Modelling Wildfire Burn Severity in Canadian Megafires

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Abstract

Wildfire activity in Canada has increased significantly in recent decades, shifting to larger, more frequent fires and the emergence of megafires (>10,000 ha) across various ecozones. These events typically exhibit complex spatial patterns of burn severity, including larger and more homogeneous patches of high severity. The burn severity patterns and their drivers in megafires remain unclear, in particular, across diverse ecozones. Remote sensing indices such as the Relativized Burn Ratio (RBR) provide an effective means of quantifying burn severity at large spatial scales. This study uses RBR to evaluate nine megafires (each >50,000 ha) representing the 95th percentile and above of fire size within varying ecozones between 2016 and 2022. These fires were used to develop two random forest models: one predicting RBR and another predicting the within-fire z-score of RBR. Within-fire standardization of RBR was conducted to see whether it alters the relative importance of environmental drivers. In the RBR model (OOB $R^2 = 0.75$), regional variables such as ecozone and fire ID, along with drought code, were dominant predictors. In contrast, the z-score model (OOB $R^2 = 0.68$) emphasized fuel characteristics, including biomass and canopy closure, with additional contributions from elevation and drought-related variables. These results suggest that broad regional and fire-regime controls exert a stronger influence on burn severity than local fuel conditions at the megafire scale. Standardizing burn severity within fires reduces this regional signal but does not improve predictive performance, highlighting the importance of accounting for regional variability in large-fire dynamics.

1. Introduction

Decades of fire suppression and compounding factors of climate change have resulted in increased forest fire size, frequency, and season length in Canada (Jain et al., 2024). This has also led to more occurrences of megafires - fires exceeding 10,000 ha (Lindley et al., 2022). Larger fires are known to have complex spatial patterns of burn severity which often include a greater extent of high-severity patches, measured by the amount of vegetation mortality, with cascading ecological impacts (Cansler & McKenzie, 2014).

Megafires occur throughout Canada and their ecological consequences vary depending on local fire regimes (Stephens, 2014). Regions historically characterized by high-severity, stand-replacing fires (such as the Boreal Plains or western subalpine forests) are likely more adapted to recover from such events. In contrast, forests with low- or mixed-severity fire regimes may experience lasting ecological shifts following high-severity fires including changes in forest structure, composition, and successional trajectories (Soverel et al,. 2010; Cansler & McKenzie, 2014).

In many landscapes, factors such as topography, moisture, and fuel heterogeneity control patterns of burn severity by limiting fire spread and intensity (Prichard & Kennedy, 2012; Haire & McGarigal, 2009). However, the huge burned area and intense fire behavior associated with megafires may exceed landscape and ecosystem constraints on fire severity. Megafires commonly occur under extreme fire weather conditions, where high temperatures, low humidity and high winds drive intense fire behaviour (Wang et al., 2015; Potter & McEvoy, 2021). In these scenarios it remains unclear whether local controls on burn severity continue to operate or whether these controls are overridden by larger-scale climatic and weather drivers.

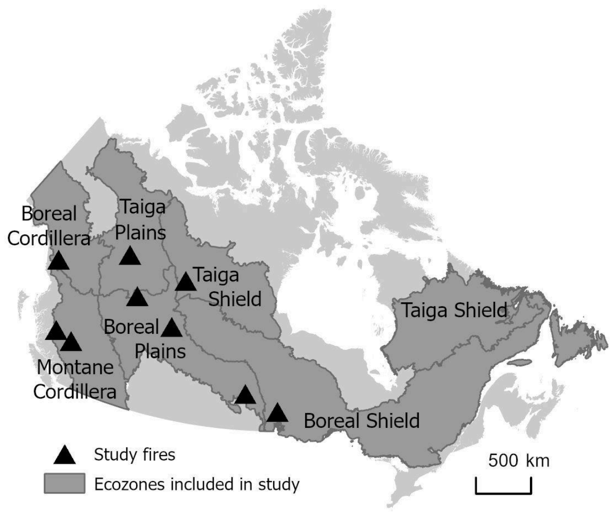

Figure 1. Map of Canada’s ecozones, with those included in this study labeled. Black triangles indicate the locations of the nine fires used to train the random forest model.

Hence, the objectives of this study are to: (1) identify the drivers of burn severity in Canadian megafires across varying ecozones and fire regime zones, and (2) determine whether these drivers differ between megafires by standardising burn severity metrics to each individual fire. Understanding the drivers of fire severity in megafires requires consistent, spatially extensive measurements of burn severity across large fire events. Remote sensing provides an essential means of assessing fire severity across large, inaccessible, or hazardous fire areas. Commonly used indices such as the Relativized Burn Ratio (RBR) estimate burn severity from spectral data by comparing pre- and post-fire

Table 1. Description of ecozones included in study, listing study fires within each ecozone (Wiken, 1986).

Ecozone	Study fires in ecozone (NBAC ID)	FBP fuel types present	Mean daily January temperature	Mean daily July tempera ture	Mean Annual Precipitation	Dominant vegetation community
Boreal Plains	2021_1064 2019_172, 2016_255	D1/D2, C2, D1, M1/M2	-17.5ºC to -22.5ºC	12.5ºC to 17.5ºC	450-500 mm	Aspen, Boreal Spruce, Leafless Aspen, Boreal Mixwood
Boreal Shield	2021_1159	D1/D2, C3, C4	-10ºC to -20ºC	15ºC to 18ºC	400 mm in the west to 1000 mm in the east	Aspen, Mature Jack or Lodgepole Pine, Immature Jack or Lodgepole Pine
Boreal Cordillera	2018_267	D1/D2, C2, C4, M1/M2	-15ºC to -27ºC	12ºC to 15ºC	400 in plateaus, 1000 mm at higher elevations	Aspen, Boreal Spruce, Immature Jack or Lodgepole Pine, Boreal Mixwood
Montane Cordillera	2017_856, 2018_2211	C4, C3, O1a, D1/D2	-7.5ºC to -17.5ºC	13ºC to 18ºC	interior 500-800 mm, 1200-2200 mm in higher elevations	Immature Jack or Lodgepole Pine, Mature Jack or Lodgepole Pine, Matted Grass, Leafless aspen
Taiga Shield	2017_211	C4, C3, O1a, D1/D2	-17.5ºC to -27.5ºC	7.5ºC to 17.5ºC	250-500 mm	Immature Jack or Lodgepole Pine, Mature Jack or Lodgepole Pine, Matted Grass, Leafless aspen
Taiga Plains	2022_162	D1/D2, C2, D1, C3	-22.5ºC to -35ºC	10ºC to 15ºC.	200-400 mm	Aspen, Boreal Spruce, Leafless Aspen, Mature Jack or Lodgepole Pine

reflectance values, quantifying vegetation loss through changes in near-infrared (NIR) and shortwave infrared (SWIR) reflectance. RBR has been shown to correspond with field-based severity metrics (Parks et al., 2014), and therefore was selected as the response variable representing burn severity in this study.

2. Methodology

2.1 Study fires

All analyses were conducted in R version 4.4.1 (R Core Team, 2013).

The National Burn Area Composite (NBAC) fire database was subset to fires within the 95th percentile of size for each ecozone–year pairing (2016–2022), from which nine fires were selected (Figure 1). All study fires exceeded 50,000 ha and burned for at least 39 days. These events were large relative to their respective fire regimes and meet commonly used definitions of “megafire” (Linley et. al., 2022; Stoof et. al., 2024; Leite et. al., 2015). The final dataset encompassed a total burned area of 2.51 million hectares across nine fires, spanning six ecozones and six years (Table 1). The study fires ranged in latitude from 50.30° to 61.35° and longitude from −94.29° to −131.60°. These fires included a diversity of dominant forest types including boreal spruce, aspen, jack or lodgepole pine, and boreal mixedwood forests. Mean annual temperature ranged from -10 to 7.5 °C, and mean annual precipitation ranged from 250 to 2200 mm.

2.2 Burn Severity data

Landsat Collection 2 data was used to create RBR rasters at a 180m x 180m pixel size for each fire in Google Earth Engine (GEE) using published code by Parks et. al. (2018; Gorelick et al., 2017). Parks’ method applies a mean-compositing approach which stacks all cloud- and smoke- free pixels within the specified date range of May 1st to September 15th. This date range was selected to include variability in growing season length among study fire regions, and reduce the differences phenological impacts could have on spectral signatures. Modifications were made to the Parks et al. (2018) quality assessment mask used to filter out clouds, shadow, water and snow to ensure compatibility with Landsat Collection 2. NBAC perimeters were used as fire boundaries for severity mapping extents and to ensure spatial alignment with the Canadian Fire Spread Dataset (CFSDS; Barber et al., 2024). A z-score transformation of RBR was calculated separately for each fire using the mean and standard deviation of RBR within that fire. This approach standardizes burn severity relative to each fire’s internal distribution, allowing high and low severity to be defined independently of regional differences in fuel loads.

2.3 Explanatory variables

The suite of explanatory variables include fuel, weather, topography and ‘other’ variables. Many model predictors were obtained from the CFSDS, where variables were compiled at 180m x 180m (Table 2). The CFSDS provides daily fire-progression mapping derived through kriging interpolation of MODIS and VIIRS hotpots within NBAC perimeters. From this dataset we utilized variables such as estimated day of burning, ignition date, and daily spread distance, as well as weather fuel and topographic variables aligned to the daily progression grid. Weather data from the ERA5-Land dataset were used to calculate Fire Weather Index (FWI) components

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Table 2. Descriptions and data sources for model predictors. Bolded variables were retained after multicollinearity testing (VIF >10). * indicates the predictor came from the Canadian Fire Spread Dataset (CFSDS; Barber et al., 2024).

Category	Predictor	Data source	Definition
Fuels	**Biomass**	SCANFI*	Total live aboveground biomass (t/ha)
	Closure	SCANFI*	Crown closure (%)
	Percent conifer	SCANFI*	Conifer component (%)
	Fuel type	SCANFI	Canadian Forest Fire Danger Rating System Fire Behaviour Prediction system fuel type
	Fire occurrence	Derived from NBAC	Number of times the pixel has previously burned since 1972
	Time since fire	Derived from NBAC	Years since most recent reburn
	Time since harvest	Derived from CanLaD	Years since most recent harvest
	Time since pest	Derived from CanLaD	Years since most recent pest defoliation
Topography	**Aspect (degrees, 0-359)** **Elevation (m)** **Slope (degrees)**	NASA ASTER Global Digital Elevation Model V003*	
	Topographic wetness index	NASA ASTER Global Digital Elevation Model V003*	Measure of areas likely to accumulate water (high values = low lying)
Weather	**Drought code, duff moisture code,** build up index, fine fuel moisture code, fire weather index, initial spread index	ERA5-Land dataset*	Fire weather indices from the Canadian Forest Fire Danger Rating System
	Vapour pressure deficit	ERA5-Land dataset*	Daily max vapour pressure deficit (hPa), a measure of atmospheric moisture demand
	Precipitation	ERA5-Land dataset*	24-hr precipitation (mm)
	Relative humidity	ERA5-Land dataset*	Noon relative humidity (%)
	Wind speed	ERA5-Land dataset*	Noon windspeed at 10 m elevation (km/h)
	Fire day	CFSDS	Day of fire (ignition day = 1)
	Tmax	ERA5-Land dataset*	Maximum daily temperature (°C)
Other	**Ecozone**	National Ecological Framework for Canada*	Geographic areas sharing biophysical characteristics
	Homogenous fire regime zone	Boulanger et al., 2014	Areas with similar fire return intervals
	Fire ID	NBAC*	Unique identifier for each fire
	Prevgrow	CFSDS	Fire growth on prior fireday (ha)
	Fire area	CFSDS	Fire growth this day (ha)
	DOB	CFSDS	Day of year burning
	Spread distance	CFSDS	Daily fire spread (m)

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(FFMC, DMC, DC, ISI, BUI, FWI, precipitation, VPD, wind speed, relative humidity) for each pixel on its estimated day of burning (Muñoz, 2019). Pre-fire fuel characteristics were derived from the Spatialized Canadian National Forest Inventory (SCANFI) which uses Landsat-based models trained on forest inventory plots to estimate biomass, crown closure, and canopy species composition (Guindon et. al., 2024). Topographic variables (elevation, slope, aspect, topographic wetness index) were calculated based on the NASA ASTER GDEM V003 30-m dataset (Abrams et. al., 2020).

In ArcGIS Pro (version 3.3.52626), all NBAC fires overlapping each pixel of a study fire were summed to derive a fire occurrence variable. The year of the most recent prior fire at each pixel was identified and subtracted from the year of the study fire to calculate time since fire, representing the most recent reburn interval. The Canada Landsat Disturbance dataset (CanLaD) was used to obtain non-fire disturbance-related variables (Perbet et al., n.d.). Pest defoliation and harvest disturbances were isolated in R, and the year of the most recent disturbance prior to each study fire was identified. Time since pest defoliation and time since harvest were then calculated by subtracting the disturbance year from the year of the study fire.

Additional regional classification of ecozone and homogeneous fire regime zone (here referred to as ‘fire zone’) were included. Ecozone represents the broadest unit of Environment Canada’s land classification system, grouping landscapes based on physical and biological characteristics (Figure 1; Ecological Stratification Working Group, 1996). Fire zone is a fire-specific classification based on fire regime attributes such as annual area burned and fire return interval (Boulanger et al., 2012). A unique fire ID from NBAC dataset was also retained for each study fire.

2.4 Multi-colinearity testing

Perfectly correlated variables were removed prior to analyses. Multicollinearity among remaining numeric predictors was assessed using the variance inflation factor (VIF) implemented in the *spatialRF* package (Benito, 2025). The predictor with the highest VIF was iteratively removed until all variables remaining had a threshold of <10. Pairwise Spearman correlations were low (<0.28) among retained predictors, confirming minimal collinearity.

2.5 Pixel-level severity sampling

Pixels were sampled (n=9000) from a six-quantile classification scheme with minimum and maximum bins constrained using fixed values (±150 for RBR and ±2.5 for z-score) to represent extreme burn severity conditions. The remaining intermediate classes were proportionally distributed, and an equal number of pixels were sampled from each bin. This creates an even geographic distribution across the study area, ensuring that pixels from fires that comprise a smaller share of observations within a given severity category are included, thereby capturing a broader range of environmental conditions nationwide.

Spatial stratification was applied within each severity category using the Generalized Random Tessellation Stratified (GRTS) method implemented in the *spsurvey* R package (Dumelle et. al.,, 2023). GRTS generates spatially balanced random samples by hierarchically ordering spatial units and selecting points to achieve broad landscape coverage while maintaining probabilistic sampling properties (Brown et. al., 2015). To reduce spatial autocorrelation, training pixels were required to be at least 150m apart, at which Moran’s I values were near zero and p-values were predominantly ≥ 0.05, indicating spatial patterns consistent with randomness.

2.6 Model building

To investigate the drivers of burn severity in megafires, we developed a random forest regression model using the *ranger* R package (Wright & Ziegler, 2017). Random forest was selected for its ability to handle large, non-parametric datasets, model non-linear relationships, and capture complex interactions commonly seen in wildfire data (Breiman, 2001). Although random forest is often used as a predictive model, it is also suited for explanatory analysis due to its interpretability features which allow assessment of predictor influence.

The model was trained with 1000 decision trees using default hyperparameters (mtry=4, max.depth=0, min.node.size=5). The dataset was partitioned into training (70%) and test (30%) subsets to evaluate model performance on unseen data. Model performance was determined using out-of-bag (OOB) R^2. The relative importance of each predictor variable was assessed by randomly permuting its values and measuring the resulting decrease in R^2. Predictors that cause a larger reduction in model performance when permuted are considered more influential, creating a variable importance measure, which was then converted to a proportion of overall importance to compare between models. To further explore the relationship between predictor variables and burn severity, partial dependence plots (PDPs) were generated, showing the marginal effect of each variable on the predicted response while averaging over all other predictors.

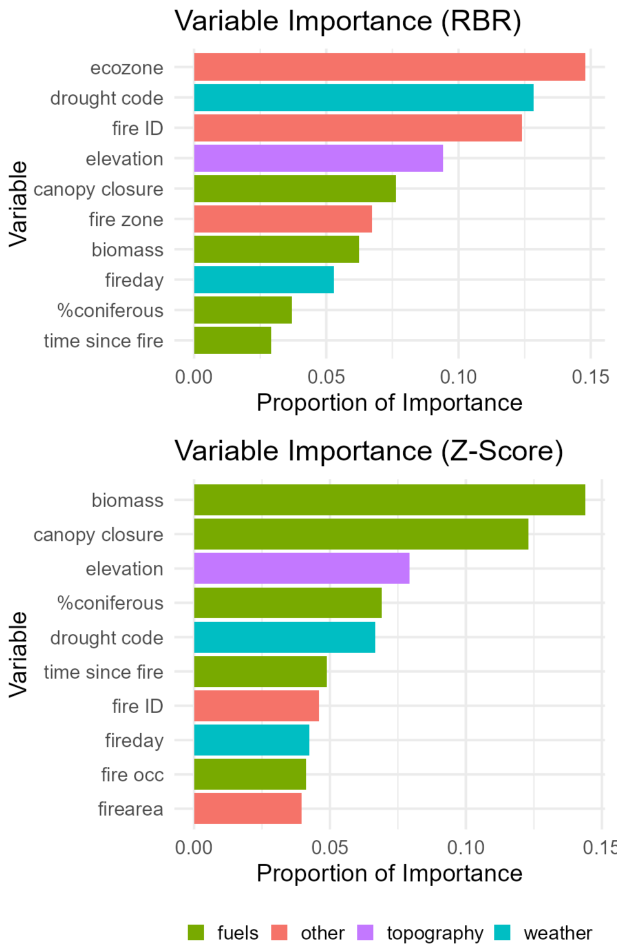

Figure 2. Relative variable importance for ten top predictors in each random forest model. Importance values are expressed as the proportional contribution of each variable to model performance.

3. Results

The random forest models achieved good predictive performance, with the RBR model yielding a higher out-of-bag (OOB) R^2 (0.75) than the z-score model (0.68).
At the landscape scale, predictor groups contributing most to model performance were “other” variables (37.3%), followed by weather (27.1%), fuels (23.9%), and topography (11.7%), which had the lowest overall importance (Table 3). Among individual predictors, ecozone (14.8%) had the highest importance, followed by drought code (12.8%), fire ID (12.4%), elevation (9.4%), and canopy closure (7.6%). Other top 10 predictors include fire zone (6.7%), biomass (6.2%), fireday (5.3%), percent coniferous (3.7%), and time since fire (2.9%).

Within megafires, the z-score model showed a different distribution of predictor importance. Fuels contributed the largest proportion to model performance (45.7%), followed by weather variables (23.8%), and “other” predictors (18.5%), while topographic variables again had the lowest cumulative importance accounting for (12.0%) of model performance (Table 3). Among individual predictors, biomass (14.4%) and canopy closure (12.3%) were the most influential, followed by elevation (7.9%), percent coniferous (6.9%), drought code (6.7%), and time since fire (5.0%). Variables classified as “other,” including fire ID (4.6%), appeared lower in the ranking relative to the landscape-scale model. Fireday (4.2%), fire occurrence (4.1%), and fire area (4.0) were also included among the top ten predictors.

Overall, the relative importance of predictor groups differed between models, with fuels contributing more to model performance within megafires, while “other” variables and ecozone had higher importance at the landscape scale.

Partial dependence plots (Figure 3) provide insight into the functional relationships between key predictors and RBR. Ecozone showed clear differences in predicted RBR among regions, with higher values in Montane Cordillera and Taiga Shield and lower values in Boreal Plains and Boreal Cordillera. Similarly, fire zones exhibited variation in predicted RBR, with some zones (e.g., Lake Athabasca, Pacific) associated with higher values and others (e.g., Southern Prairie, Western Ontario) associated with lower values.

Among continuous variables, drought code showed a pronounced nonlinear relationship, with RBR increasing sharply under moderate drought conditions before plateauing at higher levels. Elevation exhibited a positive relationship with RBR, with predicted values increasing rapidly at lower elevations and stabilizing at higher elevations. Canopy closure and biomass were both positively associated with RBR, with predicted values increasing and then leveling off at higher values. Percent conifer showed a gradual increase in predicted RBR across its range.

Table 3. Proportion of variable importance by predictor category for each model.

Category	RBR Proportion	Z-score Proportion
other	37.3%	18.5%
weather	27.1%	23.8%
fuels	23.9%	45.7%
topography	11.7%	12.0%

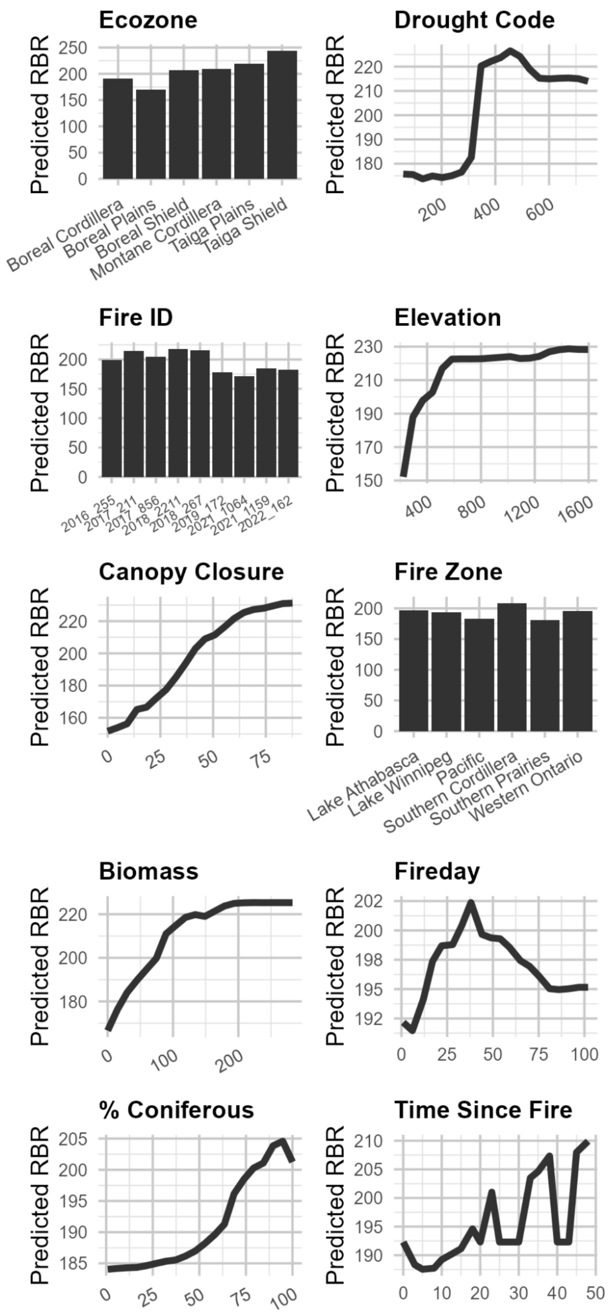

Figure 3. Partial dependence plots (PDP) for the ten most important RBR random forest model predictors. Each panel shows the marginal effect of an individual predictor on predicted RBR, while holding all other variables constant.

The partial dependence for fireday showed a unimodal pattern, with predicted RBR increasing at lower values and declining at higher values. However, because fireday represents a relative ignition-day index specific to each fire, this pattern reflects within-fire temporal progression and is not directly comparable across fires. Time Since Fire shows an overall increase with years since previous fire. Fire ID also showed variability in predicted RBR, reflecting differences among fires not captured by other predictors.

4. Discussion

4.1 Drivers of burn severity across megafires

Burn severity in Canadian megafires in the broad-scale landscape context is shaped by the interaction of fuel/topographic gradients and extreme weather events. Across all megafires studied, ecozone was the strongest predictor of burn severity, reflecting the classification’s integration of the effects of climate, vegetation type, and topography. Predicted severity was highest in the Taiga Shield and lowest in the Boreal Plains, consistent with Burton (2008), who reported higher severity (measured as greater NPP loss) in Taiga regions relative to the Boreal Plains. Within fire zones, similar patterns emerged where regions overlapping the Taiga Shield, such as Lake Athabasca, showed higher predicted severity, whereas southern prairie regions remained relatively low. These patterns suggest that large-scale environmental gradients establish the baseline potential for fire effects. Fire ID was also an important explanatory variable in the RBR model suggesting that aside from ecozone there are substantial differences between fire severity distributions between fires (Figure 2).

The Drought Code (DC) was the second-most important driver of fire severity in the RBR model and fifth-most important in the z-score model, representing 12.8% and 6.7% of importance respectively. DC is a Fire Weather Index code that tracks the fuel moisture in dense fuel beds (Hanes, 2022) and therefore represents the fuel moisture in the slowest drying fuels. Specifically, a shift to higher severity fire (RBR of 220) was seen at a threshold of ~350 DC. This supports the operational threshold at which above 400, there is higher potential for deep smouldering and thus increased suppression difficulty (Figure 3; Flannigan et. al., 2016). Sustained drought can also increase fuel connectivity through vegetation curing and decreased moisture in live vegetation (Duane et al., 2021; Nolan et al., 2020). In extreme cases of drought, landscapes such as peatlands can dry and connect landscape fuels, driving larger forest fires (Thompson et al., 2019).

As expected, lower elevations had low burn severity and increased rapidly with gains in elevations until plateauing at elevations above ~600m (Figure 3). This trend may be explained by the climatic and vegetative gradients driven by elevation. Lower elevations receive water and retain moisture, generally limiting fire severity, whereas upland sites tend to dry more rapidly, promoting higher-severity fire outcomes until a threshold is reached where additional elevation gain has minimal effect due to the limitation of tree productivity and hence, fuel load (Whitman et. al., 2018; Rogeau et. al., 2017).

The days of burning since ignition (Fireday) was the only other weather-category important predictor. While this pattern reflects within-fire temporal progression and cannot be directly compared across fires, Fireday likely serves as a proxy for extreme fire weather events during the extended burning periods of these megafires. Often it is short periods of hot, dry, and windy conditions that drive rapid fire spread, limit suppression effectiveness, and promote higher fuel consumption, thereby increasing burn severity (Wang et. al., 2015; McFarland et. al., 2025). Since fire weather indices (such as FWI, ISI) were excluded from this analysis due to multicollinearity, Fireday may serve as an indirect proxy for these conditions.

4.2 Drivers of burn severity within megafires

While burn severity in megafires across the wider landscape was primarily driven by large-scale factors (e.g., ecozone, weather variables), within-fire variability was more strongly influenced by fuel characteristics. Standardizing burn severity within each fire removed the influence of broad regional gradients and allowed for a clearer view of local drivers. However, this approach also reduced the model’s predictive accuracy by eliminating the context provided by broad-scale environmental differences.

Within each fire, areas with higher biomass and greater canopy closure burned more severely - representing important explanatory variables in both the RBR and (more so) in the z-score model. This reflects the role of fuel availability and continuity in fire behaviour and subsequent fire severity (Gaboriau et. al., 2020; Walker et. al., 2020). Higher conifer coverage also led to pixels burning more severely, consistent with known flammability differences between coniferous and deciduous species (Van Wagner, 1987; Pelletier, et. al., 2026). This suggests that local control i.e., fuel load and composition, have some influence on burn severity in all megafires, but more closely affect the relative burn severity within a fire.

Other fuel variables such as time since fire and fire occurrence were also important explanatory variables in the z-score model, representing areas that have previously burned. In general, recently reburned areas are expected to exhibit lower burn severity due to reduced fuel loads following the initial disturbance, with the effect diminishing over time as fuel (Stevens-Rumann et al., 2016). Under extreme fire conditions such as those associated with megafires, short-interval reburns can still occur when fuels are sufficiently dry, allowing fire to spread through recently burned areas despite reduced biomass (Whitman et. al., 2024).

Further, both DC and Fireday remained important predictors in the within-fire analysis, although their relative influence was reduced compared to fuel-related variables. This suggests that while fuel characteristics primarily control burn severity within megafires, drought conditions and fire weather still play a role in amplifying fire behaviour and severity. Together, these variables indicate that within-fire burn severity is not solely a function of fuel availability, but also the timing and persistence of favourable burning conditions.

5. Conclusions

Regional-level differences captured by ecozone proved the most important in explaining fire severity across megafires in Canada. These results suggest that broad regional and fire-regime controls exert a stronger influence on burn severity than local fuel conditions at the megafire scale. However, each individual fire had a unique distribution of fire severity and relationship with individual drivers. Fuel moisture, represented by the Drought Code, was important for explaining severity both across and within fires, with higher values strongly associated with higher fire severity. Contrary to initial predictions, fuel-category variables such as biomass, canopy closure and percent conifer were very important in explaining fire severity both across and within megafires while weather variables including wind speed, vapour pressure deficit and precipitation had considerably lower explanatory power.

Standardizing burn severity within fires reduced the regional signal but did not improve predictive performance, highlighting the importance of accounting for regional variability in large-fire dynamics. While the RBR model had greater explanatory power than the z-score model, the similarities and differences in the controls on fire severity, and the different patterns shown in the partial dependence plots suggests that understanding megafire severity requires looking at multiple scales and multiple metrics. The standardization of the RBR to each fire enabled a novel perspective on fire severity patterns and could be utilized in future work.

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