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ClassiFiR$_x$e: A data-driven tool to support prescribed fire planning and implementation

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ABSTRACT

Despite a growing need to expand the pace and scale of prescribed burning to address the national fire deficit, there is a lack of data-driven methods to incorporate fire danger information into prescribed fire planning. We assembled nearly two decades of prescribed fire and wildfire records across Montana and Idaho and combined these records with spatially explicit fire danger data. We implement a nonparametric cutpoint analysis to identify objective thresholds from the Energy Release Component (ERC) percentile, treating pile burns, broadcast burns, and wildfires as ordinal classes along an ERC continuum. A novel bootstrapping approach generates distributions of optimal cutpoints, creating overlap zones that quantify uncertainty between fire classes. These thresholds form the basis of a planning guide, **ClassiFiR$_x$e**, which helps managers determine whether project conditions have historically supported pile burning, broadcast burning, or wildfire and whether a proposed burn falls within a zone of confident support or greater uncertainty. Classification performance varies across regions, performing best in the forested western study area. The West of Divide guide achieves a reasonable cross-validated balanced strict recall of 65% and full recall of 77%. We demonstrate how these zones reveal seasonal patterns in burn conditions, estimate burn windows locally, and map fire danger categories across large landscapes. Such guides can be developed wherever sufficient fire weather and occurrence data exist and ordinality is satisfied, providing a scalable, interpretable, and explainable tool grounded in historical data to support prescribed fire planning and help restore fire to landscapes and reduce the fire deficit.

1. Introduction

Wildland fire is a naturally occurring, necessary ecological process in fire-dependent ecosystems where it maintains biodiversity, nutrient cycling, and forest structure (Bowman et al., 2009). However, wildfire characteristics are shifting. In recent decades, there has been a marked global increase in large, high-intensity wildfires (Cunningham et al., 2024), with the Western United States experiencing some of the most pronounced changes (Dennison et al., 2014). Despite such trends, a fire deficit exists across the US, a problem attributed to the suppression of smaller, lower intensity wildfires (Parks et al., 2025; Haugo et al., 2019; Kreider et al., 2024). This transition from frequent, low-intensity to more extreme fire events has been shown to undermine forest resilience and health (Coop et al., 2020; Falk et al., 2022) as well as increase fire emissions per unit of area burned (Zheng et al., 2021). Proactive fire management is needed to counter this trend, with a particular emphasis on increasing the pace and scale of prescribed fires (U.S. Department of Agriculture, Forest Service, 2023). Prescribed burning is consistently identified as one of the most effective fuel reduction strategies for mitigating high-severity fire behavior (Davis et al., 2024; Davim et al., 2022). Thus, improving methods to plan and implement prescribed burns at scale is critical for maintaining ecosystems and reducing wildfire risk worldwide.

Prescribed fires are typically utilized to mitigate forms of wildfire risk (Alcasena et al., 2018; Finney et al., 2007), yet their implementation remains constrained by planning complexities. Once project locations are established, land managers need robust tools to plan and implement prescribed fire activities at scales commensurate with the demands for risk reduction, ecological maintenance, or restoration. Prescribed fires require the development of 'burn plans' (National Wildfire Coordinating Group, 2021). These burn plans define the project area and objectives, such as hazardous fuels reduction or ecosystem restoration (Penman et al., 2011). The plans then evaluate the fire weather, fire behavior, and fire effects that would best meet the objectives (Johnson and Miyanishi, 1995) and detail 'prescription' parameters

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to determine the most suitable burn days. Prescriptions are often a blend of fire modeling and local expertise. Environmental conditions are then monitored to identify favorable prescribed burn windows for project implementation. Thus, tools used for planning should allow identification of real-time conditions that meet burn windows.

Fire modeling efforts are iterative and require multiple simulations over a range of weather conditions to identify weather parameters that meet objectives. Outputs provide a set of weather conditions that would allow the safe implementation of a prescribed burn. Although fire behavior models are useful tools, they are primarily calibrated using wildfire observations (Hiers et al., 2020). These models often assume single-point ignitions under extreme weather conditions, making them less reliable when applied to prescribed fires characterized by multi-point and line ignitions under moderate weather conditions (Hiers et al., 2020; Chatterjee et al., 2023). Fire behavior models also still lack an integrated decision-making framework, leaving fire managers to make subjective choices based on ambiguous risk signals (Coen et al., 2024; Thompson et al., 2016). Despite their effectiveness in some applications, modeling-based prescriptions rarely incorporate historical fire danger data, although this information is congressionally mandated (U.S. Senate, 2016) and often cited as a key factor in prescribed fire escapes across the United States (Office of the Chief, 2022).

A cumulative, historical analysis of successful burns across particular fire units or regions is rarely considered when planning prescribed fires (Fernández-Guisuraga and Fernandes, 2024). This is one reason fire danger metrics are not used for planning on a widespread or systematic basis. A better approach would adapt existing fire danger planning methods, which define thresholds for wildfire preparedness and response, to identify similar thresholds for prescribed fires like pile and broadcast burns. Fire danger analyses use historical relationships between fire danger index values and wildfire activity to set appropriate fire danger levels, determine relevant staffing needs, implement wildfire prevention plans and support a host of other fire management decisions (Andrews et al., 2003; Jolly et al., 2024). By applying these methods to prescribed fire, an exploration of the entire continuum of wildland fire activity along gradients of fire danger is possible. Additionally, these analyses could provide a useful tool for planning and implementing prescribed burns while also informing wildfire response activities. However, three major obstacles prevent the widespread implementation of such a data-driven approach: (1) a lack of harmonized wildfire and prescribed fire data, (2) challenges in normalizing fire danger indices across space, and (3) the absence of objective analytical methods for cutpoint determination that incorporate uncertainty.

The first challenge to this approach is the lack of geospatial prescribed fire data that aligns with national wildfire occurrence datasets such as the Fire Program Analysis, Fire Occurrence Database (FPA-FOD) (Short, 2022). The 'FOD' facilitates nationwide comparisons between fire danger and wildfire occurrence (Walding et al., 2018), allowing system users to set fire danger thresholds or cutpoints objectively. A comparable prescribed fire dataset, with each burn associated with a normalized metric of fire danger conditions for its date and location, could enable the derivation of similar objective fire danger cutpoints for prescribed fires. In this study we use the Energy Release Component (ERC), a widely used and climate-driven fire danger index reflecting the potential energy released at a fire's flaming front (Bradshaw et al., 1984), as this metric.

An additional challenge is representing fire danger conditions in a way that is comparable across regions and contexts. Because absolute ERC values vary with climate and location, raw values are not often meaningful outside their local setting (Riley et al., 2013). Normalization approaches such as percentile conversion address this by facilitating spatial comparability, though the choice of normalization strategy can influence threshold identification and should be considered as part of the model-tuning procedure (de Amorim et al., 2023). Even with normalization, the relationship between fire danger and fire class may vary with fuel structure, climate, and land management context, thus it is necessary to determine the scalability of these relationships.

The final limitation is the absence of objective criteria for defining and evaluating breakpoints. Historically, fire danger breakpoints in the United States have been developed using logistic regressions to determine the fire danger component or index that best explains the days where new wildfires, large wildfires, or multiple wildfires ignite (Andrews et al., 2003). While this method has improved the ability to link fire danger indices with fire occurrence data, it does not provide an objective, repeatable way to develop breakpoints between different types of fire activity. Receiver Operating Characteristic (ROC) curves (Hajian-Tilaki, 2013) and similar cutpoint determination methods (Thiele and Hirschfeld, 2021) are alternatives that can produce more objective breakpoints from binary relationships commonly found in wildland fire management.

In response to these challenges, we hypothesize that harmonizing prescribed fire and wildfire occurrence data with spatially normalized fire danger indices and a nonparametric cutpoint analysis can yield an integrated, data-driven prescribed fire planning tool, **ClassiFiR$_x$e**. If classification performance is robust across varying spatial extents, then this framework offers a scalable, interpretable, and explainable tool grounded in historical data. Such a tool, will aid managers in determining where and when conditions across a project area have historically been associated with pile burning, broadcast burning, or wildfire occurrence, and decide whether a proposed burn falls within a zone of confident historical support or greater uncertainty. These classifications can be applied to characterize burn opportunity seasonality, estimate burn windows at local scales, and generate maps, forecasts, and other visualizations to support prescribed burn planning, approval, and retrospective analysis. Ultimately, filling a gap in prescribed fire management that can help restore fire to landscapes and reduce the fire deficit.

2. Materials and methods

2.1. Data and study area

In this study we curate a novel database of prescribed fire and wildfire records spanning 18 years across Montana and Idaho. Each fire record is intersected with a spatially normalized fire danger metric, the Energy Release Component (ERC), corresponding to its date and location of ignition.

Prescribed (Rx) fire records from 2004–2022 were obtained from the Montana and Idaho Airshed Group, MIAG (Montana/Idaho Airshed Group, 2010). Comprised of 29 "airsheds", each Airshed has a designated coordinator as a point of contact across 17 Impact Zones. Executive board member representatives build a pre-season burnlist online (smokemu.org). Burns are submitted from this list by noon on the day prior to burning (Mountain Time). All, or a portion of the acres, can be proposed. Members return an accomplished acres figure confirming successful execution of the burn. Each record in the MIAG Rx fire database is classified by one of ten different burn types. These were reclassified into two fire classes: pile burns, defined as burns where fuels are arranged into discrete piles, ignited from a point source, and not intended to spread across the burn unit; and broadcast burns, defined as burns where fuels are ignited along a line source and intended to carry fire across the burn unit (Table 1).

Federal, state and local wildfire records were obtained from the Fire Program Analysis, Fire Occurrence Database, FPA-FOD (Short, 2022) which contains georeferenced spatial records of data such as ignition day and final fire size for wildfires in the US from 2004–2020. These data were appended with additional wildfire records covering 2021–2022 from Interagency Fire Occurrence Reporting Modules (InFORM) (National Interagency Fire Center, 2024).

Table 1
Reclassification of Montana/Idaho Airshed Group (MIAG) (Montana/Idaho Airshed Group, 2010) "burn type" categories into pile burn and broadcast burn fire classes used in this analysis.

Fire class	MIAG burn type
Pile burn	Hand piles Dozer piles Landings Other mechanical
Broadcast burn	Broadcast Understory Range Wildlife habitat Jackpot Rights of way

Dates and locations of prescribed fires and wildfires were intersected with a 4 km gridded climatology of Energy Release Component (ERC) calculated using a timber fuel model (Y). ERC is an output of the National Fire Danger Rating System (NFDRS) related to the available energy (BTU) per unit area (square foot) within the flaming front at the head of a fire (Bradshaw et al., 1984). ERC is both a composite metric representing the contribution of all live and dead fuels to potential heat release and a build-up index that accounts for the past 7-days of live curing and dead fuel drying (Bradshaw et al., 1984). ERC was selected over other fire danger indices such as the Burning Index (BI) because it does not require wind speed as an input, making it more spatially stable when computed from gridded meteorological data where wind estimates are subject to substantial uncertainty from local terrain effects (Forthofer et al., 2014). ERC is also one the most widely used index for operational wildland fire decision-making in the United States (Jolly et al., 2019).

The ERC climatology was created by running the algorithms from the US National Fire Danger Rating System Version 4.0 (Jolly et al., 2024) with gridded weather data from gridMET (Abatzoglou, 2013). GridMET includes data needed for the ERC calculation (temperature, relative humidity, and precipitation) at a daily timescale, for the continental United States from 1979-present. We first downloaded daily, gridded, maximum and minimum temperature, maximum and minimum relative humidity, precipitation and solar radiation from gridMET. Because we were only interested in the Energy Release Component, windspeed was not needed for these calculations. We temporally downscaled the daily data to four times per day by creating diurnal temperature and relative humidity curves fit between the daily minimums and maximums. Precipitation was allocated over multiple hours using a relationship between daily amount and duration published (Jolly et al., 2019). Solar radiation was spread over the day based on the daylength calculations from NFDRS. NFDRS calculations were performed on the synthetic, four times daily data and the value coincident with the maximum temperature and minimum relative humidity were retained as the daily, worst case fire danger conditions. These computations were done in Python Version 3.11.13 with the Python bindings for NFDRS4 (Jolly et al., 2024) (https://github.com/firelab/NFDRS4/tree/master/swig) using Dask-backed Xarray (Rocklin et al., 2015; Hoyer and Hamman, 2017). This created a daily, 4 km resolution ERC dataset covering the extent of Montana and Idaho from 2004–2023. When intersected with the fire occurrence data, this provided a consistent, spatially-explicit fire danger value for every prescribed fire and wildfire within the study region for the full study period.

2.2. Developing a categorical wildland fire guide

We developed a robust, parsimonious, and reproducible method to identify Energy Release Component (ERC) breakpoints that best separate pile burns from broadcast burns and broadcast burns from wildfires. As such, pile burns, broadcast burns and wildfires are labeled as fire classes and treated as ordinal events that occur along an ERC continuum. Using ERC as the sole predictor in a univariate framework isolates the influence of fuel dryness on fire occurrence, consistent with its established importance in fire behavior and severity modeling (Parks et al., 2018). The resulting breakpoint framework provides the foundation for a categorical wildland fire guide, hereafter referred to as **ClassiFiR$_x$e**.

A cutpoint analysis was the primary method used to differentiate fire classes based on ERC values. Cutpoint (or threshold) analyses are binary classification models commonly employed in scientific research to explore the dichotomy of binomial events. In ecological applications, they have been used to detect transition points or zones of change between ecosystem states or conditions (McClanahan et al., 2011). Other fields, including psychology and medicine, have similarly adopted optimal cutpoint approaches to define biomarker thresholds, such as cholesterol or body mass index levels (Al-Lawati et al., 2008).

Building on this cutpoint analysis, we adapted the approach to address uncertainty in cutpoint retrieval and to account for conditions in which multiple fire classes occurred at similar relative rates. This adaptation led to the definition of four ERC cutpoints that delineate five ERC ranges, referred to as *Categorical Wildland Fire Zones* (CWlFZ), defined as:

- **Pile Burning (PB) Zone**: ERC range where the historical rate of pile burns exceeded broadcast burns.
- **Pile Burning-Broadcast Burning (PB-BB) Overlap Zone**: ERC range where pile burn and broadcast burn historical rates were similar.
- **Broadcast Burning (BB) Zone**: ERC range where broadcast burn historical rates exceeded those of pile burns and wildfires.
- **Broadcast Burning-Wildfire (BB-WF) Overlap Zone**: ERC range where broadcast burn and wildfire historical rates were similar.
- **Wildfire (WF) Zone**: ERC range where wildfire historical rates exceeded broadcast burns.

Identification of these categorical wildland fire zones followed a six-step process, building on the data preparation outlined in Section 2.1. A schematic overview of these steps is presented in Fig. 1.

2.2.1. Step 1: Collect data and verify assumptions

The essential data for this analysis consist of fire occurrence records for three fire classes (Rx pile burns, Rx broadcast burns, and wildfires) and a quantitative fire danger variable, ERC in our case, associated with the ignition or discovery date. We recommend including additional information such as date and location (latitude/longitude) to allow for spatial normalization of the fire danger variable, and unique fire identifiers to track records and avoid duplication.

After collection, the subsequent nonparametric analysis requires two simple assumptions to be met.

Ordinality

Larger ERC values are expected to correspond consistently to higher fire classes (pile burn < broadcast burn < wildfire). This ordinal relationship allows pairwise thresholds to reflect systematic differences in relative fire success rates when distributions are sufficiently separated (Agresti, 2010). Although some overlap is inevitable, if large portions of the distributions are homogeneous or lack a clear monotonic trend, practical cutpoints may be difficult to identify, reducing interpretability and operational relevance. Accordingly, no threshold is identified between pile burns and wildfires.

We assessed ordinality by visualizing distributions with density plots and confirming that median predictor values followed the expected ranking. Additionally, Spearman's rank correlation (Spearman, 1987) and the Jonckheere–Terpstra test (Jonckheere, 1954) were used to formally evaluate monotonic trends across fire classes. With large sample sizes, statistically significant p-values can be obtained even when the practical strength of the ordinal relationship is weak. We

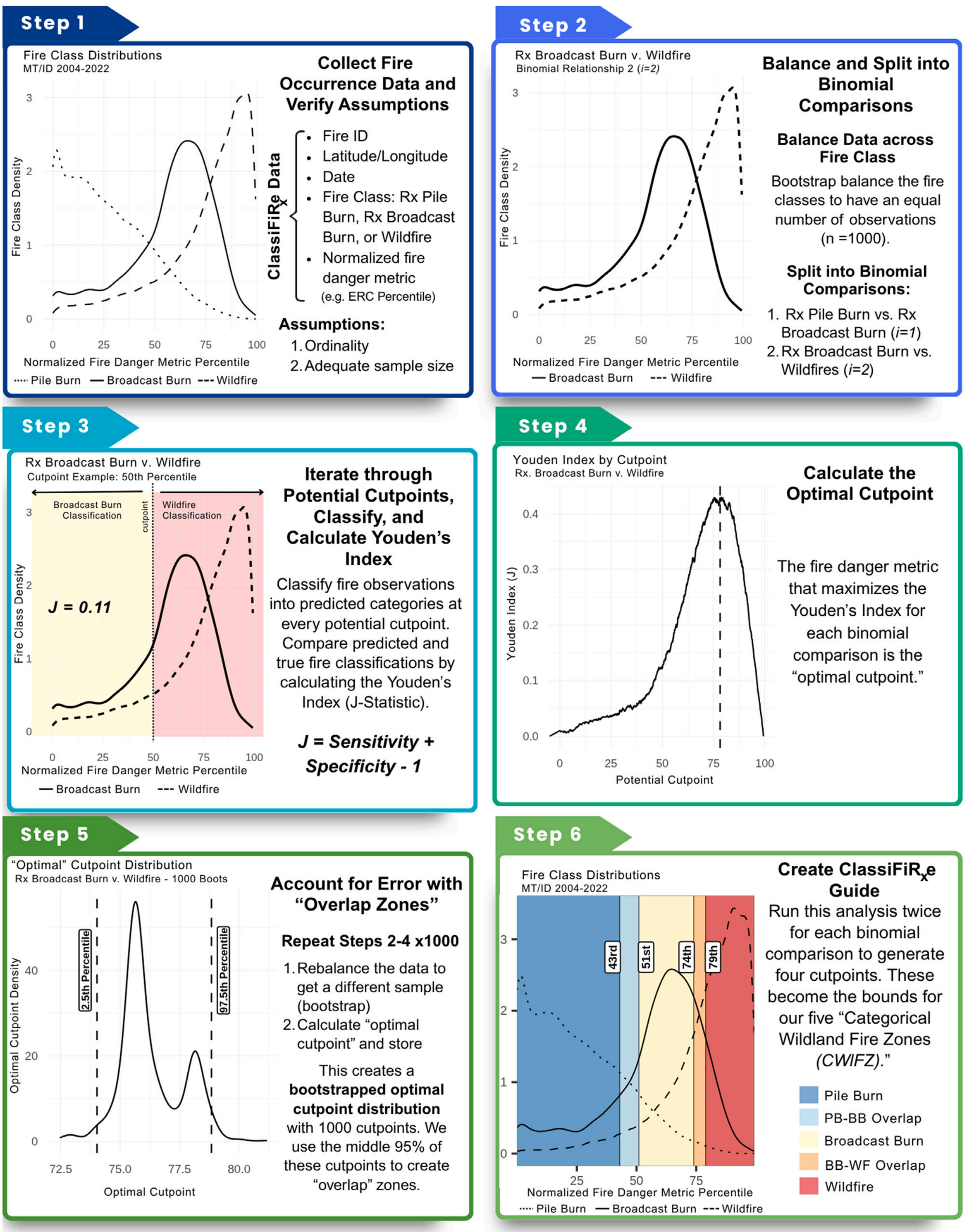

Fig. 1. Schematic figure developing a categorical wildland fire guide using bootstrapped cutpoint analysis method. The 6 steps are expanded in Section 2.2.

recommend evaluating both the p-value and the magnitude of ρ when assessing whether the ordinality assumption is sufficiently met.

Adequate Sample Size

Cutpoint selection is often sensitive to sampling variability (Perkins and Schisterman, 2006). Adequate sample size is therefore important for stable estimation of cutpoints. While the bootstrapping element of our framework (see Step 5) mitigates some small-sample effects, extremely sparse datasets may still produce wide or unstable overlap zones. Thus, each fire class must contain enough observations to allow for resampling without repeatedly drawing the same events.

To evaluate how sample size affects cutpoint stability, we conducted a simulation study (Thiele and Hirschfeld, 2023). Stratified sub-samples of varying sizes (50–1000 per class) were drawn without replacement from the full dataset. For each subsample, our cutpoint analysis framework was run and the resulting overlap zone widths were recorded. Each sample size was repeated 50 times with different sub-samples to capture variance. We then examined how overlap zone widths changed across increasing sample sizes, with the expectation that estimates would stabilize once a sufficient number of observations per class was reached. To test this we compare the standard deviations of the overlap zone widths across sample sizes.

2.2.2. Step 2: Establish balanced binomial comparisons

The data were first split into two separate binomial comparisons as follows:

1. Pile burns versus broadcast burns ($i = 1$).
2. Broadcast burns versus wildfires ($i = 2$).

For each binomial comparison, class-balanced datasets were generated by sampling $n = 1000$ records with replacement from each fire class. Balancing ensures that performance based metrics, such as sensitivity and specificity, are not biased by class proportions (He and Garcia, 2013). In an imbalanced setting, thresholds may appear optimal simply by favoring the majority class, leading to inflated specificity or sensitivity at the expense of the minority class (He and Garcia, 2013). Sampling with replacement (bootstrapping) allows consistent sample sizes across fire classes regardless of their original frequency, while preserving the empirical distribution within each class (Efron and Tibshirani, 1994). By equalizing class sizes, the cutpoint optimization reflects true discriminatory performance rather than the effect of class imbalance (He and Garcia, 2009). In cases of more extreme class imbalance, alternative oversampling methods such as SMOTE or ADASYN (He and Garcia, 2009) could also be considered.

2.2.3. Step 3: Calculate Youden index

Cutpoint analyses were performed using the R package *cutpointr* (Thomas et al., 2021) in R version 4.5.0 (R Core Team, 2024). For each binomial comparison established in Step 2, the optimal cutpoint was identified using the Youden index (Youden's J statistic), which assumes equal importance of sensitivity (Se) and specificity (Sp) (Kallner, 2018).

The Youden index is calculated at every candidate cutpoint c over the range of ERC values $min[ERC] \leq c \leq max[ERC]$, as:

$$J(c) = \mathrm{Se}(c) + \mathrm{Sp}(c) - 1 \tag{1}$$

where sensitivity (Se) is the true positive rate, and specificity (Sp) is the true negative rate (1 – false positive rate):

$$Se(c) = \frac{\mathrm{TP(c)}}{TP(c) + FN(c)} \tag{2}$$

$$Sp(c) = \frac{TN(c)}{TN(c) + FP(c)} \tag{3}$$

TP(c), FN(c) and FP(c) are the number of true positives, false negatives and false positives, respectively, evaluated at each candidate cutpoint. The Youden index ranges from 0 to 1, where 0 indicates that c has no ability to distinguish fire classes and 1 indicates perfect separation.

Table 2
Conceptual ERC ranges corresponding to each Categorical Wildland Fire Zone (CWlFZ), defined using quantile-based thresholds from bootstrapped cutpoint distribution.

CWlFZ	PB zone	PB-BB overlap zone	BB zone	BB-WF overlap zone	WF zone
ERC range	[Min., $\mathrm{LB_1}$)	[$\mathrm{LB_1}$, $\mathrm{UB_1}$)	[$\mathrm{UB_1}$, $\mathrm{LB_2}$)	[$\mathrm{LB_2}$, $\mathrm{UB_2}$)	[$\mathrm{UB_2}$, Max.]

2.2.4. Step 4: Identify optimal cutpoint

Formally, the optimal cutpoint for the ith binomial comparison, c_i^*, is the cutpoint that maximizes the Youden Index ($J(c)$) :

$$\begin{aligned} J_{max} &= max\{J(c)\} \\ c_i^* &= \arg \max_{c \in ERC} J(c) \end{aligned} \tag{4}$$

If multiple cutpoints satisfy Eq. (4), the mean of these cutpoints is used as the optimal cutpoint, c_i^*. This is shown to induce less bias in cutpoint selection, particularly when iterating across dense potential cutpoint data (Luebke and Szepannek, 2023).

2.2.5. Step 5: Account for error with bootstrapped optimal cutpoint distribution

Deriving optimal cutpoints is limited by a susceptibility to sample-specific characteristics, which can artificially inflate estimates of diagnostic accuracy (Perkins and Schisterman, 2006). To address this, a bootstrapping procedure is used to estimate the variability of optimal cutpoints and incorporate sampling error into the classification scheme. This procedure forms the basis for identifying the PB-BB and BB-WF overlap zones.

To achieve this, **Steps 2–4** are repeated $B = 1000$ times. In each bootstrap iteration b, we resample with replacement ($n = 1000$ per class) for each binomial comparison ($i = 1, 2$), and compute an optimal cutpoint using the Youden-maximizing rule from Eq. (4). Bootstrapping to estimate confidence intervals around Youden-based optimal cutpoints has been proposed in related diagnostic classification problems, such as logistic regression and survival analysis (Zhang et al., 2020; Lado-Baleato et al., 2024). This procedure yields a distribution of bootstrapped optimal cutpoints for each fire class comparison:

$$\{c_i^{*1}, c_i^{*2}, \ldots, c_i^{*B}\} \tag{5}$$

From this distribution, a 95% bootstrap percentile confidence interval is computed (Ramachandran and Tsokos, 2021):

$$\begin{aligned} &\text{Lower Bound}_i(\mathrm{LB}_i) = \mathrm{Q}_{0.025}\left(\{c_i^{*b}\}_{b=1}^{B}\right) \\ &\text{Upper Bound}_i(\mathrm{UB}_i) = \mathrm{Q}_{0.975}\left(\{c_i^{*b}\}_{b=1}^{B}\right) \end{aligned} \tag{6}$$

Using bootstrap confidence intervals replaces a singular threshold with a variance-capturing transition region that is more robust to sample variability and better reflects uncertainty in binning a continuous predictor (Deckert and Kummerfeld, 2019; Thiele and Hirschfeld, 2021). Incorporating these overlap regions preserves the categorical structure of the fire zones while accounting for uncertainty and providing a practical way to identify transitional conditions between fire classes.

2.2.6. Step 6: Establish categorical wildland fire zones

The lower and upper bounds, $[LB_i, UB_i)$, of the optimal cutpoints from **Step 5** provide a data-driven foundation for defining categorical wildland fire zones. For each binomial fire class comparison, the lower and upper bounds from Eq. (6) are used to delineate five ordered categories along the ERC percentile axis. The resulting five "Categorical Wildland Fire Zones" are defined in Table 2.

2.3. ERC normalization

Energy Release Component (ERC) values were normalized prior to cutpoint analysis to ensure comparability across locations with differing climate and fire danger distributions. Absolute ERC values vary with local climate, and raw values are not often meaningful outside their local setting (Riley et al., 2013; Eastaugh et al., 2012). There is no single best-in-class normalization method for all problems, and choosing an appropriate strategy should be considered part of the model-tuning procedure (de Amorim et al., 2023; Lima and Souza, 2023). We normalized ERC values using a percentile-based approach, which converts raw ERC to a relative ranking within the local historical distribution (Eq. (7)). This approach is widely used in fire danger assessment (Riley et al., 2013; Jolly et al., 2019), is intuitive for operational use, and facilitates spatial comparability across the study region by removing the influence of local climate on absolute ERC magnitude. A comparison of four alternative normalization strategies against the non-normalized raw ERC is presented in Supplementary Materials Section **S2**, along with associated performance metrics. Based on this comparison and its established use in operational fire danger assessment, percentile normalization was selected for the remainder of the analysis.

$$\text{ERC Percentile}_{ld} = \frac{\text{rank}(ERC_{ld})}{n_d} \tag{7}$$

where n_d is the total number of days in the climatology, and ranks are averaged for tied values, such that if m days share the same ERC occupying ranks $r_1, r_2, \dots, r_m$, the percentile is computed as:

$$\text{ERC Percentile}_{ld} = \frac{(r_1 + r_2 + \cdots + r_m)/m}{n_d} \tag{8}$$

2.4. Validation

We adopted a stratified 10-fold cross-validation approach to evaluate the performance of the guide and compare normalization methods (Prusty et al., 2022). The dataset was split into 10 approximately equal folds while retaining the original fire class proportions, ensuring adequate representation of minority classes in each fold. Each fold was used once as a test set, with the remaining nine folds serving as training data. Cutpoints were derived from the training set and then applied to the corresponding test set to evaluate guide performance (Figure S1).

The primary metric used for guide evaluation was recall (sensitivity). However, because CWlFZs include overlap zones where multiple fire classes may occur at similar ERC values, it is necessary to account for these transitional regions in evaluation. We therefore define two complementary metrics: strict recall and full recall.

Strict recall considers only observations that fall within the CWlFZ assigned exclusively to their fire class (e.g., pile burns in the pile burn zone), excluding any adjacent overlap regions. This metric quantifies performance under unambiguous classification conditions and is defined as:

$$\text{Strict Recall}_{fc} = \frac{\text{TP}^{\text{strict}}_{fc}}{\text{TP}^{\text{strict}}_{fc} + \text{FN}^{\text{strict}}_{fc}} \tag{9}$$

where fc is a fire class (pile burn, broadcast burn, or wildfire), $\text{TP}^{\text{strict}}_{fc}$ is the number of fires of class fc correctly predicted to fall within the exclusively assigned CWlFZ, and $\text{FN}^{\text{strict}}_{fc}$ is the number of fires of class fc that fall outside this zone.

Full recall extends this definition to include adjacent overlap zones, capturing transitional fire behavior where multiple classes may co-occur:

$$\text{Full Recall}_{fc} = \frac{\text{TP}^{\text{full}}_{fc}}{\text{TP}^{\text{full}}_{fc} + \text{FN}^{\text{full}}_{fc}} \tag{10}$$

where $\text{TP}fc^{\text{full}}$ counts fires of class fc that fall within either the exclusively assigned CWlFZ or the adjacent overlap zones, and $\text{FN}fc^{\text{full}}$ counts fires outside these combined zones.

Both strict and full recall are computed for all fire classes and averaged to produce a single balanced recall metric:

$$\text{Balanced Recall}^{(z)} = \frac{1}{n_{fc}} \sum_{fc \in FC} \text{Recall}^{(z)}_{fc} \tag{11}$$

where FC is the set of all fire classes, $n_{fc} = 3$, and z indicates whether strict or full recall is used.

Median values are calculated across the 10 folds for each class-specific and balanced metric. This provides a robust measure of guide performance under sample variation. This method was used to inform the selection of the most appropriate normalization method (Supplementary Materials Section **S2**) as well as comparing guide performance built at different spatial extents.

Additionally, mean fire size by CWlFZ was examined as an independent empirical validation of the classification framework, using accomplished acres from the MIAG prescribed fire database (Montana/Idaho Airshed Group, 2010) and reported fire size from the FPA-FOD (Short, 2022) and InFORM (National Interagency Fire Center, 2024) for wildfires.

2.5. Spatial sensitivity and scalability

To evaluate the spatial sensitivity of the **ClassiFiR$_x$e** framework, we conducted two supplementary analyses examining guide performance across ecologically distinct spatial subsets of the study area.

2.5.1. Continental divide split

To assess sensitivity to broad-scale spatial variation in fuel structure, we divided the study area into eastern and western regions using the Continental Divide as a boundary. This division is ecologically meaningful, as forests dominate the western portion of the study area and are better represented by the timber fuel model (Model Y) used in ERC calculations. In contrast, grasslands, shrublands, and cultivated lands characterize the eastern portion (Fig. 2; Buchhorn et al., 2020), for which Model Y may be less appropriate (Jolly et al., 2024).

For each region, we independently verified the ordinality assumption, trained a separate **ClassiFiR$_x$e** guide, and evaluated performance using the same 10-fold stratified cross-validation approach described in Section 2.4. Resulting cutpoints and recall metrics were compared between regions and against the full statewide guide to quantify spatial sensitivity.

2.5.2. Lolo national forest

To evaluate spatial scalability at a finer spatial extent, we applied the **ClassiFiR$_x$e** framework to fire occurrence and ERC data restricted to the Lolo National Forest in western Montana. This region was selected because it represents a spatially coherent ecological unit with fuel structure predominantly consisting of forested vegetation (Davis et al., 1980) well suited to ERC Model Y. It also contained a sufficient sample size across all three fire classes to support stable cutpoint estimation. As with the Continental Divide analysis, we first verified the ordinality assumption before training a local guide and evaluating performance using 10-fold stratified cross-validation (Section 2.4).

2.6. Implementation

Based on the spatial sensitivity analysis, subsequent implementation analyses focus on western Montana and Idaho, where the ordinality assumption is more strongly satisfied and classification performance is substantially higher. Daily gridded ERCs from 2004–2022 were used to assess the temporal patterns of historical burn conditions across western Montana and Idaho. Each 4 km daily raster contains maximum daily ERC percentiles for individual grid cells, relative to their historical distributions. Then, using the cutpoints for the region west of the Continental Divide (hereafter referred to as “West of Divide”), each daily

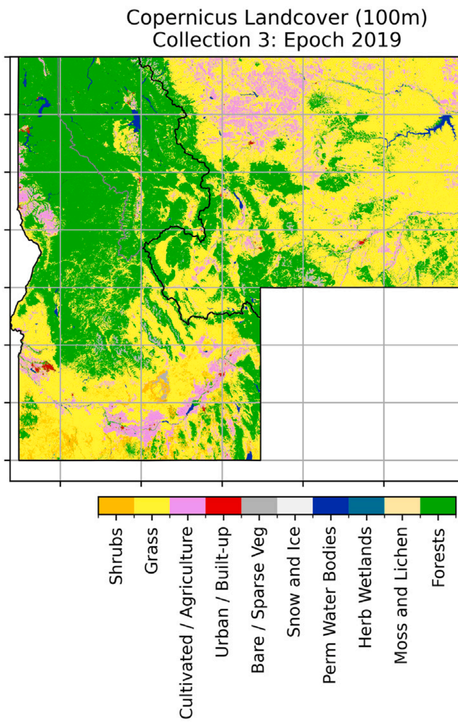

Fig. 2. Copernicus Land Cover classification (100 m resolution, Collection 3, Epoch 2019) (Buchhorn et al., 2020) for Montana and Idaho. The Continental Divide is shown as a black line.

gridded ERC raster was classified at the pixel level into its corresponding CWlFZ. With these classified rasters the seasonality of the CWlFZs was characterized both spatially and as an aggregate of the western study area. We then explored more localized and temporally-granular implementations.

2.6.1. Seasonality of categorical wildland fire zones

ERC values were aggregated into bi-weekly periods for temporal summarization, a resolution chosen to reduce day-to-day noise inherent to ERC while retaining seasonal variation that would be obscured by monthly aggregation (Van Leeuwen, 2008). For each bi-weekly period we calculated the median ERC percentile and interquartile range across the western study area to quantify central tendency and variability in burn conditions, as well as the proportion of land area classified into each CWlFZ.

We also generate monthly rasters (January–December) representing the proportion of days assigned to each CWlFZ across the 2004–2022 period for spatial summarization. To reduce classification granularity and facilitate interpretation, the broadcast burning class and its adjacent overlap zones were aggregated into a composite "BB+Overlap" category.

2.6.2. Finer temporal and spatial resolution implementation

To examine higher-resolution spatial and temporal patterns of CWlFZs, we again use the daily 4 km gridded ERC data across western Montana and Idaho. We chose four representative dates from 2022 that highlight spatial variability in zone coverage across the western study area. At all selected dates, again each grid cell was classified into its corresponding CWlFZ using the West of Divide cutpoints, and the proportion of land in each zone was calculated. These daily maps also enabled exploration of spatial pattern by aggregating landscape characteristics, in our case mean elevation, within each zone. The finer temporal resolution explores the identification of more precise, region-specific prescribed burn opportunities that might be obscured in the coarser seasonality summaries.

Additionally, we analyzed daily CWlFZ classifications for a single location by using ERC percentiles recorded at the Blue Mountain Remote Automated Weather Station (RAWS) in Missoula, Montana, during 2020. Given the station's location within the Lolo National Forest, the Lolo National Forest guide cutpoints were applied for this analysis. This localized analysis focused on identifying multi-day burn windows, defined as consecutive days classified within the same CWlFZ. Three definitions were compared: (1) simple consecutive-day stretches, (2) a definition requiring at least two consecutive days within the zone to open a window and at least two consecutive days outside the zone to close it, and (3) a stricter definition requiring at least three consecutive days within the zone to open it and at least three consecutive days outside the zone to close it (Abatzoglou and Kolden, 2011). Comparing these definitions allows for an assessment of how the operational interpretation of a burn window affects the identified opportunities.

3. Results

The prescribed fire database covering Montana and Idaho from 2004–2022 contained 19,186 records: 14,730 classified as pile burns and 4456 as broadcast burns (Fig. 3). Nearly three-quarters of these records were entered from 2016 onward. This increase likely reflects expanded use of the reporting system, as participation grew from 10 members in 2004 to 20 in 2022. The U.S. Forest Service accounted for 57% of all entries, with other federal and state agencies contributing 21% and industry 22%.

Wildfire data included 51,488 incidents from the FPA-FOD (2004–2020) and 8406 from InFORM (2021–2022), totaling 59,894 reported wildfires during the 19-year study period (Fig. 3). Of these, 36% occurred within National Forests. Fire cause attribution showed that 42% were lightning-caused, 54% were human-caused, and the remaining 4% were undetermined or missing causal information.

3.1. Seasonality

Broadcast burning exhibited a bimodal seasonal pattern, with relative maxima in the spring (weeks 16–18) and fall (week 42) (Fig. 4). Approximately 54% of broadcast burns occurred from March through May, and 39% from September through November. In contrast, pile burning was concentrated in the fall and early winter, with 89% taking place between September and December and a peak in early November (week 44) (Fig. 4). Wildfires peaked distinctly in the summer, with 62% of ignitions occurring in July and August (≈30% and ≈32%, respectively), and a maximum around the second week of August (week 32) (Fig. 4).

3.2. Developing a categorical wildland fire guide

3.2.1. Assumptions

Ordinality

There is a clear monotonic increase in ERC percentiles with the progression of fire classes (Fig. 5), pile burn → broadcast burn → wildfire (median percentiles: pile burn = 23rd, broadcast burn = 62nd, wildfire = 82nd). Additionally, the presence of a significant positive Spearman rank correlation ($\rho = 0.59$, $p < 0.001$), together with a highly significant Jonckheere–Terpstra test for ordered alternatives ($p < 0.001$), provides strong statistical evidence that ERC percentiles increase monotonically across fire classes.

Sample Size

The sample size simulation indicates a strong inverse relationship between sample size and the standard deviation of overlap zone widths, which we use as a proxy for model stability (Fig. 6). Across both fire comparisons ($i = 1, 2$), the relationship approximates a negative exponential form. At smaller sample sizes (<300 observations per class),

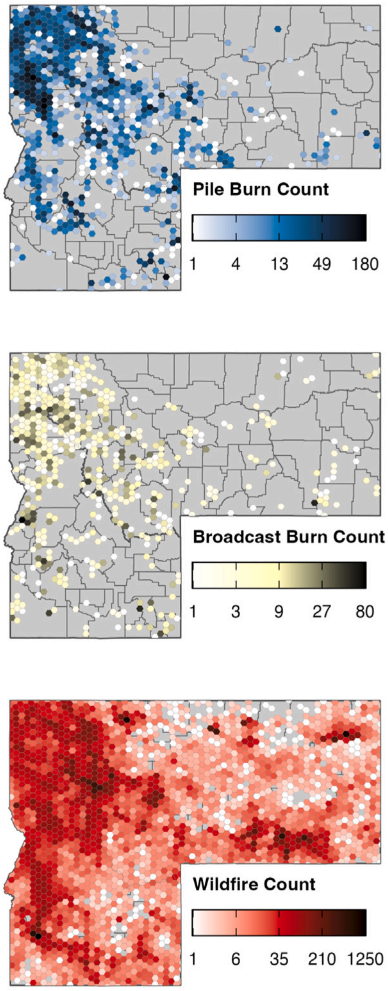

Fig. 3. Spatial distribution of fire occurrences in Idaho and Montana, aggregated using the H3 hexagonal grid system (resolution = 5; each hexagon ≈252 km^2). Separate panels show pile burns, broadcast burns, and wildfires, with shading proportional to the log-transformed number of events per hexagon.

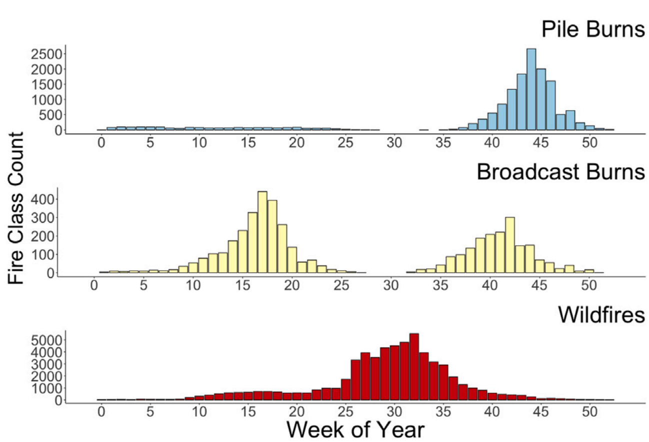

Fig. 4. Weekly counts of pile burns, broadcast burns, and wildfires occurring across Montana and Idaho from 2004–2022.

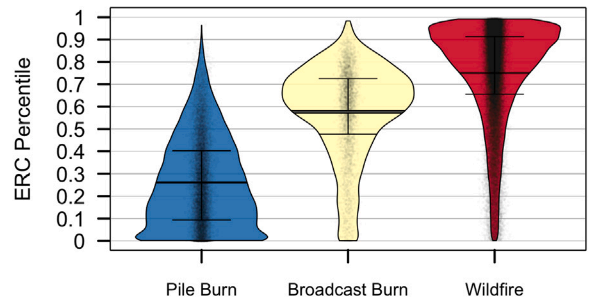

Fig. 5. Distribution of ERC percentiles by fire class. Black lines represent the first quantile, median and third quantile values. The raw data are represented with semi-transparent dots. Shapes reflect the underlying distribution of data. Fire occurrence data was derived from Montana and Idaho from 2004–2022 and intersected with gridded 4 km ERC percentile data.

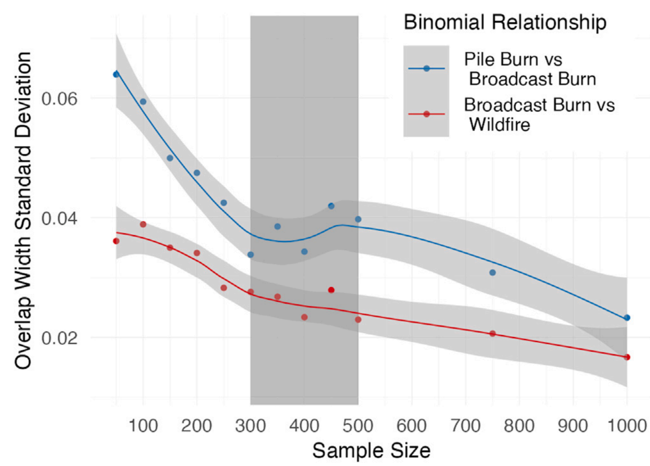

Fig. 6. Standard deviation of overlap zone width estimates across increasing sample sizes for pile burns vs. broadcast burns ($i = 1$) and broadcast burn vs. wildfires ($i = 2$). Points represent observed standard deviations at each sample size. The smoothed line and shaded band represent a LOESS fit with 95% confidence interval. The shaded region (300–500 samples per class) indicates where estimates begin to stabilize.

variability in estimated overlap zone widths is high, reflecting sampling uncertainty. This pattern shifts at an apparent inflection region around 300–500 observations per class, beyond which the reduction in variability slows and the extents of the cutpoint classification zones exhibit greater stability. Gains in precision continue at large sample sizes (e.g. > 750 observations per class) but their magnitudes decrease. This pattern is supported by strong negative correlations between sample size and the standard deviation of overlap widths (pile burns vs. broadcast burns: $r = -0.86$; broadcast burns vs. wildfires: $r = -0.92$). Nonetheless, we use a sample size of 1000 for the remainder of the analyses to ensure the overlap zones are least affected by the value of B selected for the bootstrapping procedure.

3.3. Spatial sensitivity and scalability

3.3.1. Continental divide split

The full data split by divide showed the eastern dataset contained 2082 pile burns (14% of total pile burns), 750 broadcast burns (17% of total broadcast burns), and 20,458 wildfires (34% of total wildfires) of their respective totals (29.5% of the total dataset), while the western dataset contained 12,648 pile burns (86%), 3706 broadcast burns (83%), and 39,436 wildfires (66%) (70.5% of the total dataset). A clear imbalance in samples size is present, particularly for prescribed burns. Both the eastern and western regional guides satisfied the ordinality assumption, with median ERC percentiles increasing monotonically across fire classes in both regions (East: PB = 32nd, BB = 60th, WF =

Table 3
Median ERC percentile cutpoints across spatial extents derived from 10-fold stratified cross-validation.

Spatial extent	PB zone	PB-BB overlap zone	BB zone	BB-WF overlap zone	WF zone
Full-region guide	[0, 43rd)	[43rd, 52nd)	[52nd, 74th)	[74th, 80th)	[80th, 100th]
West of Divide	[0, 43rd)	[43rd, 51st)	[51st, 74th)	[74th, 79th)	[79th, 100th]
East of Divide	[0, 44th)	[44th, 59th)	[59th, 76th)	[76th, 87th)	[87th, 100th]
Lolo NF	[0, 47th)	[47th, 52nd)	[52nd, 79th)	[79th, 83rd)	[83rd, 100th]

74th; West: PB = 21st, BB = 62nd, WF = 84th). However, the strength of the ordinal relationship differed markedly between regions, with the western region exhibiting a substantially stronger Spearman rank correlation ($\rho = 0.701$, $p < 0.001$) than the eastern region ($\rho = 0.304$, $p < 0.001$), suggesting that ERC percentiles are a stronger discriminator of fire class west of the Continental Divide.

The resulting regional cutpoints are presented in Table 3. The western guide produced cutpoints closely aligned with the full statewide guide, while the eastern guide diverged moderately, particularly at the upper boundaries that separate broadcast burning from wildfire conditions. This reflects the weaker separation between fire classes in the eastern region.

Classification performance differed substantially between regions (Table 4). The western guide performed comparably to the full statewide guide, achieving a balanced strict recall of 0.651 and balanced full recall of 0.771. In contrast, the eastern guide showed considerably weaker performance, with a balanced strict recall of 0.419 and balanced full recall of 0.647. Class-specific strict recalls for broadcast burning (0.273) and wildfire (0.318) in the east were particularly low, suggesting that ERC percentiles alone provide limited discrimination between fire classes in grassland and rangeland dominated landscapes.

Given the weaker classification performance east of the Continental Divide, we present the West of Divide guide as the recommended ClassiFiR$_x$e for the forested western portion of the study region and use these cutpoints for all subsequent implementation analyses.

3.3.2. Lolo National Forest

The Lolo National Forest dataset contained 864 pile burns, 498 broadcast burns, and 2585 wildfires, and satisfied the ordinality assumption with median ERC percentiles increasing strongly and monotonically across fire classes (PB = 20th, BB = 68th, WF = 85th) and a Spearman rank correlation of $\rho = 0.705$ ($p < 0.001$), comparable to the western regional guide. The derived cutpoints (Table 3) were closely aligned with both the full statewide guide and the western regional guide, suggesting that the framework produces consistent classification boundaries when applied to an ecologically similar forested region.

Classification performance at the Lolo National Forest scale was strong, with a balanced strict recall of 0.701 and balanced full recall of 0.812 (Table 4), exceeding the full statewide guide across all metrics. Broadcast burning strict recall improved substantially to 0.700 compared to 0.488 in the full-region guide, and pile burning strict recall reached 0.866. These results suggest that the ClassiFiR$_x$e framework is scalable to finer spatial extents, and that when the ordinality assumption is strongly satisfied and fuel structures are well represented by the chosen fire danger metric, locally derived cutpoints can yield reasonable classification performance.

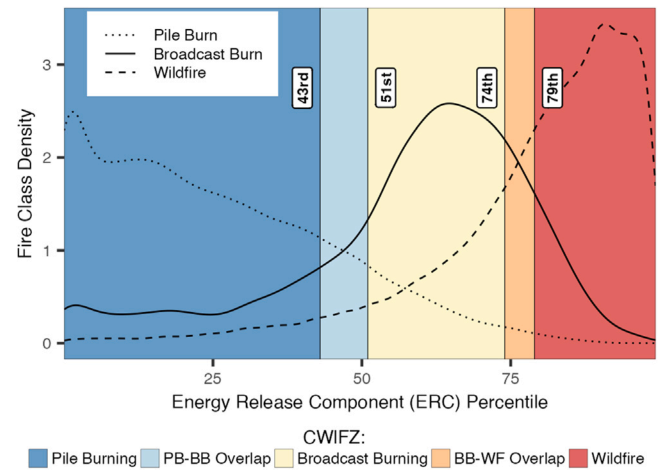

Fig. 7. **ClassiFiR$_x$e** for western Montana and Idaho. ERC percentile distributions for each fire class underlaid with colored zones representing the Categorical Wildland Fire Zones generated from the West of Divide cutpoint analysis. Fire class distributions are derived from western Montana and Idaho from 2004–2022.

3.3.3. West of divide ClassiFiR$_x$e guide performance

Using the 10-fold cross-validation study, we report the median West of Divide cutpoints across the 10 trained guides. These results are presented in Table 3 and visualized in Fig. 7.

As reported in Table 4, the West of Divide cutpoint classifier trained using percentile normalization has a median balanced strict recall of 0.651, indicating that on average across the three fire classes, approximately 65% of fires were correctly classified into their exclusively assigned Categorical Wildland Fire Zone in the validation study. The median full balanced recall was 0.771, indicating that on average across the three fire classes, approximately 77% of fires were classified in either their exclusively assigned CWIFZ or an adjacent overlap zone.

The West of Divide guide best classified pile burns with a median strict recall of 0.802, suggesting on average 80% of pile burns were classified in the "pile burning zone". Including the PB-BB overlap zone, the full recall for pile burning was 0.888, suggesting about 89% of pile burns were classified in the "pile burning zone" or "PB-BB overlap zone".

As with all spatial extents tested, broadcast burns exhibited the worst strict classification. This is likely a result of the error considered on both ends of this class's frequency distribution, an issue unique to the broadcast burning zone. Nonetheless, the guide classified about 51% of broadcast burns in broadcast burning conditions. The full broadcast burn recall was 0.700, suggesting about 70% of broadcast burns were classified in the "broadcast burning zone", "PB-BB overlap zone", or "BB-WF overlap zone".

Finally, the strict wildfire recall was 0.631, suggesting 63% of all wildfires were classified in the "wildfire zone". A median full wildfire recall of 0.724 suggests about 72% of wildfires were classified in "wildfire conditions" or the "BB-WF overlap zone".

3.3.4. CWIFZ fire size

Mean fire size varied systematically across Categorical Wildland Fire Zones in a manner consistent with the intended classification framework (Table 5). Pile burns were largest when classified in the Pile Burning zone (42.2 acres) and decreased progressively as conditions moved toward higher ERC zones, suggesting the guide identifies conditions most conducive to pile burning operations. Broadcast burns were largest in the BB–WF Overlap and Wildfire zones (121.0 and 103.0 acres respectively), reflecting the inherently larger scale of broadcast operations conducted under more aggressive fire weather conditions,

Table 4
Cross-validated median class-specific and balanced strict and full recalls across spatial extents. PB = Pile Burning, BB = Broadcast Burning, WF = Wildfire.

Spatial extent	PB strict	BB strict	WF strict	Balanced strict	PB full	BB full	WF full	Balanced full
Full-region guide	0.785	0.488	0.534	0.601	0.875	0.700	0.640	0.739
West of Divide	0.802	0.512	0.631	0.651	0.888	0.700	0.724	0.771
East of Divide	0.668	0.273	0.318	0.419	0.844	0.627	0.469	0.647
Lolo NF	0.866	0.700	0.590	0.701	0.896	0.860	0.679	0.812

Table 5
Mean fire size (acres) by fire class and Categorical Wildland Fire Zone (CWIFZ) for western Montana and Idaho (2004–2022) using West of Divide cutpoints.

Fire class	CWIFZ	n	Mean (acres)
Pile burn	Pile burning	10,204	42.2
	PB–BB overlap	1,009	34.4
	Broadcast burning	1,267	19.8
	BB–WF overlap	94	6.9
	Wildfire	74	7.8
Broadcast burn	Pile burning	694	49.9
	PB–BB overlap	300	70.3
	Broadcast burning	1,947	97.4
	BB–WF overlap	357	121.0
	Wildfire	408	103.0
Wildfire	Pile burning	1,887	14.1
	PB–BB overlap	1,035	79.7
	Broadcast burning	7,933	63.5
	BB–WF overlap	3,850	209.0
	Wildfire	24,728	499.0

while broadcast burns occurring in the Pile Burning zone were notably smaller (49.9 acres). Wildfires showed the most pronounced size gradient, with mean fire size increasing dramatically from 14.1 acres in the Pile Burning zone to 499.0 acres in the Wildfire zone. The concentration of the largest wildfires in the Wildfire and BB–WF Overlap zones provides independent empirical support for the classification framework, suggesting that the guide is capturing meaningful differences in fire behavior potential across zones rather than simply reflecting arbitrary ERC thresholds.

3.4. Implementation

3.4.1. Seasonality of categorical wildland fire zones

When applying the West of Divide cutpoints to historical climatology, bi-weekly ERC percentiles and zone proportions highlight clear seasonal windows for different burn condition zones (Fig. 8). From November through mid-March, the pile burning zone dominates the western landscape, encompassing >68% of land area with median ERC percentiles remaining below the 34th percentile and relatively low variability. Broadcast opportunities begin to emerge as early as the first bi-week of March (≈22% of land area), expanding to roughly one-third of the landscape by early April. Broadcast burning peaks in the second two weeks of April and first half of May (median = 53rd–63rd percentile; ≈42%–43% of land area), when the PB–BB overlap zone also reaches its greatest extent (≈13% of land area). Substantial broadcast zone areas continue into late May and June (34%–35% of land area), though these bi-weeks experience the highest variability (IQR ≈38 ERC percentiles) with frequent overlap between broadcast and wildfire zones peaking in mid-to-late June (≈12% of land area in BB–WF overlap), reflecting uncertainty in potential burn conditions.

From early July through mid-September, the majority of the western landscape is classified in the wildfire zone (>65% of land area). Median ERCs exceed the 82nd percentile throughout this period, with peak

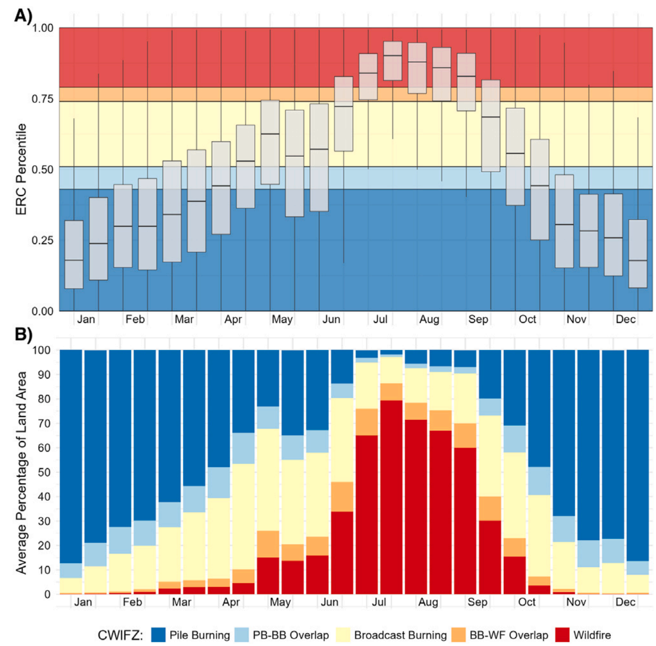

Fig. 8. **(A)** ERC percentile box-plot calendar aggregated at a biweekly temporal resolution with cutpoint analysis derived Categorical Wildland Fire thresholds underlaid. Data are derived from 4 km gridded daily maximum ERC percentiles across western Montana and Idaho from 2004–2023.
(B) Stacked bar chart depicting percentage of land area (grid cells) in each cutpoint analysis derived Categorical Wildland Fire Zones aggregated at a biweekly temporal resolution. The percentages are averaged across the 20-year sample size. Data are derived from 4 km gridded daily maximum ERC percentiles across western Montana and Idaho from 2004–2023.

wildfire coverage occurring in late July when ≈79% of land area falls in this zone. Variability during this period is low (IQR < 20 percentiles), indicating consistently extreme conditions and minimal opportunity for prescribed fire. By late September, median ERCs decline rapidly and broadcast burning conditions begin to reemerge.

October briefly experiences a larger portion of the landscape in the broadcast zone (≈34%–36% of land area) with moderate variability. By November, the pile burning zone again occupies the majority of the landscape, signaling the seasonal return to lower fire danger conditions.

Some of the variability within bi-weekly aggregates observed in the temporal ERC percentile boxplots (Fig. 8**A**) reflects spatial heterogeneity across western Montana and Idaho. This variation is illustrated in monthly aggregated ternary maps of the landscape (Fig. 9). Western Montana and Idaho exhibit a strong and consistent seasonal CWIFZ pattern – spring and fall broadcast burning, summer wildfire, and winter pile burning – though the timing and intensity of these transitions varies spatially across the region. The high IQR values observed during late spring and early summer in the bi-weekly boxplots reflect this spatial heterogeneity, where some portions of the landscape

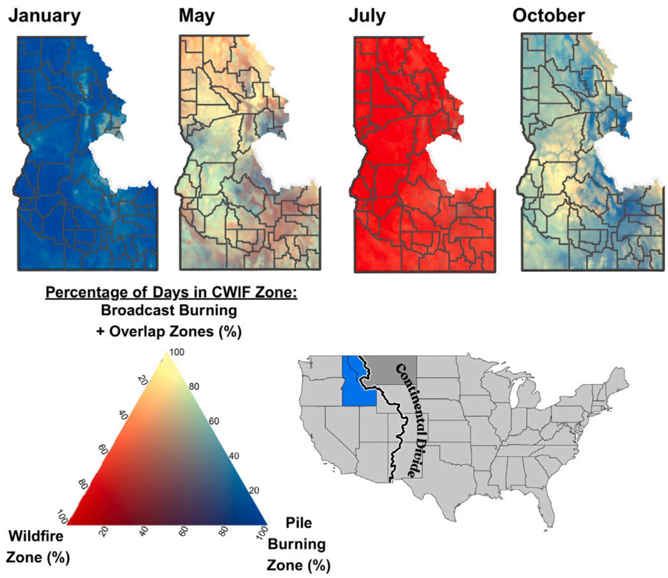

Fig. 9. Spatial distribution of the proportion of days in each Categorical Wildland Fire Zone (CWLFZ) for four months across western Montana and Idaho from 2004–2022 at 4 km resolution. For each grid cell, monthly values represent: (1) Pile Burning Zone (% days in PB), (2) Broadcast Burning Zone (sum of % days in BB, PB–BB overlap, and BB–WF overlap zones), and (3) Wildfire Zone (% days in WF). Composite colors were generated by mapping PB, BB+Overlap, and WF percentages to custom colors used throughout the analysis. Colors were blended via weighted additive color mixing, proportional to the relative prevalence of each zone in that cell for the given month. State and county boundaries, as well as the continental divide vector are overlaid for reference.

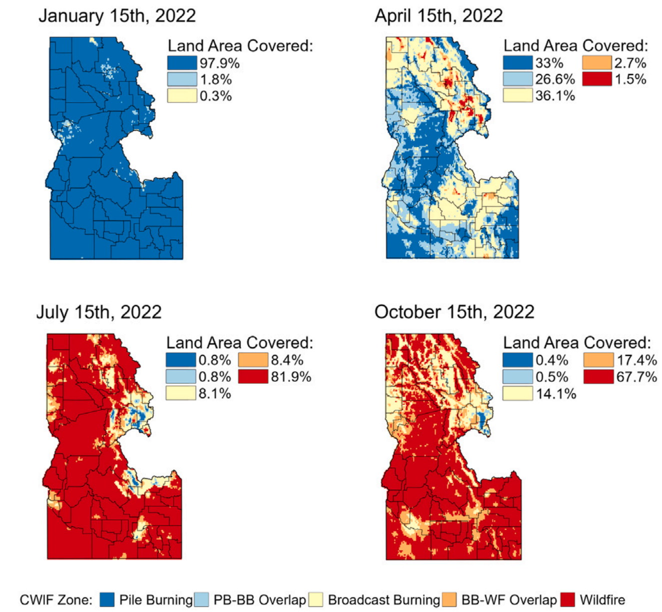

Fig. 10. Categorical Wildland Fire Zones (CWlFZ) classified at each 4 km grid cell across western Montana and Idaho on four representative dates in 2022. Percentages in the legend denote the relative land area covered by each zone on the corresponding date.

have already transitioned into wildfire conditions while others retain broadcast burning or overlap zone classifications and vice versa.

3.4.2. *Finer temporal and spatial resolution implementation*

Daily classification of CWlFZs revealed notable spatial variability across western Montana and Idaho on individual dates (Fig. 10). On January 15, 2022, 97.9% of western land area was classified in the pile burning zone, illustrating the near-complete dominance of pile burning conditions during mid-winter. On April 15, 2022, the landscape had transitioned into a more heterogeneous mix, with 36.1% in broadcast burning conditions, 33.0% in pile burning, and 26.6% in the PB–BB overlap zone, while 1.5% had already transitioned into wildfire conditions, underscoring the dynamic and spatially variable nature of spring prescribed burn opportunities. By July 15, 2022, 81.9% of the western landscape was classified in the wildfire zone, reflecting the near-complete transition to peak summer fire danger conditions and minimal opportunity for prescribed fire. October 15, 2022 illustrates the slow and spatially variable fall transition, where 67.7% of land area remained in wildfire conditions, while broadcast burning (14.1%) and BB–WF overlap (17.4%) conditions were beginning to re-emerge across portions of the landscape, particular in the north.

These spatial differences are also topographically structured. On April 15, 2022, the broadcast burning zone differed in mean elevation from the wildfire zone by approximately 365 ft, while pile burning and wildfire zones differed by roughly 649 ft. Across all of 2022, Tukey HSD post-hoc tests confirmed statistically significant differences in mean elevation between the broadcast burning and pile burning zones ($p < 0.001$) and between the broadcast burning and wildfire zones ($p < 0.001$), indicating a consistent topographic gradient in burn condition classifications. Interestingly, pile burning and wildfire zones did not differ significantly in mean elevation ($p = 0.874$).

We applied the burn-window analysis described in Section 2.6.2 to the Blue Mountain RAWS in Missoula, Montana (Fig. 11), using the Lolo National Forest guide cutpoints given the station's location within this unit. In 2020, the station classified 143 days within the Broadcast Burning (BB) zone. Under the simple consecutive-day definition, the longest BB window lasted 23 days (March 19–April 10). When applying the more robust two-day criterion, the longest BB window extended to 57 days (March 19–May 14), and under the three-day criterion extended further still to 60 days (March 19–May 17). Notable additional BB windows were identified in late winter (February 25–March 13), late May through late June (May 28–June 5; June 10–27), mid-July (July 6–19), and fall (September 16–October 11), with these windows identical under both the 2-day and 3-day definitions (Table S4).

The Pile Burning (PB) zone occurred on 142 days, with the longest window lasting 80 days (October 13–December 31) consistently across all three definitions. The Wildfire (WF) zone was present for 43 days under the simple definition, concentrated within a single 44-day window (July 25–September 6) under both the two-day and three-day criteria. The Broadcast–Wildfire overlap zone included 18 days, primarily adjacent to the wildfire period. Finally, 44 days were classified in the PB–BB overlap zone, appearing in all months except August, November, and December, with the majority occurring during the early spring thaw period.

The three burn window definitions produced notably similar results at Blue Mountain RAWS in 2020 (Table S4), with the primary difference being a modest extension of window duration under stricter consecutive-day criteria rather than any substantive change in timing or number of opportunities.

4. Discussion

This study demonstrates that operationally relevant classification of fire classes (pile burning, broadcast burning, and wildfire) can be achieved using a transparent cutpoint analysis of Energy Release Component (ERC) distributions. By curating one of the largest datasets of prescribed fire days assembled to date, we found that the ERC distributions for the three fire classes are sufficiently distinct in western Montana and Idaho to enable non-parametric discrimination without requiring complex probabilistic modeling. Treating the three fire classes

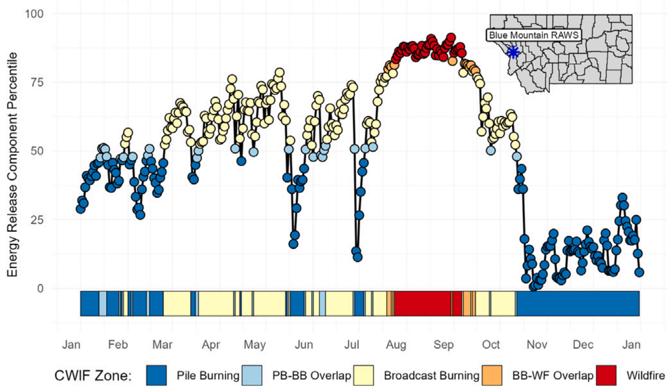

Fig. 11. Daily Energy Release Component (ERC) percentiles for 2020 at the Blue Mountain Remote Automated Weather Station (RAWS) classified by Categorical Wildland Fire Zones (CWlFZ) generated from Lolo National Forest Guide. Consecutive temporal periods of each CWlFZ are displayed using the colored bar along the *x*-axis. An inset map with the location of the RAWS station in Montana is included.

as ordered categories along the ERC continuum provided a natural framework for sequentially defining categorical fire zones.

We incorporated bootstrapping into the cutpoint analysis to further enhance robustness. Sampling variability was captured by generating distributions of optimal thresholds for both fire class comparisons (Pile Burning vs. Broadcast Burning, Broadcast Burning vs. Wildfire). This allowed us to define transitional overlap zones (PB–BB Overlap and BB–WF) that explicitly account for uncertainty in cutpoint selection, addressing a known limitation of traditional cutpoint methods (Perkins and Schisterman, 2006). These overlap zones not only incorporate sample-specific error but also theoretically capture nuanced transitional conditions along the ERC continuum, where wildland fire behavior is less discernible across fire classes. The resulting West of Divide ClassiFiR$_x$e guide effectively distinguished fire classes and achieved a reasonable performance from a univariate classifier. More importantly, this approach offers a replicable methodology that explicitly quantifies uncertainty while maintaining the decision-making structure present in prescribed fire management.

The cutpoint analysis framework was selected over alternative classification approaches for several reasons grounded in the operational context of this work. Unsupervised methods such as k-means clustering and hierarchical cluster analysis do not use fire class labels during model fitting and cannot ensure that resulting groups correspond meaningfully to pile burn, broadcast burn, and wildfire conditions along an ordinal continuum (James et al., 2013). Supervised classification trees can produce strong classification performance but sometimes lack interpretability and do not provide a principled mechanism for deriving transition uncertainty without subjective pruning (Bonasera and Carrizosa, 2026). Fuzzy logic methods can model transitional zones and may represent a promising avenue for future exploration, though standard implementations require analyst-specified membership function shapes and boundaries and can result in complex and overfit models (Ouellet et al., 2021), whereas our method derives transition regions empirically from the data.

More broadly, the primary design requirement of this framework was to produce outputs that are interpretable, repeatable, and explainable to fire managers operating within established fire danger rating systems. We view our method as complementary to more complex fire danger modeling efforts such as the development of ERC itself (Jolly et al., 2024), offering a means to ground these indices in historical fire occurrence data and translate their outputs into interpretable fire class expectations that are directly meaningful to practitioners.

Normalization strategy selection is an underappreciated but critical design decision in cutpoint-based fire danger classification, as it directly shapes the statistical distribution of ERC values and consequently the placement of classification boundaries (Mazziotta and Pareto, 2022; de Amorim et al., 2023). A full comparison of normalization strategies is presented in the Supplementary Materials. Percentile normalization was selected for the final guide due to its slight improvement in classifying prescribed burns and, more importantly, its established use in operational fire danger assessment. It should also be noted that, Min–Max and Outlier-Adjusted Min–Max normalization produced marginally better wildfire classification, likely because these methods do not cap ERC values at a fixed upper bound, preserving the full magnitude of extreme fire weather values.

The spatial sensitivity analysis revealed important patterns in how the ClassiFiR$_x$e framework performs across ecologically distinct regions. A notable imbalance exists in the training data, with 70.5% of fire records originating west of the Continental Divide, including 86% of pile burns and 83% of broadcast burns. As a result, the full MT/ID guide most closely resembles the West of Divide guide (Table 3), and both guides achieve comparable classification performance (Table 4). This suggests the full-region guide is best interpreted as a western-region guide. For this reason, we report the West of Divide guide performance and explore the potential implementation of the Categorical Wildland Fire Zones with these cutpoints.

Classification performance east of the Continental Divide was considerably weaker with particularly poor discrimination of broadcast burning and wildfire. While the ordinality assumption was statistically satisfied east of the Continental Divide, the substantially weaker Spearman correlation relative to the west suggests ERC percentiles alone provide limited discriminatory power in this region. We hypothesize two contributing factors. First, the ERC timber fuel model (Model Y) used throughout this analysis is designed for forested fuel structures and likely does not adequately represent the grassland and shrubland fuel types that dominate east of the Continental Divide (Davis et al., 1980). Second, the underlying poor ordinality of fire classes in grass and shrubland systems may be inherently less defined along the ERC continuum. Fire behavior in grassland systems is strongly driven by wind speed and more complex grass curing processes that are not captured by ERC alone (Yurkonis et al., 2019). Prescribed burning in these systems are also commonly timed to phenological windows and management objectives, such as invasive species control, woody encroachment prevention, and forage improvement (Fire Effects Information System, 2018). These objectives differ substantially from the fuel reduction objectives that dominate forested prescribed burning in the western portion of our study area (Davis et al., 2024).

The Lolo National Forest analysis demonstrates that when the ordinality assumption is strongly satisfied, sample sizes are adequate, and the fire danger metric reflects the underlying fuel structure, the framework is feasibly scalable to finer spatial extents. Moreover, the Lolo National Forest ClassiFiR$_x$e guide yielded meaningfully improved classification performance relative to region-wide cutpoints, with broadcast burning strict recall improving from 49% in the full-region guide to 70% at the Lolo scale and balanced full recall reaching 82%. These results suggest that if these conditions are met, practitioners may find that locally trained guides outperform region-wide cutpoints.

Given the spatial imbalance in training data and the limited representativeness of the full-region guide east of the Continental Divide, we report the West of Divide guide performance and explore the potential implementation of the Categorical Wildland Fire Zones using these cutpoints. The West of Divide guide performs reasonably across all three fire classes, achieving a balanced strict recall of 65% and balanced full recall of 77%, with pile burning best classified (strict recall = 80%) and broadcast burning showing the weakest strict recall (51%), consistent with its position in the middle of the ERC continuum where error is expected on both sides. Moreover, an examination of mean fire size by fire class and CWlFZ (Table 5) provides independent empirical support for the classification framework. Pile burns are largest when classified in the Pile Burning zone and decrease progressively toward higher ERC zones, while wildfires show a dramatic size gradient from 14 acres in the Pile Burning zone to 499 acres in the Wildfire zone. Importantly, fires that are misclassified into zones outside their expected range tend to be smaller, suggesting that the most consequential fire events are being captured in their correct zones.

Bi-weekly ERC percentiles and Categorical Wildland Fire Zone (CWlFZ) proportions for western Montana and Idaho reveal clear and consistent seasonal patterns. Broadcast burning opportunities emerge in early spring, expanding rapidly through April and peaking in the second half of April and first half of May. A small drop in median ERCs and increase variance in late May and June likely reflects the year-to-year variability in snow-melt and subsequent precipitation (need a citation here). Uncertainty in burn planning is common as portions of the landscape transition into wildfire conditions while others retain broadcast burning classifications.

July through mid-September is dominated by wildfire conditions, with low inter-quartile variability indicating consistently unfavorable conditions for prescribed fire across the western region. Fall marks a rapid transition away from wildfire conditions, with broadcast burning reemerging broadly in October and typically disappearing as November begins. Though fall broadcast burn opportunity windows are shorter than spring, they precede the pile burning conditions of winter and therefore are likely safer for conducting fire management activities.

These seasonal patterns are also spatially variant across western Montana and Idaho, as illustrated in the monthly aggregated ternary maps (Fig. 9), where the timing and intensity of seasonal zone transitions varies substantially across the landscape. This is especially noticeable again in the "shoulder seasons" of May and October.

Tracking categorical zones at daily time scales allows for the identification and quantification of multi-day burn windows, or consecutive periods of favorable conditions useful in burn planning. At Blue Mountain RAWS in 2020, broadcast burning windows extended up to 60 days in spring under the three-day criterion, while pile burning windows spanned up to 80 days in fall and winter, illustrating the potential of the CWlFZ framework for identifying site-specific prescribed burn opportunities (Fig. 11).

The three burn window definitions produced notably similar results at this station and year, with stricter consecutive-day criteria primarily extending window duration rather than altering the timing or number of identified opportunities. The similarity across definitions is likely a product of the underlying gap structure of the data at Blue Mountain RAWS in 2020, where out-of-zone breaks tended to be either very short or long enough to close all definitions equally. Analyses at different stations or years may show greater divergence, and the logistical requirements of a given burn program may ultimately inform which burn window definition is most appropriate for a given application.

ERC percentile cutpoints underlying the CWlFZ framework are derived from historic fire ignition and discovery dates rather than process data describing multi-day sustained burning. As a result, the continuous burn windows identified here reflect periods of favorable ignition conditions, which may not fully capture the range of conditions experienced over the course of a multi-day prescribed burn.

Traditionally, prescribed fire burn plans are anchored to a representative remote automated weather station in the area of the planned activity, and these plans rarely make use of gridded weather data. Though our classification methodology can be adapted to point-based weather stations as demonstrated with the Blue Mountain RAWS analysis, combining it with moderate-resolution ERC modeling enables classification at the pixel level, capturing spatial variability that is often obscured by local weather station data. The daily maps produced from these classifications reveal localized differences in burn opportunities across the western landscape (Fig. 10), and statistically significant elevation differences among CWlFZs in 2022 suggest that topography plays an important role in structuring the spatial distribution of burn condition classifications. With advances in real-time fuel monitoring (Benali et al., 2025) and in the National Fire Danger Rating System (Jolly et al., 2024), ERC and other fire danger metrics are forecast up to 7 days in advance at 2.5 km resolution. These data can be used to generate daily, region-wide CWlFZ maps that identify areas where pile burning and broadcast burning conditions are expected, potentially expanding opportunities for prescribed fire at landscape scales (Jolly et al., 2019).

4.1. Limitations

4.1.1. Analysis

The CWlFZ cutpoint analysis framework relies on binning a continuous predictor (ERC percentile) into categorical zones. While this approach enhances parsimony and models real-world decision-making structure, it inherently entails information loss. Observations within each zone are treated equivalently, though they may have subtle differences (Deckert and Kummerfeld, 2019; Harrell, 2015). For example, a broadcast burn near the upper boundary of its zonal threshold may be more difficult to control than one near the lower boundary, yet both are classified identically. Conversely, fire behavior across zones may be similar at boundary overlaps, despite differences in fire class type. For example, high intensity prescribed burns exhibit similar behavior and resource benefit to low intensity wildfires (Wu et al., 2023), yet are treated as different classes in this method and are observed at similar ERCs. We aim to discriminate between these two classes, though this may not be the most operationally meaningful cutpoint. Thus, a filter to remove smaller fires from the training dataset may improve classification performance by reducing noise in the ordinal relationships.

Bootstrapping in the cutpoint analysis improves the robustness of cutpoint selection and formalizes transitional overlap zones, reducing bias from sample-specific variability and provided clearly delineated uncertainty zones (Thiele and Hirschfeld, 2021). However, it does not recover the fine-scale variability lost during binning. Consequently, binning can increase the likelihood of Type I and Type II errors and may oversimplify the underlying relationship between ERC and fire behavior (Deckert and Kummerfeld, 2019; Perkins and Schisterman, 2006).

Furthermore, the nonparametric nature of the cutpoint approach requires large sample sizes to reduce variability in cutpoints and reliably characterize the relationship between ERC and fire class. Large datasets both stabilize cutpoint estimates and decrease bias in Youden's index, improving the detection of optimal cutpoints (Fluss et al., 2005). Due to the challenge of assembling sufficiently large datasets for fire modeling, particularly for prescribed fire (Tong and Quaife, 2024), limited external evaluation was conducted in this study. Maximizing data collection should remain a priority when applying this method.

Our classification method utilizes a data balancing scheme. Balancing fire classes during cutpoint estimation ensures that each class contributes equally to sensitivity and specificity calculations, preventing cutpoints from being skewed by the most frequently occurring fire class (He and Garcia, 2013). However, these balanced thresholds do not represent the true prevalence or probability of each fire class in the historical record. Thus, the cutpoints optimize class discrimination statistically but may over- or under-represent typical conditions in absolute terms (Van den Goorbergh et al., 2022).

Despite the robust nature of the methods used here and the spatio-temporal pixel-level normalization of the fire danger data, the spatial sensitivity analysis demonstrates that generalizing cutpoints at large spatial scales can result in poor fire class classification in under-represented regions, as observed east of the Continental Divide in our full-region guide. As discussed, this may be attributable to heterogeneity in fuel structure or to an underlying relationship between fire danger and fire class that is not sufficiently ordinal in certain landscape types. However, as demonstrated by the Lolo National Forest guide, if data are available, ordinality is met, and regional dynamics are well represented by the chosen fire danger variable, we are confident in the scalability of this framework. Notably, our study only addressed one spatial scope (Montana and Idaho) and further training and testing of the method across differing regions should be carried out.

4.1.2. Data challenges

We use wildfire occurrence to represent conditions where prescribed burning is unfavorable, but this is an imperfect proxy. We chose this approach because characterizing where prescribed fire and wildfire conditions overlap may be useful for operations, helping flag when additional resources or tighter contingencies are warranted to avoid an escape. However, a direct comparison between escaped, or otherwise failed or abandoned, prescribed burns and successful burns would yield more accurate cutpoints, but such a comparison is challenging due to the rarity of escapes and even further obscurity of these records (Black et al., 2020; Wildland Fire Lessons Learned Center, 2013). Most wildfires ignite without the planning, ignition control, and suppression readiness of prescribed burns. They also lack operational features such as multiple ignition points, patterned ignitions, and managed fireline interactions (Hiers et al., 2020; Furman, 2018), which can alter fire–weather relationships. These differences may cause the Broadcast Burn–Wildfire cutpoint to underestimate the ERC percentile at which truly uncontainable wildfires ignite, as many recorded wildfires, particularly smaller ones, may not have required suppression or could have remained controllable under prescribed-burn-level monitoring. Conversely, without canceled or abandoned burn records, the model lacks any signal of risk-averse conditions where managers decline to burn. Instead, wildfire is used as the proxy, which tends to occur at higher ERC, introducing a survivorship bias that may produce cutpoints higher than true risk tolerance supports. Large sample sizes and overlap zones were incorporated into this framework specifically to help account for these potential biases.

Our prescribed burn records have limitations beyond the absence of escape data. The MIAG database only provides a "proposal date" (the planned burn date, entered in advance), and location accuracy is uncertain (Montana/Idaho Airshed Group, 2010). Errors in either could result in burns being paired with inaccurate weather conditions, introducing error into ERC calculations.

When proposed activity dates are correct, they still only represent conditions on the ignition day. Some prescribed burns last multiple days, yet our analysis can only use weather observations from the start date. Fire growth conditions, arguably more critical than ignition, are not captured. For example, pile burns sometimes escape weeks after ignition when residual heat meets favorable weather (U.S. Department of Agriculture, Forest Service, 2023). Without fire progression data, we cannot evaluate conditions across the full burn window. Improved temporal documentation of prescribed burns would enable more accurate assessment of risk and better alignment of ERC cutpoints with operational decision-making. One method for capturing these data could be documenting the daily area burned within large and multi-day prescribed fire projects in operational fire reporting databases.

This framework also does not account for specific operational considerations such as ignition-techniques, containment methods such as black-lining, dormant versus growing season burning, resource availability, or regional smoke management restrictions, which can meaningfully influence prescribed fire outcomes independent of fire danger conditions (Hiers et al., 2020). For example, certain regions like Missoula County do not allow open burning before March 1st. Wide-spread and standardized documentation of these types of operational variables could help further isolate the true relationship between fire danger and fire class prevalence. Because prescribed burning is already structured around established seasonal and regulatory practice, some of the observed ERC separation between fire classes may reflect existing practice rather than the relationship between fire danger and fire class.

In the United States, new efforts are being made to incorporate prescribed fire occurrence data alongside wildfire data into authoritative data archives. Systems such as InFORM (National Interagency Fire Center, 2024) collect real-time wildfire and prescribed fire occurrence data, but only when prescribed fire data are voluntarily shared. Prescribed fire data collection is not mandatory and is therefore often spatially limited to specific areas, whereas wildfire data collection is mandatory nationwide. Although detailed data are best, only a minimal set of variables are required for any wildland fire class (such as location, ignition date and time and fire class) to easily apply our methods more broadly across the United States. This can help guide prescribed fire planning and decision-support nationwide.

4.2. Operational guidance

4.2.1. Building a ***ClassiFiR$_x$e*** guide for a new study area

The CWlFZ thresholds presented here are sensitive to sample-specific limitations and spatial variance in ERCs. As such, we recommend users, if possible, replicate our methods on their own study areas rather than universally apply the specific thresholds presented here. The bootstrapped cutpoint analysis framework provides a structured method for deriving categorical fire thresholds that can be tailored to specific regions or datasets. The four steps required to build a regional ClassiFiR$_x$e guide are summarized in Table 6 and described below.

Sample Size. In our sample size simulation study, variability in overlap zones stabilized with approximately 300–500 samples per fire class, suggesting this range is generally sufficient to provide relatively stable cutpoint estimates. However, the exact sample size required may depend on the underlying distribution of fire danger values, which is expected to vary across regions and contexts. More important than identifying a universal minimum is ensuring each class adequately represents the true range of conditions under which those fires occur. Thus, although diminishing returns were observed in our case study, larger sample sizes remain preferable when feasible. We recommend conducting analogous simulation studies with local datasets to determine when stability is achieved. Alternatively, the *cutpointr* R Shiny web application includes a Sample Size Planning tab (Thiele, 2022) that can aid in estimating effective sample sizes prior to data collection.

Fire Danger Variable Selection. We recommend selecting a fire danger variable that is representative of the fuel structure present in the study region. In our analysis, ERC calculated using the timber fuel model (Model Y) performed well in the primarily forested western Montana and Idaho but showed substantially weaker discriminatory power east of the Continental Divide, where grassland and shrubland fuel types dominate. Users should consider whether their chosen fire danger metric are appropriate for the landscape in question before proceeding with the cutpoint analysis.

Ordinality. Normalized fire danger distributions by fire class should be visualized to ensure a monotonic trend across fire classes (pile burn < broadcast burn < wildfire). Statistical tests such as the Spearman rank correlation or the Jonckheere–Terpstra test can be used to formally evaluate ordinality. It is important to note that with large sample sizes, statistically significant p-values can be obtained even when the practical strength of the ordinal relationship is weak, as observed east of the Continental Divide in our analysis. We therefore recommend evaluating both the p-value and the magnitude of ρ when assessing whether the ordinality assumption is sufficiently met to proceed with the cutpoint analysis.

4.2.2. Interpretation and use

For interpreting the Categorical Wildland Fire Zones, we emphasize that the strict zones represent ERC ranges where the historical rate of one fire class exceeded that of adjacent classes, and the overlap zones represent ERC ranges where those historical rates were similar. ClassiFiR$_x$e characterizes fire danger conditions by relating them to previously successful prescribed burns and historical wildfire occurrence. Thus, the framework cannot identify prescribed burn opportunities at fire danger levels outside the historical range of observed burns. It reflects practitioner experience opposed to theoretical fire behavior potential. It should also be noted that the CWlFZ framework is built on ERC alone, and is blind to other variables known to influence fire danger, such as wind and topography.

Table 6
Steps required to build a regional ClassiFiR$_x$e guide.

Step	Action	Description
(1)	Collect data	Assemble fire occurrence records with fire class labels and an associated fire danger metric. Minimum recommended sample size: 300–500 per fire class.
(2)	Normalize fire danger data	Intersect fire occurrence records with spatially normalized fire danger data by location and date. Normalization should be performed within each grid cell or RAWS station.
(3)	Verify ordinality	Confirm that fire danger values increase monotonically across fire classes. Visualize distributions and evaluate statistically using Spearman rank correlation or the Jonckheere–Terpstra test.
(4)	Run cutpoint analysis	Apply the bootstrapped cutpoint analysis following Steps 2–6 in Fig. 1.

Additionally, we acknowledge that the classification performance remains moderate and error is present. While mean fire size by CWlFZ (Table 5) provides empirical support that the most consequential fires are broadly captured in their expected zones, misclassification does occur across all fire classes. Encouragingly, fires occurring outside their expected zones tend to be smaller, suggesting that the most operationally significant events are more reliably classified.

Given this performance and the limitations outlined in Section 4.1, ClassiFiR$_x$e is best understood as a complementary planning and decision-support tool rather than a standalone decision-making system. We envision ClassiFiR$_x$e as most valuable when integrated into the formal burn planning process, such as within NWCG prescribed fire plan development (National Wildfire Coordinating Group, 2021) and the burn approval phase. Observed and seven-day forecast Energy Release Component percentiles can now be obtained from the Fire Environment Mapping System (FEMS) across the United States and these values can be combined with CWlFZ to assist with Go/No Go decision for prescribed fires and for weekly operational planning.

Although managers already associate certain seasons with pile, broadcast, or wildfire conditions, as is apparent in Fig. 4, season itself is a fixed proxy for the underlying fire danger conditions it is meant to represent, whereas ClassiFiRxe classifies those conditions directly. This allows the tool to account for year-to-year variability, such as early snowmelt, delayed spring precipitation, or extraordinary warm or cool spells. By linking fire danger directly to fire class, managers can gauge whether current conditions in a project area align with historically favorable pile burning, broadcast burning, or wildfire conditions, or fall instead within a zone of greater historical uncertainty. The framework is also well suited for retrospective analyses of historical fire seasons, allowing managers to evaluate past prescribed burn opportunities relative to the CWlFZ framework and assess progress toward seasonal burning goals.

4.3. Future work

The ClassiFiR$_x$e framework presented here focuses on distinguishing between three broad wildland fire classes, but the underlying cutpoint methodology is flexible and could support further stratification in several directions. For example, fires that fall squarely within the Wildfire zone could be further subdivided to explore transition points between fires that are easily suppressed and fires that escape initial attack, as others have attempted (Plucinski et al., 2023). Allowing smaller or less intense wildfires to burn has been shown to be beneficial for resource management (Wu et al., 2023) and distinction of wildfire intensity could be explored by reclassifying smaller fires in the training dataset. We also recommend exploring Min-Max or Outlier-Adjusted Min-Max normalization in future studies that further partition wildfires, as these methods preserve the unbounded upper end of raw fire danger values and may enable clearer separation of fire classes under extreme fire weather conditions.

The framework could also be stratified by additional landscape characteristics such as elevation gradients or by operational burning practices such as dormant versus growing season burns. These may exhibit sufficiently distinct fire danger signatures to support meaningful classification. Critically, the spatial sensitivity analysis presented here demonstrates that the choice of fuel model is a key determinant of classification success. In our study, we used a fixed timber fuel model (Model Y) across the full study region despite known landscape-level variations in landcover between forests and grasslands (Jolly et al., 2015). The new version of the US National Fire Danger Rating System enables ERC calculation for different fuel types (Jolly et al., 2024), and future studies should explore whether leveraging local fire regimes, fuel class or landcover types improves classification performance. This is particularly necessary in grassland and shrubland dominated regions where the fixed fuel model approach showed clear limitations.

Further training and testing of the framework across differing regions and fuel types is necessary to better understand the broader capabilities and limitations of this approach. Future work should also explore post-hoc zonal analyses of fire characteristics within each CWlFZ, similar to the fire size analysis conducted here, examining attributes such as vegetation type, elevation, and fire cause to better understand the ecological and operational drivers of fire class distributions.

As fire occurrence and fire danger records accumulate and data collection becomes more precise and standardized, the stratifications suggested above become increasingly feasible, allowing guides to remain temporally and spatially relevant under shifting fire regimes and climate conditions.

Additionally, this method functions as a univariate classifier, which facilitates interpretability and avoids multicollinearity issues. However, by relying solely on ERC, our method likely over-simplifies the complex interactions among weather, fuel, and landscape factors that drive fire behavior (Hiers et al., 2020). Notably, ERC does not incorporate wind, despite wind being a primary driver of unexpected fire spread and escape risk during prescribed burn operations. Using additional indices such as the Burning Index or composite indices such as the Severe Fire Danger Index (Jolly et al., 2019), both of which incorporate wind, may improve discrimination between fire classes and warrants exploration in future studies. These likely require higher resolution climatology to avoid local and complex terrain influence (Forthofer et al., 2014).

Future work should explore whether alternative classification frameworks such as fuzzy logic or ordinal classification trees can replicate or improve upon the empirically derived transition zones produced here, particularly in regions where the ordinal relationship between fire danger and fire class is weaker. Other more complex modeling approaches such as Bayesian spatio-temporal models or formal spatial statistical methods such as semivariogram analysis could complement this framework by formally characterizing the spatial and temporal structure of CWlFZ distributions.

More importantly, improvements to data collection, both in quantity and quality (especially for prescribed burning) are imperative for methods such as ours to be both transferable and strengthened. For example, collecting data on proposed burns that were not executed could help characterize the full range of conditions under which prescribed burns are planned and canceled. Other data such as daily-updated records from multi-day burns and operational goals, when collected in a standardized format, can improve this method. Additionally, downscaling of the underlying meteorological data to finer spatial resolutions may improve guide performance at local scales more fundamentally than classification-based spatial subsetting alone.

Our methodology alone is not enough to change the process of planning and decision-making for prescribed fire. Moving away from point-based weather stations and leveraging gridded fire danger information is a crucial next step for managers to consider and will require a concerted training effort in new methods. One benefit of our research is its applicability with point-based weather stations in addition to gridded climatology. This can build confidence in new tools when attempting field transitions from station-based information towards more gridded representations of the fire environment. More work is needed to build these Categorical Wildland Fire Zones into burn plan development and anchor daily prescribed fire go-no/go decisions to spatial forecasts of expected fire classes across the project area.

5. Conclusion

Here we have curated the largest prescribed fire and wildfire database known to date across two Western USA states and developed a cutpoint analysis method that ordinates fire classes along a spatial fire danger continuum. We have shown that bootstrapping combined with quantile-based intervals captures sampling error, thereby facilitating the delineation of overlap zones between fire classes and making the overall categorization framework more robust and representative of real-world variability while keeping the decision-making structure of prescribed burn planning. We have also shown that percentile-based fire danger normalization plays a critical role in model performance, and that the choice of fire danger variable and spatial extent of training data are key determinants of classification success. A spatial sensitivity analysis revealed that the framework performs best where the ordinal relationship between ERC and fire class is strongly satisfied and the fire danger metric reflects local fuel structure, as demonstrated by the strong classification performance of both the West of Divide and Lolo National Forest guides. We have shown that these cutpoints can be used to develop spatial and temporal visualizations of Categorical Wildland Fire Zones (CWlFZs) at both local and landscape scales to improve interpretation of fire danger indices and identify potential burn opportunities. We also demonstrate the use of the tool for examining seasonal patterns of CWlFZs across large regions and show how these may vary spatially. Ultimately, these techniques demonstrate that where sufficient wildfire, prescribed fire, and spatio-temporal fire danger data exist and the ordinality assumption is met, this data-driven framework offers a repeatable and interpretable tool to support the planning and implementation of prescribed fires.

Despite an increase in fire intensity across the United States, a wildland fire deficit remains (Parks et al., 2025). Our results show promise in providing better tools to increase the pace and scale of prescribed burning of fire dependent ecosystems across large landscapes. Ultimately, by leveraging our data-driven approach, fire and land managers can better map and monitor expected fire conditions and better identify prescribed fire opportunities that can reduce the fire deficit, mitigate wildfire risk, and promote healthy ecosystems.

CRediT authorship contribution statement

Benjamin E. Sweeney: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **W. Matt Jolly:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Project administration, Investigation, Conceptualization. **Patrick H. Freeborn:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Data curation, Conceptualization. **Chloe L. Ochocki:** Writing – review & editing, Writing – original draft, Visualization, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ecoinf.2026.103970.

Data availability

All analysis R code has been made publicly available in the Class iFiRxe GitHub Repositorywith an accompanying README that walks users through the repository structure and analysis steps. The gridded ERC climatology data is too large to host on the platform, so users wishing to reproduce the full analysis locally are directed to contact the corresponding author via the README. An R Shiny application for streamlined production of regional ClassiFiR$_x$e guides is currently in development.

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