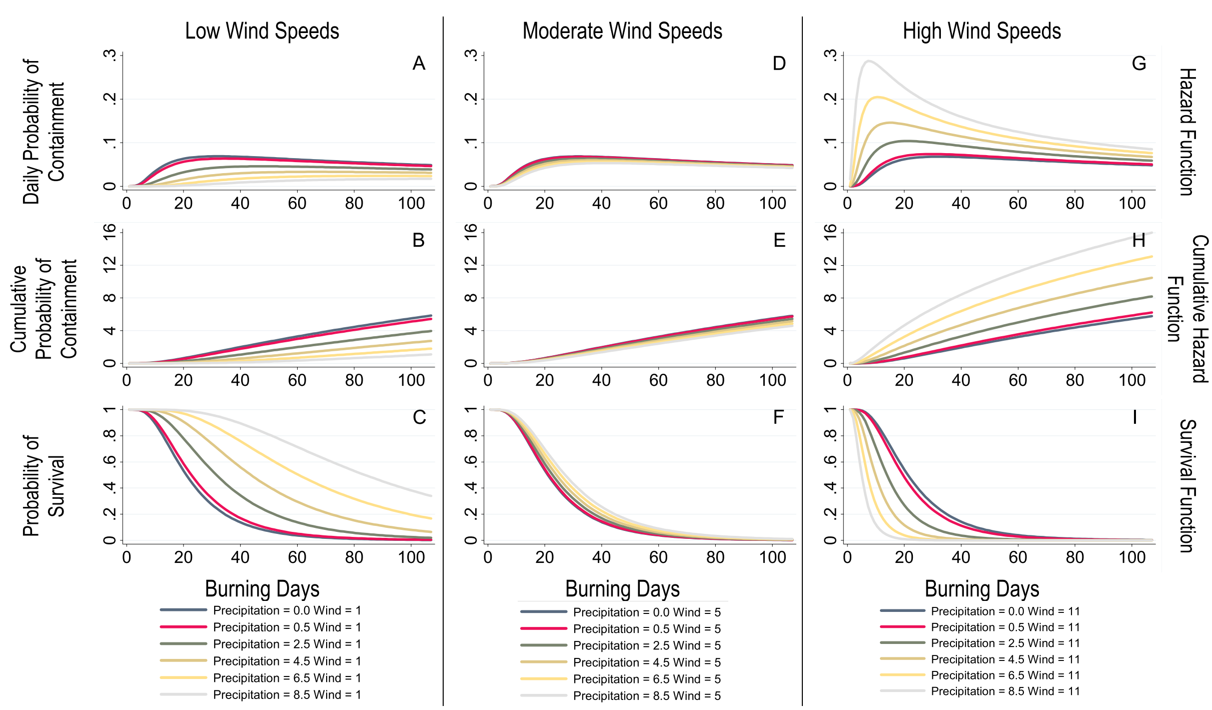

Fig. 7. Interactive effects between WIND (miles per hour) and PRECIPITATION (tenths of an inch) in a series of daily hazard functions, cumulative hazard functions, and survival functions over a low, moderate, and high WIND speeds, *ceteris paribus*. With low WIND speeds of 1 mph (A–C), an increase in PRECIPITATION increased fire duration. With high WIND speeds of 11 mph (G–I), an increase in PRECIPITATION decreased fire duration.

We also showed evidence that managed fires burned for significantly longer durations under arid conditions with high fuel moisture (AvgRH ≅ 10–30%; ERC ≅ 20–30 BTUs/ft^2); under humid conditions with low fuel moisture (AvgRH ≅ 50–85%; ERC ≅ 100–160 BTUs/ft^2); or under calm, wet conditions (≅1–3 mph WIND with active PRECIPITATION). These conditions are most likely to occur early in the fire season and well after the widespread moisture and windy conditions of the North American monsoon have peaked. Furthermore, these shoulder fire-seasons contain ideal burn windows that can be used to extend a fire's duration through burn-out operations where land management policies allow.

Conversely, managed fires burned for shorter durations under humid conditions with high fuel moisture (AvgRH ≳70%; ERC ≲15 BTUs/ft^2) as the result of natural containment; or under arid conditions with low fuel moisture (AvgRH ≲35%; ERC ≳190 BTUs/ft^2) as the result of a suppression strategy being deployed in response to increased fire hazards. Additionally, up-trending ERCs concurrent with down-trending AvgRH is associated with the impending peak fire season and the need for additional fire management resources (Flannigan et al., 2013). Under these conditions, it is more likely that managed fires will be contained to increase resource availability for other suppression efforts.

An elevated presence of HOUSES AT RISK also significantly limited the duration of managed fires. In part this may be due to land management policies not allowing managed fires in the wildland-urban-interface; a policy that is being eased in some regions. Other limiting forces could include risk aversion, the current reward systems of fire managers, the personal preference of private land and home owners, and/or the request of local political representatives (Calkin et al., 2015).

The statistical procedures presented in this publication implicitly modeled the use of historic tactics associated with the strategic response to wildland fire hazards. Furthermore, the managed fire containment model in combination with forecasted or predicted *burning* and *weather metrics* could be used to map-out or predict shoulder fire seasons amenable to managed fire activity in future climate change scenarios. Similar techniques could be used to develop a suppression fire containment model to better inform containment probabilities in a changing climate. Such models would inform future fire management policy and budgeting (Finney et al., 2009).

In an effort to strengthen future fire management policy, we also suggest the need for an assessment of other possible constraints to managed fire. Areas in need of investigation include agency culture, rural housing density, air-shed quality and restrictions, outcomes of nearby previously managed fires (North et al., 2012), and the location of other valuable assets on the landscape like transmission lines and key ecosystems (Allen et al., 2002; Scott et al., 2013). A quantification of constraints may help extend the burning duration and hazardous fuel reduction of managed fires. However longer durations do not necessarily translate into increased hectares, and low-severity burns may not always achieve resource objectives in a single application (Huffman et al., 2017).

6. Conclusions

Wildland fire management policies in the United States have increasingly provided a flexible construct to meet resource objectives (US DOI/USDA, 1995, 2001, 2009). Using these policies as guidance, fire managers in the Southwest have diversified their strategic response to wildland fires, resulting in diverging drivers of containment based on fire management objectives. Our statistical models confirmed that suppression fires with protection objectives are commonly controlled opportunistically during extended periods of quiescence fire weather (Finney et al., 2009; Flowers et al., 1983), while managed fires with multiple resource objectives are commonly controlled as fire hazards increase. Other managed fire insights included postponing containment until burn-out operations can be performed to further reduce hazardous fuels, and the limited application of suppression tactics when burning conditions and weather allow. Our results can be used in scenario planning models to examine how changing wildland fire suppression policies can restore fire resilience to frequent fire ecosystems and reduce future suppression costs (Barros et al., 2018; Spies et al., 2014). We also encourage increased attention to careful record keeping of wildland fires that are managed to meet resource objectives to facilitate future fire classification and the exploration of fire effects and management.

Conflicts of interest

The authors declare that they have no conflicts of interest.

Acknowledgements

This research was funded by the McIntire-Stennis Cooperative Forestry Research Program (#G1003488). Special thanks goes to Douglas Dalenberg for suggesting time-to-event modeling procedures, Mark Finney for advising in the generalization of the managed fire containment model, and the fire management community in the Southwest for their valuable insights in fire management variables, and identifying wildland fires with multiple resource objectives. Specifically we want to thank personnel from the US Forest Service, Southwest Region and US National Parks Service, Grand Canyon National Park.

Appendix A

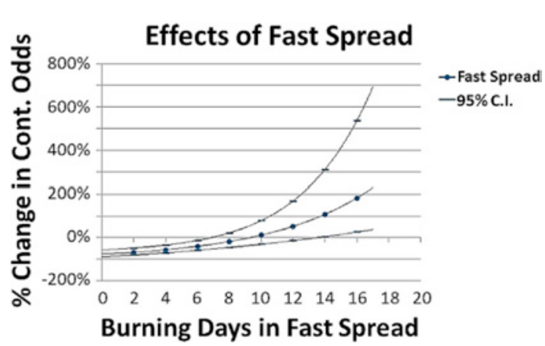

Fig. A1. Effects of fast SPREAD interval of managed fires over a range of burning days within the interval ((OR - 1) * 100). The odds of managed fire containment increased as the number of burning days (NDAYS) in a fast SPREAD interval increased in an exponential fashion. Confidence intervals are based on clustered standard errors.

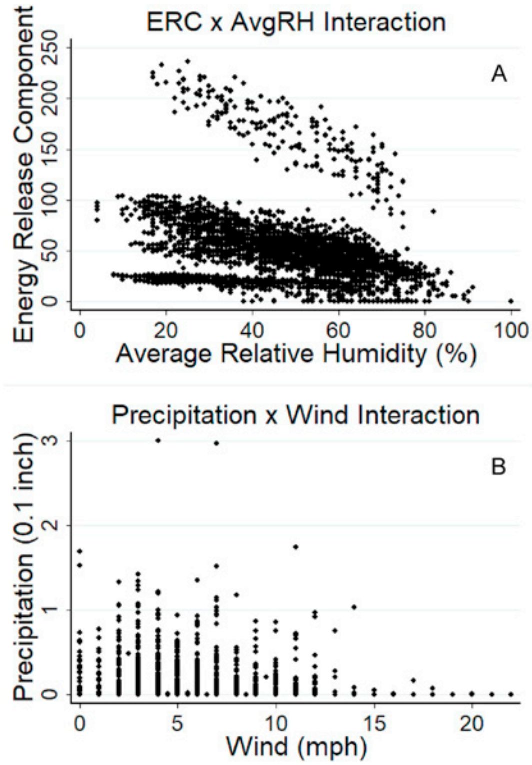

Fig. A2. Scatter plot between *burning metrics* of energy release component (ERC) and average relative humidity (AvgRH) (A) and *weather metrics* of PRECIPITATION and WIND (B). There are three distinct populations in A. B shows a right skewed distribution of WIND conditioned on PRECIPITATION.

Table A1
Phrases used to identify wildland fires that were managed to meet resource objectives.

- Wildland Fire Use (WFU)
- Resource objectives
- Multiple objectives
- Resource benefit
- Natural role
- Fire use team
- Forest restoration
- Ecosystem restoration
- Reduce fuel accumulation
- Allow fire to spread naturally
- Fire for resource management
- Re-introduction of fire into the ecosystem
- Maximizing benefit to resources
- Resource benefit will be maximized by allowing fire to back (burn)
- Lightning caused fire to run its natural course in fire adapted ecosystem

Note: List is not intended to be a comprehensive list of SIT-209 language used to describe resource objectives.

Table A2
Summary statistics of suppression and managed fires in the Southwest (2002–2016) used in Generalized Linear (Mixed) Models (GLM, GLMM) and time-to-event models.

Explanatory Variables	Obs.	Mean	Std. Dev.	Min	Max
Suppression Fires – GLMM, GLM					
TIMBER	475	0.387368	0.487663	0.0	1.0
NDAYS	475	4.012632	3.970865	1.0	30.0
NPI	475	1.848421	2.427465	0.0	16.0
SPREAD	475	0.454737	0.498472	0.0	1.0
Managed Fires – GLMM, GLM					
TIMBER	668	0.543413	0.498485	0.0	1.0
NDAYS	668	6.399701	6.495793	1.0	51.0
NPI	668	2.284431	2.840581	0.0	16.0
SPREAD	668	0.443114	0.497126	0.0	1.0
Managed Fires – Time-to-Event					
Burning Metrics					
ERC	4206	5.178150	3.567542	0.0	23.6
AvgRH	4206	9.350095	3.307624	0.8	20.0
Weather Metrics					
PRECIPITATION	4206	0.642321	1.872466	0.0	30.0
WIND	4206	6.278293	3.094374	0.0	22.0
Risk Metric					
HOUSES AT RISK	4206	0.013576	0.318937	0.0	20.0

Table A3
Generalized managed fire containment model fit with managed fires in the Southwest (2002–2016) using a lognormal time-to-event model.

Explanatory Variables	Southwest Managed Fires		
	Lognormal Time-to-Event		
	Time Ratio[a]	Clustered	Jackknife
	(TR)	Std. Error	Std. Error
Burning Metrics			
ERC = 0	0.9930	0.0159	0.0169
div(ERC) = 0[b]	1.1987	0.0637***	0.0662***
ERC x div(ERC)	0.9887	0.0050**	0.0056**
Weather Metrics			
ΔERC = 0[c]	0.7911	0.1039**	0.1096**
WIND = 0	0.9868	0.0142	0.0145
ΔERC x WIND	1.0335	0.0154**	0.0164**
Risk Metric			
HOUSES AT RISK	0.7717	0.0493***	0.0656***

Southwest managed fires = 177; burning days (n) = 4206. AIC = 320.37; BIC = 377.47.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.
[a] Coefficient = ln (TR), e.g. ERC coefficient = ln (0.9930) = −0.0070.
[b] TRs: 1.1744*** | ERC = 18 points; 1.0869* | ERC = 86 points.
[c] TR: 1.3393* | WIND = 16 mph.

Appendix B. Time-to-event modeling techniques: Managed fire containment model

B1.1. Semi-parametric Cox Model – Additional empirical methods

The proportional-hazard, semi-parametric Cox model declares a hazard rate for subject j for any time t, i.e. $h(t|x_j)$:

$$h(t|x_j) = h_0(t)\exp(x_j\beta_x),$$

where $h_0(t)$ is the baseline hazard that is un-estimated, x_j is a vector of covariates, β_x is a vector of corresponding covariate parameters estimated by the model, and $\exp(x_j\beta_x)$ represents a multiplicative shift in the baseline hazard function (Cleves et al., 2004, p. 121). Though the baseline hazard, $h_0(t)$, is allowed to fluctuate to fit the data, it is assumed to be the same functional form for each subject (Cleves et al., 2004, p. 121). We developed (2002–2008) and validated (2009–2016) a managed fire containment model using the semi-parametric Cox modeling framework.

B1.2. Semi-parametric Cox Model – Diagnostics

To confirm underlying assumptions of the semi-parametric Cox model were not violated, we ran a series of model diagnostics on the managed fire containment model fit with the complete dataset from 2002 to 2016 (177 wildfires). To test for omitted variable bias we used a re-estimation link test with no appreciable signs detected ($hat^2 = -0.213$, $p = 0.225$).[4]

We then used a number of techniques to examine the proportional hazard assumption that "effects do not change with time except in ways that you have already parameterized" (Cleves et al., 2004, p. 176). We examined time-varying covariates of each variable in Table 2. PRECIPITATION was found to significantly vary or interact with the natural log of time ($p = 0.038$). This suggested that the proportional-hazard assumption may be violated, and a time-varying covariate for PRECIPITATION may need to be included in proportional-hazard models to obtain valid standard errors. However, when testing the significance of the auto-correlative parameters *rho* (memory from one day to the next) for each parameter, all variables were found to be stationary, or have effects that do not vary with time or the natural-log of time (lowest p[5] = 0.49).[6]

Further support that the proportional hazard assumption has not been violated include a visual display of the Kaplan-Meier curve, $\hat{S}(t)$, for PRECIPITATION after a transformation -ln (-ln ($\hat{S}(t)$)) plotted against burning days (time) (Fig B1). The Kaplan-Meier curve mapped out survival for managed fires that received and did not receive PRECIPITATION. Survival curves that are roughly parallel and do not overlap suggest the proportional-hazard assumption has not been violated (Cleves et al., 2004, p. 112, 183). Though model diagnostics are not unanimous on the inclusion of a time-varying covariate for PRECIPITATION, we proceeded with the assumption that PRECIPITATION is stationary and a time-varying covariate was not warranted. In part this is due to limited autocorrelation that was likely driven by an abundance of repetitive zeros in daily PRECIPITATION.

We also examined the underlying baseline hazard of the Cox model (Fig B2, A). The daily baseline hazard of managed fire containment reflected a non-monotonic lognormal pattern that increased at a decreasing rate until peaking, which was then followed by a general pattern of decay over time. Incremental additions in the cumulative probability of containment captured the long-term increase in the probability of managed fire containment (Fig B2, B).

[4] H_0: There were no signs of omitted variable bias. Used Breslow method to break ties.
[5] For the natural log of time estimate of *rho* for PRECIPITATION.
[6] Used a robust variance-covariance matrix. Though this test has been shown to be robust to a heterogeneous population, if heterogeneity is evident some care should be taken during interpretation.

B2.1. Parametric time-to-event model – Additional empirical methods

To improve model efficiency we fit a parametric, time-to-event lognormal model that is derived in an accelerated failure-time framework due to its non-proportional nature (Cleves et al., 2004, p. 240). The lognormal model declares the baseline survivor function t_i, i.e. $S(t_i|z_i)$:

$$S(t_i|z_i) = S_0\{\exp(-z_i\alpha_z)t_i\},$$

where $S_0\{()t_i\}$ is the baseline survival, z_i is a vector of covariates or regressors, α_z is a vector of corresponding covariate parameters estimated by the model, and exp($-z_i\alpha_z$) represents a multiplicative acceleration of the baseline survival function (Cleves et al., 2004, p. 238).

B2.2. Parametric time-to-event model – Diagnostics

We then validated that managed fire containment in the Southwest had an underlying hazard that followed a lognormal distribution as suggested by the semi-parametric Cox model. This included conversations with fire managers, and comparing nested and un-nested parametric models. We compared nested models using a generalized gamma model and compared un-nested models using Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).

Upon fitting the generalized gamma model to examine the preference of competing nested distributions, a non-significant Wald test on the parameter kappa $\hat{\kappa} = 0$ suggests that a lognormal underlying hazard of containment is preferred to that of a Weibull or exponential distribution (95% $C.I._{\hat{\kappa}}$ = [-0.34, 0.12]; $p = 0.33$) (Cleves et al., 2004, p. 246). Additionally, the lognormal distribution is preferred to non-nested loglogistic and Gompertz distributions as assessed by AIC and BIC (Table B1) (Cleves et al., 2004, p. 246).

The lognormal model underwent diagnostics to assess omitted variable bias, managed fire heterogeneity, and Goodness-of-Fit. The link test under the lognormal distribution revealed no signs of detectable omitted variable bias ($hat^2 = -0.119$; $p = 0.18$)[7] (Cleves et al., 2004, p. 175).

We also fit a lognormal frailty model with a gamma-distributed population hazard of containment to investigate managed fire heterogeneity. Managed fire heterogeneity manifests when population hazards differ from individual hazards if frail individuals in the population are contained, while robust individuals under similar conditions survive for extended periods of time (Cleves et al., 2004, p. 287). A likelihood ratio test to evaluate the frailty model parameter theta, $\hat{\theta} = 0$, found little evidence to support a heterogeneous population ($\bar{\chi}^2 = 0.17$; $p = 0.34$). However, standard errors clustered on managed fires were validated using jackknife simulation techniques (Table 6), giving evidence of some heterogeneity in the managed fire sample. Model heterogeneity is most evident in the changing level of significance in HOUSING AT RISK of managed fire effects.

We assessed Goodness-of-Fit of the lognormal model with a comparison of the Cox-Snell residual and the Nelson-Aalen cumulative hazard (Fig. B3). Limited departure of the Nelson-Aalen cumulative hazard from the 45° reference line (Cox-Snell residual plotted against itself) suggests a good model fit (Cleves et al., 2004, p.193).

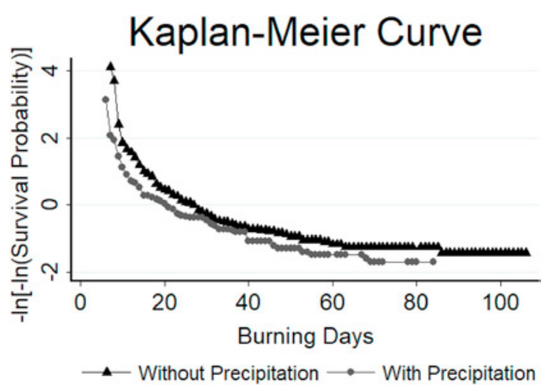

Fig. B1. Kaplan-Meier survival curves over burning days (time). Survival curves that are roughly parallel and do not overlap suggest the proportional hazard assumption has not been violated.

[7] H_0: There were no signs of omitted variable bias. Used Breslow method to break ties.

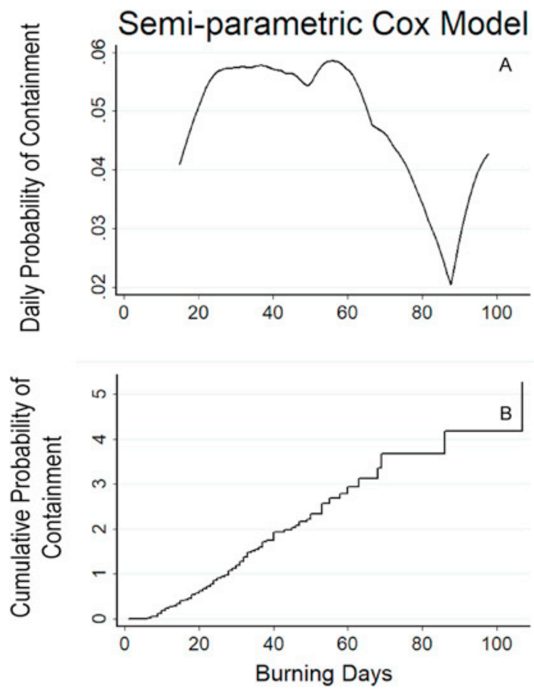

Fig. B2. A: The daily baseline hazard of containment represents the daily probability of containment for each burning day of a managed fire. B: The cumulative probability of containment is the summation of the daily probability of containment for each burning day of a managed fire. Daily probability represents the containment hazard flow, while cumulative probability represents the amassed containment hazard stock.

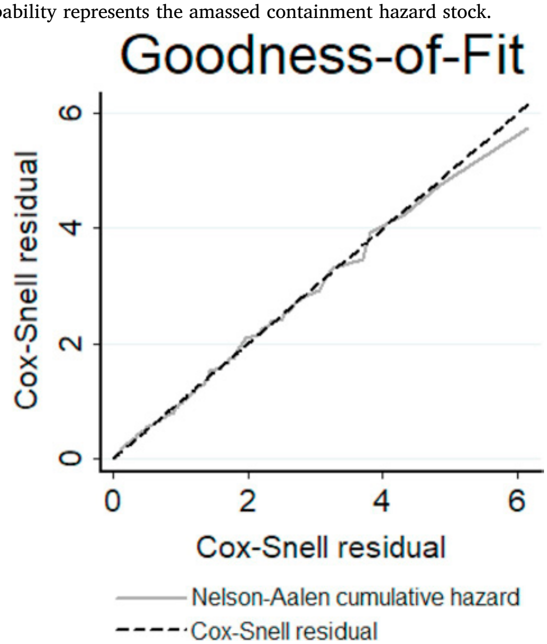

Fig. B3. Cox-Snell residual plot to assess model Goodness-of-Fit. The 45° reference line is the Cox-Snell residual plotted against the Cox-Snell residual. A lack of deviation of the Nelson-Aalen cumulative hazard from the reference line suggests a good fit.

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