

Towards improving wildland firefighter situational awareness through daily fire behaviour risk assessments in the US Northern Rockies and Northern Great Basin

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Abstract. Wildland firefighters must assess potential fire behaviour in order to develop appropriate strategies and tactics that will safely meet objectives. Fire danger indices integrate surface weather conditions to quantify potential variations in fire spread rates and intensities and therefore should closely relate to observed fire behaviour. These indices could better inform fire management decisions if they were linked directly to observed fire behaviour. Here, we present a simple framework for relating fire danger indices to observed categorical wildland fire behaviour. Ordinal logistic regressions are used to model the probabilities of five distinct fire behaviour categories that are then combined with a safety-based weight function to calculate a Fire Behaviour Risk rating that can be plotted over time and spatially mapped. We demonstrate its development and use across three adjacent US National Forests. Finally, we compare predicted fire behaviour risk ratings with observed variations in satellite-measured fire radiative power and we link these models with spatial fire danger maps to demonstrate the utility of this approach for landscape-scale fire behaviour risk assessment. This approach transforms fire weather conditions into simple and actionable fire behaviour risk metrics that wildland firefighters can use to support decisions that meet required objectives and keep people safe.

Additional keywords: fire danger, safety, weather.

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Introduction

Wildland fires are a common ecosystem disturbance that burn $\sim 3.50 \times 10^8$ ha of global vegetation each year (Giglio *et al.* 2010). Intentional wildland fires are human-ignited to clear forests, promote grazing and establish plants (Bowman *et al.* 2011), and undesired wildland fires are suppressed to protect human lives and property (Finney 2005). Globally, the number of days that wildland fires are likely to burn is increasing (Jolly *et al.* 2015), making the probability of unplanned wildland fires more common. However, attempting to contain wildland fires comes with the direct transfer of risk to firefighting personnel. This risk is underscored each year by line-of-duty deaths of wildland firefighters throughout the world. Over the last 20 years, 49 US firefighters have died when they were overtaken by erratic or rapidly spreading wildfires (National Interagency Fire Center 2015). Wildland firefighting is inherently risky but daily and seasonal variations in fire weather can compound that risk.

Wildland fire behaviour is controlled by the interactions between available fuels, topography and local weather conditions (Countryman 1972). Because fuels and topography vary spatially but do not change during the days or weeks while a wildland fire is burning, these variables can be mapped and known before fires start. However, weather conditions vary across space and time

and therefore can have profound effects on the type and behaviour of a wildland fire. For this reason, US firefighters are expected to assess current and future fire weather and fire behaviour when developing tactics and strategies during any wildland fire engagement, as set by the following set of Standard Firefighting Orders (National Wildfire Coordinating Group 2014):

- (1) Keep informed on fire weather conditions and forecasts.
- (2) Know what your fire is doing at all times.
- (3) Base all actions on current and expected behaviour of the fire.
- (4) Identify escape routes and safety zones and make them known.
- (5) Post lookouts when there is possible danger.
- (6) Be alert. Keep calm. Think clearly. Act decisively.
- (7) Maintain prompt communications with your forces, your supervisor, and adjoining forces.
- (8) Give clear instructions and ensure they are understood.
- (9) Maintain control of your forces at all times.
- (10) Fight fire aggressively, having provided for safety first.

Despite the fact that firefighters are required to keep informed on fire weather and to base their actions on safety and expected fire behaviour, very few resources are available to inform the tactical decisions made during the wildland fire

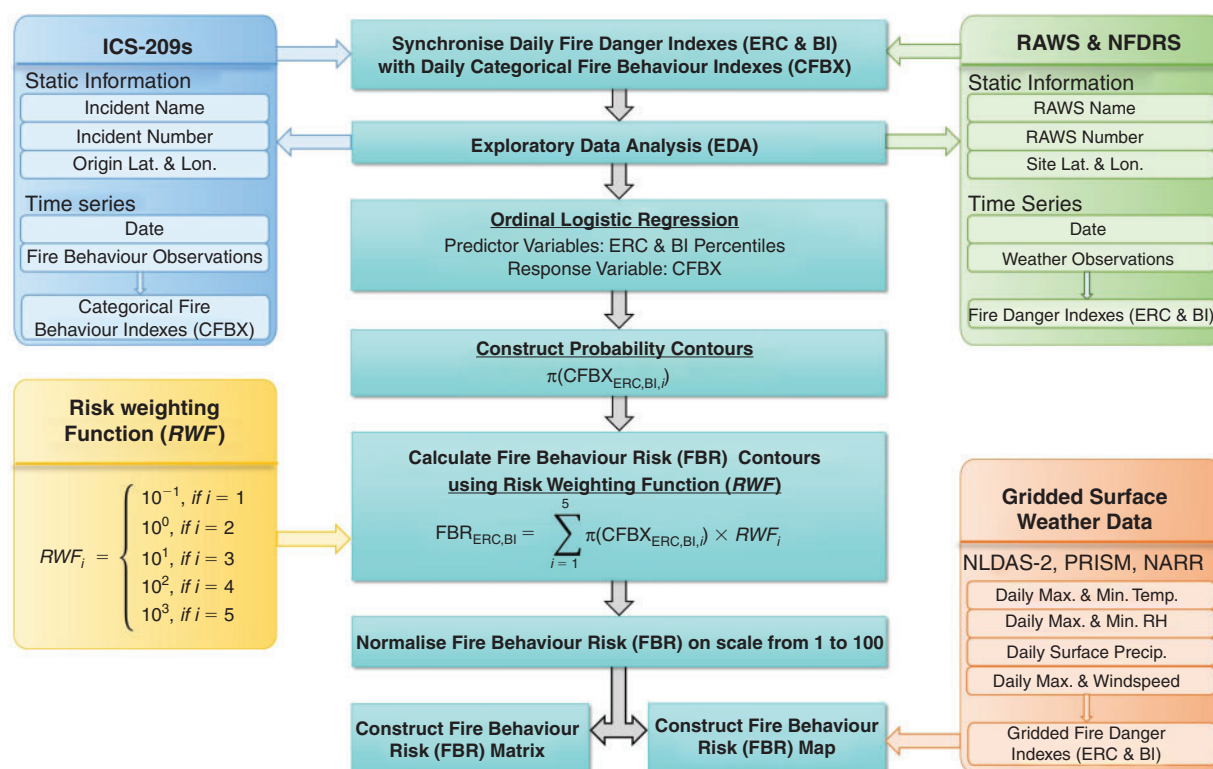


Fig. 1. Workflow of the fire behaviour risk analysis framework. ICS, Incident Command System; ERC, Energy Release Component; BI, Burning Index; CFBX, Categorical Fire Behaviour Index; RAWS, Remote Automated Weather Station; NFDRS, National Fire Danger Rating System; RWF, Risk Weighting Function; FBR, Fire Behaviour Risk; NLDAS, North American Land Data Assimilation System; PRISM, Parameter-elevation Regressions on Independent Slopes Model; NARR, North American Regional Reanalysis.

initial response, or initial attack (IA), and no simple resources exist to utilise weather forecasts to predict fire behaviour risk across large landscapes. The emergence of long-term datasets like gridded weather climatologies and daily incident reports provides the historical information necessary to make these associations. Methods that synchronise and build statistical relationships between these quantitative and qualitative datasets could ultimately be implemented within a tool that transforms current and expected fire weather conditions into simple and actionable metrics of fire behaviour risk. If such a tool were developed, it would improve firefighters' situational awareness and ensure that tactical decisions are better aligned with both current and expected fire weather and fire behaviour potential.

Here, we present the initial development of a framework that combines fire danger information derived from surface weather stations with daily information about worst-case observed categorical fire behaviour to predict the probability of five distinct fire behaviour types. Categorical fire behaviour probabilities are then weighted based on their potential effects on firefighter safety to produce an expected fire behaviour risk metric that can be used to inform daily operational wildland fire decisions. Finally, we compare these predictions with the daily maximum fire radiative power (FRP) measured by Moderate Resolution Imaging Spectroradiometer (MODIS) to characterise the relationship between fire behaviour risk and maximum energy release rate, and we demonstrate the utility of this

approach by mapping fire behaviour risk across three adjacent US National Forests using daily, moderate-resolution gridded surface weather data.

Materials and methods

Fig. 1 illustrates the data streams, processing and formulae used to calculate fire behaviour risk. First, keywords describing fire behaviour types are transcribed from daily incident reports and converted into a time series of categorical fire behaviour indexes (CFBX). The daily fire behaviour indexes are in turn synchronised with daily fire danger indexes obtained from the nearest or most representative surface weather station. Next, ordinal logistic regression analyses are used to model the probability of observing a categorical fire behaviour type as a function of fire danger. These probabilities are then multiplied by an *a priori* weighting function intended to quantify the effect of a categorical fire behaviour type on wildland firefighter safety. Ultimately, the output is a daily index reflecting the fire behaviour risk that wildland firefighters are exposed to.

Study area

The study area comprises three adjacent US National Forests: the Lolo National Forest (LNF), the Bitterroot National Forest (BRF) and the Salmon–Challis National Forest (SCF). The LNF and BRF cover 0.9 and 0.6 Mha respectively within the Northern Rockies Geographic Area, whereas the SCF covers 1.7 Mha in

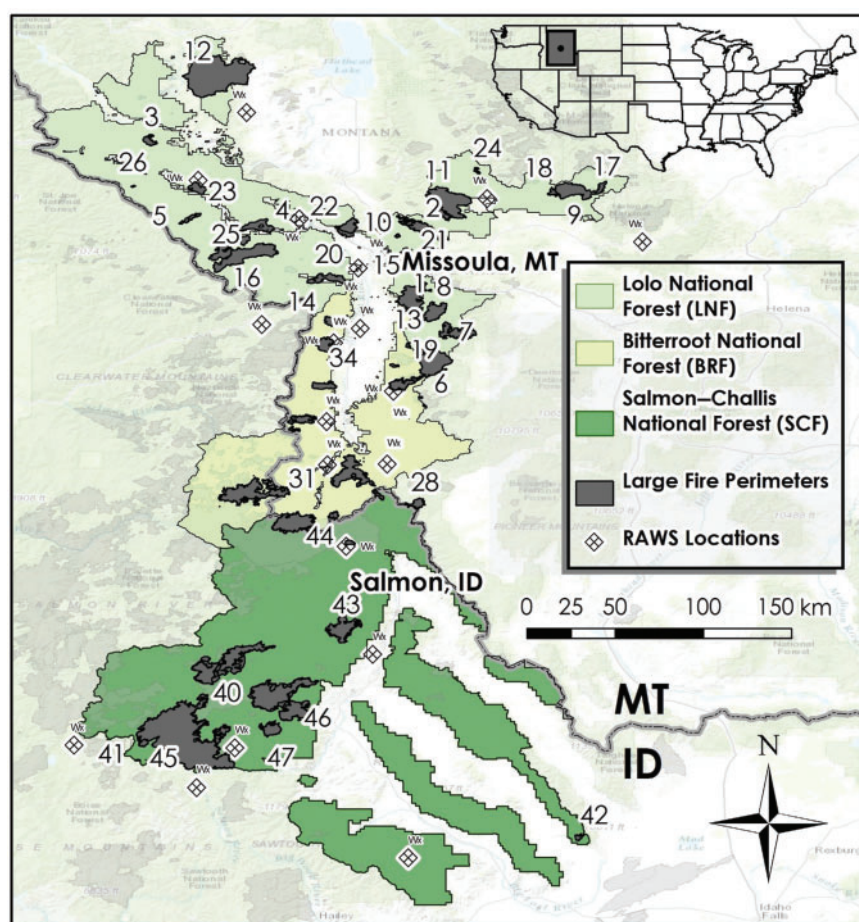


Fig. 2. Map of the study area. From north to south: the Lolo National Forest (LNF), the Bitterroot National Forest (BRF) and the Salmon–Challis National Forest (SCF). Fires included in the analysis are labelled and summarised in [Appendix 1](#). RAWs, remote automated weather station.

the northern Great Basin Geographic Area ([Fig. 2](#)). From north to south, there is a general gradient towards warmer, drier and windier fire weather conditions, higher and steeper terrain, and a transition from timber fuel models to shrub and grass fuel models ([Table 1](#)).

Fire behaviour and fire danger associations

The Incident Command System (ICS) Incident Status Summary form 209 (ICS-209) provides a field where fire managers can record daily, detailed descriptions of fire behaviour observations. The US Forest Service Fire and Aviation Management Web Applications site (FAMWEB, <https://fam.nwcg.gov/fam-web/>, accessed 23 May 2017) hosts an archive of historical ICS-209 forms organised by Geographic Area Command Center (GACC), year (2002–15), and incident name and number. Incidents were selected from this archive based on the following criteria: (i) the origin was located within the study area; (ii) either the LNF, BRF or SCF were primarily responsible for managing the incident; or (iii) an appreciable amount of the area that burned during the incident occurred within the study area. Information transcribed from the ICS-209 forms included the

incident name and number, origin latitude and longitude, report date, and a description of the fire behaviour observed during the current reporting period. A list of all incidents used in the present study is given in [Appendix 1](#).

Fire behaviour descriptions written on the ICS-209s were translated into one of five CFBXs based on the following keywords: (1) smouldering, (2) creeping or spreading, (3) running, spotting, or torching, (4) crowning or crowning and spotting, or (5) extreme or erratic. If a fire behaviour description contained keywords that spanned several categories, then the maximum CFBX was assigned to the incident on that day. This procedure ultimately produced a daily time series of CFBX codes for each incident. A daily CFBX code was not assigned if an ICS-209 was not submitted, or if an ICS-209 was submitted but lacked any fire behaviour keywords.

Each incident with a daily time series of CFBX codes was assigned to a single Remote Automated Weather Station (RAWs) either by the fire behaviour specialists who ran analyses in the Wildland Fire Decision Support System (WFDSS) or otherwise based on proximity. Station information (location, climate class, green-up date, etc.) and weather observations at 1300 hours (air temperature, relative humidity, 20-foot (~6.1 m)

Table 1. Climate, topography and fuels summary for the Lolo National Forest (LNF), the Bitterroot National Forest (BRF) and the Salmon–Challis National Forest (SCF)

Climate statistics are derived from the Remote Automated Weather Stations (RAWS) used in the fire behaviour risk analysis (see Fig. 1), and the topographic and fuels summaries are derived from the most recent LANDFIRE version, 1.3.0 (Rollins 2009)

Climate		Lolo National Forest (LNF)	Bitterroot National Forest (BRF)	Salmon–Challis National Forest (SCF)
		Range		
Daily mean temperature at 1300 hours (°C)	Jul	23–27	23–27	24–27
	Aug	21–27	21–26	22–27
	Sept	16–22	16–22	16–22
	Oct	5–15	6–16	6–15
Daily mean relative humidity (RH) at 1300 hours (%)	Jul	38–28	37–27	27–20
	Aug	38–28	37–25	29–20
	Sept	50–34	51–31	38–24
	Oct	65–42	61–38	54–34
Daily mean windspeed (m s ⁻¹)	Jul	2.1–2.7	2.3–2.9	2.8–3.3
	Aug	2.1–2.6	2.3–2.9	2.6–3.6
	Sept	2.0–2.6	2.2–2.9	2.4–3.2
	Oct	1.8–2.5	1.7–2.5	1.9–2.9
Topography		Proportion of landscape (%)		
Elevation class (m)	0–1000	3.6	0.4	0.1
	1001–2000	86.9	56.4	20.4
	2001–3000	9.4	43.2	76.5
	3001–4000	0.0	0.0	3.0
Slope class (%)	0–25	66.0	62.7	58.9
	26–40	33.2	34.7	38.9
	41–55	0.8	2.5	2.1
	56–75	0.0	0.1	0.1
	>75	0.0	0.0	0.0
Fuels		Proportion of landscape (%)		
Fire Behaviour Fuel Model (FBFM13)	FBFM 1	10.1	15.6	16.6
	FBFM 2	10.2	10.6	23.5
	FBFM 3	0.0	0.0	0.0
	Grass group total	20.2	26.2	40.1
	FBFM 4	0.1	0.1	0.4
	FBFM 5	17.0	16.2	22.7
	FBFM 6	0.0	0.0	0.3
	FBFM 7	0.0	0.0	0.0
	Shrub group total	17.2	16.4	23.5
	FBFM 8	21.7	23.9	13.5
	FBFM 9	13.3	12.2	10.6
	FBFM 10	27.7	21.3	12.3
	Timber group total	62.6	57.5	36.4

windspeed, etc.) were downloaded from FAMWEB, and imported into FireFamily Plus (Bradshaw and McCormick 2000) to calculate daily values of the Energy Release Component (ERC) and the Burning Index (BI) for the US National Fire Danger Rating System (NFDRS). ERC is an index that is related to the maximum energy release at the flaming front of a fire and BI is proportional to the flame length at the head of a fire (Bradshaw *et al.* 1983). Although BI is calculated in part using ERC, BI incorporates windspeed into the calculation and thus adds more information than simply the fuel dryness indicated by ERC. To ensure that ERC and BI values are comparable between locations, we constrained calculations to a single fuel model (Fuel Model G), which has been demonstrated to have a strong relationship with the occurrence of large fires (Andrews *et al.* 2003; Riley *et al.* 2013). Daily ERCs and BIs at each RAWS were converted into percentiles based on the most recent 20

years (1996–2015) of seasonal data between 1 June and 31 October.

Synchronising the daily time series of ERC and BI percentiles with the CFBX codes resulted in multiple pairs of fire danger and CFBX codes for the same incident: one pair for every day that an ICS-209 was submitted and contained a description of fire behaviour. If multiple fires were burning simultaneously, then multiple pairs of fire danger percentiles and CFBX codes exist for the same day. A simple exploratory data analysis (EDA) was performed to summarise the distribution of fire danger percentiles and CFBX codes in each forest. Based on this EDA, categorical fire behaviour observations were restricted to the most representative fire danger conditions by removing outliers where the ERC or BI percentile exceeded ± 3 times the median absolute deviation (MAD) (Iglewicz and Hoaglin 1993).

Ordinal logistic regressions

The CFBX codes are ordinal data because they are ranked from 1 to 5 in order of progressively more extreme fire behaviour. For each of the three national forests, we use ordinal logistic regression methods (Agresti 1984) to model the cumulative probability (γ) of observing a categorical fire behaviour type as a function of fire danger. The approach is an extension of binary logistic regression methods whereby cumulative probabilities are transformed by the logit function so that the log of the cumulative odds is linearly related to the predictor variables, as follows:

$$\text{logit}[\gamma(\text{CFBX})] = \alpha_i + \beta_{\text{ERC}}\text{ERC} + \beta_{\text{BI}}\text{BI}, i = 1, 2, 3, 4 \quad (1)$$

where i represents the four different cut-points of CFBX that divide the five fire behaviour types into two groups while still preserving their order, α_i are the intercepts associated with the cut-points, β is the cut-point-independent coefficient adhering to the parallel slopes or proportional odds assumption, and the predictor variables ERC and BI are expressed as percentiles. After obtaining the parameter estimates, the cumulative odds are transformed into cumulative probabilities and differenced to obtain the probability of observing the i th fire behaviour type, $\pi(\text{CFBX}_i)$, with the fifth and final probability obtained based on the identity that all probabilities must add up to one. Different models are obtained if only one fire danger index is used as the predictor variable and either β_{ERC} or β_{BI} is dropped from Eqn 1. If only one fire danger index is used, then $\pi(\text{CFBX}_{\text{ERC},i})$ and $\pi(\text{CFBX}_{\text{BI},i})$ are probability curves, and if both fire danger indexes are used, then $\pi(\text{CFBX}_{\text{ERC,BI},i})$ is a two-dimensional probability contour.

As geographic variations in fuels, weather and topography can induce spatial gradients in the likelihood of certain types of fire behaviours, probability curves and contours are generated for each forest using local associations between the CFBX codes, ERC and BI. For example, $\pi(\text{CFBX}_{\text{ERC},i}^{\text{LNF}})$ represents the probability of observing the i th fire behaviour type as a function of ERC for the Lolo National Forest, as indicated by the superscript. It is also important to note that the probability of the i th fire behaviour type (as calculated here) is not the same as the burn probability, or how often or how likely a fire burns an area at a given intensity level (Finney 2005). Instead, $\pi(\text{CFBX}_i)$ is a conditional probability indicating the likelihood of observing the i th categorical fire behaviour type on a day when a fire is already (or expectedly) present on the landscape.

Fire behaviour risk

Per the framework of Finney (2005), probability contours for each forest are incorporated into a fire behaviour risk analysis. Daily fire behaviour risk (FBR) is calculated as follows:

$$\text{FBR}_{\text{ERC,BI}}^{\text{NF}} = \sum_{i=1}^5 \pi(\text{CFBX}_{\text{ERC,BI},i}^{\text{NF}}) \times RWF_i \quad (2)$$

where the daily FBR for each national forest, identified by the superscript NF, depends on the daily fire danger rating, $\pi(\text{CFBX}_{\text{ERC,BI},i})$ is the probability of the i th fire behaviour type

occurring on a day with a particular combination of ERC and BI percentiles, and RWF_i is a risk weighting function intended to capture the magnitude of the effects of the i th categorical fire behaviour type on firefighter safety, which, as of yet, is assumed independent of fuels, weather and topography:

$$RWF_i = 10^{i-2} \quad (3)$$

Together, Eqns 2 and 3 combine the probabilities and the consequences of different categories of fire behaviour to yield a fire danger-driven, safety-based risk metric that reflects firefighters' exposure to potential fire behaviour.

Fire behaviour risk contours for each forest are made more intuitive by normalising the scale from 1 to 100 by dividing the FBR value by the maximum FBR (typically found at the 100th percentile of both ERC and BI) and multiplying by 100. For more convenient use in fire management applications, the normalised FBR contours are then divided into five ERC and five BI percentile classes (0–57, 58–77, 78–91, 92–96, 97–100) based on the Northern Rockies South-west Zone Fire Danger Operating Plan (Lolo NF 2015), and the maximum normalised FBR in each percentile classes is used to construct a 5×5 fire behaviour risk matrix for each forest.

Finally, we used fire danger indexes calculated from gridded surface weather data to demonstrate how these models could be used to estimate FBR across landscapes. We used a gridded surface weather dataset that was derived by downscaling a combination of the North American Land Data Assimilation System (NLDAS-2) and monthly gridded precipitation from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) (Abatzoglou 2013). This dataset provides daily measures of 2-m maximum and minimum temperature, 2-m maximum and minimum relative humidity, and total daily surface precipitation from 1979 to 2015. We combined those data with gridded daily maximum windspeed from the North American Regional Reanalysis (Mesinger *et al.* 2006), downscaled to 4-km resolution using nearest-neighbour resampling, to calculate the ERC and BI for the US NFDRS based on the same algorithms used to calculate fire danger (Bradshaw *et al.* 1983) and for consistency, we use Fuel Model G for all calculations as noted earlier. We expressed each daily gridded ERC and BI as percentiles from the entire 37-year time series. We used the individual forest-level models developed for the LNF, BRF and SCF to map potential FBR for two example time periods in 2015 that represent non-fire season (9 April, yearday 100) and fire season (27 August, yearday 240) using fire danger calculations from a gridded meteorological dataset solely to demonstrate the utility of our fire behaviour risk model to map firefighter exposure in real time.

Verification

MODIS FRPs from both the Aqua and Terra platform provide instantaneous estimates of flaming and smouldering energy release rates (Kaufman *et al.* 1998; Wooster *et al.* 2003). We extracted subdaily FRP observations from the MODIS Collection 5.1 active fire (MCD14ML) products for all active fire pixels that fell within the fire perimeters of all fires used in the test data. Fire perimeters were obtained from incident data or were

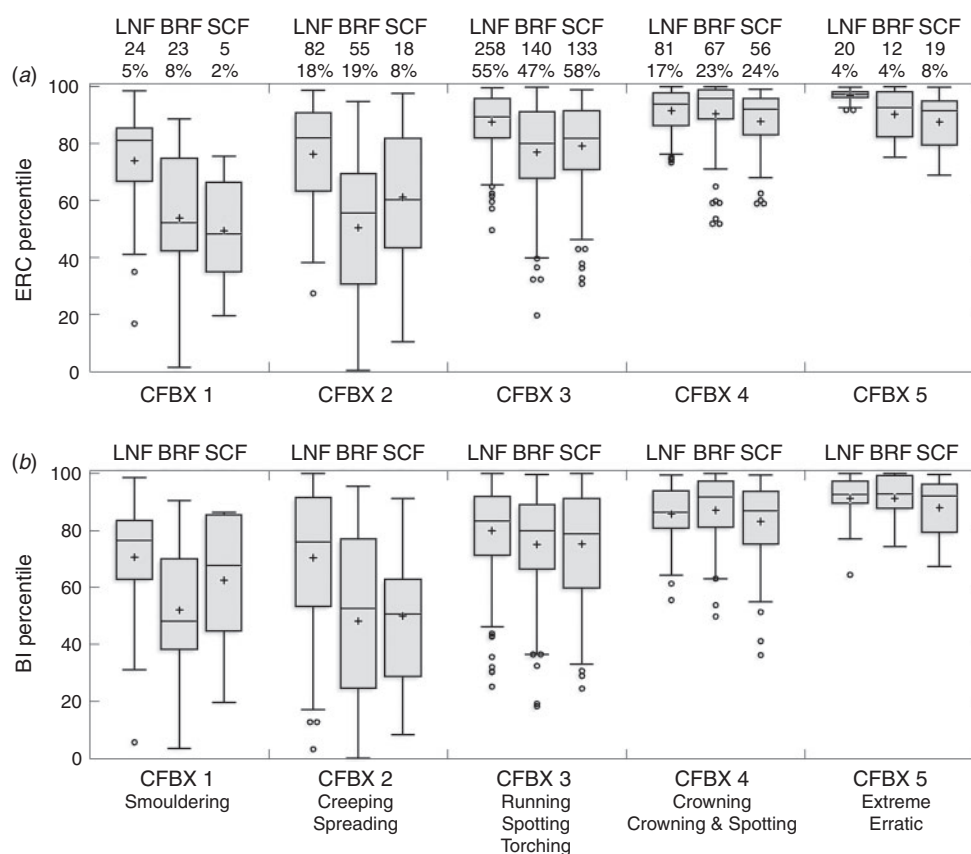


Fig. 3. Exploratory data analysis (EDA) for the Lolo (LNF), Bitterroot (BRF) and Salmon–Challis (SCF) National Forests comparing distributions of (a) the Energy Release Component (ERC); and (b) the Burning Index (BI) on days when a categorical fire behaviour index (CFBX) was recorded. The number of observations and relative proportions (in parentheses) for each forest and each CFBX are shown along the top of panel (a). Outliers (± 3 times the mean absolute deviation) are shown as circles and are removed before the ordinal logistic regression analysis.

extracted from the Monitoring Trends in Burn Severity project (Eidenshink *et al.* 2007). From these data, the maximum FRP of all active fire pixels detected per fire and per day (FRPmax) was summarised by categorical fire behaviour index and also compared with fire behaviour risk using quantile regressions (Koenker 2005) fitted to the 50th (median), 75th and 95th percentiles.

Results

Datasets for the LNF, BRF and SCF consist of 26, 13 and 8 wildland fires respectively, with 465, 297, and 231 (total $n = 993$) daily pairs of fire danger and categorical fire behaviour indexes. Depending on the duration of an incident, the number of observations collected on an individual fire ranged from 1 to 68 daily pairs. Over half (53%) of the daily pairs were collected on days when the fire was observed to be running, spotting, or torching (CFBX 3), and 51% of the daily pairs were collected when either the ERC or BI exceeded their 89th percentile.

Distributions of ERC and BI percentiles for each category of fire behaviour (Fig. 3) demonstrate that, in general, more vigorous fire behaviour is observed at higher fire danger. Moreover, there is a noticeable lower limit of fire danger

conditions that will support certain categories of fire behaviour, and this threshold increases with increasingly active fire behaviour. In contrast to smouldering fires (CFBX 1), which can occur over nearly the entire spectrum of fire danger, extreme or erratic fires (CFBX 5) are limited to the narrow, upper range of the hottest, driest and windiest conditions. The median ERC percentiles recorded on extreme or erratic fire behaviour days were 97, 93 and 92% for the LNF, BRF and SCF respectively, and BI percentiles were 93, 93 and 92% respectively.

After removing outliers (± 3 times the median absolute deviation) identified during the EDA (Fig. 3), datasets for the LNF, BRF and SCF were reduced to 418, 264 and 203 (final total $n = 885$) daily pairs of fire danger and categorical fire behaviour indexes. A summary of the Ordinal Logistic Regressions between fire danger and categorical fire behaviour indexes is given in Table 2. For the univariate regressions, the coefficients β_{ERC} and β_{BI} were significant for all three forests, suggesting that ERC and BI are suitable as independent predictors of fire behaviour for these forests. Coefficients for both ERC and BI were significant in the combined model for the SCF, and only β_{ERC} was significant for the Lolo and Bitterroot. However, the univariate plots (Fig. 4) and the bivariate plots (Fig. 5) for each forest show that the likelihood

Table 2. Results of the ordinal logistic regression analysis performed for each forest in the study area

The probability of observing a particular fire behaviour type (CFBX) is modelled using only the Energy Release Component (ERC) percentile in (a), only the Burning Index (BI) percentile in (b), and both ERC and BI in (c). The coefficients and intercepts are used to construct the probability curves shown in Fig. 4 and the probability contours shown in Fig. 5, as indicated

		Lolo National Forest (LNF)		Bitterroot National Forest (BRF)		Salmon–Challis National Forest (SCF)	
		Parameter estimate	<i>P</i> value	Parameter estimate	<i>P</i> value	Parameter estimate	<i>P</i> value
(a) ERC only		Fig. 4, top left panel		Fig. 4, top middle panel		Fig. 4, top right panel	
Coefficient	β_{ERC}	0.084	0.000	0.075	0.000	0.093	0.000
Intercepts	α_1	3.844	0.000	1.524	0.001	2.362	0.007
	α_2	5.909	0.000	4.289	0.000	4.804	0.000
	α_3	8.843	0.000	7.434	0.000	8.923	0.000
	α_4	10.796	0.000	9.740	0.000	10.567	0.000
(b) BI only		Fig. 4, bottom left panel		Fig. 4, bottom middle panel		Fig. 4, bottom right panel	
Coefficient	β_{BI}	0.045	0.000	0.065	0.000	0.064	0.000
Intercepts	α_1	0.419	0.479	0.812	0.057	0.312	0.660
	α_2	2.331	0.000	3.381	0.000	2.369	0.000
	α_3	5.090	0.000	6.346	0.000	6.244	0.000
	α_4	7.009	0.000	8.606	0.000	7.849	0.000
(c) ERC and BI		Fig. 5, top panels		Fig. 5, middle panels		Fig. 5, bottom panels	
Coefficients	β_{ERC}	0.075	0.000	0.068	0.000	0.070	0.000
	β_{BI}	0.010	0.278	0.007	0.581	0.027	0.020
Intercepts	α_1	3.893	0.000	1.528	0.001	2.492	0.005
	α_2	5.963	0.000	4.300	0.000	5.033	0.000
	α_3	8.902	0.000	7.442	0.000	9.240	0.000
	α_4	10.858	0.000	9.750	0.000	10.896	0.000

of expected fire behaviour is sensitive to ERC as well as BI. Therefore, both variables are retained in the final FBR metrics for all forests for consistency.

The individual probabilities of observing a given category of fire behaviour were very intuitive. Smouldering surface fires (CFBX 1) are most likely to occur at low fire danger (Fig. 4). As either ERC or BI increased, the probability of only observing a smouldering surface fire diminished and the probabilities of observing more intense categorical fire behaviours began to increase. Probabilities for creeping and spreading surface fires (CFBX 2) peaked between approximately the 40th to 55th percentiles of ERC and the 20th and 30th percentiles of BI. As fire danger increased, the probabilities of running, spotting and torching fires (CFBX 3) peaked at approximately the 70th to 80th percentiles of either ERC or BI. As fire danger increases above the 80th percentiles of ERC and BI, the likelihood for crowing, crowning and spotting (CFBX 4) or extreme or erratic fire behaviour (CFBX 5) increased to their highest probabilities.

The normalised and partitioned risk matrix is given in Fig. 6. The highest FBR was found in the combined highest ERC and highest BI bins. Within a given ERC bin, FBR increased with increasing BI percentiles, illustrating that fire behaviour is sensitive to changes in both ERC and BI. The lowest FBR was found in the lowest combined ERC and BI bins.

The daily maximum FRP (FRPmax) of all active fire pixels detected by MODIS was strongly related to the most extreme fire behaviour described on the same day and for the same fire (Fig. 7a). Increasing MODIS detection probabilities and an upward shift in the distributions of FRPmax values with increasing CFBX demonstrate that localised hotspots were larger or more intense on days when fire observers reported increasingly extreme fire behaviour types. The MODIS detection algorithm

was not sensitive enough to identify hotspots when fires were smouldering, but MODIS did detect at least one active fire pixel within the final fire perimeter on 98% of the days that crowning was reported. Likewise, the upper limit of FRPmax continually increased at and above CFBX 2, with median values more than doubling between consecutive categorical fire behaviour indexes (CFBX 2: 39.7 MW, CFBX 3: 113.1 MW, CFBX 4: 304.4 MW, CFBX 5: 894.0 MW). Ultimately the relationship between daily FBR and daily FRPmax reveals that an increase in fire behaviour risk is accompanied by an expanding window of fire behaviour potential (Fig. 7b). Quantile regressions fitted to the 50th, 75th and 95th percentiles (τ) are all significant ($P < 0.001$). In particular, the quantile regression fitted to the 95th percentile captures the trend in the upper limit of fire behaviour potential, which over the full range of FBR exhibits a more than 4-fold increase in the maximum heat release rate.

Example maps of FBR are shown in Fig. 8. FBR was consistently low across all three forests during the spring on yearday 100 in 2015 but it was highly variable and reached maximum values on yearday 240 during the peak of the fire season in the Northern Rockies and Great Basin. Despite areas with extremely high FBR, other areas during the same time period were near minimum values, suggesting that this method is capable of capturing asymmetric fire behaviour potential across landscapes.

Discussion

The framework presented here is the first attempt at systematically correlating indices from the US NFDNR with observed, categorical descriptions of wildland fire behaviour. The ordinal logistic regression results are intuitive and show promise in differentiating relationships between fire danger and categorical

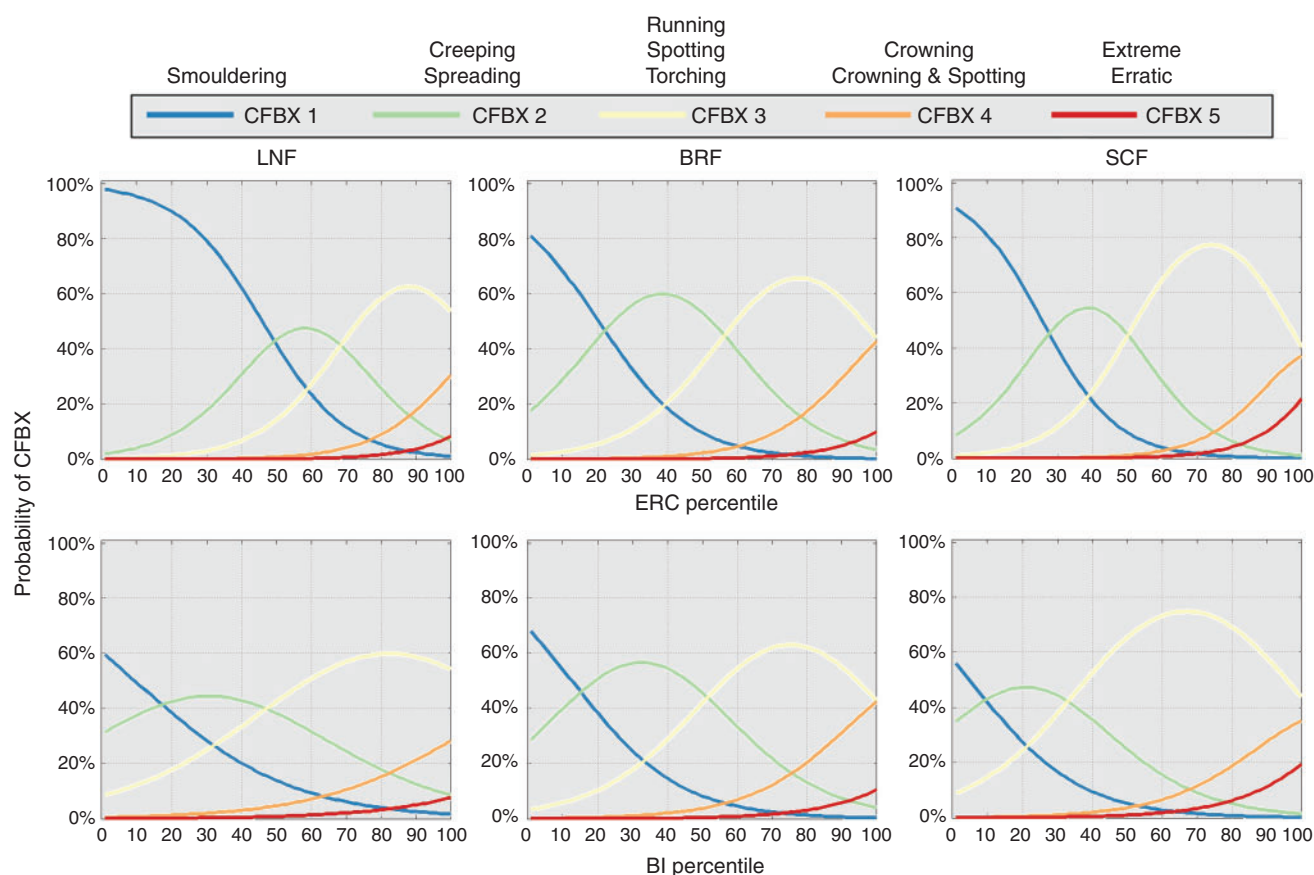


Fig. 4. Results of the ordinal logistic regression analysis performed for the Lolo (LNF), Bitterroot (BRF) and Salmon–Challis (SCF) National Forests. The probability of a categorical fire behaviour index (CFBX) is modelled using one predictor variable only: either the Energy Release Component (ERC) percentile (top panels), or the Burning Index (BI) percentile (bottom panels). Each probability curve is constructed from the coefficients and intercepts summarised in Table 2.

fire behaviour probabilities across a narrow range of western US forests. This fire behaviour risk framework can serve as the foundation for new tools that provide up-to-date, daily potential fire behaviour information to support strategic and tactical decision making.

The fire behaviour risk framework is primarily composed of four components: (i) qualitative, categorical fire behaviour observations (CFBX), (ii) normalised fire weather observations (ERC and BI), (iii) categorical probability modelling, and (iv) risk weighting. Each of these components has strengths and weakness that are detailed below.

Categorical fire behaviour observations are recorded once or twice per day on ICS-209 forms. These categories are loosely coupled with physical fire properties that can be quantified and measured, such as reaction intensity (W m^{-2}), fireline intensity (W m^{-1}), spread rate (m s^{-1}) and flame length (m). If these properties could be measured everywhere on a fire and throughout the day, each CFBX code would capture a broad range of values due to spatial and temporal fluctuations in fire behaviour. Moreover, the magnitude of the measurements for the same CFBX code would differ between regions depending on the local fuels, weather and topography, and the measured differences between successive CFBX codes would not be constant.

Conveniently, the risk analysis framework implemented here is based on the probabilities of a given categorical fire behaviour rather than a discrete prediction of it. This allows for the possibility of any fire behaviour type on a given day but those categorical fire behaviour types are limited to the fire danger conditions under which they have been observed.

Only using ICS-209 reports to obtain CFBX codes biases our dataset towards larger and generally more complex incidents. Undoubtedly, the timeliness and representativeness of the fire behaviour descriptions affect the resulting magnitudes and shapes of probability curves and contours. For example, a delay in the submission of the first ICS-209 would fail to record the extreme fire behaviour that likely contributed to the rapid initial development of the fire, thus resulting in fewer observations of the upper CFBX classes. Conversely, the continued submission of ICS-209s during the later stages of the fire's lifetime would preferentially include more observations of the lower CFBX classes even though fire behaviour is likely more influenced by suppression operations. Assigning the highest CFBX code to a particular day based on the worst-case fire behaviour description neglects the spatial and temporal distribution of fire behaviour. ICS-209s rarely described where on the fire and in what fuels the maximum fire behaviour was observed, and it is entirely

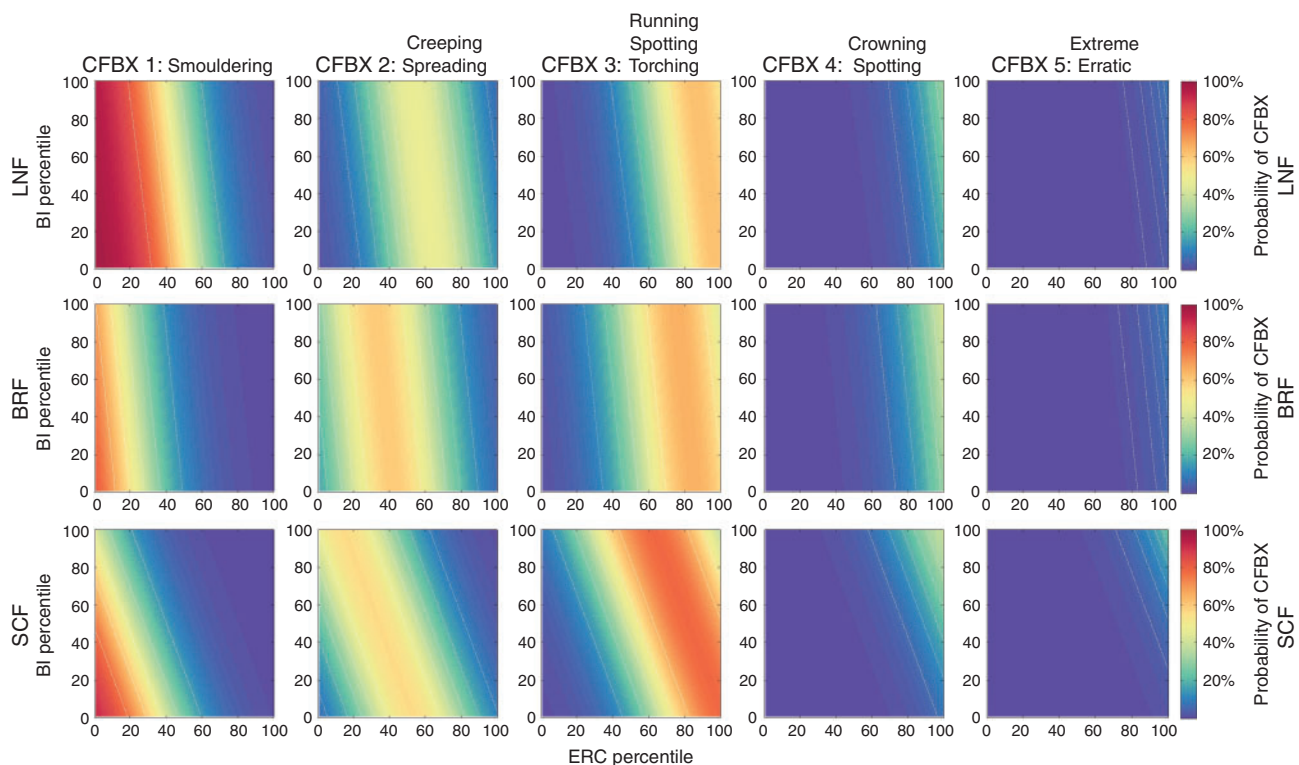


Fig. 5. Results of the ordinal logistic regression performed for the Lolo (LNF), Bitterroot (BRF) and Salmon–Challis (SCF) National Forests. The probability of a categorical fire behaviour index (CFBX) is modelled using two predictor variables: both the Energy Release Component (ERC) percentile and the Burning Index (BI) percentile. Each probability contour is constructed from the coefficients and intercepts summarised in Table 2.

possible that the maximum fire behaviour was never observed or was observed but never recorded. In reality, large fires rarely exhibit consistent fire behaviour across their entire fireline. Therefore, field-based observations that are more localised could also improve the data collection for our approach. Future improvements aim to include fire behaviour observations from ICS-209 reports with observations made during IA and field observer reports from large fires to improve our ability to rate fire behaviour over the full range of environmental conditions.

Owing to the coarse spatial resolution of the fire behaviour observations, we develop the probability curves using the ERCs and BIs from the fire danger rating area of the nearest or most representative RAWs. However, it is possible that the localised weather conditions influencing the fire at the time the categorical fire behaviour observations were made were different to the conditions measured at the nearby weather station. Future improvements to fire weather analyses used in the present framework may include the use of higher-resolution gridded data that can better represent local-scale influences on fuel moistures and fire potential (Holden and Jolly 2011).

The ordinal logistic regression analysis performed here directly relates fire weather conditions with the likelihood of different types of fire behaviours, and is therefore a well-suited component of the fire risk calculation. However, linking fire danger information with observed fire behaviour to predict potential fire behaviour has been part of the Canadian Fire Behaviour Prediction System for decades (Stocks *et al.* 1989; Hirsch 1996; Taylor *et al.* 1997). These predictions are provided

to firefighters as part of their Fire Behaviour Prediction (FBP) field guide (Taylor *et al.* 1997). In addition to quantitative descriptions of fire behaviour such as rates of spread, indices from the Canadian Forest Fire Danger Rating System (CFFDRS) along with information about fuel types are used to provide predictions of the type of fire behaviour expected, such as surface fire, intermittent crown fire (i.e. torching) and continuous crown fire. However, our method is complementary to the FBP approach because it expresses the individual probabilities of each fire behaviour category and thus allows a more complete interpretation of potential fire behaviour and, when combined with the Risk Weighting Factors, it can be used to better express the potential exposure risk to firefighters.

The safety-based *RWF* created here is simply used as a temporary place holder. Future work will focus on quantifying spatially varying *RWFs* based on local fuels and terrain. A more appropriate *RWF*, for example, could integrate information about the fuel size distribution and loadings in order to approximate the fireline intensity for a particular fire behaviour type. Fireline intensity varies by orders of magnitude as flames carry from the surface into tree crowns (Alexander 1982). It is therefore possible that a more complete method for rating risk could quantify the potential fireline intensity of each fuel stratum and use fireline intensity directly as a weighting factor for quantifying fire behaviour risk.

Our FBR is a numerical rating of the sum of the categorical fire behaviour probabilities and consequences of each type of fire behaviour occurring under a given combination of ERC and

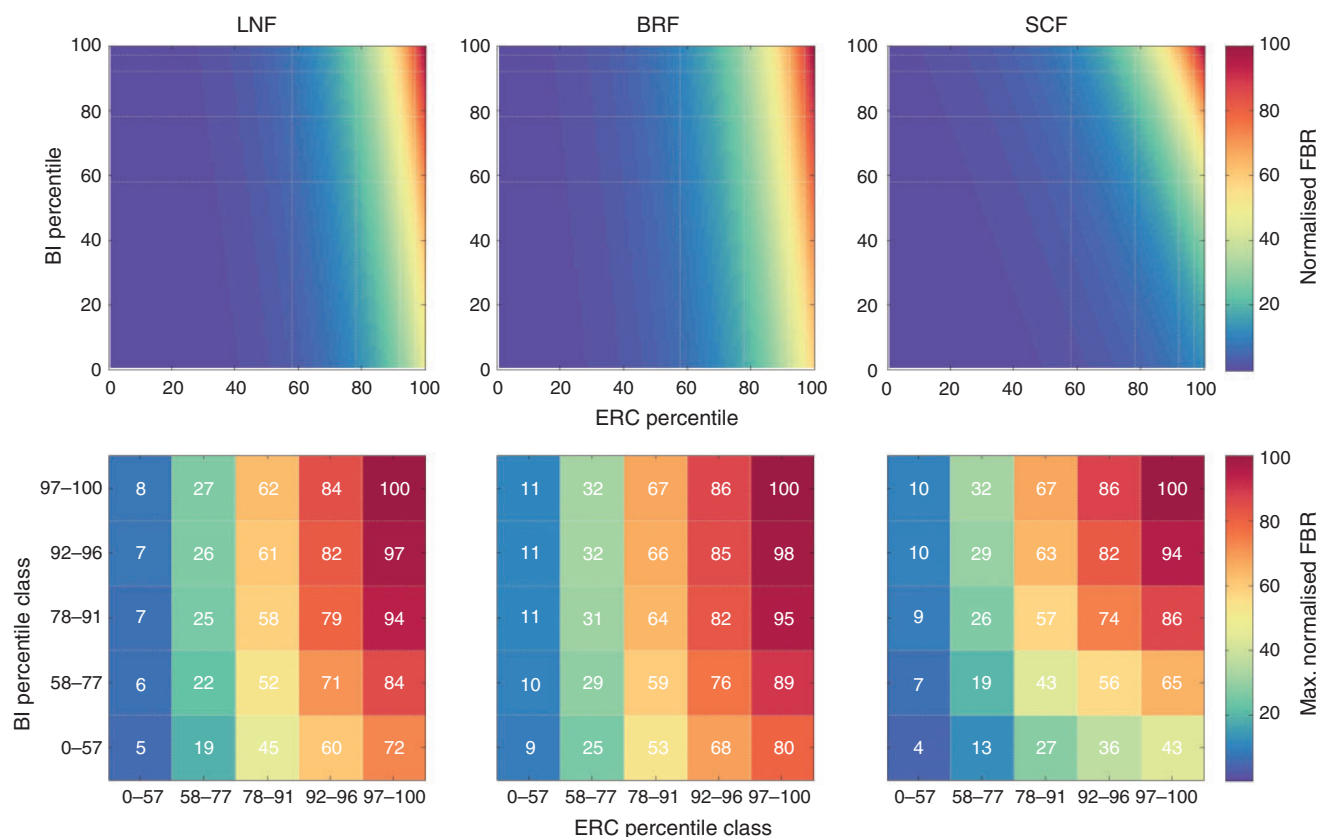


Fig. 6. Final results of the fire behaviour risk (FBR) analysis performed for the Lolo (LNF), Bitterroot (BRF) and Salmon-Challis (SCF) National Forests. The maximum normalised FBR (top panels) in each fire danger class is used to construct the 5 × 5 FBR matrices (bottom panels).

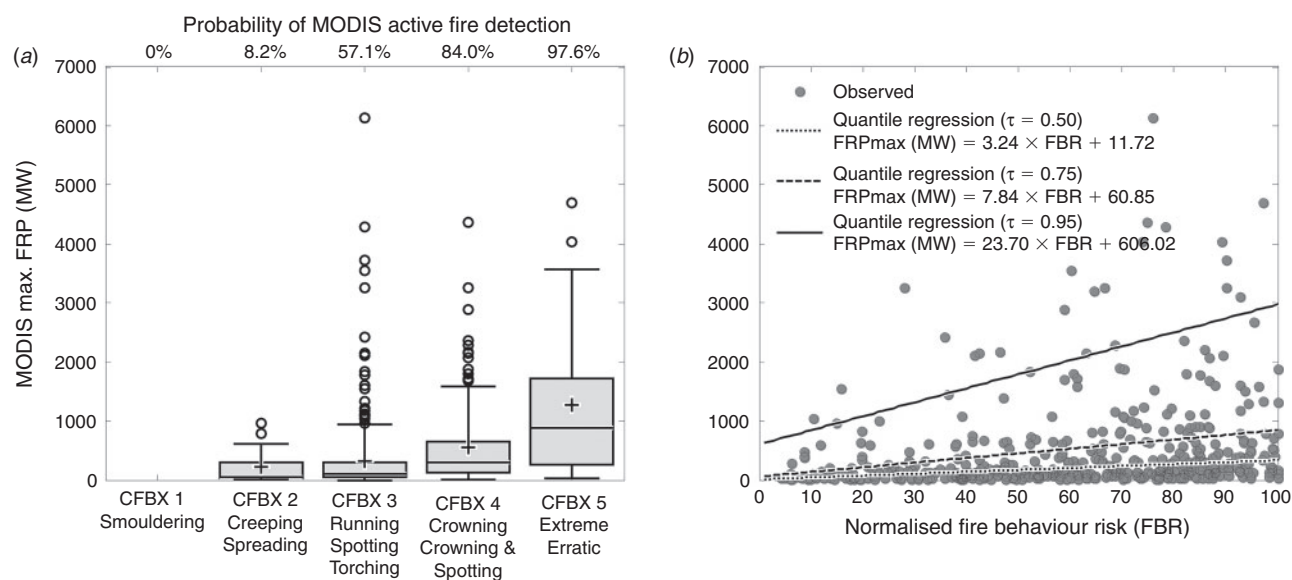


Fig. 7. Relationship between qualitative observations of Categorical Fire Behaviour Indexes (CFBX) and daily maximum fire radiative power (FRP) detected by Moderate Resolution Imaging Spectroradiometer (MODIS) are shown in (a). Quantile regressions relating normalised Fire Behaviour Risk (FBR) with the daily maximum FRP are shown in (b). Results are based on data combined from all three forests in the study area.

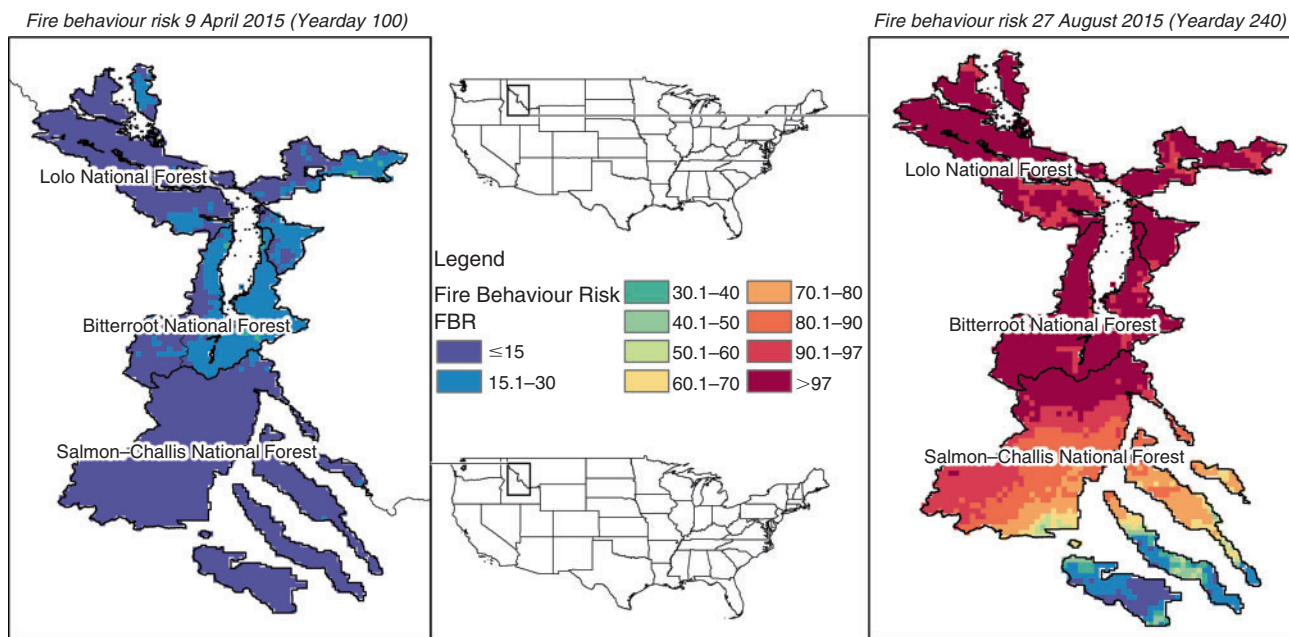


Fig. 8. Example Fire Behaviour Risk (FBR) maps calculated from gridded Energy Release Component and Burning Index percentiles for 2 days in 2015: 9 April (yearday 100) and 27 August (yearday 240).

BI percentiles. In order to apply this metric appropriately, it will need to be translated into a categorical risk rating that can be tied directly to operational wildland fire management decisions aimed at mitigating risk (Garvey and Lansdowne 1997). Similarly to adjective fire danger ratings, the adjective risk ratings could be used to inform firefighters during briefings, and could be incorporated into fire behaviour risk matrices (Fig. 6) for display on local forest pocket cards (Andrews *et al.* 1998). In addition to pocket cards, the emergence of web-based map displays is changing the way that fire weather and fire danger information are delivered to support wildland fire decision making (Horel *et al.* 2014). Our example maps (Fig. 8) show promise that this new tool could be combined with forecast fire danger indices to map FBR across landscapes. Such a tool could inform both strategic and tactical wildland fire management decisions and could transform the way that we prioritise and respond to wildland fires.

Independently and quantitatively substantiating descriptions of fire behaviour across multiple years and multiple forests is only feasible by satellite remote sensing of active fires. Larger and more intense fires emit more radiant heat and are therefore more likely to be detected by MODIS. In this regard, our work corroborates the fire behaviour descriptions recorded by incident managers on ICS-209 forms because we show that higher CFBX categories coincide with higher detection probabilities and larger FRP measurements. Ultimately, our fire behaviour risk metric was well correlated with the upper limit (i.e. 95th percentile) of daily maximum FRP, a threshold we suggest is a good indicator of the maximum potential fire behaviour measured on a spatial scale (nominally 1-km resolution) commensurate with the tactical decisions made by wildland firefighters.

The analysis framework presented here provides a roadmap for applying these methods to other forests where the full range

of CFBX is documented. In the US, any fire greater than 100 acres (~40.47 ha) in timber or 300 acres (~121.41 ha) in grass or that has national firefighting resources assigned must have an ICS-209 report completed each day. These reports are entered into an online database and have been archived electronically since 2002. Therefore, a wealth of fire behaviour observations has been recorded and is available nationwide. Additionally, there are more than 2200 fire weather stations throughout the US and these data are archived and available. In essence, the critical data needed to develop local relationships between fire danger and categorical fire behaviour probabilities already exist across the United States. Future work will aim to streamline and expand the opportunities for data collection. For example, updated versions of the ICS-209 forms would benefit from a field that allows incident management personnel to directly enter the CFBX code, thereby eliminating the need to manually search for keywords. Aside from large and complex incidents, fire behaviour observations could also be collected and recorded during IA or during prescribed fires or wildfires when ICS-209 forms are not required to be submitted. More work will need to be done to categorise fire behaviour in other ecosystems such as grasslands and shrublands, where colloquialisms other than 'torching' and 'crowning' may be used to describe fire behaviour types. Future work will also determine how best to implement this framework within non-forested ecosystems, perhaps leveraging both expert fire behaviour observations as well as satellite-based estimates of radiant heat release.

Ultimately, the present framework is the first of its kind to combine both fire danger and fire behaviour observations to predict the probabilities of different categorical fire behaviour types. Although the case studies presented here are solid examples of the system's flexibility, it can easily be expanded for use in other locations through the world through the

collection of simple fire behaviour observations and the calculation of fire danger indices. This new approach can lay the foundation for a nationwide, gridded, forecastable FBP system that can provide objective criteria about fire behaviour risk to inform both strategic and tactical wildland fire management decisions that meet required objectives while keeping people safe.

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References

- Abatzoglou JT (2013) Development of gridded surface meteorological data for ecological applications and modelling. *International Journal of Climatology* **33**, 121–131. doi:10.1002/JOC.3413
- Agresti, A (1984) 'Analysis of Ordinal Categorical Data.' (Wiley: Hoboken, NJ, USA)
- Alexander ME (1982) Calculating and interpreting forest fire intensities. *Canadian Journal of Botany* **60**, 349–357. doi:10.1139/B82-048
- Andrews PL, Bradshaw LS, Bunnell D, Curcio GM (1998) Fire danger rating pocket card for firefighter safety. In 'Proceedings of the Second Symposium on Fire and Forest Meteorology', 11–16 January 1998, Phoenix, AZ, USA. (American Meteorological Society: Boston, MA, USA) Available at http://www.ncforestservice.gov/fire_control/pdf/fdpocket_cards.pdf [Verified 28 June 2017]
- Andrews PL, Loftsgaarden DO, Bradshaw LS (2003) Evaluation of fire danger rating indexes using logistic regression and percentile analysis. *International Journal of Wildland Fire* **12**, 213–226. doi:10.1071/WF02059
- Bowman DMJS, Balch J, Artaxo P, Bond WJ, Cochrane MA, D'Antonio CM, DeFries R, Johnston FH, Keeley JE, Krawchuk MA, Kull CA, Mack M, Moritz MA, Pyne S, Roos CI, Scott AC, Sodhi NS, Swetnam TW (2011) The human dimension of fire regimes on Earth. *Journal of Biogeography* **38**, 2223–2236. doi:10.1111/J.1365-2699.2011.02595.X
- Bradshaw LS, McCormick E (2000) FireFamily Plus user's guide. USDA Forest Service, Rocky Mountain Research Station, General Technical Report RMRS-GTR-67-WWW. (Fort Collins, CO, USA)
- Bradshaw LS, Deeming J, Burgan R, Cohen J (1983) The 1978 NFDRS: technical documentation. USDA Forest Service, Intermountain Research Station, General Technical Report GTR-INT-169, (Ogden, UT, USA)
- Countryman CM (1972) The fire environment concept. National Wildfire Coordinating Group, PMS-433. (Boise, ID, USA)
- Eidenshink JC, Schwind B, Brewer K, Zhu Z-L, Quayle B, Howard SM (2007) A project for monitoring trends in burn severity. *Fire Ecology* **3**, 3–21. doi:10.4996/FIREECOLOG.0301003
- Finney MA (2005) The challenge of quantitative risk analysis for wildland fire. *Forest Ecology and Management* **211**, 97–108. doi:10.1016/J.FORECO.2005.02.010
- Garvey PR, Lansdowne ZF (1997) Risk matrix: an approach for identifying, assessing, and ranking program risks. *US Air Force Logistics Journal* **XXII**, 18–21.
- Giglio L, Randerson JT, van der Werf GR, Kasibhatla PS, Collatz GJ, Morton DC, DeFries RS (2010) Assessing variability and long-term trends in burned area by merging multiple satellite fire products. *Biogeosciences* **7**, 1171–1186. doi:10.5194/BG-7-1171-2010
- Hirsch KG (1996) Canadian Forest Fire Behavior Prediction (FBP) System: user's guide. Canadian Forest Service, Northwest Region, Northern Forestry Centre number Special Report 7. (Edmonton, AB, Canada)
- Holden ZA, Jolly WM (2011) Modeling topographic influences on fuel moisture and fire danger in complex terrain to improve wildland fire management decision support. *Forest Ecology and Management* **262**, 2133–2141. doi:10.1016/J.FORECO.2011.08.002
- Horel JD, Ziel R, Galli C, Pechmann J, Dong X (2014) An evaluation of fire danger and behaviour indices in the Great Lakes Region calculated from station and gridded weather information. *International Journal of Wildland Fire* **23**, 202–214. doi:10.1071/WF12186
- Iglewicz, B, Hoaglin, D (1993) Vol. 16: how to detect and handle outliers. In 'The ASQC Basic Reference in Quality Control: Statistical Technique'. (ASQ Quality Press: Milwaukee, WI, USA)
- Jolly WM, Cochrane MA, Freeborn PH, Holden ZA, Brown TJ, Williamson GJ, Bowman DMJS (2015) Climate-induced variations in global wildfire danger from 1979 to 2013. *Nature Communications* **6**, 7537. doi:10.1038/NCOMMS8537
- Kaufman YJ, Justice CO, Flynn LP, Kendall JD, Prins EM, Giglio L, Ward DE, Menzel WP, Setzer AW (1998) Potential global fire monitoring from EOS-MODIS. *Journal of Geophysical Research – D: Atmospheres* **103**, 32215–32238. doi:10.1029/98JD01644
- Koenker R (2005) 'Quantile Regression.' (Cambridge University Press: Cambridge, UK)
- Lolo NF (2015) Northern Rockies Southwest Zone fire danger operating plan. Available at https://www.wfas.net/resources/docs/LoloNFDRS-plan2015_2016Final.pdf [Verified 24 May 2017]
- Mesinger F, DiMego G, Kalnay E, Mitchell K (2006) North American regional reanalysis. *Bulletin of the American Meteorological Society* **87**, 343–360. doi:10.1175/BAMS-87-3-343
- National Interagency Fire Center (2015) Wildland fire fatalities by year. Available at https://www.nifc.gov/safety/safety_documents/Fatalities-by-Year.pdf [Verified 23 May 2017]
- National Wildfire Coordinating Group (2014) Incident response pocket guide. Number PMS-461. (Boise, ID, USA)
- Riley KL, Abatzoglou JT, Grenfell IC, Klene AE, Heinsch FA (2013) The relationship of large fire occurrence with drought and fire danger indices in the western USA, 1984–2008: the role of temporal scale. *International Journal of Wildland Fire* **22**, 894–909. doi:10.1071/WF12149
- Rollins MG (2009) LANDFIRE: a nationally consistent vegetation, wildland fire, and fuel assessment. *International Journal of Wildland Fire* **18**, 235–249. doi:10.1071/WF08088
- Stocks BJ, Lynham TJ, Lawson BD, Alexander ME, Wagner CEV, McAlpine RS, Dubé DE (1989) Canadian Forest Fire Danger Rating System: an overview. *Forestry Chronicle* **65**, 258–265. doi:10.5558/TFC65258-4
- Taylor SWP, Pike RG, Alexander ME (1997) Field guide to the Canadian Forest Fire Behavior Prediction (FBP) System. Canadian Forest Service, Northern Forestry Centre number Special Report 11. (Edmonton, AB, Canada)
- Wooster M, Zhukov B, Oertel D (2003) Fire radiative energy for quantitative study of biomass burning: derivation from the BIRD experimental satellite and comparison to MODIS fire products. *Remote Sensing of Environment* **86**, 83–107. doi:10.1016/S0034-4257(03)00070-1

Appendix 1. List of fires used in the fire behaviour risk analysis

Fig. 2

		Origin			ICS-209 report date			
Map ID	Fire name	Latitude	Longitude	Year	First	Last	RAWS ID	RAWS name
Lolo National Forest								
1	Cooney Ridge Complex	46.623	−113.826	2003	13-Aug	15-Sep	241513	Blue Mtn
2	Mineral-Primm	47.008	−113.758	2003	15-Aug	19-Sep	241519	Point Six
3	Cherry Creek	47.473	−115.192	2003	8-Aug	3-Sep	241308	Pardee
4	I-90	46.997	−114.472	2005	5-Aug	18-Aug	241507	Ninemile
5	Prospect	47.055	−115.004	2005	7-Aug	1-Sep	241308	Pardee
6	Wyman number 2	46.358	−113.716	2007	29-Jul	31-Jul	242904	Stevi
7	Fisher Point	46.499	−113.663	2007	29-Jul	31-Jul	242904	Stevi
8	Sawmill	46.607	−113.701	2007	31-Jul	15-Sep	242904	Stevi
9	Conger Creek	47.216	−113.037	2007	18-Jul	22-Sep	241904	Lincoln
10	Black Cat	47.022	−114.152	2007	15-Aug	1-Sep	241513	Blue Mtn
11	Jocko Lakes	47.199	−113.729	2007	3-Aug	20-Sep	241508	Seeley Lake
12	Chippy Creek	47.808	−114.997	2007	31-Jul	8-Sep	241211	Hspring
13	Alder Creek	46.438	−113.851	2010	22-Aug	31-Aug	242911	Gird
14	Packer Meadows	46.653	−114.539	2010	27-Jul	11-Aug	101049	Roundtop
15	West Riverside	46.716	−113.888	2011	23-Aug	5-Sep	241519	Point Six
16	Granite Pass	46.652	−114.634	2011	28-Aug	4-Sep	101049	Roundtop
17	Falls Point	47.220	−112.909	2012	30-Jul	26-Sep	241904	Lincoln
18	Wedge Creek	47.211	−113.112	2012	19-Aug	11-Oct	241904	Lincoln
19	Harrys Flat	46.530	−113.764	2013	1-Sep	24-Sep	242912	Smith Creek
20	Lolo Creek Complex	46.773	−114.251	2013	18-Aug	7-Sep	241513	Blue Mtn
21	Gold Creek	47.089	−113.783	2013	16-Jul	14-Aug	241519	Point Six
22	Mill Creek	47.017	−114.203	2013	25-Jul	29-Jul	241507	Ninemile
23	West Mullan	47.214	−114.943	2013	14-Jul	1-Aug	241308	Pardee
24	Morrell Complex	47.313	−113.516	2015	14-Aug	6-Nov	241508	Seeley Lake
25	West Fork Fish Creek	46.873	−114.849	2015	14-Aug	30-Oct	241308	Pardee
26	Little Joe	47.241	−115.250	2015	28-Aug	15-Sep	241308	Pardee
Bitterroot National Forest								
27	Frog Pond	45.692	114.033	2003	22-Jul	23-Jul	242905	Sula
28	Black Frog Complex	45.608	−113.834	2003	24-Jul	8-Aug	242905	Sula
29	Rockin	46.053	114.401	2005	4-Aug	7-Nov	242914	Little Rock Creek
30	Gash Creek	46.395	114.254	2006	25-Jul	8-Dec	242912	Smith Creek
31	Rombo Mountain	45.748	−114.235	2007	31-Jul	6-Nov	242907	West Fk
32	Kootenai Creek	46.553	114.235	2009	21-Jul	18-Dec	242912	Smith Creek
33	Dominic Point	46.324	113.941	2010	25-Jul	3-Aug	242911	Gird
34	Downing Mtn	46.242	−114.250	2010	27-Aug	20-Oct	242914	Little Rock Creek
35	Forty One Complex	46.222	113.942	2011	30-Aug	3-Nov	242911	Gird
36	Saddle–Bitterroot Branch	45.550	114.450	2011	23-Aug	21-Oct	242907	West Fk
37	Sawtooth	46.228	114.308	2012	2-Sep	31-Oct	242914	Little Rock Creek
38	Chrandal Creek	45.561	114.221	2012	9-Jul	6-Aug	242907	West Fk
39	Gold Pan Complex	45.657	114.780	2013	27-Jul	3-Oct	242907	West Fk
Salmon–Challis								
40	Shower Bath	44.621	−114.622	2007	1-Aug	14-Sep	101801	Bonanaza
41	Banner	44.380	−115.210	2010	20-Aug	16-Sep	101221	Bearskin
42	Black Canyon	43.908	−112.973	2011	31-Aug	21-Oct	101804	Copper Basin
43	Salt	44.983	−114.236	2011	26-Aug	13-Oct	101314	Ezra Creek
44	Indian	45.422	−114.150	2011	19-Jul	14-Aug	101303	Indianola
45	Halstead	44.446	−115.166	2012	30-Jul	18-Oct	101809	Stanley RS
46	Lodgepole	44.528	−114.458	2013	20-Jul	29-Aug	101801	Bonanaza
47	Elevenmile	44.450	−114.569	2015	24-Aug	14-Sep	101801	Bonanaza