**Title:** Aspen's influence on fire radiative power and burn severity is moderated by forest composition, structure, and fire weather in the Southern Rockies

**Alt title:** Aspen reduced fire intensity and severity across Southern Rockies forests (2017-2023)

**Target journal:** [Ecology Letters](https://onlinelibrary-wiley-com.colorado.idm.oclc.org/page/journal/14610248/homepage/forauthors.html#tips1)

**Alt:** [Forest Ecology and Management](https://www.sciencedirect.com/journal/forest-ecology-and-management)

**Code:** <https://github.com/maxwellCcook/aspen-fire/tree/main/Aim2>

Abstract (150 words max)

Increasing fire activity across western US forests requires mitigation solutions – aspen trees, given their lower flammability, may offer a new mechanism. We harmonized satellite proxies of fire intensity and severity alongside imputed wall-to-wall forest inventory and geographic setting to test the hypothesis that aspen moderates fire behavior in the Southern Rockies. Intensity, proxied by cumulative Fire Radiative Power (FRPc), was on average 4-21% lower in aspen, relative to conifer neighbors. Burn severity, estimated using bias-corrected Composite Burn Index (CBIbc), was lower with greater proportions of aspen compared to all other forest types. For example, for every increase of 1.4 ha (10% of gridcell area) of aspen forest cover there was a commensurate reduction in burn severity of ~5.4%. We demonstrate that aspen reduced both fire intensity and severity in flammable Southern Rockies forests, giving scientific backing to a forest management strategy that may complement other ways of reducing fire hazard.

Highlights

Keywords

# Introduction

Forest composition, or the abundance, dominance and diversity of forest species, has an important influence on fire activity and post-fire ecosystem impacts (Hagmann et al., 2021). Alongside climate and topography, forest composition and species traits help govern fire regimes and fire effects at a variety of spatial and temporal scales (Johnstone et al., 2016). Tree species composition and structure (*e.g.*, cover, height, diameter), for example, help drive *fire intensity*, or how hot a fire burns, and *fire severity*, or the consumption of organic matter (Keeley, 2009). Fire intensity and severity influence suppression difficulty (Thompson et al., 2018), impacts to the built environment (Penman et al., 2014), and ecosystem responses such as post-fire tree recruitment (Chapman et al., 2020; Meigs & Krawchuk, 2018). Given recent extreme fire activity and changes to the composition, structure and fire regimes of western North American forests (Hagmann et al., 2021; Hessburg et al., 2021), there is an urgent need to understand the influence of forest species composition and structure on contemporary fire intensity and severity.

The modification of forest composition and structure is a viable management tool often leveraged to reduce wildfire hazard to communities and ecosystems (Prichard et al., 2021). These management actions often involve reduction of fuels through mechanical treatment or prescribed fire, thereby reducing the potential for extreme fire intensity and severity (Agee & Skinner, 2005; Stephens et al., 2009). However, this presents a persistent management problem where treatments must be revisited to maintain positive benefits. Furthermore, while far more prescribed fire is ultimately needed to restore increasingly fire-starved ecosystems in the western U.S. (Parks et al., 2025), its use is limited by policy restrictions, public support, and a shortening window of appropriate weather conditions for burning (Schultz et al., 2019; Swain et al., 2023). The promotion of “fire-resistant” species, which may provide natural buffers to extreme fire behavior that are more self-sustaining, presents a complimentary management tool to reduce extreme fire behavior (Girardin & Terrier, 2015). With increasing fire activity and hazards, particularly across the western U.S. (Parks & Abatzoglou, 2020), assessments of which species may provide these benefits and under what conditions they are likely to do so are needed.

In some regions of western North America, quaking aspen (*Populus tremuloides Michx.*) is one forest species potentially capable of reducing extreme fire hazard (Fechner & Barrows, 1976). Aspen, which is also the most widely distributed tree species in North America and often considered a keystone species (Rogers et al., 2020), has been characterized by fire-moderating traits such as lower canopy bulk density, higher canopy base height, and greater leaf moisture content (DeByle & Winokur, 1985; Shepperd, 1990; Shinneman et al., 2013). Existing in a functional gradient of seral (*e.g.*, having a conifer component) to stable (*e.g.*, pure stands), aspen exhibits varying fire regimes and degrees of fire resistance (Rogers et al., 2014; Shinneman et al., 2013). Generally, seral aspen exhibits more extreme fire behavior compared to stable aspen and, in turn, fire activity drives the persistence of either functional type (Morris et al., 2019; Shinneman et al., 2013). Evidence points to fire weather and stand condition influencing the fire behavior in aspen, where even pure stands are likely to burn when the conditions align (DeRose & Leffler, 2014). However, with these potentially fire-moderating traits, aspen may offer a natural buffer, a so-called *living fire break*, to extreme fire intensity and severity. Despite this recognition, there remains a knowledge gap between management and scientific understanding of how, when, and where aspen moderates fire, especially relative to other forest types and during recent extreme fire activity at regional-to-continental scales (Nesbit et al., 2023).

Widespread availability of satellite remote sensing data before, during, and after wildfires presents a unique opportunity to quantify the influence of aspen on wildfire activity across large spatial scales. Burn severity mapping, which is based on differences between pre- and post-fire multispectral imagery, is one of the most commonly applied uses of satellite remote sensing in fire ecology (Szpakowski & Jensen, 2019). Satellite-based metrics of burn severity, such as the composite burn index (CBI), have been shown to correlate well with field-based measurements, enabling large-scale assessments of ecosystem impacts and their drivers (Parks et al., 2019). In tandem, active fire detection, which relies on middle-infrared (~ 4 µm) imagery, has become a crucial tool for monitoring global fire activity (Wooster et al., 2021). Spectral radiance in the middle-infrared is used to calculate fire radiative power (FRP), which is a measure of the energy released by actively burning fires and is highly correlated with the rate of biomass consumption per unit time (Kaufman et al., 1998; Schroeder et al., 2010; Wooster et al., 2003). Studies have applied FRP to, for example, track wildfire smoke emissions (Li et al., 2019, 2020) and investigate the relationship between energy released and fire size (Laurent et al., 2019). However, as a proxy for fire intensity, FRP has been underutilized to assess the influence of forest composition and structure, fire weather, and landscape factors on fire activity. The harmonization of satellite-derived burn severity metrics such as CBI and fire intensity proxies like FRP alongside forest inventories is a promising approach to exploring these relationships.

To investigate the influence of aspen and other forest types on fire intensity and burn severity during recent (2017-2023) wildfires, we harmonized satellite-based FRP and CBI with imputed wall-to-wall forest inventory data derived from the United States Forest Service (USFS) Forest Inventory and Analysis (FIA) program. Using Bayesian spatial hierarchical modeling, we investigate three primary questions: (**i**) how do dominant forest types influence FRP and CBI *relative to aspen*; (**ii**) how does forest composition and structure, such as forest canopy cover, stand density, tree height and diameter, influence FRP and CBI; and (**iii**) where aspen co-occurs with other forest types, how does its dominance, measured as the proportion of live basal area, influence FRP and CBI both with and without mediating effects of fire weather. To account for landscape and climatic effects on fire activity, we include variables describing the topography and fire weather. Given the spatial-temporal dependence of wildfires, we also include random effects for day-of-burn and a structured spatial model, uncovering the landscape patterns of FRP and CBI. The results of this study have important implications for management of aspen and other common forest types in the context of fire intensity and burn severity in the Southern Rockies. We also highlight a novel application of satellite-derived FRP as a proxy for fire intensity to investigate the biotic and abiotic controls and spatial patterns of fire heat. These methods can be applied across large geographic regions to answer a variety of important questions related to forest and fire management.

# Materials and Methods

## 2.1. Study System and Wildfire Census

The Southern Rockies includes portions of southern Wyoming, central and western Colorado, and northern New Mexico. Aspen is the dominant deciduous forest type, encompassing an estimated 9,482 km2, 7.4% of total land area (Cook et al., 2024). In this region, aspen co-occurs with all major forest types including ponderosa mixed-conifer, lodgepole, and spruce-fir, and across a wide range of elevation and site conditions (Bartos, 2001). We collected a census of recent (2017-2023) wildfire events from the ICS-209-PLUS (St. Denis et al., 2023; updated through 2023). Since 2017, 113 wildfires burned approximately 1.68M acres including five large events (>100k acres): Calf Canyon / Hermit’s Peak (New Mexico, 2022), East Troublesome (Colorado, 2020), Cameron Peak (Colorado, 2020), Mullen (Colorado/Wyoming, 2020) and Spring Creek (Colorado, 2018). Where possible, we obtained fire perimeters from the Monitoring Trends in Burn Severity (MTBS; Eidenshink et al., 2007) using the link to MTBS in the ICS-209-PLUS database. For fire events without an MTBS identifier, we gathered perimeter data from FIRED (Balch et al., 2020). These fire perimeters were used to locate the associated active fire detections (*Section 2.3*).

A diagram of a map and a distribution of fire size

AI-generated content may be incorrect.

**Figure 1.** Study region and wildfire census data. (**A**) Map of the Southern Rockies and fire census; (**B**) Annual area burned (2017-2023); (**C**) Distribution of forest types within burned area from the *TreeMap* (see *Section XX*).

## 2.3. Active fire detections and fire radiative power (FRP)

Active fire detections from the Visible Infrared Imaging Radiometer Suite (VIIRS) Collection 2 Active Fire product (Schroeder et al., 2014) were collected across the study region. These data were produced in 6-minute temporal satellite increments (swaths) at 375 m spatial resolution at-nadir from VIIRS sensors aboard the NASA/NOAA Suomi National Polar-orbiting Partnership (S-NPP; VNP14IMG) and Joint Polar Satellite System (JPSS-1 or NOAA-20; VJ114IMG) satellites. Acquisitions occur twice daily around 1:30AM and 1:30PM at mid latitudes. We queried the cloud-hosted swaths using the *earthaccess* Python library (Barrett et al., 2024) for all burn dates in the fire census. From the swaths, we extracted coordinates of active fire pixels and attributes including swath sample position, detection confidence, acquisition datetime, and FRP. Only detections meeting the “nominal” or “high” confidence were retained. We used the swath sample position to assign along-scan and along-track pixel dimensions, accounting for changes in pixel area as the sample gets further from nadir (Li et al., 2018; Schroeder et al., 2014). Coordinates were buffered by these dimensions to generate the “true” ground area of the detection (**Figure S2**). We identified duplicate detections resulting from adjacent scans by flagging those acquired at the same datetime and with >30% spatial overlap (*ref*). For duplicates, we retained the detection with the higher FRP value. To aggregate FRP retrievals into a consistent spatial unit, we created a geospatial fishnet of 375 m(140,625 m2) gridcells (the approximate resolution of the VNP/VJ114IMG at nadir) across the entire Southern Rockies and assigned FRP based on fractional overlap of true pixel areas. This involved first converting FRP to watts/km2 for a consistent area-based measurement. Then, FRP was assigned to grid cells based on the fractional overlap (*FRP \* grid cell overlap %*). Only gridcells which had greater than 50% spatial overlap with detections were retained for analyses, limiting the contribution of gridcells with low fractional FRP. The total number of acquisitions, day/night counts, datetime of acquisition, and FRP summary statistics (cumulative, maximum and percentiles) were calculated. For analysis, this study focused on the *cumulative* FRP (hereafter FRPc) as a useful proxy for fire intensity and to leverage the full accounting of detections throughout the fire event.

## 2.4. Composite Burn Index (CBI)

We created burn severity rasters for each wildfire in the census using pre- and post-fire Landsat 8 imagery following methods from Parks et al. (2019) in Google Earth Engine (GEE; Gorelick et al., 2017). While this method produces a variety of burn severity metrics based on spectral indices, we use the bias-corrected CBI (CBIbc) for analysis as it adjusts for values at the extreme ends of the range, better quantifying the variability in burn severity (Parks et al., 2019). We calculated zonal statistics of CBIbc within fishnet gridcells, aligning the spatial scale with FRP aggregations including the average, standard deviation, and percentiles. For analysis, we use the 90th percentile CBIbc which emphasizes more extreme gridcell burn severity while capturing some variability.

## 2.5. Forest Composition and Structure

To assess the influence of forest composition and structure on FRPc and CBIbc, we gathered information from the ca. 2016 USFS TreeMap (Riley et al., 2022). TreeMap imputes Forest Inventory and Analysis (FIA) plot identifiers onto 30 m2 LANDFIRE (Picotte et al., 2019) pixels based on a set of LANDFIRE biophysical characteristics including topography, vegetation type, and disturbance (Riley et al., 2021, 2022). The FIA is a nationally consistent forest inventory monitoring program consisting of thousands of systematically located and revisited 675 m2 plots at a density of one plot per 24.3 km2 (Gray et al., 2012; Riley et al., 2021). While representing a sparse network of field plots, the TreeMap demonstrates good agreement with existing vegetation, enabling estimation of wall-to-wall forest characteristics (Riley et al., 2021, 2022). We use the TreeMap to, (**i**) identify gridcell majority forest cover type, and (**ii**) estimate forest composition and structure metrics from the *Tree Table*, which links TreeMap pixels to their imputed FIA tree-level data. Each gridcell is composed of approximately 182 TreeMap pixels (30 m2 spatial resolution). We focused efforts on commonly occurring forest types in the Southern Rockies including lodgepole pine, ponderosa pine, spruce-fir (Engelmann spruce and subalpine fir), Douglas-fir, white fir, pinon-juniper, Gambel oak, and quaking aspen (**Appendix X**).

For (**i**), we used the algorithmic forest type (*FORTYPCD*), which closely aligns with LANDFIRE existing vegetation type, to calculate the proportion of gridcell forested area for each forest type present. The majority forest type simply represents the type with the maximum proportional area in the gridcell. For (**ii**), following methods from Riley et al. (2021), we linked TreeMap pixels to their imputed tree-level information (the TreeMap *Tree Table*) using the *TM\_ID* attribute. We calculated the live basal area of each measured tree using its diameter (*DIA* in the *Tree Table*), which was then multiplied by the number of trees per acre it represents (*TPA\_UNADJ* in the *Tree Table*) and summed for each species in the plot. We converted this to live basal area *per pixel* using a conversion factor (0.222395 acres/pixel). The total live and dead trees per pixel (TPP), hereafter referred to as tree abundance, was also calculated using this conversion factor. These metrics were then multiplied by the total number of pixels for each FIA plot identifier in the gridcell to estimate the total live and dead basal area, total live and dead tree abundance, average tree height and average diameter for each species. We derived common forest stand structure metrics at the gridcell level for each forest type including the stand density index (SDI), average live basal area per tree, and the average height to diameter ratio (HDR). These metrics represent important forest structure characteristics and minimize statistical correlations between the raw values of live basal and area and tree abundance, for example (**Figure SX**).

In addition, we used the ca. 2016 remap LANDFIRE (Picotte et al., 2019) to calculate gridcell average forest canopy cover (%), as this metric has the lowest agreement between TreeMap and FIA tree-level measurements (Riley et al., 2022). Given the importance of forest canopy structure in the context of FRP retrievals and potential interception of radiative energy (Roberts et al., 2018), we calculated the canopy percent from LANDFIRE, which derives these measurements more directly from satellite data rather than from imputed forest inventories.

## 2.6. Climate and Topography

Elevation data were sourced from a 1/3 arc-second (~10 m) digital elevation model (*ref*), which was used to calculate elevation, slope, and aspect. Aspect was converted to northness by taking the cosine of aspect in radians, where values closer to one indicate north-facing slopes (*ref*). Gridcell average Topographic Position Index (TPI), derived at a 270 m resolution (Theobald et al., 2015), was also calculated to represent the landscape position (e.g., valley bottom, ridgetop). To characterize fire weather, we gathered vapor pressure deficit (VPD), energy release component (ERC), and wind speed from gridMET, a daily 4 x 4 km gridded meteorological product (Abatzoglou, 2013). Both VPD and ERC represent atmospheric and fuel aridity and correlate well with fire activity (Abatzoglou & Williams, 2016). For ERC, we calculated the deviation from the 15-year average (ERCdv) to represent the more extreme fuel dryness in the western U.S. during recent history (Parks & Abatzoglou, 2020). Gridcells were spatially aggregated by the first VIIRS detection day and the average VPD, ERCdv, and wind speed was calculated.

## 2.7. Statistical analysis

To assess the influence of forest composition and structure on FRPc and CBIbc, we fit Bayesian hierarchical spatial models using the Integrated Nested Laplace Approximation (INLA) framework, implemented in *R-INLA* (R Core Team, 2024; Rue et al., 2009). Unlike traditional Markov Chain Monte Carlo (MCMC) methods, INLA leverages deterministic (Laplace) approximations, providing a computationally efficient alternative for Bayesian inference that has been widely applied in recent years (e.g., Gomez-Rubio, 2020; Niekerk et al., 2019). These models are particularly well-suited for dynamic ecological systems, offering precise inference on spatial processes and rapid computation of posterior distributions (Beguin et al., 2012; Engel et al., 2022; Niekerk et al., 2019; Sadykova et al., 2017). *R-INLA* allows fitting complex hierarchical models to account for structured and unstructured random effects such as fire-level variability, temporal day-of-burn effects, and spatial dependence. We fit separate models for FRPc and 90th percentile CBIbc to address three primary aims: 1) establish the differences between dominant forest types on fire intensity and severity *relative to aspen*, 2) assess how forest composition and structure effect FRPc and CBIbc, and 3) quantify how increasing aspen dominance influences FRPc and CBIbc in different co-occurring forest types both with and without fire weather mediation.

We fit separate models for FRPc and CBIbc in *R-INLA* to address aims (1) and (2) and establish the difference between major forest types *relative to aspen* and the influence of forest structural metrics including percent cover of the majority forest type, species-level SDI, HDF, and average live basal area for all species present in each gridcell. A categorical variable for the gridcell majority forest type (i.e., by proportion of forested area) was included using aspen as the baseline level, allowing us to compare the differences between forest types relative to aspen while holding other fixed effects at their means. We included interactions between species and their structural metrics (SDI, average live basal area, and HDR) as well as fixed effects for gridcell topography and day-of-burn fire weather (**Table SX**). Only forest types which contributed to at least 10% of the total live basal area in a gridcell were retained to address potential noise in the forest inventory data. For aim (3), to test the influence of aspen dominance where it co-occurs with other forest types, we first identified fires which had any pre-fire aspen cover (N=65). Aspen dominance was measured as the proportion of total live basal area. An interaction term between the gridcell majority forest type and aspen dominance was used to test the effect of aspen co-occurrence across major forest types, including gridcells where aspen was the majority type. To assess the influence of fire weather mediation, an interaction term was set with VPD (i.e., majority *forest type \* aspen dominance \* VPD*).

*2.7.1. Model parameters and assessment*

Models were parameterized using the gaussian family for log-transformed FRPc and gamma for 90th percentile CBIbc based on their observed distributions (**Figure SX)**. Penalized complexity priors were used for fixed and random effects to allow for flexibility in model variance. Baseline models without random and spatial effects were compared to increasingly complex model structures using fit statistics, specifically Watanabe-Akaike information criterion (WAIC) and conditional predictive ordinates (CPO), two measures of model robustness and predictive power, respectively, commonly used to compare model outputs in *R-INLA* (Gomez-Rubio, 2020). For FRPc models only, additional covariates were included to represent the cumulative detection overlap percentage and the proportion of daytime detections within each grid to account for the aggregation method (*Section 2.3*). Other fixed effects included a gridcell distance to fire perimeter, the gridcell forest canopy percent, the gridcell total live and dead basal area, topography, and fire weather (**Table SX**). Prior to fitting models, we tested correlations between predictor variables using a Spearman correlation coefficient (**Figure SX**).

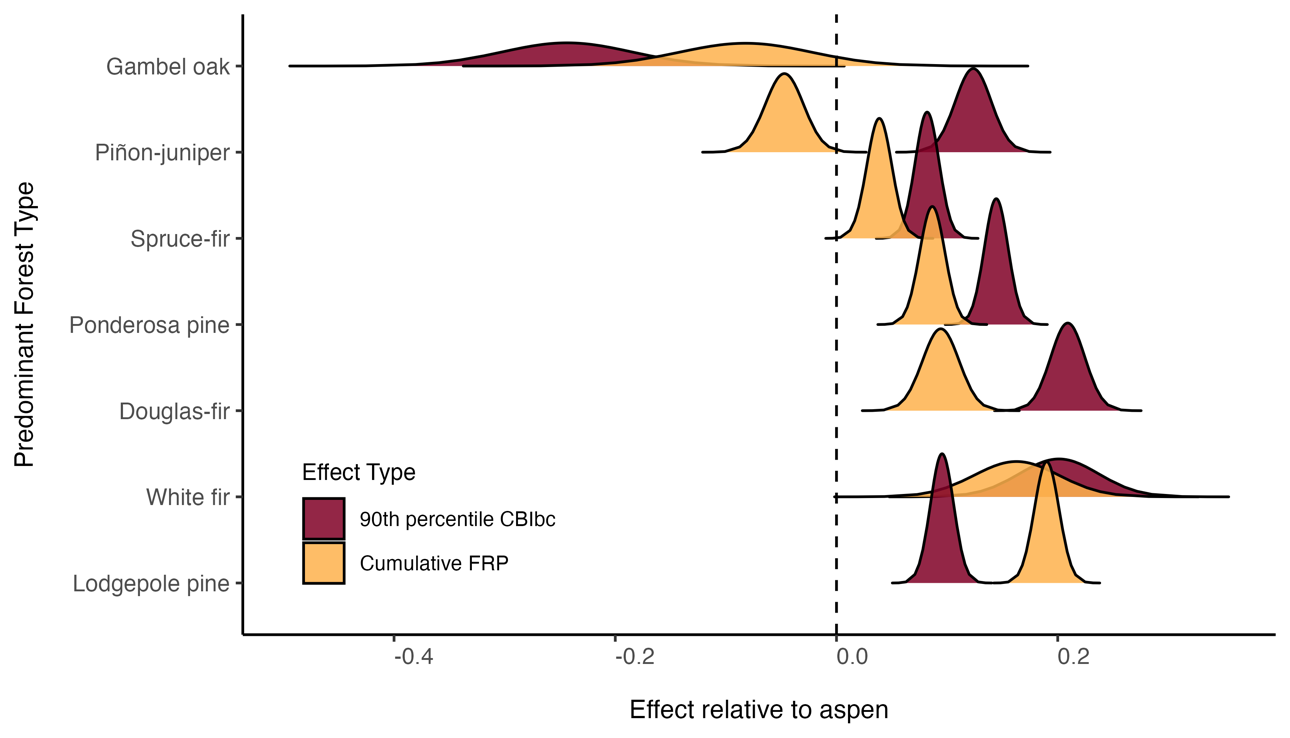
### 2.7.1. Spatial mesh

Wildfires are inherently spatially dependent processes, requiring careful assessment of model covariates. To account for this spatial dependence, we implemented the Stochastic Partial Differential Equation (SPDE) approach, which is a key innovation within the INLA framework for modeling spatial processes (Lindgren et al., 2011). The SPDE efficiently approximates continuous spatial Gaussian random fields (GRFs) using sparse precision matrices, linking GRFs to Gaussian Markov Random Fields (GMRFs) through a triangulated mesh representation (Bakka et al., 2018). We developed a spatial mesh for the Southern Rockies designed to reflect the expected within-fire spatial dependence and minimize the influence of between-fire dependence. The mesh parameters, including maximum edge, cutoff, offset, and priors were chosen to balance computational efficiency with observed spatial process based on semivariograms fit for individual fires using the *gstat* R package (Gräler et al., 2016). Specifically, the mean spatial range was estimated for both FRPc and CBIbc (**Figure SX**).

# Results

## 3.1. Differences between dominant forest types relative to aspen

In the Southern Rockies, dominant forest types influenced FRPc and CBIbc *relative to aspen*, demonstrated by the posterior distribution of effects (**Figure 2**). For FRPc, lodgepole pine showed the strongest positive baseline effect, with 20.9% higher FRPc than aspen (95% CI: 18.3%, 23.6%). Douglas-fir, white fir, ponderosa pine, and spruce-fir forest types also showed significant positive effects relative to aspen, although the credible intervals for white fir were wider, suggesting more uncertainty in the model estimates. Gambel oak and pinon-juniper had negative effects relative to aspen, although the credible intervals were more extreme and passed zero for Gambel oak, indicating insignificance in model estimates. For all forest types except pinon-juniper, the effect on CBIbc was significant and positive, showing that burn severity is typically higher in other forest types relative to aspen. Douglas-fir and white fir showed the greatest positive effect on CBIbc, with a 23.3% (95% CI: 19.6%, 27.1%) and 22.3% (95% CI: 13.9%, 31.2%) increase relative to aspen, respectively. For both models, inclusion of fire-level random effects alongside a spatial model significantly improved fit statistics demonstrated by the improved WAIC and CPO (**Table 1**).



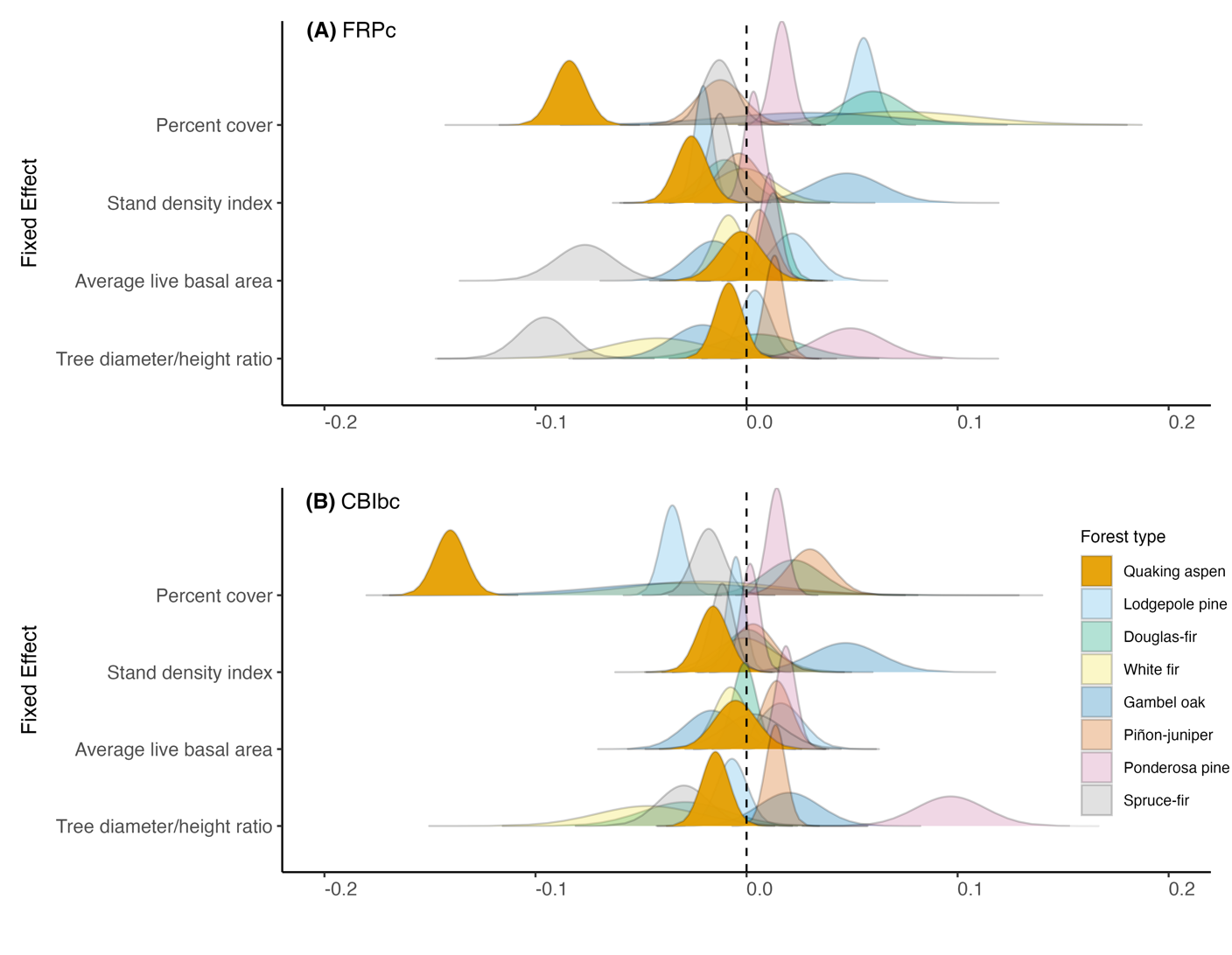
**Figure 2.** Posterior distributions of effects of predominant forest types on FRPc and CBIbc *relative to aspen* as the baseline holding other model covariates at their centers. Lodgepole, Douglas-fir, white fir, ponderosa pine, and spruce-fir forest types had significant positive effects on both FRPc and CBIbc compared to aspen. Gambel oak and pinon-juniper forests showed a lower FRPc, though credible intervals pass zero for Gambel oak. Except for Gambel oak, all forest types showed significant positive effects on CBIbc relative to aspen.

**Table 1.** Model comparisons using fit statistics and effective number of parameters. Spatial models with random effects for fire event and day-of-burn were far more complex (greater number of effective parameters) and performed significantly better based on WAIC and CPO.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Response | Model | WAIC | Mean CPO | Effective # of Parameters |
| **FRP** | **W/Fire + Temporal + Spatial Effect** | **261898.96** | **0.34** | **4700.02** |
| FRP | W/Fire + Temporal Effect | 282012.54 | 0.31 | 506.49 |
| FRP | W/Fire Random Effect | 288571.70 | 0.30 | 145.79 |
| FRP | Baseline | 295284.82 | 0.29 | 53.99 |
| **CBI** | **W/Fire + Temporal + Spatial Effect** | **264356.09** | **0.36** | **4159.85** |
| CBI | W/Fire + Temporal Effect | 273861.08 | 0.34 | 501.89 |
| CBI | W/Fire Random Effect | 278836.15 | 0.33 | 495.64 |
| CBI | Baseline | 293617.54 | 0.30 | 51.99 |

3.2. Effect of forest composition and structure

Forest composition and structure influenced FRPc and CBIbc, with aspen clearly demonstrating a moderating effect based on posterior distributions (**Figure 3**). We characterized composition and structure using the gridcell proportion of the majority forest type (percent cover), species-level SDI, HDR, and average live basal area. Aspen percent cover had a significant negative effect on both FRPc (**Figure 3A**) and CBIbc (**Figure 3B**). For every standard deviation increase in aspen percent cover, there was a -8.1% (95% CI: -9.4%, -6.6%) reduction in FRPc and -13.1% (95% CI: -14.4%, -11.8%) reduction in CBIbc (**Table SX**). This effect was prominent for aspen compared to other forest types, although increasing percent cover of ponderosa, Douglas-fir, and lodgepole pine had significant positive effects on FRPc. Increasing percent cover of ponderosa and pinon-juniper had significant positive effects on CBIbc. The influence of species-level SDI, HDR, and average live basal area were less pronounced for aspen, however, significant effects did emerge. For every unit increase in aspen SDI, FRPc was reduced by an average of -1.6% (95% CI: -3.0%, -0.01%). Increasing aspen HDR also had a significant negative effect on both FRPc and CBIbc though no discernable effect of average stand diameter was found. In spruce-fir forests, the average stand diameter and HDR had significant negative effects on FRPc but had insignificant effects on CBIbc. Ponderosa forests showed a strong positive effect of HDR on both FRPc (mean effect 0.08) and CBIbc (mean effect 0.10).

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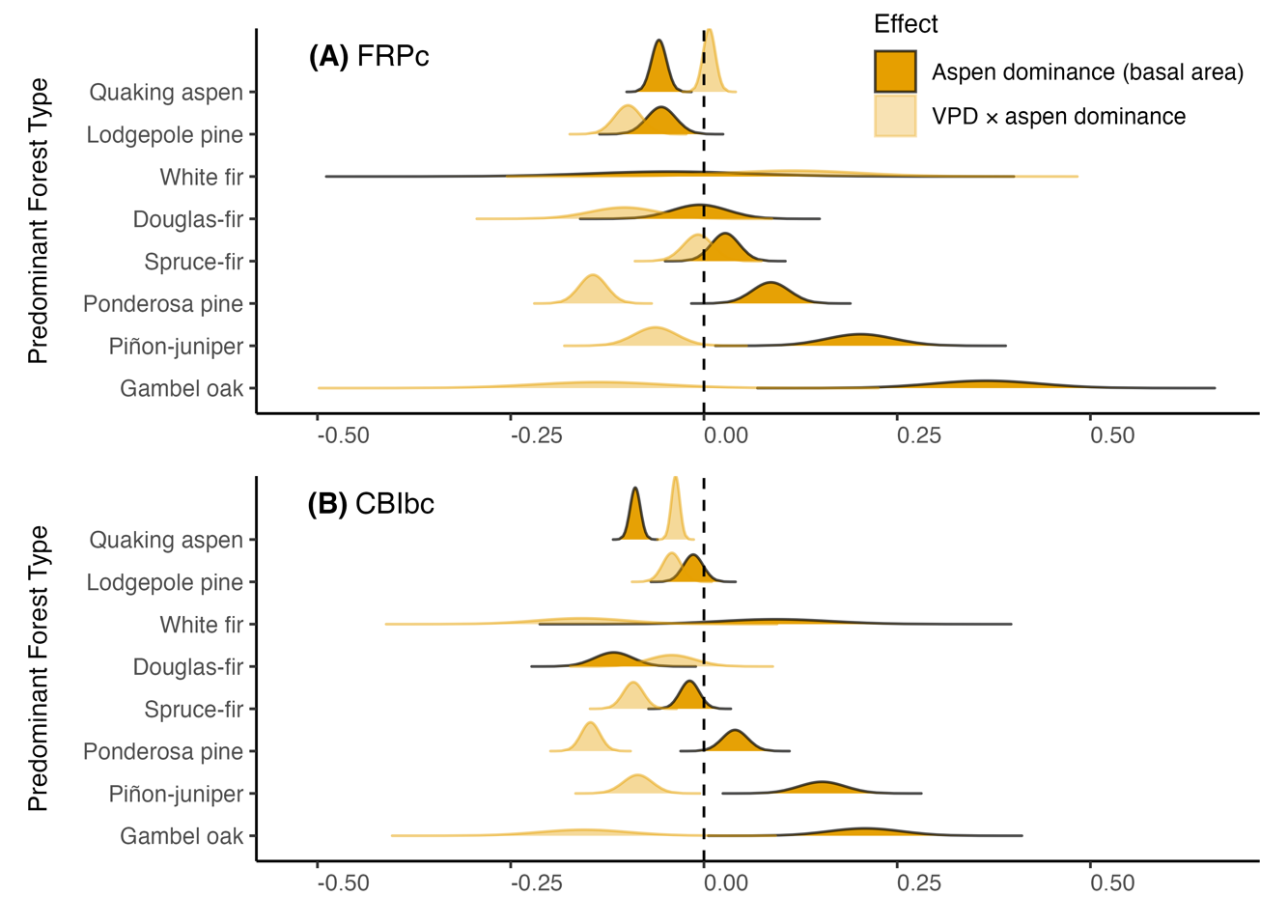
**Figure 3.** Posterior distribution of effects for forest composition and structure metrics on (**A**) FRPc, and (**B**) 90th percentile CBIbc.

**3.3. Topography and fire weather and other fixed effects**

Topography and fire weather influenced FRPc and CBIbc alongside forest composition and structure, with some key differences (**Table SX**, **Figure SX**). Elevation, for example, had a significant negative effect on FRPc, but a non-significant effect on CBIbc. Topographic features such as ridges and hilltops, characterized by higher TPI, had significant positive effect on both responses. Steeper slopes had a weak but significant positive effect on both responses. North-facing slopes tend to weakly decreased FRPc but have little effect in our models on CBIbc. Fire weather generally had a stronger positive effect on FRPc than CBIbc in our models. For every unit increase in VPD, there was a +15.1% (0.95 CI: +13.8%, -16.5%) increase in FRPc (**Table SX**). ERCdv had a positive effect which was strongest for FRPc (+11.5% for every unit increase), though positive and significant for CBIbc as well (**Table SX**). Unsurprisingly, the distance to fire perimeter had a strong positive effect on both FRPc and CBIbc and likely helps constrain model estimates where gridcells at the fire edge had significantly lower values.

## 3.4. Aspen co-dominance and fire weather mediation

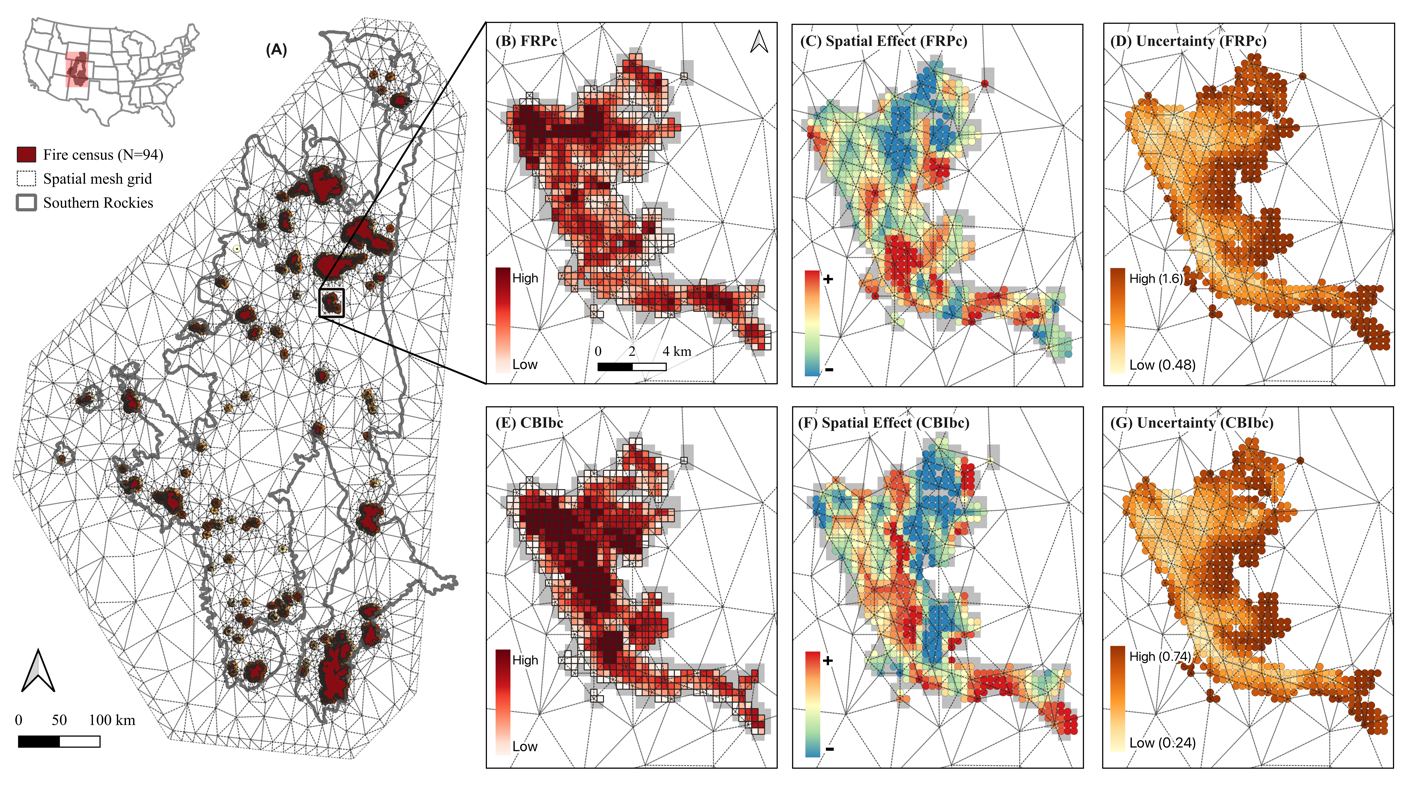
Where aspen co-occurs with other major forest types, its proportional live basal area (i.e., *dominance*) influenced FRPc and CBIbc differently, and these effects were often mediated by VPD (**Figure 4, Table SX**). Where aspen was the majority, increasing dominance significantly decreased FRPc (-5.4% for every unit increase) and CBIbc (-8.7% for every unit increase). However, VPD-mediation had a pronounced influence, with the effect of aspen dominance either diminishing greatly (CBIbc, **Figure 4b**) or becomes slightly positive with a non-significant effect (FRPc, **Figure 4a**). In lodgepole forests, the effect of increasing aspen dominance on FRPc was significant and negative (-3.5% for every unit increase), with VPD-mediation further increasing the magnitude of this effect (-5.7%). The influence of aspen dominance was strongest in lodgepole forests for FRPc and weaker for CBIbc where only VPD-mediation showed a significant but weak signal for reducing burn severity in lodgepole forests. In spruce-fir, ponderosa, Douglas-fir, and pinyon-juniper, increasing aspen dominance showed either a positive or non-significant effect on FRPc *without* VPD-mediation. However, this effect on FRPc became negative and significant for ponderosa, Douglas-fir and pinon-juniper when interacting with VPD, suggesting that as fire weather was more extreme aspen dominance had a larger effect on reducing fire activity in these forest types. This influence was pronounced, with -17.8% reduction in FRPc in ponderosa forests when interacting with VPD compared to a +6.8% increase in effect without VPD-mediation, for example (**Table SX**). In spruce-fir forests, VPD-mediation moved the influence of aspen dominance to a non-significant effect on FRPc, demonstrating a lack of evidence for aspen moderation in this forest type. In the case of CBIbc, spruce-fir forests did benefit from aspen dominance during more extreme fire weather, with a reduction by X% in burn severity for every unit increase in aspen dominance. For Gambel oak and white fir, which are relatively rare in the sample (**Figure S1**), the effects of aspen dominance exhibited extreme credible intervals for both models. These forest types rarely co-occur with aspen in great proportions (**Figure SX**), which helps explain the wide credible intervals and uncertain estimates.

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**Figure 5.** Posterior distribution of effects of quaking aspen *proportional live basal area* relative to co-occurring predominant forest types. Solid colors represent the effect of increasing proportional live basal area on FRPc and CBIbc and transparent shades represent the VPD-mediated effect which was modeled as an interaction term in R-INLA (*e.g.*, *VPD \* predominant forest type****:****aspen proportional live basal area*).

### 3.1.4. Spatial patterns in FRPc and CBIbc

Substantial spatial structure emerged for both FRPc and CBIbc, defined by the SPDE structured random effects model implemented in *R-INLA* (**Figure 5**). Semivariogram analysis provided an initial assessment of the expected spatial range (**Figure SX**), suggesting an expected mean range for FRPc of ~2.2 km and ~2.9 km for CBIbc. Results from the SPDE indicate alignment with these expectations alongside fixed and random effects, with slight differences. For FRPc, the mean effective range of spatial dependence was 0.017 degrees (~1.7 km), suggesting a fine-scale clustering and influence of localized conditions unexplained by fixed or random effects (**Figure 5C**). A relatively large standard deviation (mean 0.796) indicated moderately strong spatial variation in FRPc, and residual spatial effects left unexplained by the model. In the case of CBIbc (**Figure 5F**), the effective range of spatial dependence was 0.013 (~1.3 km), with a lower standard deviation (mean 0.326), suggesting that CBIbc may be better explained by the fixed and random effects such as forest composition and structure, fire weather and topography.



**Figure 3.** Southern Rockies spatial mesh grid for SPDE spatial model and example for the Williams Fork Fire, CO (2020). (**A**) Spatial mesh grid and fire census covering the Southern Rockies (2017-2023); (**B**) Cumulative FRP (FRPc); (**C**) Spatial effect of FRPc; (**D**) Uncertainty in the spatial effect of FRPc; (**E**) 90th percentile CBIbc; (**F**) Spatial effect of CBIbc; and **(G)** Uncertainty in the spatial effect of CBIbc. Tighter spatial clustering was observed for FRPc compared to CBIbc, and spatial dependence is strongest within ~1.4 km indicating finer-scale spatial patterns compared to ~X km for CBIbc.

# Discussion

Significant differences between FRPc and CBIbc relative to aspen emerged across forest types in the Southern Rockies during recent wildfires. Aspen forest composition and structure had significant moderating effects on fire intensity and severity compared to other forest types. For example, we found that compared to lodgepole pine, aspen averaged 20.9% lower FRPc and 10.0% lower CBIbc. In this forest type, and where lodgepole and aspen co-occur, every unit increase in proportional live basal area decreased FRPc by -3.5% and (-5.7% with VPD-mediation), highlighting the capacity for aspen to reduce fire intensity in lodgepole forests even under more extreme conditions. The results of this study have widespread implications for forest and fire management in the context of fire hazards, suppression and response, and fuels treatments. We introduce a novel index, FRPc, as a proxy for fire intensity and successfully harmonize this with satellite-derive burn severity, imputed wall-to-wall forest inventory data, and characteristics of topography and weather to elucidate the biotic and abiotic controls on fire intensity and post-fire ecosystem impacts.

## 4.1. Aspen turns down the heat during recent wildfires

Aspen forests had a strong moderating effect on both FRPc and CBIbc, especially where it was the dominant forest cover. Lodgepole pine, Douglas-fir, white fir, ponderosa pine, and spruce-fir forests types all exhibited significantly higher FRPc and CBIbc *relative to aspen* while holding landscape and climatic effects such as forest composition and structure, fire weather, and topography at their means. This result aligns with expectations of fire activity in aspen forests, which is generally considered to be lower than adjacent conifer forest types (Nesbit et al., 2023). Previous studies have shown that fire activity is determined also by aspen stand structure and function type (e.g., seral or stable), where stable stands are less likely to burn than seral stands (Shinneman et al., 2013). Our results support this during recent wildfires in the Southern Rockies, with a -8.1% reduction FRPc for every unit increase in aspen percent cover (**Figure 3A**) – indicating a more pronounced cooling effect of aspen forests when they make up a greater proportion of the landscape area. Where aspen co-occurs with other forest types, significant moderating effects emerged especially when interacting with VPD (**Figure 4**). In lodgepole, for every unit increase in aspen dominance (proportion of live basal area), there was -3.5% effect on FRPc and -5.8% in CBIbc, respectively (**Table SX**). Importantly, this moderating effect was more pronounced when interacting with VPD, suggesting that even under more extreme fire weather conditions aspen may reduce fire intensity and severity where it co-occurs with lodgepole. Conversely, the influence of aspen dominance in ponderosa, pinon-juniper, and Douglas-fir weakly increased fire intensity and severity in some cases *except* when interacting with VPD. While this dynamic deserves more attention in subsequent studies, it indicates that under more extreme fire weather aspen may provide a buffer in these forest types. Given associations between increasing VPD and increasing fire activity in the western US (Abatzoglou & Williams, 2016), this is potentially significant finding. However, These forest types often occupy low-elevation sites where the future habitat suitability of aspen is in question (Hart et al., *In review*). This VPD-mediation also highlights an important consideration in areas already dominated by aspen forests – the influence of increasing dominance becomes insignificant when fire weather is more extreme. This aligns with simulated studies of aspen fire behavior in northern Utah, where torching and crowning events were just as likely in aspen compared to conifer when fire weather was more extreme (DeRose & Leffler, 2014). Still, both FRPc and CBIbc are lower in aspen forests relative to other types, this effect may just be diminished by extreme fire weather. Future efforts should focus on this dynamic to untangle the influence of fire weather on fire behavior in different forest types.

## 4.2. Forest composition and structure effects align with expected fire regime characteristics

Forest-specific fire regime characteristics emerged when assessing the influence of structural metrics on fire heat and burn severity. For example, the interesting relationships between SDI and HDR corroborate expected fire regime characteristics in aspen, ponderosa pine and spruce-fir forests. The SDI relates the total number of trees per unit area to their average stem diameter where low values represent less dense stands and high values represent dense, high volume stands (*ref*). Significant effects of aspen SDI emerged showing that as SDI increases, FRPc and CBIbc decreases by -2.6% and -1.6%, respectively (**Figure 4**). This indicates that where aspen stands were more densely packed (*i.e.*, representative of a more stable functional type) they reduce both heat and severity of fire. Similarly, as aspen HDR increased, FRPc and CBIbc both decreased weakly but significantly. High HDR implies tall, slender trees which is more indicative of seral aspen forests with little understory regeneration and a few large individuals (*ref*). This aligns with expected fire regime characteristic in stable aspen types which generally experience lower intensity fire than seral types (Shinneman et al., 2013). Similar interesting effects emerged in spruce-fir forests for FRPc but not for CBIbc. In these forest types, significant negative effects of SDI (weak but significant), average live basal area, HDR indicate that densely packed forests tend to have lower FRPc. High-elevation dense spruce-fir forests are characterized by relatively high surface fuel and soil moisture which is often retained later in the year than other forest types and can have significant limitations on fire intensity under most conditions (*ref*). Still, these forests readily burn at high severity when conditions align (*ref*), a possible explanation for the lack of significant effects on CBIbc. Relative to aspen, spruce-fir forest types only demonstrated a weakly positive effect on FRPc (**Figure 2**) and the influence of aspen dominance on reducing fire heat was only uncovered when interacting the VPD (**Figure 4**), suggesting that specific fire weather conditions influence the flammability of spruce-fir relative to aspen, aligning with expectations that spruce-fir is more climate-limited than fuel-limited (*ref*). For ponderosa pine, which is a low-elevation dry conifer forest type historically evolved with high frequency, moderate to low severity/intensity wildfire (Kaufmann et al., 2006), opposite effects emerged. These forests have been particularly impacted by a century of fire-exclusion leading to a forest structure that is characterized by densely packed even-aged stands and resulting in changing fire behavior (Battaglia et al., 2018; Veblen et al., 2000). We found significant positive effects on FRPc and CBIbc for ponderosa where average live basal area and HDR increases and a weak positive effect of SDI (**Figure 4**). This aligns with expectations, where smaller individual trees and dense forest structure results in higher fire intensity and severity compared to a more open park stand structure (*ref*). These findings are significant, as these methods provide an accurate way to assess the influence of forest composition and structure on *observed* fire behavior; an important consideration when planning fuels treatments or assessing their effectiveness in different forest types and fire regimes.

## 4.4. Opportunities, limitations and future directions

Broadly speaking, the methods of this study are widely applicable to other regions, forest types, and satellite-derived information. We demonstrate a novel application of satellite-derived FRP as a proxy for fire intensity and our results highlight the potential of these data to understand how landscape factors influence fire intensity, an important measure of how difficult a fire will be to control. These data could, for example, be leveraged to monitor fuel treatment effectiveness, the influence of beetle-kill on fire intensity, and understand the influence of more fine-scale measurements of live fuel moisture. The VIIRS data in particular offer an important source of *globally* available FRP information. The aggregation of active fire detections in the present study could also be used to integrate data across sensors, such as VIIRS, MODIS, and GOES, to fill the spatial and temporal gaps in detections. As new satellites come online, such as the FireSat constellation scheduled for 2026, these methods may become more applicable with higher temporal and spatial resolution imagery measuring fire activity and heat.

While we demonstrate a successful harmonization of satellite-derived FRP and CBI with imputed forest inventory data, there are some considerations for future work. These data still represent a sparse network of field sampling locations (one plot per 24.3 km2), introducing uncertainty into our estimates of forest structure. Future efforts will benefit from integrating this approach with other satellite-based or field measurements on forest composition and structure to better define these relationships. Despite this uncertainty, our results indicate agreement with expectations of fire intensity and severity in common forest types of the Southern Rockies, highlight important advancement in the integration of satellite-derived FRPc as a proxy for fire intensity with wall-to-wall forest metrics from TreeMap and the information provided in the *Tree Table* provides unique estimates of understory and mixed-forest composition which have been understudied at landscape scales.

# Conclusion

This study demonstrates the influence of forest composition and structure on fire intensity and severity and elucidates the potential moderating influences of quaking aspen forests in the Southern Rockies. From a management perspective, the expansion of aspen forests may reduce the risk of extreme fire behavior under certain conditions, although this influence is likely mediated by the specific forest structure and the fire weather conditions. The moderating influence of aspen forests is more stable in lodgepole-dominated areas and targeted management of aspen in these forests is likely to provide a larger benefit of wildfire risk reduction. Given this information, aspen management in lodgepole forests can be targeted to provide a potential buffer in regions near communities where wildfire risk and suppression difficulty are high. This study provides important insights into the effects of not only aspen forests, but other predominant forest types and their structure, on observed fire intensity and severity in the Southern Rockies, with implications for wildfire risk reduction and forest management planning activities.

Overall, this effort contributes a significant advancement in the use of satellite-derived FRP as a proxy for fire intensity and demonstrates successful harmonization of these data with burn severity, forest inventory data, fire weather, and topography. The results have widespread implications for management of aspen and other forest types in the context of fire hazards and fuels management in the Southern Rockies and the open-source methods (see *Code Availability*) provide a framework for future research using satellite-derived FRP.

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# Author Contributions

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# Code Availability

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