Burn Severity in Canada's Mountain National Parks: Patterns, Drivers, and Predictions

Weiwei Wang1, Xianli Wang2, Wanni Wu1, Futao Guo3, Jane Park4, and Guangyu Wang1

1National Parks Research Centre, Department of Forest Resources Management, Faculty of Forestry, University of British Columbia, Vancouver, BC, Canada, 2Northern Forestry Centre, Canadian Forest Service, Natural Resources Canada, Edmonton, AB, Canada, 3College of Forestry, Fujian Agriculture and Forestry University, Fuzhou, China, 4Banff Field Unit, Banff National Park, Parks Canada Agency, Banff, AB, Canada

Abstract Fine-scale estimation of burn severity in the Canadian Rocky Mountain region with mixed-severity fires is of substantial implications but still lacking. We investigated satellite-derived burn severity from 1985 to 2015 at 30-m resolution in three mountain national parks in Canada: Banff, Kootenay, and Yoho National Parks. Results show that fuel type had the most significant influence on burn severity, whereas the three groups of continuous variables (topography, vegetation, and climate) contributed equally to the model, indicating the complex mechanism of environmental controls on fire behavior in this heterogeneous mountain region. The predicted burn severity potentials of the whole parks in 2002 and 2012 showed overall consistent spatial patterns, and lightning-caused fires produced more high-severity burn areas than prescribed fires. Generally, local communities in the intensive fire management zone were predicted to have relatively low burn severity, reflecting the fire management effectiveness.

Plain Language Summary Understanding the spatial pattern of burn severity is crucial for fire-related ecological research and effective fire management. The Canadian Rocky Mountain region is characterized by mixed-severity fires, which makes fine-scale burn severity investigation a challenge. This study used random forest models to establish the relationships between observed burn severity and various environmental predictors (fuel type, fire cause, management zone, topography, vegetation, and climate) and identify key drivers of burn severity in three Canada's mountain national parks (Banff, Kootenay, and Yoho). The prediction models were applied to predict the burn severity potentials by human- and lightning-caused fires for all forest locations in the study area in 2002 and 2012, that is, the 2 years with available data. The results contribute to a more comprehensive understanding of regional fire behavior. The estimated important influences of fuel type, topography, vegetation, and climate on regional burn severity indicate the complex mechanism of environmental controls on fire behavior. The predictions of burn severity in the parks showed an overall consistent spatial pattern over time, which provide a baseline for relevant fire ecology research and useful information for park conservation.

1. Introduction

Burn severity refers to the magnitude of fire-induced environmental change, that is, the loss of aboveground and belowground organic matter (Keeley, 2009; Key & Benson, 2006). The term has been used interchangeably with fire severity, but remote sensing applications preferentially use “burn severity” (Keeley, 2009). A comprehensive understanding of burn severity pattern is essential for fire-related ecological research, such as the assessment of post-fire vegetation responses and soil structure changes (e.g., Crotteau et al., 2013; Jian et al., 2018; Johnstone & Chapin, 2006), fire effects on landscape heterogeneity (e.g., Schoennagel et al., 2009; Turner et al., 1994), and forest resilience to wildland fires (e.g., Turner et al., 2019). Furthermore, appropriate estimation of burn severity is also crucial for effective and adaptive fire management (Eidenshink et al., 2007; Schoennagel et al., 2017), fuel treatment efficacy evaluation (e.g., Lydersen et al., 2017; Price & Bradstock, 2012), post-fire hazard management (e.g., Benavides-Solorio & MacDonald, 2001; Robichaud, 2005), and ecological fire use for biodiversity conservation (e.g., Hoffman et al., 2021).

Substantial studies have been conducted to investigate key drivers of burn severity. Vegetation variables have often been identified as important drivers of burn severity in many regions of North America. For example, Parks, Holsinger, Panunto, et al. (2018) investigated high-severity fires in 19 forested ecoregions in the western...
United States during 2002–2015 and found that live fuel (measured by satellite-derived vegetation indices) was the most influential driver, followed by fire weather, climate, and topography. In a study of large forest fires in the northern Rockies of the United States during 2005–2011, the importance of vegetation cover and topography ranked higher than climate and weather for predicting burn severity (Birch et al., 2015). Similarly, previous studies in the boreal forest of North America also demonstrated higher importance of bottom-up controls (vegetation characteristics and topographical context) than top-down controls (fire weather at the time of burning) on wildfire burn severity measured by field metrics or carbon combustion during 2004–2015 (Walker et al., 2020; Whitman et al., 2018). However, contrasting results have also been found. For example, LiDAR-measured pre-fire forest structure explained less of burn severity variance than many other environmental factors for the large 2013 Rim fire and pre-Rim fires in the western United States (Kane et al., 2015). More complicated patterns were also found in the coastal mountain region of the western United States (Huang et al., 2020), where some topography, climate, and vegetation variables all showed substantial influences on the burn severity levels of fires during 1984–2017. The results varied during extreme wet and dry periods.

For diverse management and research needs, many field-measured burn severity metrics have been developed, such as the Composite Burn Index (CBI) (Key & Benson, 2006), surface Burn Severity Index (BSI) (Loboda et al., 2013), Canopy Fire Severity Index (CFSI) (Kasischke et al., 2000), and percent overstory mortality (MORT) (Whitman et al., 2018). However, the measurement and collection of field data are typically expensive and time-consuming. Multispectral satellite data provide an attractive alternative for the rapid and straightforward estimation of burn severity by detecting changes in pre- and post-fire images. Commonly used remotely sensed burn severity metrics include the differenced Normalized Burn Ratio (dNBR) (Key & Benson, 2006), Relativized dNBR (RdNBR) (Miller & Thode, 2007), and Relativized Burn Ratio (RBR) (Parks et al., 2014). These satellite-derived metrics are strongly related to field-measured burn severity of wildfires in many regions of North America (Hall et al., 2008; Harvey et al., 2019; Parks, Holsinger, Voss, et al., 2018; Parks et al., 2019; Whitman et al., 2018, 2020). In Canada, several national fire effect products have been developed based on the dNBR from Landsat imagery, such as the national wildfire change magnitude data set (Hermosilla et al., 2016) and the Canada Landsat Burned Severity product (CanLaBS) (Guindon, Villemaire, et al., 2020).

A wide range of models have been developed to estimate burn severity based on field-measured or satellite-derived data, and Random forests (Breiman, 2001) is one of the most commonly used (Birch et al., 2015; Collins et al., 2018; Dillon et al., 2011; Gibson et al., 2020; Holden et al., 2009; Huang et al., 2020; Kane et al., 2015; Parks et al., 2019). Other widely employed models comprise linear and generalized linear models (e.g., Fernández-García et al., 2018; Pelletier et al., 2021; Whitman et al., 2018) and boosted regression trees (BRT) (e.g., Fang et al., 2018; Parks, Holsinger, Panunto, et al., 2018). Some machine learning models (Gaussian process regression, random forests, and support vector regression) were found to outperform conventional multiple linear regression for burn severity prediction (Hultquist et al., 2014). Some studies used satellite-inferred burn severity metrics as exclusive explanatory variables to estimate field-measured burn severity (Collins et al., 2018; Fernández-García et al., 2018; Pelletier et al., 2021). The incorporation of climatic, geographic, stand-structure, and other biophysical variables (e.g., pre-fire beetle outbreak severity) with satellite metrics has been demonstrated to improve the estimation accuracy of burn severity across large geopolitical regions of North America (Harvey et al., 2019; Parks et al., 2019).

The Rocky Mountain region of Canada has complex mixed-severity fires (Chavardès & Daniels, 2016; Davis et al., 2016; Tande, 1979). Important drivers of regional fire behavior included climate change (Davis et al., 2016; Hallett & Walker, 2000; Johnson & Larsen, 1991; Johnson & Wowchuk, 1993), vegetation attributes (Davis et al., 2016; Hallett & Walker, 2000), topographic variation (Rogeau & Armstrong, 2017; Rogeau et al., 2016), and human activities (Hawkes, 1990; Keane et al., 2002; Ryan et al., 2013). Modeling burn severity in this region is challenging but critical for fire-related ecological research and effective fire management. Fine-scale burn severity variability and its key drivers remain sparsely documented in this region. Therefore, this study focuses on three mountain national parks, that is, Banff, Kootenay, and Yoho, as examples to conduct a comprehensive investigation of regional burn severity patterns. Various natural and anthropogenic variables (fuel type, fire cause, management zone, topography, vegetation, and climate) are used to estimate satellite-derived burn severity. Specific objectives are to (a) characterize historical burn severity patterns in the parks, (b) identify key drivers controlling burn severity, and (c) model the spatial variation of potential burn severity for human- and lightning-caused fires in the study area.
2. Materials and Methods

2.1. Study Area and Data

Our study area consists of three adjacent mountain national parks (Banff, Kootenay, and Yoho) straddling the provincial boundary between British Columbia and Alberta (Figure 1). It contains three ecoregions with different vegetation types (Johnson & Wowchuk, 1993; Rogeau et al., 2004; Weir et al., 1995; White, 1985). The montane ecoregion (1,350–1,650 m) is largely dominated by Douglas-fir, trembling aspen, and lodgepole pine. The subalpine ecoregion (up to 2,100 m) is covered mainly by lodgepole pine, Engelmann spruce, and subalpine fir. The alpine ecoregion (2,100–3,400 m) is mostly un-vegetated. The climate is characterized by relatively long, cold winters and short, mild summers (Johnson & Wowchuk, 1993; White, 1985). Most fires have occurred from April to early October, with the largest area burned by lightning fires in July and August (Johnson & Wowchuk, 1993; Wierzchowski et al., 2002). Fires tend to be smaller and more frequent (20–50 years) in the montane ecoregion but are infrequent (50–400 years) and of high intensity in the subalpine ecoregion (Rogeau et al., 2004; Weir et al., 1995; White, 1985).

Satellite-derived burn severity was used as the dependent variable. The burn severity data from 1985 to 2015 (Figure 1b) were extracted from the 30-m resolution geospatial CanLaBS product (Guindon, Villemaire, et al., 2020), which estimated pixel-level burn severity using the dNBR values from Landsat imagery (Guindon, Gauthier, et al., 2020). The dNBR values were scaled by $10^{-3}$ to obtain their real values. Pixels with missing remote sensing data 1 year after the fire or with more than one fire during the period (~8%) were removed. Pixels with dNBR values less than 0.1 or greater than 1.3 (~0.6%) were also removed because they are likely unburned areas, post-fire regrowth, or cloud effects (Key & Benson, 2006). In total, 180,926 burned pixels were used, with 2003 being the extreme fire year burning ~63% of them.

Overall, three categorical variables (fuel type, fire cause, and management zone) and three groups of continuous variables (topography, vegetation, and climate) were used as predictors (Table S1 in Supporting Information S1). Data for the three categorical variables were all obtained from Parks Canada (https://open.canada.ca/en/open-government-licence-canada). Specifically, five forested fuel types (Figure 1a) were included, that is, Spruce-Lichen Woodland (C1), Boreal Spruce (C2), Mature Lodgepole Pine (C3), Immature Lodgepole Pine (C4), and Douglas Fir (C7). Two fire causes (Figure 1b) were considered, that is, prescribed burning (PB) and...
lightning (LI). Three management zones (Figure 1b) were used, that is, the intensive (Int), intermediate (Inm), and extensive (Ext) zones. The intensive zone prioritizes minimizing fire spread and risks, the intermediate zone promotes confining spread within a defined perimeter, and the extensive zone encourages minimal intervention to meet some ecological goals.

Pertaining to continuous variables, 30-m resolution elevation data were extracted from the Shuttle Radar Topography Mission (SRTM) (Farr et al., 2007) digital elevation data (DEM). The Topographic Position Index (TPI) was further calculated at scales of 300 m (TPI_300), 1,000 m (TPI_1,000), and 2,000 m (TPI_2000) considering its scale-dependence (Weiss, 2001) using the topography tools (Dilts, 2015) in ArcGIS 10.7. Four pre-fire vegetation attributes from the CanLaBS product (Guindon, Villemaire, et al., 2020) were used: crown closure (CC_p, %), total living biomass (Biom_p, tons/ha), conifer proportion (Coni_p, % of total biomass), and deciduous proportion (Deci_p, % of total biomass). Seasonal climatic variables from 1985 to 2015 were computed using the Climate NA software (Wang et al., 2016). Pearson's correlation analysis was conducted to reduce the redundancy of 45 initial climatic variables (Table S2 in Supporting Information S1) using the R package corrplot v0.88 (Wei & Simko, 2021; please see Figure S1 in Supporting Information S1 for more detailed results). Finally, four climatic variables were used: spring degree-days below 18°C (DD_18_sp), spring mean maximum temperature (Tmax_sp, °C), winter relative humidity (RH_wt, %), and summer precipitation (PPT_sm, mm).

2.2. Burn Severity Models

Pixel-level burn severity prediction models were developed using random forests (Breiman, 2001), one of the most popular modeling approaches, in the R package randomForest v4.6.14 (Liaw & Wiener, 2002). Observed burned pixels were randomly partitioned into 10 independent calibration (70%) and validation (30%) subsets, which were used to establish random forest models and evaluate the prediction accuracy respectively. In each calibration subset, 500 trees were grown in the model, and the number of variables randomly sampled as candidates at each split was determined using the tuneRF() function (arguments: ntree = 500, mtryStart = 1, stepFactor = 2, improve = 0.01). All other hyperparameters used default values. Accuracy was assessed with the mean absolute error (MAE), the root mean square error (RMSE), and the adjusted coefficient of determination ($R^2_{\text{adjusted}}$) between the observed and predicted burn severity values of the validation subsets. Moreover, the relative importance of each predictor was estimated by measuring the decrease in accuracy after permuting it in the model to identify key environmental drivers of burn severity. The overall results of prediction accuracy and variable importance were estimated as the average of the 10 subsets.

The prediction models were used to predict burn severity in the whole study area. Only the locations with the five fuel types (C1, C2, C3, C4, or C7) were included, and both fire causes (PB and LI) were considered for each location. Maps of Canada's forest attributes (Beaudoin et al., 2017, 2018) were used to derive analogs of the four pre-fire vegetation attributes for predictions. Due to the availability, only maps in 2001 and 2011 were obtained and predictions were therefore conducted exclusively for 2002 and 2012, respectively. These 250-m resolution maps were then resampled to 30 m using bilinear interpolation to provide spatial data comparable to the other data sets. The four climatic variables were further computed for all fuel locations in 2002 and 2012. Final predictions were computed as the average results of the models developed from the 10 subsets as described above. Overall, four basic prediction maps were derived (2 years × 2 fire causes) to determine the potential burn severity of fires with different causes under different environmental conditions.

To better summarize burn severity characteristics, comparisons of burn severity of different categorical variables were conducted using type II ANOVA, that is, a three-way ANOVA for historical data and a two-way ANOVA for prediction results. Due to the large sample size in this study, ANOVA was performed repeatedly using 100 subsets with 150 pixels randomly and equally sampled from different categorical variables for each subset. The final results were calculated as the average of all 100 subsets. All analyses were performed using R 4.0.4 (R Core Team, 2021).
3. Results

3.1. Summary Statistics

Overall, all observed burned pixels (180,926) showed a mean dNBR value of 0.671 (±0.215), indicating a high severity level based on the thresholds of Key and Benson (2006) (Figure S2 in Supporting Information S1). Burn severities were significantly different for different fuel types and fire causes (α = 0.05; Table S3 in Supporting Information S1), and fuel type explained most of the variance in the mean burn severity. Dominant distributions of burned pixels for each categorical variables were fuel type C4 (79.4%), lightning-caused fires (82.3%), and extensive management zone (87.8%). High dNBR values were found in fuel types C2 and C4 (0.720 ± 0.208) and lightning fires (0.711 ± 0.188) (Figure S2 in Supporting Information S1). The intensive zone exhibited the lowest severity level with a mean dNBR value of 0.478 (±0.204), whereas the dNBR values for the other two zones were high (~0.682 ± 0.234) (Figure S2 in Supporting Information S1).

3.2. Key Environmental Drivers

The random forest models achieved good performance in estimating the observed burn severity of the parks, with an MAE of 0.09, an RMSE of 0.12, and an $R^2_{\text{adj}}$ of 0.67. The relative importance of predictors (Figure 2) indicated that fuel type had the strongest influence on burn severity, followed by three continuous variables: elevation (topography), Coni_p (vegetation), and DD_18_sp (climate). These were followed by Biom_p (vegetation) and two climatic variables: PPT_sm and Tmax_sp. Less important variables included one categorical variable (management zone) and three continuous variables (Deci_p (vegetation), RH_wt (climate), and TPI_300 (topography)). On average, the three groups of continuous variables contributed approximately equally to burn severity.

3.3. Predicted Burn Severity Potentials

Only 1,184 burned pixels from fires occurred in 2002 and 2012 were obtained and used for prediction validation. The burn severity (i.e., dNBR) predictions for the parks in the 2 years showed an MAE of 0.15, an RMSE of 0.18, and an $R^2_{\text{adj}}$ of 0.44, exhibiting weaker performance than the validation results when developing the models, but they were still acceptable. Validation results also showed a smaller range of variation for the predicted values than observed values, and no systematic biases were found in the prediction performance (Figure S4 in Supporting Information S1). The spatial pattern of the predicted burn severity was visually consistent over time, although different fire causes resulted in differences in burn severity (Figure 3). Lightning-caused fires generated more high-severity areas than prescribed fires, regardless of the prediction years. Burn severity was lower in 2012 than in 2002, and the differences were more pronounced at some locations (Figure 4), but the overall patterns were similar (Figure 3). Local examples illustrated that severe burns in Banff National Park were predicted to occur mostly in the extensive and intermediate zones for lightning-caused fires, especially in 2002 (Figure 4a). The intensive zone was predicted to have generally moderate or low burn severity under most conditions. Similar patterns were also found in Kootenay National Park (Figure 4b) and Yoho National Park (Figure 4c).

The predicted burn severity was significantly different for different fuel types but insignificantly different for different management zones (Table S4 in Supporting Information S1). Overall, the parks were predicted to have mean dNBR values of 0.547 (±0.062) for prescribed fires and 0.609 (±0.092) for lightning-caused fires in 2002 and 2012 (Figure S3). Fuel type C4 had the highest burn severity level among the five fuel types, and its predicted mean dNBR ranged from 0.596 (±0.071) for prescribed fires in 2012 to 0.707 (±0.071) for lightning-caused fires in 2002. In addition, C2 also had a relatively high burn severity potential, particularly for lightning-caused fires (mean dNBR of 0.689 in 2002 and 0.652 in 2012). The predicted mean dNBR values of different management zones were around 0.545 (±0.062) for prescribed fires in the 2 years (Figure S3). More severe conditions were
predicted for lightning-caused fires in the extensive and intermediate zones (mean $dNBR$ of 0.638 in 2002 and 0.598 in 2012).

4. Discussion and Conclusions

Knowledge of regional burn severity patterns has theoretical and practical implications; thus, many studies investigated this topic (e.g., Huang et al., 2020; Johnstone & Chapin, 2006; Price & Bradstock, 2012; Schoennagel et al., 2009; Whitman et al., 2018). However, modeling burn severity is a challenging task, especially at a fine resolution. This study investigated 30-year burn severity patterns and key drivers in three Canada's mountain national parks, an area featured with complex mixed-severity fires. We used random forest models to determine the relationship between burn severity and various environmental predictors, identified the key drivers of burn severity.
severity, and produced prediction maps for the study area. Although the dominant driver of burn severity was found to be fuel type, topography, vegetation, and climate variables also contributed significantly and equally to burn severity. This result is quite unique compared to earlier studies (e.g., Birch et al., 2015; Parks, Holsinger, Panunto, et al., 2018; Walker et al., 2020; Whitman et al., 2018), which found that pre-fire vegetation attributes were typically the dominant drivers. We believe the diversity of environmental factors in the study area and the strong interaction between these factors may have contributed to our results. Historical and predicted burn severities were the highest for fuel type C4 (Immature Lodgepole Pine) and lightning-caused fires. The consistent spatial patterns of the predicted burn severity confirmed the effectiveness of fire management in the parks; for example, the intensive management zone exhibited the lowest burn severity level.

4.1. Burn Severity Pattern and Drivers

Fuel type showed the largest influence on burn severity in the parks, which may be due to distinct fuel characteristics. The largest proportion of burned pixels with high severity was found in fuel type C4. Areas with this fuel type have a dense stand structure, vertical and horizontal fuel continuity, and heavy surface fuel loading (Forestry Canada Fire Danger Group, 1992), producing high-intensity fires and high burn severity. Fuel type C2 also showed generally high burn severity, which could be associated with its widest distribution in the parks and typically high burn intensity. C2 is characterized by moderately well-stocked stands with a deep and compacted organic layer, trees with flaky bark, and near-ground tree crowns (Forestry Canada Fire Danger Group, 1992), which contribute to fire spread. Similarly, Hall et al. (2008) investigated the influence of fuel type on the dNBR in the western Canadian boreal forest, and found larger dNBR values for C2 (boreal spruce) than C3 (mature jack or lodgepole pine), D2 (aspen-green), and M2 (boreal mixedwood-green).

A much higher severity level was found for lightning-caused fires than prescribed fires. This result was expected because prescribed burning is designed to achieve specific ecological fire effects and predominantly occurs in the early and late fire season with cooler, moister conditions and usually lower severity (Ryan et al., 2013; White

Figure 4. Examples of the predicted burn severity with relatively large changes for different fire causes and prediction years in (a) Banff National Park, (b) Kootenay National Park, and (c) Yoho National Park.
et al., 2011). In contrast, lightning-caused fires occur mainly during the high fire season and typically result in large burned areas with high burn severity (Wierzchowski et al., 2002), which is consistent with our results. The majority of burned areas in the extensive zone and the lowest burn severity in the intensive zone are in agreement with the objectives of the parks’ management zones (Hawkes, 1990; Tymstra et al., 2020). Observed burn severity patterns could be the consequences of a combination of these factors. For example, lightning strikes under fire-conducive weather conditions combined with minimal intervention in the extensive zone produced correspondingly large, severe fires.

Since the interactions of topographic features, vegetation attributes, and weather patterns are inseparable, it is perceivable that all three factors contribute significantly to fire severity, especially in mountain areas. Many studies have demonstrated the substantial influence of topography on burn severity (e.g., Birch et al., 2015; Dillon et al., 2011; Huang et al., 2020; Kane et al., 2015; Whitman et al., 2018) and significant associations between elevation and fire behavior in the Canadian Rocky Mountains (Rogeau & Armstrong, 2017; Rogeau et al., 2016), which agrees with our results. Pre-fire vegetation attributes have been widely identified as key drivers of burn severity (e.g., Birch et al., 2015; Huang et al., 2020; Parks, Holsinger, Panunto, et al., 2018; Walker et al., 2020; Whitman et al., 2018); therefore, it is unsurprising to observe that the pre-fire conifer proportion showed high importance in our study. Some studies have found relatively low contributions of climatic variables to burn severity (e.g., Birch et al., 2015; Dillon et al., 2011; Parks, Holsinger, Panunto, et al., 2018) in contrast to our results. The relatively high spatial resolution (30 m) in this study might have played a role (in comparison to 1–4 km or fire-event-level resolution in their studies). There were also some studies observed significant correlations between climatic variables and burn severity (e.g., Holden et al., 2007; Parks & Abatzoglou, 2020), which supports our results.

4.2. Burn Severity Predictions

Developed random forest models performed well in predicting burn severity for the parks. A major limitation comes from the characteristics of the datasets. For example, the annual CanLaBS product cannot be used to analyze seasonal changes in burn severity. This countrywide product has other limitations, such as making no normalization for data set noise reduction in order to minimize inconsistencies and biases (Guindon, Gauthier, et al., 2020). The ability of derived dNBR in representing burn severity of the parks needs more assessments. The inclusion of field measurements could enhance the analyses. Moreover, the implementation of other modeling approaches instead of random forests and the supplementation of other relevant variables (such as fine-scale fire weather) as additional predictors may improve the performance of existing prediction models and provide more insights into regional burn severity patterns.

The burn severity predictions in 2002 and 2012 had a lower validation accuracy than the results of model development, which might be attributed to the forest attribute data from different sources, limited observations available for the validation, and overfitting associated with random forests. The similarity of the predictions in the 2 years indicates an overall consistent spatial pattern of burn severity at the study area scale. The predicted maps are consequently meaningful to illustrate the spatial variations of burn severity in the parks. Predicted high burn severities for lightning-caused fires and in areas with fuel types C4 and C2 are in agreement with the characteristics of the samples used to develop the models. Relatively low burn severity was predicted in the intensive zone with local communities, implying low regional social-economic impacts of fires since these communities are crucial for park operations and visitations. The largest difference in the predicted burn severity between 2002 and 2012 was observed in the northern part of Kootenay National Park, which likely resulted from the extensive biomass loss during the 2003 extreme fire year and very limited recovery after 10 years.

The predicted burn severity maps provide a snapshot of the spatial variation of burn severity potentials for different fire causes under contemporary environmental conditions in the parks. These predictions are with the premise of fire occurrence in each location. The integration of fire occurrence predictions (e.g., the likelihood of fire ignition and spread) will provide more informative guidance for effective park fire management. Predictions that consider future climate change scenarios and other potential environmental dynamics may also have different management implications. Studies in determining the optimal severities for the long-term sustainability of different vegetation types will further contribute to the park conservation. Although these studies are outside of the scope of this research, our findings can provide a baseline for them.
Data Availability Statement

Burn severity and pre-fire vegetation data were obtained from the Canada Landsat Burned Severity (CanLaBS) product (https://doi.org/10.23687/b1f61b7e-4ba6-4244-bc79-c1174f2f2cd). Fuel type, fire cause, and park fire management zone data were obtained from Parks Canada under the Open Government Licence (https://open.canada.ca/en/open-government-licence-canada). The elevation data were extracted from the Google Earth Engine platform (https://earthengine.google.org/, accessed on 10 May 2021). Canada’s forest attributes in 2001 and 2011 are available online (https://doi.org/10.23687/ce9e2659-1c29-4ddd-87a2-6aced147a990). The seasonal climatic variables were computed using the Climate NA software (http://climatena.ca). The R 4.0.4 software used for the analyses is available online (https://www.R-project.org/).

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