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Influence of mountain pine beetle outbreaks on large fires in British Columbia

Hyeyoung Woo[1] | **Christopher Bone**[1] | **Khurram Nadeem**[2] | **Stephen W. Taylor**[3]

[1]Department of Geography, University of Victoria, Victoria, British Columbia, Canada

[2]Department of Mathematics and Statistics, University of Guelph, Guelph, Ontario, Canada

[3]Natural Resources Canada, Pacific Forestry Centre, Victoria, British Columbia, Canada

Correspondence
Hyeyoung Woo
Email: hywoo@uvic.ca

Present address
Hyeyoung Woo, Forest Analysis and Inventory Branch, British Columbia Ministry of Forests, Victoria, BC, Canada.

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Abstract

A key uncertainty in understanding climate change effects on wildfires in western North America is the role of mountain pine beetle (MPB) outbreaks in driving wildfire occurrence and severity. In this study, we investigated the complex relationship between MPB outbreaks, other environmental factors, and wildfire occurrence in British Columbia (BC), Canada. We adopted a fire risk analysis method developed for fire occurrence prediction to separate the effect of changing fuel conditions on wildfires in BC when neither post-outbreak fuel conditions, climate, nor management is stationary. Using lasso-logistic regression and a novel variable ranking procedure, we determined that MPB-affected areas had 1.7 times more large lightning-caused fires (≥100 ha), as the likelihood of large lightning-caused fires increased by 40% in these areas and likely contributed to the increased burned areas in BC. Meanwhile, the likelihood of large human-caused fires decreased in MPB-affected areas. Fire weather factors were most influential for both lightning- and human-caused fires, while anthropogenic factors were most influential for human-caused fires. Fuel dynamics following MPB outbreaks vary across the wide distribution of a host species such as lodgepole pine, at stand and landscape levels. Furthermore, the expression of the effects of MPB and other disturbances on wildfire is also conditional on, as well as confounded with, many other environmental factors and management activities that vary across western North America. Therefore, a lack of consensus on the impacts of MPB on wildfire is not surprising.

KEYWORDS

confounding factors, fire cause, lasso-logistic regression model, mountain pine beetle, response-based sampling, variable ranking and selection, wildfire characteristics

INTRODUCTION

Wildfires and mountain pine beetle (MPB; *Dendroctonus ponderosae*) outbreaks are two of the most significant disturbances that affect lodgepole pine (*Pinus contorta*) (Bentz et al., 2009; Hanes et al., 2019), the dominant tree species on over 26 million ha of forest in western North America (Lotan & Critchfield, 1990). Since the early

1990s, wildfire occurrence and area burned has increased to unprecedented levels across much of this region (Dennison et al., 2014), which is largely attributed to climate change impacts such as earlier snowmelt (Morgan et al., 2008) and higher vapor pressure deficits (Abatzoglou & Williams, 2016). However, the occurrence of MPB outbreaks across this region has led to a complex relationship between fuels and fire occurrence that has yet to be reconciled.

In this study, we examine the influence of MPB outbreaks on the occurrence of wildfires, with specific attention to large wildfires (≥100 ha in burned area) in the province of British Columbia (BC), Canada. While a number of potential *mechanisms* by which MPB outbreaks may affect wildfire behavior at the stand-level have been proposed, there is still much uncertainty about the *degree* of impact MPB outbreaks have at the landscape scale (Dhar et al., 2016) because of the variable dynamics of MPB outbreaks, subsequent fuel succession, and other confounding factors.

MPB outbreaks occur at the landscape scale when the co-occurrence of large areas of susceptible host trees and favorable weather allow for the rapid expansion of an incipient or endemic MPB population (Safranyik, 2003). The degree of tree mortality during an MPB outbreak varies with the age/size structure and tree species composition in forest stands and landscapes and over time (Simard et al., 2011). This is because (1) while lodgepole and ponderosa pine grow in pure stands, they also occur in mixed stands with varying proportions of other tree species; (2) MPB only attack pines, preferentially larger, older trees with thick phloem; and (3) a stand may be attacked by MPB over several years depending on the MPB population densities and the host defense capacity in the affected stands.

Variability in the timing and severity of tree mortality in MPB outbreaks influences the dynamics of a number of forest fuel characteristics and environmental conditions that can affect surface and crown fire behavior (Meigs et al., 2011). Crown fire theory holds that fire transitions from the surface to the canopy when the critical surface fire intensity needed to heat crown foliage to the point of combustion is reached (Van Wagner, 1977); surface fire intensity is influenced by surface fuel and weather-related factors, while crown fire initiation and spread is influenced by the height of the live crown base, foliar moisture content, and crown bulk density. MPB-induced tree mortality affects both surface and crown fuel properties. If a tree is killed in an MPB attack, mortality is evident the following spring as needles turn red and the foliar moisture content drops from about 90%–120% in live needles to <20% in dead needles, increasing crown flammability (Jenkins et al., 2012). The red attacks stage may persist for up to 3 years (Amman, 1982), during which time dead needles and fine branches continue to fall off, leading to an increase in the surface fuel load. As this stage progresses, dead gray branches and stems become more apparent, marking the beginning of the gray attack phase. In this stage, branches break off and trees fall down over a period of approximately 15–20 years (Mitchell & Preisler, 1998), greatly increasing surface fuel load and potential fire intensity. Increased light and wind penetration through defoliated crowns may lead to more rapid drying of surface litter and organic matter, promoting fire spread in some ecosystems (Bonan & Shugart, 1989). Conversely, increased snow loads following defoliation (Winkler et al., 2014) and reduced transpiration from live trees may increase soil and organic layer moisture (Sagar & Waterhouse, 2015) that, along with increased light penetration, may promote the growth of understory vegetation and tree regeneration in other ecosystems (Pec et al., 2015) and retard surface fire spread. Defoliation also results in lower crown fuel load and bulk density, which may limit crown fire spread (Page & Jenkins, 2007).

To add to the complexity of stand-level fuel dynamics following a MPB attack, the relationship between forest fuel and wildfire characteristics is *conditional* on and confounded with other environmental and anthropogenic factors that influence ignition and fire growth at a landscape scale (e.g., lightning occurrence, human activities causing ignitions, weather and fuel moisture, and fire management actions limiting fire growth). Furthermore, lodgepole pine occupies a range of climates and site conditions (with mean annual precipitation ranging from at least 250–500 mm), thus making an assessment of causal factors related to MPB-induced tree mortality more difficult.

Because of the variation in outbreak and fuel dynamics over the vast range of MPB-affected forests in western North America and the difficulty in obtaining information on and separating the impact of confounding environmental factors, the influence of MPB outbreak on fire characteristics lacks clear consensus (Hicke et al., 2012; Romualdi et al., 2023).

In this study, we compiled comprehensive spatial data reflecting fire occurrence, MPB outbreak, fire weather, vegetation, topographic conditions, and human presence in BC from 1980 to 2020. We used a two-stage process to model the binary responses of fire occurrence and large fire occurrence (≥100 ha) at a daily scale using lasso-logistic regression, following a probabilistic fire risk analysis approach pioneered by Brillinger et al. (2003). We assume that these outcomes reflect two-separate processes: fire ignitions and rapid or sustained fire spread. Because earlier studies found that different suites of environmental factors were important to human-caused fire (HCF) and lightning-caused fire (LCF) occurrence (Magnussen & Taylor, 2012; Nadeem et al., 2019), and because HCF and LCF have distinct spatial distributions in BC, we modeled them separately in this study. We adopted a novel method suggested by Nadeem and Jabri (2023) to evaluate the importance of the variables using ranks and drop rates from multiple model fits. By obtaining the relative importance and coefficients of the MPB-related variables compared to the other covariates, we answer the following research questions: (1) How much did the 1999–2015 MPB outbreak in BC affect the risk of fire and large fire occurrence, after accounting for the confounding environmental factors? (2) Did the impact of the MPB outbreak differ between HCF and LCF? We hypothesize that, because of faster fire spread rates and more firebrand spotting observed following the MPB outbreak in BC (Perrakis et al., 2014), MPB mortality had a significant effect on the occurrence of large fires. We also hypothesize that the influence of the MPB outbreak will be greater for LCF than HCF because fire suppression limits the size of HCF to a greater extent. Our study distinguishes the effects of MPB-induced mortality from that of changing climate on large fires in BC by including multiple confounding covariates in the analysis. Greater understanding regarding the interaction between MPB, wildfires, and weather/climate on forest ecosystems will support both ecologists and decision-makers in preparing for climate change impacts that are expected to further accelerate the occurrences of these two disturbances.

STUDY AREA

The study area encompasses the province of BC, Canada, which has an area of about 94.5 million ha extending from approximately 48.5° N to 60° N latitude and 114° W to 139° W longitude (Figure 1a). Approximately two-thirds of BC (60 million ha) is forested. It is an ecologically and physically diverse landscape, comprised of five ecozones (Wiken, 1986) (Figure 1a) extending from temperate rainforests on the Pacific coast to dry mixed conifer forests in the southern interior to boreal forests in the northeast.

Lodgepole pine is the principal tree species over about 14 million ha and is distributed over the full latitudinal span in BC (Figure 1b). Lodgepole pine stands that regenerated after historically large fires on the interior plateaux are more contiguous (Barclay et al., 2005) than in the southeast cordillera where historic fires were typically smaller. Wildfire suppression over the last century is thought, in part, to have allowed large areas of pine to mature (60+ years) by the late 1990s (Taylor et al., 2006) and become highly susceptible to MPB attack. An outbreak that erupted in 1999 in west-central BC (Aukema et al., 2006) spread through the province over about 15 years (Figure 1c), affecting up to 10.1 million ha at the peak in 2007 (Figure 2a). The outbreak collapsed in BC in about 2015 when there were not enough suitable host trees remaining to support epidemic populations.

About 1500 fires occur throughout BC each year of which 55% and 45% are lightning- and human-caused, respectively. LCFs are widely dispersed, but with a higher density in the highlands and mountain ranges in southern interior BC, while HCFs mainly occur near developed areas at lower elevations and valley bottoms.

The coastal ecozone has fewer lighting ignitions and smaller fires than the interior zones. While the southern half of BC generally has a larger number of fires and longer fire seasons than the north, fires in the northern interior fires tend to be larger.

The fire management strategy in BC is to prevent and respond to unwanted fires, particularly near communities, while maintaining the natural role of wildfire in ecosystems (BC Wildfire Service, 2010). After wildfires are reported, they are actioned by initial attack crews or airtankers; about 93% of fires are contained to <4 ha in the first burning period. If the initial attack is unsuccessful, additional extended attack resources are allocated to most fires, although a small proportion of fires in remote areas receive a modified response (mainly observation). The area burned by wildfires increased since about 2003 (Parisien et al., 2023) (Figure 2b), mostly due to large LCF (≥100 ha burned area) (Figure 2c).

DATA

Spatiotemporal sampling unit

Our sampling space covers daily fire occurrence in the study area from 1981 to 2020. We used a 20 × 20 km national forest inventory (NFI) grid (Gillis et al., 2005) to discretize the study area into 2541 grid cells (Figure 1c). Each grid cell was linked with the daily record fire occurrence records (0, 1 or more) during 40 fire seasons (e.g., mid-March to mid-October 1981–2020). Thus, we obtained over 15 million spatiotemporal sampling units (voxels) by combining the grid cell location and the date (year-month-date). Fire ignitions are rare events at this scale. We settled on the 400-km^2 grid × day sampling unit to capture variability in the large landscape and daily fire weather during a fire season, while mitigating the class imbalance problem (many 0 s and few 1 s) that increases exponentially as grid cell size decreases. Our

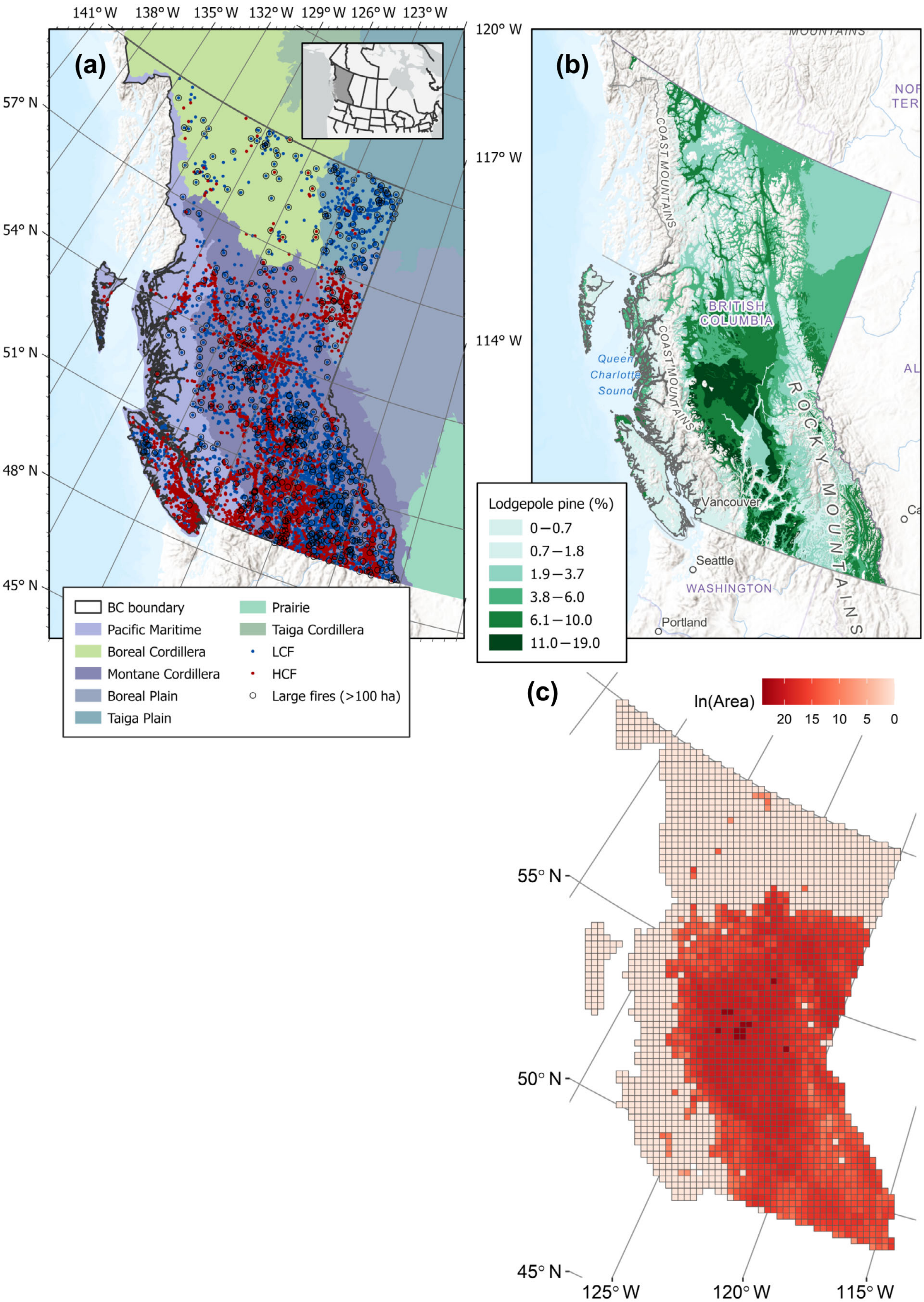

FIGURE 1 Legend on next page.

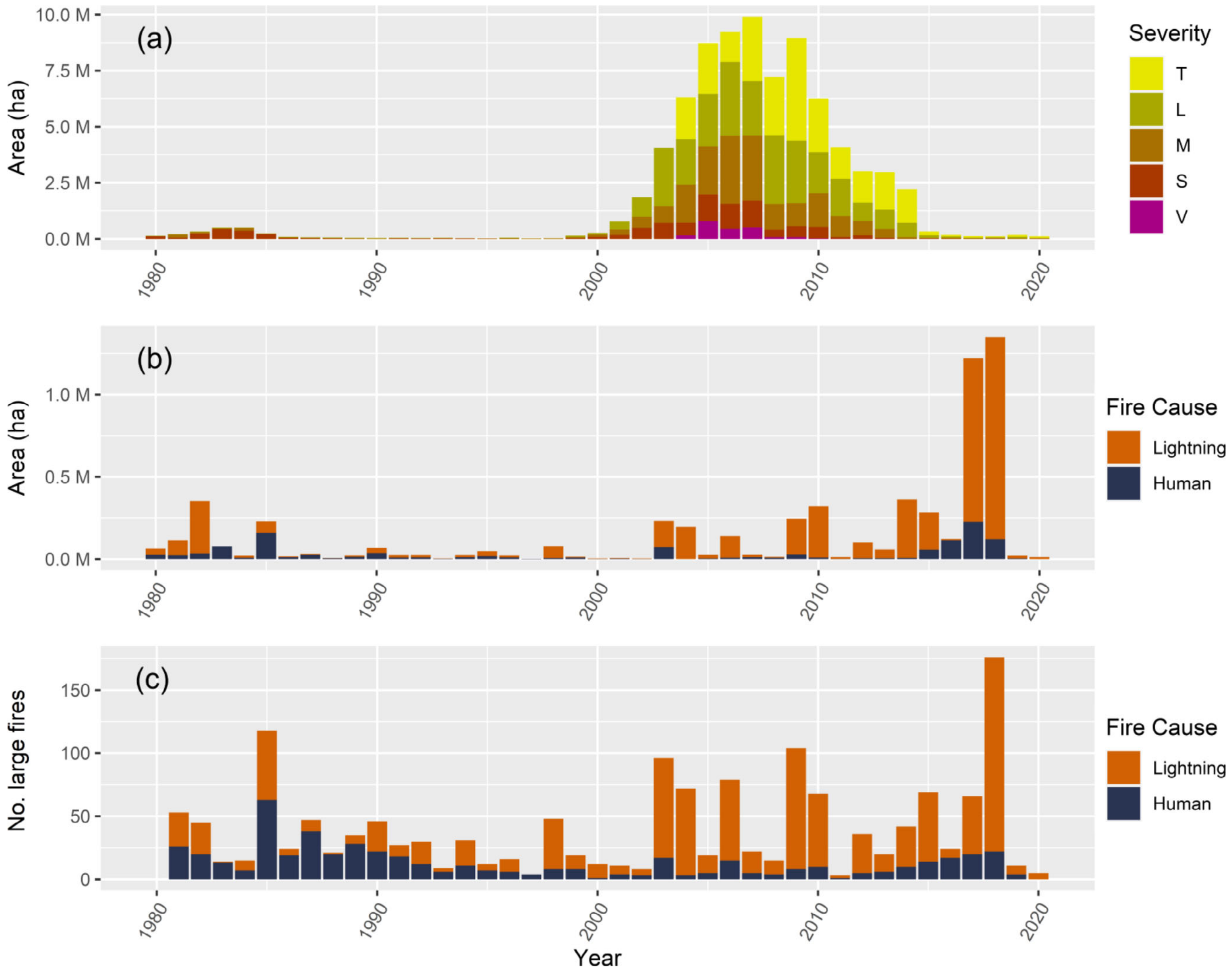

FIGURE 2 (a) Area affected by mountain pine beetle (MPB), (b) area affected by wildfires, and (c) number of large fires (≥100 ha) 1980–2020 in British Columbia. The severity of the MPB outbreak was classified into five categories: trace (T, <1% tree mortality), light (L, 1%–10%), moderate (M, 11%–29%), severe (S, 30%–49%), and very severe (>50% tree mortality).

response variables (i.e., fire occurrence and large fire occurrence conditional on fire occurrence), MPB-related variables, and environmental covariates associated with the sampling units are described in the following sections.

MPB data compilation and variables

Visible forest insect outbreak damage in BC, including MPB, has been mapped through annual aerial overview surveys (AOS) since the 1950s (BC Ministry of Forests, 2000) and subsequently digitized. The annual landscape-level surveys are planned to ensure adequate coverage of outbreak areas based on the pre-survey reports and information about the historic damage conditions (BC Ministry of Forests, 2000). We obtained digital maps of MPB outbreaks comprising polygons of affected forest stands and associated attributes including the year, area of red attack with continuous and homogeneous severity, and one of five severity classes based on the proportion of red tree crowns.

FIGURE 1 (a) The geographic locations and ecozones of the study area: the province of British Columbia (BC), Canada, and locations of human-caused fire (HCF) and lightning-caused fire (LCF) occurrences in the study period (1981–2020), (b) spatial distribution of the lodgepole pine forests (in percentages), and (c) area of mountain pine beetle outbreak (in square meters, logged scale) in 2007 over 20 × 20 km national forest inventory grid cells.

Because the annual AOS assesses the damage that is currently visible, regardless of the past or cumulative mortality (BC Ministry of Forests, 2000), the spatial polygons of the MPB-affected area can overlap each year. The overlapping polygons may have different MPB severities, and severity does not necessarily change in one direction; a forest stand with a very severe MPB outbreak in one year can be recorded as having light or moderate severity in the next year, or vice versa. Therefore, instead of combining the cumulative records, we decided to consider the annual records of the MPB outbreak separately to avoid overlapping problems.

We overlaid the 20 × 20-km NFI grids onto the MPB polygon maps to summarize the MPB-affected area by year. We calculated the percentages of the MPB-affected forested area within each grid cell for each severity class represented in the cell. The forest area data used for this analysis were obtained from the 250-m maps of forest characteristics in Canada (Beaudoin et al., 2014). Further details regarding these data will be provided in the *Environmental covariates* section below. The tree mortality caused by the MPB outbreak was calculated as the percent of trees with red attack defined by the midpoint of each severity class (e.g., Ainslie & Jackson, 2011; Kurz et al., 2008; Meddens et al., 2012; Wulder et al., 2009). We followed Wulder et al. (2009) for the midpoint scale considering the changes in the severity classification in BC MPB data since 2003 (Table 1).

We created a time series of indicator variables based on the area affected by MPB and tree mortality in each grid cell in each year in the study period, considering the year of detection relative to the subject year (Table 2). First, we identified whether the cell experienced a MPB attack in any year before the subject year (MPB OUTBREAK). Second, we derived the tree mortality in one to three years before the subject year (MPB MORTALITY LAG 1–3) to estimate the severity of the recent MPB outbreak. MPB MORTALITY LAG 1–3 denotes 1–3 years since attack, respectively. To account for the most severe past MPB attack, we also considered the maximum tree mortality (MPB MORTALITY PEAK) that each of the grid cells experienced during the study period prior to the subject year.

TABLE 1 Classification of mountain pine beetle severity in British Columbia data.

Severity	Code	Percentage of trees in polygon recently killed	Midpoint (Wulder et al., 2009)
Trace	T	<1	0.5
Light	L	1–10	4.5
Moderate	M	11–29	20.5
Severe	S	30–49	65.5 before 2003; 40.5 after 2003
Very severe	V	>50	75

Note: The classes "Trace" and "Very severe" were added after 2003.

TABLE 2 Description of mountain pine beetle (MPB)-related covariates used for the analyses.

Variable	Description
MPB OUTBREAK	1 if MPB outbreak with any severity was previously detected, 0 otherwise
MPB MORTALITY LAG 1; MPB MORTALITY LAG 2; MPB MORTALITY LAG 3	Total tree mortality (in %) due to MPB outbreak in one (LAG 1), two (LAG 2), and three (LAG 3) years before the measurement
MPB MORTALITY PEAK	Maximum tree mortality tree mortality (in %) due to MPB outbreak that the grid cell ever had before the measurement

Fire data compilation

The historical records of HCF and LCF in BC during the study period (1980–2020) were obtained from the BC Wildfire Service (https://catalogue.data.gov.bc.ca/dataset/fire-incident-locations-historical). The data include information on fire locations (latitude and longitude), ignition dates, causes (human or lightning), and size in hectares. We identified the grid cell where the location of each fire fell on the ignition date and produced the ignition indicator variables for HCF and LCF. A total of 60,381 out of 15,230,776 grid cells were identified as having at least one fire, accounting for approximately 0.4% of the entire samples. Among them, 54% were LCF and 46% were HCF. Approximately 200 grid cells had both HCF and LCF on the same day.

We labeled the fires that exceeded 100 ha in size as large fires. Only 2.6% of the fires exceeded 100 ha but they accounted for over 97% of the total area burned. A greater proportion of the area burned by large fires were due to LCF (54%) than to HCF (46%). We limited our analysis of MPB outbreak influence on large fire occurrence in relation to three ecozones with a significant amount of MPB host species (e.g., lodgepole, ponderosa, western white, and whitebark pine): Montane Cordillera, Boreal Plain, and Taiga Plain; because the pine stands in these zones are the population of interest. It is also important to note that our analysis of large fire occurrence in this study is conditional on all fire occurrences. This constraint avoids potential confounding factors associated with the distribution of large fires over the study area.

Environmental covariates

We considered a total of 79 covariates (including transformations) in four different groups: fire weather, vegetation, geography, and ecumene (accessibility to human infrastructure) to account for environmental influences on fire occurrence (Appendix S1: Tables S1 and S2). The fire weather covariates vary over space and time, whereas other groups were assumed to be constant over the study period. Details about the data and compilation process will follow.

Fire weather

Historical daily weather observations for 1981–2020 were obtained for weather stations in BC and within 60 km of the BC boundary from the Meteorological Service of Canada, the National Weather Service, and BC, Alberta, and Yukon wildfire agency remote automated weather stations. The information includes 24-h precipitation, temperature, relative humidity, and wind speed at noon each day during the fire season. The daily weather information at stations was interpolated onto the 20-km grids using a thin plate spline regression technique from the R package *fields* (Nychka et al., 2017) with elevation and corresponding NARR reanalysis variables as covariates as described in Nadeem et al. (2019). Precipitation records for 3 days prior to subject day were used to calculate 1–3 day lagged and cumulative precipitation for four days to account for the lagged impact of precipitation on soil moisture content (Tuttle & Salvucci, 2016).

The daily fire danger indices of the Canadian Forest Fire Danger Rating System (Van Wagner & Pickett, 1985) were calculated using the gridded weather observations and the R package *cffdrs* (Wang et al., 2017), namely, the Fire Weather Index (FWI), fine fuel moisture code (FFMC), duff moisture code (DMC), drought code (DC), Initial Spread Index (ISI), Buildup Index (BUI), Daily Severity Rating (DSR), and sheltered duff moisture code (SDMC). The probability of sustained flaming (PSUF) was computed based on Beverly and Wotton (2007).

When additional transformations and interactions between fire danger indices and weather variables (e.g., temperature and inverse cumulative precipitation) were added, a total of 41 fire weather covariates were considered (Appendix S1: Table S1).

Vegetation

We derived the proportions of the vegetated (VEGETATED) and treed area (TREED), conifer and deciduous tree cover (CONIFER COVER, DECIDUOUS COVER), and the percentages of the treed area in each cell made up of conifer (% CONIFER), deciduous (% DECIDUOUS), and mixed species (% MIXEDWOOD) from 250-m forest cover maps of Canada (Beaudoin et al., 2014). The 250-m grid cells were resampled to match the 20-km NFI grids using the aggregation by average in ArcGIS Pro (version 3.0).

The normalized difference vegetation index (NDVI) was evaluated for each grid cell to account for the seasonally varying phenological attributes (e.g., leaf and understory vegetation flush). We obtained daily Advanced Very High-Resolution Radiometer NDVI data from the National Center for Environmental Information (Vermote et al., 2014) with 250 m resolution. The daily records of NDVI were averaged by the day-of-year over the study period using the time series spline regression (Craven & Wahba, 1978). The average NDVI values were resampled into 20-km grids, similar to the fire weather variables. Including transformations, 11 variables were added to the vegetation covariate group (Appendix S1: Table S2).

Geography

The mean elevation and roughness (i.e., SD of elevation) of each grid cell were obtained by resampling the 225-m Global Multi-resolution Terrain Elevation Data of the study area from the US Geological Survey (https://earthexplorer.usgs.gov/). Broad-scale ecological influences were represented with indicator variables corresponding to the terrestrial ecozones (Wiken, 1986) of the grid cell: Boreal Cordillera, Boreal Plain, Pacific Maritime, Taiga Plane, and Montane Cordillera ecozones (Figure 1a). Including longitude and latitude and a transformation of elevation (e.g., the squared value of elevation), a total of 10 geographic variables were considered (Appendix S1: Table S2).

Ecumene

Six measures of human presence were considered to account for the anthropogenic influence on fire occurrence. Population counts were obtained for dissemination block polygons in the 2011 Canadian census and interpolated to our grids using the Districting tool in ArcGIS. The National Road Database was also obtained from the

2015 Canadian census to compute the total road length (in kilometers) in each grid cell. Considering the close relationship between fire risks and the wildland-urban interface (WUI; Calviño-Cancela et al., 2017; Radeloff et al., 2018) and wildland-industrial interface (WII), we calculated the proportions of WUI and WII area within the grid cells from data of Johnston and Flannigan (2017). We also calculated the distances from WUI and WII polygons to grid cell midpoints. To assess the temporal patterns of human activities, days (Monday–Sunday) of the fire occurrence were identified as indicator variables. As a result, the ecumene group consisted of 17 covariates including transformations of population, road length, and distances from WUI and WII (Appendix S1: Table S2).

METHODS

Lasso-logistic regression model

We fitted the least absolute shrinkage and selection operator (lasso)-logistic regression model (Tibshirani, 1996) to determine the influence of MPB and environmental covariates on the probability of fire and large fire occurrence. The lasso method penalizes the standard logistic regression likelihood by adding a constraint involving the magnitude of coefficients associated with the regression covariates. Mathematically, the log-likelihood function is maximized with the penalty, which is regulated by a tuning parameter, λ, and is expressed as follows:

$$l_{\text{lasso}}(\beta) = -\sum_{i=1}^{n}[(1-y_i)\beta x_i + \ln(1+\exp(-\beta x_i))] - \lambda\sum_{j=1}^{P}|\beta_j|, \quad (1)$$

y_i and x_i are the response variable and the covariates, respectively, and β_j is the estimated parameter (i.e., coefficient) for the jth covariate ($j = 1, ..., P$). A large value of β_j may denote an overfit of the model or inflation due to collinearity with the other βs (Kuhn & Johnson, 2013). In the lasso-logistic regression, any β_j that does not contribute to maximizing the log-likelihood as much as the added penalty $\lambda\sum_{j=1}^{P}|\beta_j|$ will be set to zero. The value of λ is chosen by cross-validation and determines the number of covariates to be included in the model (Ribbing et al., 2007). Therefore, the lasso-logistic regression enables the automatic selection of important variables; however, it does not require the user-specified p value (Ribbing et al., 2007), unlike the stepwise selection procedures. Lasso-logistic regression is efficient in terms of model accuracy and precision, as well as in computation (Wang et al., 2015). Also, the coefficients obtained from model fitting are readily interpretable, unlike nonparametric methods. Our study deals with rare fire events with a large set of environmental covariates; thus, lasso-logistic regression was appropriate to evaluate the importance of MPB-related variables among other confounding factors.

Response-based sampling

Because fires are rare events over a large area at a fine temporal resolution, our samples of grid cells were extremely imbalanced in terms of the binary responses of fire occurrence as well as large fire occurrence conditional on fire occurrence. Severely imbalanced samples cause low performance of prediction models especially for the rarer class (Huang et al., 2006; Marqués et al., 2013). A stratified resampling within the responses can remedy the imbalance problem at the data level without affecting the inferences about covariate coefficients (Scott & Wild, 1986). We adopted a response-based undersampling approach to balance the sample size between the grid cells with and without fire occurrences, considering the computational simplicity and fair performance for highly imbalanced data (Marqués et al., 2013; Wang et al., 2015). The response-based sampling used in our study produced subsets of data for fire occurrence models containing (1) all the grid cells with fire occurrence ($Y_1 = 1$) and (2) the same number of samples randomly selected from grid cells without fire occurrence ($Y_1 = 0$). We generated 100 subsets of the balanced datasets separately for the HCF and LCF occurrences to maintain data diversity. Similarly, for the large fire occurrence models, 300 samples were randomly selected from all the grid cells with a fire occurrence consisting of (1) all of the grid cells with large ($Y_2 = 1|Y_1 = 1$) and (2) the same number of grid cells without large fires ($Y_2 = 0|Y_1 = 1$) separately by fire cause; the samples thus represent the conditional outcome of large fire occurrence given a fire occurrence (i.e., L-LCF|LCF and L-HCF|HCF). We used more subsets for the large fire models because of the smaller sample size compared with the fire occurrence models (approximately 820 and 410 L-LCF and L-HCF, respectively).

Model fitting and evaluation of variable importance

We fitted four separate models of the probability of (1) HCF: human-caused fire occurrence, (2) LCF: lightning-caused fire occurrence, (3) L-HCF|HCF: large human-caused fire occurrence, and (4) L-LCF|LCF: large lightning-caused fire occurrence using the five MPB outbreak (Table 2) and 79 environmental variables (Appendix S1: Tables S1 and S2). The latter two models are of the conditional probability of a large fire, given an HCF or LCF occurrence, respectively (e.g., Preisler et al., 2009).

In developing the four models, each balanced dataset was randomly split into training (80%) and test data (20%) for model fitting and verification, respectively. The optimal value of the tuning parameter, λ, determined the number of covariates to be included in the model and was estimated by 10-fold cross-validation. This procedure was iterated for the 100 and 300 balanced datasets for the HCF and LCF, and L-HCF|HCF and L-LCF|LCF models, respectively. To evaluate model performance, we created 2×2 confusion matrices for the predicted responses using the test data and computed the overall accuracy, sensitivity, and specificity. The cutoff value for the prediction was chosen as 0.5 considering our response-based balanced datasets (Lombardo & Mai, 2018). The model fitting and validation process was conducted using the R package *caret*.

To evaluate the variable importance, we determined the drop rate for each of the variables selected by lasso-logistic regression (e.g., Lombardo & Mai, 2018; Wang et al., 2015). The drop rate was computed as the percentage of times that the variable was dropped from the model during the iterations. We also calculated the absolute value of the *t*-statistics of the mean standardized covariant coefficients from the 100 or 300 model fits (Kuhn, 2008). To determine the ranks of the MPB covariates within the covariate set, we applied a novel procedure, called stable variable ranking and selection (SVRS), developed for regularized logistic regression models with severely imbalanced datasets (Nadeem & Jabri, 2023). The SVRS algorithm produces stabilized aggregate covariate rank scores by assessing both the relative magnitude of the contribution of the variable and the consistency of variable selection in the model. The contribution of variables based on the standardized coefficients can vary depending on the different response-based samples, especially when there are strong correlations and noises among the covariates (Zou, 2006). Therefore, the algorithm considers threshold selection based on change-point detection (Killick & Eckley, 2014) from stabilized mean rank scores. We examined whether the mean rank scores of the MPB-related variables were above the threshold values, which means that the variables are significantly and consistently contributing to the fire and large fire occurrence responses, along with the other environmental factors. The average marginal effect of the significant MPB-related variables was estimated from each resampled subset and summarized as the original response scale (i.e., probability of fire occurrence and large fire) by correcting class probabilities as in Borgan et al. (2018).

RESULTS

Model evaluation

The four models—HCF, LCF, L-HCF|HCF, and L-LCF|LCF—realized approximately 75%–84% accuracy (Table 3) indicating that the variables we considered explained fire occurrence reasonably well. The models for LCF performed better than those for HCF in terms of overall accuracy, sensitivity, and specificity. The large fire models showed lower performance compared with the fire occurrence models for both causes, possibly due to the smaller sample sizes and complexity of fire growth dynamics.

Variable importance

The rank and the drop rate of the covariates in the HCF and LCF models are listed in Table 4 and Figure 3. We considered that the 33 and 38 variables were most influential in the HCF and LCF models, respectively, based on the change point in the drop rate. With a few exceptions, the covariates with high variable importance tended to exhibit a low drop rate (black datapoints in Figure 3); BUI was one of the outliers that had relatively high importance in the HCF model (rank 20th out of 84) but a 17% drop rate, indicating that it was not significant in all data subsets.

The covariates that were selected in the large fire occurrence models (i.e., L-HCF|HCF and L-LCF|LCF) are listed in rank order (Figure 4). There were fewer highly influential variables in the L-HCF|HCF and L-LCF|LCF occurrence models (9 and 22, respectively, out of 82 covariates) than in HCF and LCF occurrence models based on change points in the drop rate. These are listed in Table 5.

Influence of MPB outbreak variables

The influence of the MPB outbreak variables on fire occurrence varied greatly among fire models. While MPB-related variables had little to no influence on the probability of (and so the number of) fire occurrences, importantly, they had a significant impact on the number of L-HCF and L-LCF. Specifically, MPB MORTALITY

TABLE 3 Evaluation (average model accuracy, sensitivity, and specificity; mean ± SD) of fire occurrence and large fire occurrence models for human- and lightning-caused fires.

Model	Accuracy	Sensitivity	Specificity
Fire occurrence model			
Human-caused	0.813 ± 0.004	0.840 ± 0.005	0.787 ± 0.006
Lightning-caused	0.842 ± 0.003	0.862 ± 0.004	0.822 ± 0.005
Large fire occurrence model			
Human-caused	0.751 ± 0.028	0.749 ± 0.042	0.753 ± 0.044
Lightning-caused	0.754 ± 0.019	0.762 ± 0.030	0.746 ± 0.030

Note: The large fire occurrences are conditional on fire occurrences. The fire occurrence models were fitted using lasso-logistic regression based on 100 response-based samples, and the large fire occurrence models were fitted based on 300 samples.

PEAK was negatively associated with the likelihood of LCF occurrence (p(LCF); Table 4 and Figure 5a). However, the likelihood of a L-LCF (p(L-LCF|LCF)) increased by an order of magnitude along with the tree mortality due to MPB in peak year (Figure 5a) and was 1.7 times more frequent on average in the MPB-affected area (Figure 5b). The mean standardized coefficients of MPB OUTBREAK and MPB MORTALITY PEAK in the L-LCF|LCF model were 0.17 and 0.34, respectively (Table 5), indicating that the relative risk of large fire occurrence was 19% higher in MPB-affected areas and 40% greater as the tree mortality due to MPB increased by 1 SD (about 6%) (Figure 5). The MPB outbreak variables were not influential on the likelihood of HCF; however, the likelihood of a L-HCF|HCF given a fire occurs (p(L-HCF|HCF)) was lower in the MPB-affected area by 1% on average (Table 5 and Figure 5b). The impact of the recent tree mortality due to MPB (MPB MORTALITY LAG 1–3) was not influential with the presence of MPB OUTBREAK and MPB MORTALITY PEAK.

Influence of other environmental variables

HCF occurrence was most strongly affected by fire weather and ecumene characteristics (42% and 17% of the important covariates, respectively). Geography and vegetation covariates consisted of about 15% of the important covariates, respectively. The five most influential covariates in the HCF model were ROAD LENGTH$^{0.5}$, ROAD LENGTH, SDMC, distance to wildland-industrial interface (WII DISTANCE), and the interaction of FFMC and cumulative precipitation (FFMC..ACCUM PRECIP).

LCF occurrences were mainly affected by fire weather and vegetation characteristics (53% and 21% of the important covariates, respectively), followed by geographic factors (16%). The top five covariates in the LCF model were RELATIVE HUMIDITY > SDMC > TEMPERATURE > RELATIVE HUMIDTY^2 and % CONIFER. The coefficients of all 84 environmental covariates were reported in Appendix S1: Tables S3 and S4.

Similar to the HCF, L-HCF|HCF occurrences were most strongly affected by fire weather and ecumene characteristics (56% of the important covariates). The five most important covariates in the L-HCF|LCF model were ISI × TEMP interaction, WUI AREA, ROAD LENGTH$^{0.5}$, MPB OUTBREAK, and BOREAL PLAIN (Table 5).

L-LCF|LCF occurrences were strongly influenced by fire weather (45% of the important variables) followed by geographic, ecumene, and vegetation characteristics (18%, 18%, and 9%, respectively). The five most important environmental covariates in the L-LCF|LCF model were SDMC, LATITUDE, TEMPERATURE^2, WIND SPEED, and MONTANE CORDILLERA (Table 5).

DISCUSSION

MPB outbreaks influenced large fire occurrence

The analyses in this study showed that the MPB-induced tree mortality in BC, Canada, exerted a significant influence on fire occurrence and particularly large fire occurrence at a landscape level, even while considering environmental factors that are critically associated with fire characteristics. Because large fires account for 97% of the burned area in BC, we can conclude that MPB-induced tree mortality also contributed to the sharp increase in area burned in BC since about 2003, which has largely been attributed to changing climate (Parisien et al., 2023).

Based on our large sample size and comprehensive covariate information—including fire weather, vegetation, geography, and accessibility to human infrastructure over four decades—our lasso-logistic regression models consistently included MPB-related variables as

TABLE 4 Ranks, rank scores, and coefficients (Coef.) of the selected environmental covariates above the thresholds of human-caused fire (HCF) and lightning-caused fire (LCF) occurrence models.

Rank	Covariate	Score	Coef.
HCF			
1	ROAD LENGTH$^{0.5}$	80.99	1.128
2	ROAD LENGTH	78.53	−0.614
3	SDMC	78.13	0.604
4	WII DISTANCE	77.22	−0.549
5	FFMC..ACCUM PRECIP	76.46	0.521
6	WUI DISTANCE	74.72	−0.467
7	BUI^2	72.52	−0.459
8	RELATIVE HUMIDITY	72.10	−0.406
9	ISI	71.98	0.433
10	DC^2	70.55	0.373
11	POPULATION$^{0.5}$	70.14	0.367
12	% DECIDUOUS	69.15	0.357
13	WII DISTANCE^2	68.65	0.339
14	FWI..TEMP	65.49	−0.307
15	DC	63.38	−0.278
16	% CONIFER	62.42	0.262
17	% DECIDUOUS^2	60.74	−0.241
18	SDMC^2	60.48	−0.232
19	ROUGHNESS	57.68	0.197
20	LATITUDE	57.02	−0.193
21	MONTANE CORDILLERA	56.52	0.189
22	POPULATION	56.51	−0.189
23	LONGITUDE	56.01	−0.187
24	ELEVATION^2	55.19	−0.182
25	DMC	54.69	0.215
26	WUI DISTANCE^2	53.80	0.176
27	FWI..ACCUM PRECIP	53.10	−0.199
28	WUI AREA	52.63	0.161
29	DECIDUOUS COVER	51.52	0.155
30	DC..ACCUM PRECIP	49.74	−0.139
31	DC..TEMP	46.35	0.147
32	VEGETATED	45.72	0.115
33	BUI	44.95	0.204
LCF			
1	RELATIVE HUMIDITY	77.00	2.588
2	SDMC	75.69	1.917
3	TEMPERATURE	74.79	1.760
4	RELATIVE HUMIDITY^2	74.52	−1.733
5	% CONIFER	72.37	0.723
6	SDMC^2	71.09	−0.629
7	ISI	70.98	0.655
8	LONGITUDE	69.57	0.514
9	AVERAGE NDVI	69.38	0.509
10	AVERAGE NDVI^2	65.73	−0.377
11	ROAD LENGTH$^{0.5}$	62.03	0.306
12	SDMC..ACCUM PRECIP	60.67	−0.350
13	DC..TEMP	59.85	−0.287
14	ROUGHNESS	59.81	0.280
15	ELEVATION^2	59.65	−0.287
16	ISI..TEMP	58.01	−0.316
17	BUI	57.95	0.283
18	% CONIFER^2	57.18	−0.268
19	VEGETATED	56.86	−0.254
20	DC..ACCUM PRECIP	55.12	−0.234
21	PRECIPITATION	53.78	0.222
22	DECIDUOUS COVER	53.77	0.227
23	CONIFER COVER	53.67	0.259
24	ROAD LENGTH	52.51	−0.213
25	WIND SPEED	52.23	−0.208
26	TREED	51.31	−0.216
27	FWI^2	50.68	−0.210
28	FFMC^2	50.36	−0.209
29	BOREAL CORDILLERA	48.72	−0.180
30	BUI^2	45.69	−0.172
31	FFMC..TEMP	45.12	0.226
32	WUI DISTANCE^2	44.38	0.145
33	MONTANE CORDILLERA	44.20	0.145
34	PRECIPITATION LAG 1	42.94	−0.135
35	**MPB MORTALITY PEAK**	**41.07**	**−0.121**
36	PRECIPITATION LAG 3	40.20	−0.116
37	ELEVATION	39.87	0.140
38	FWI..ACCUM PRECIP	39.74	0.178

Note: The MPB-related variable appears in boldface. See Appendix S1: Tables S1 and S2 for list and definitions of the fire weather, vegetation, geography, and ecumene covariates.
Abbreviation: MPB, mountain pine beetle.

significant predictors for the occurrence of both L-HCF|HCF and L-LCF|LCF. The amplified occurrence of L-LCF|LCF in MPB-affected areas supports previous research that found increased burn severity of L-LCF|LCF after MPB outbreak (e.g., McCarley et al., 2017; Prichard & Kennedy, 2014; Turner et al., 1999). Conversely, the severity of the MPB outbreak had a small

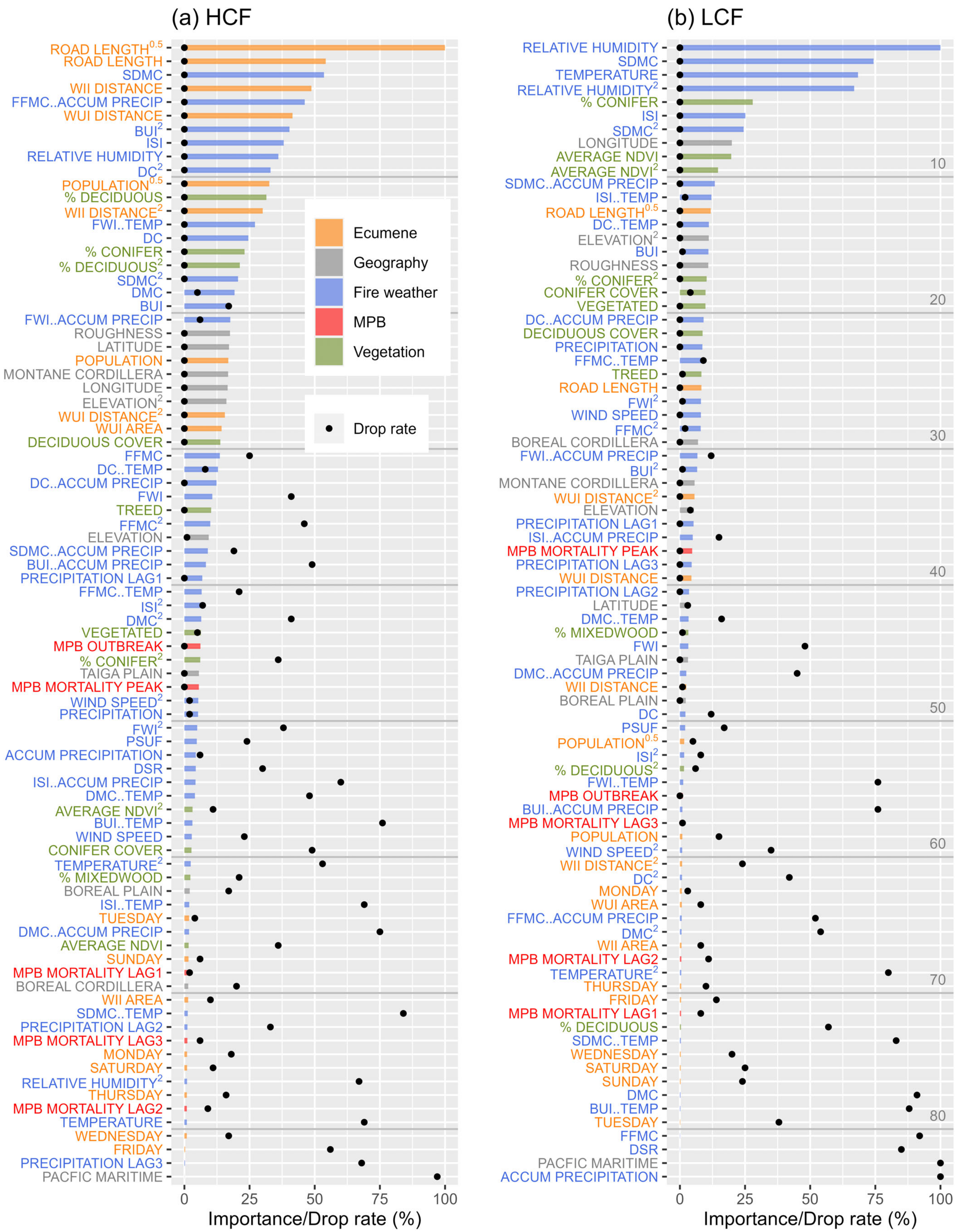

FIGURE 3 Legend on next page.

negative impact on LCF occurrences across all sizes. Meanwhile, HCFs did not significantly increase in areas that experienced MPB attack. The conflicting findings related to MPB outbreaks impacts on fire cause and size may explain the broader lack of consensus related to MPB-wildfire relationships.

LCFs result from a lightning strike hitting and passing through a live tree, which ignites ground fuels of a duff layer near the tree base (Johnson & Miyanishi, 2001). The lower incidence of LCF following MPB attack may reflect that dead trees are poor lightning conductors and that deeper organic layers have a higher moisture content in forests with high mortality and low transpiration (Sagar & Waterhouse, 2015). In contrast, HCFs are mainly ignited in surface fuels such as fallen leaves and twigs and primarily depend on human accessibility. Consequently, the statistical analysis revealed that MPB-induced tree mortality did not have a significant impact on HCF when the covariates related to human settlement and activity (ecumene) and fine fuel flammability were taken into account.

The effects of MPB and other environmental variables on fire size may also be conflated with fire management. In BC for example, the wildfire service increased the number of 20-person fire suppression crews in the interior by 50% from the early 2000s to 2010, and the number of available air tankers increased by 54% from 2010 to 2022 partly in response to the MPB outbreak (Nessman, 2022, personal communication, 21 November). The intensified fire management may have reduced the likelihood of L-HCF|HCF to a greater degree than LCFs. HCFs tend to occur in more accessible, developed areas where there is earlier detection and reporting, faster response times, greater suppression effort, and more roads available for use as firebreaks in response efforts (Narayanaraj & Wimberly, 2012). That MPB outbreaks had a greater impact on L-LCF|LCF occurrences in more remote areas suggests that MPB may have had a greater effect on wildfire extent in earlier epochs without fire suppression.

Our results differ from previous studies that found weak or no connection between MPB attack and fire characteristics in the Western United States (e.g., Hart et al., 2015; Harvey et al., 2014; Kulakowski & Veblen, 2007; Meigs et al., 2015; Mietkiewicz & Kulakowski, 2016; Nelson et al., 2016) and in a sub-boreal forest in BC (e.g., Talucci et al., 2022; Talucci & Krawchuk, 2019). Only a few studies suggested a potential increase in crown fire in a post-MPB fuel bed (Perrakis et al., 2014). There are several possible reasons for our differing results: (1) The MPB outbreak in BC was more extensive and severe than elsewhere in western North America. Approximately 18 million ha of pine and mixed pine forest was affected by MPB in BC and 5.2 million in the Western United States (Hicke et al., 2016) between 1999 and 2015. This is supported by Meddens et al. (2012) who found that the estimates of MPB-induced tree mortality in BC were higher than that in the United States in a combined aerial survey observation. We suspect that there were likely larger areas of high severity MPB outbreak in BC than in the Western United States, especially across the Interior Plateau of BC where historically large fires followed by decades of fire suppression led to areas of mature contiguous lodgepole pine with high traversability to MPB (Barclay et al., 2005). In the Western United States, lodgepole pine forests tend to occur at cooler higher elevations in the Cascade and southern Rocky Mountains with relatively low to intermediate susceptibility to MPB attack (Hicke & Jenkins, 2008; Liang et al., 2014), while lodgepole pine forests in BC range from low elevation to alpine areas (Pojar, 1985). Furthermore, the range of MPB in BC has expanded due to climate change (Carroll et al., 2004), which may also have increased traversability. (2) Our spatiotemporal analytical framework, which included daily fire weather and annually updated MPB outbreak status, may have had greater power to distinguish the impacts of MPB-induced tree mortality over the 15-year outbreak in BC and afterward. (3) We analyzed the relationship between MPB-induced tree mortality and fire occurrence separately by fire cause. This reduced the sample size but may also have resulted in more power. Because different suites of environmental and anthropogenic variables influence HCF and LCF occurrences, the effects of MPB outbreaks are confounded with these different suites of variables and need to be considered separately. (4) Many other environmental factors and management activities are confounded with the expression of the effects of MPB on wildfire behavior, and these can be expected to vary across the wide geographic range of lodgepole pine (as well as management regimes). Thus, consensus on landscape-scale impacts in western North America is not expected. For example, BC

FIGURE 3 The bar chart of the mean variable importance and the drop rate (datapoints; %) in rank order of 84 environmental covariates in (a) human-caused fire (HCF) occurrence and (b) lightning-caused fire (LCF) occurrence model, obtained from 100 model fits using response-based balanced datasets. The covariates are in order of relative importance (0–100; a higher number means higher importance) with their drop rate (datapoints ranged between 0 and 100; the number of drops in 100 model fits). MPB, mountain pine beetle. See Appendix S1: Tables S1 and S2 for list and definitions of the fire weather, vegetation, geography, and ecumene covariates.

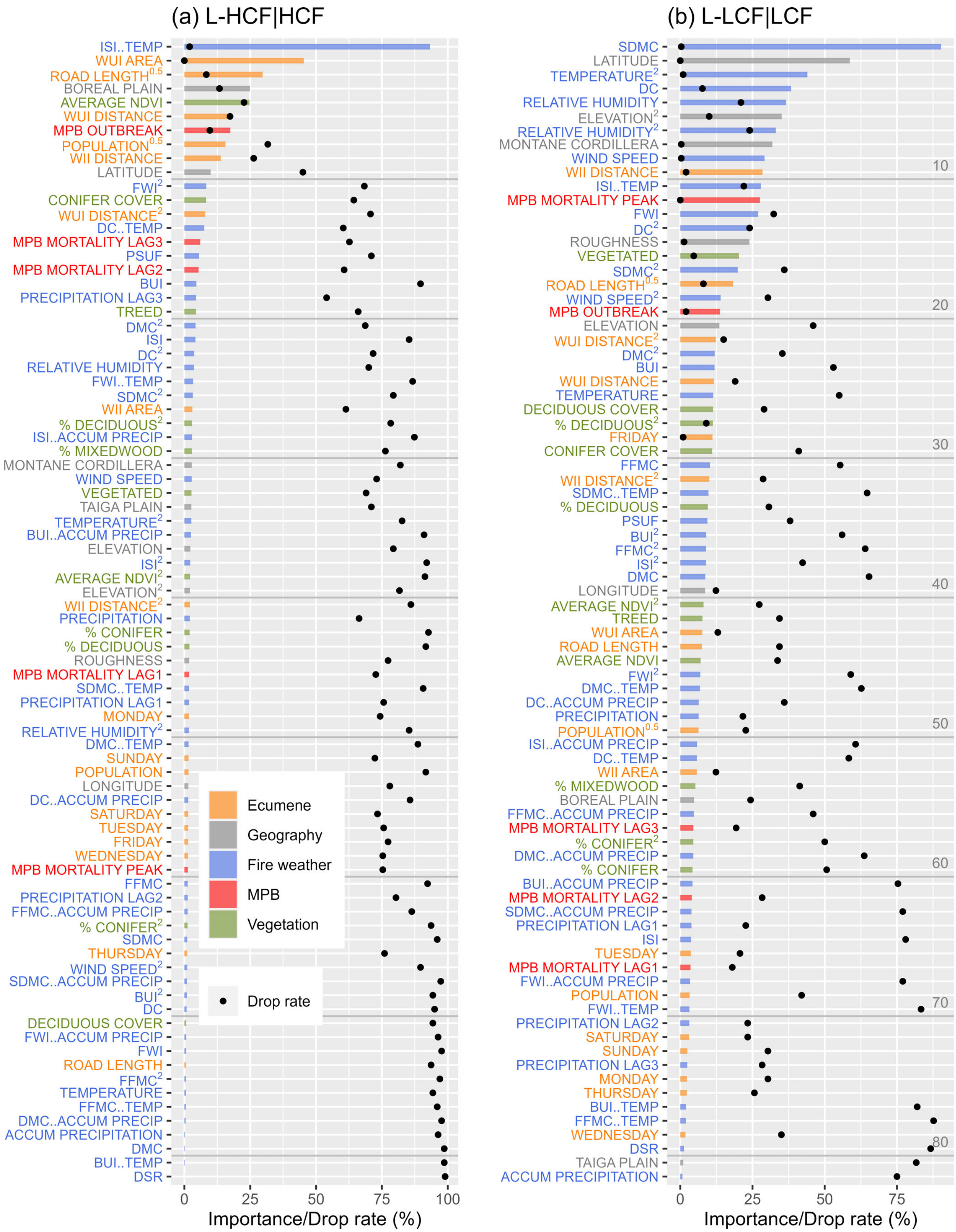

FIGURE 4 The bar chart of the mean variable importance and the drop rate (datapoints; %) in rank order of 82 environmental covariates in (a) large human-caused fire (L-HCF|HCF) and (b) large lightning-caused fire (L-LCF|LCF) occurrence model, obtained from 300 model fits using response-based balanced datasets. MPB, mountain pine beetle. See Appendix S1: Tables S1 and S2 for list and definitions of the fire weather, vegetation, geography, and ecumene covariates.

TABLE 5 Ranks, rank scores, and coefficients (Coef.) of the selected environmental covariates above the thresholds of large human-caused fire (L-HCF|HCF) and large lightning-caused fire (L-LCF|LCF) occurrence models.

Rank	Covariate	Score	Coef.
L-HCF|HCF			
1	ISI..TEMP	70.75	0.682
2	WUI AREA	68.94	−0.308
3	ROAD LENGTH$^{0.5}$	60.94	−0.204
4	**MPB OUTBREAK**	**58.27**	**−0.132**
5	BOREAL PLAIN	57.57	0.186
6	WUI DISTANCE	53.09	0.129
7	AVERAGE NDVI	52.46	−0.215
8	WII DISTANCE	46.76	0.103
9	POPULATION$^{0.5}$	43.93	−0.136
L-LCF|LCF			
1	SDMC	78.56	1.632
2	LATITUDE	74.91	0.799
3	TEMPERATURE^2	70.50	0.722
4	WIND SPEED	66.55	0.463
5	MONTANE CORDILLERA	65.23	−0.401
6	DC	64.74	−0.707
7	WII DISTANCE	63.67	0.397
8	**MPB MORTALITY PEAK**	**63.29**	**0.341**
9	ROUGHNESS	61.62	0.325
10	ELEVATION^2	59.79	0.462
11	VEGETATED	55.35	−0.265
12	RELATIVE HUMIDITY	55.27	−0.738
13	RELATIVE HUMIDITY^2	52.52	0.668
14	**MPB OUTBREAK**	**51.56**	**0.174**
15	ISI..TEMP	50.70	0.317
16	ROAD LENGTH$^{0.5}$	50.24	−0.200
17	FRIDAY	49.48	−0.142
18	DC^2	48.86	0.463
19	% DECIDUOUS^2	46.64	−0.167
20	FWI	45.41	−0.587
21	WUI DISTANCE^2	44.38	−0.189
22	SDMC^2	42.11	−0.444

Note: MPB-related variable are highlighted in bold. See Appendix S1: Tables S1 and S2 for list and definitions of the fire weather, vegetation, geography, and ecumene covariates.
Abbreviation: MPB, mountain pine beetle.

experienced several years of severe fire weather in the past two decades that were very challenging for fire suppression that may have amplified the expression of the mortality-induced fuel changes.

Environmental and human factors affecting fire occurrence

Spatiotemporal patterns and characteristics of fire vary significantly depending on fire causes (Vázquez & Moreno, 1998; Wang & Anderson, 2010); thus, the impact of the key covariates to fire characteristics can be also different by fire cause (e.g., Narayanaraj & Wimberly, 2012). The influence of environmental covariates on fire occurrence, other than the MPB-related covariates, was very consistent with the results of Nadeem et al. (2019), especially for LCF. Relative humidity, SDMC, temperature, BUI, and precipitation were highly influential on LCF occurrence in both this study and Nadeem et al. (2019). The counterintuitive influence of humidity and precipitation on fire occurrence was also identical. Relative humidity was negatively associated with HCF occurrences (i.e., more HCF occurrences with lower relative humidity) but positively associated with LCF occurrences because high humidity in the atmospheric boundary layer is necessary for the development of thunderstorms (Stull, 2015). The key difference between Nadeem et al. (2019) and our study is that we did not include baseline risk factors (e.g., average daily count of observed fire occurrence in a cell) and ignition indicators (e.g., number of lightning strikes per day) in the covariate set; our objective was to elucidate the relationship between fires and environmental factors, not to maximize the predictive skill of fire occurrence models. Thus, our model accuracy was also somewhat lower than the ones reported by Nadeem et al. (2019). The different covariate set used for this study explains the minor discrepancy in the selected covariates compared with Nadeem et al. (2019). Our LCF occurrence model picked up several more fire weather covariates with a squared term for the leveling-off effect (Nadeem et al., 2019) and included ISI instead of the PSUF as an important variable. ISI is based on fine fuel moisture content and wind speed (Van Wagner, 1974), while PSUF is dependent on ISI and fuel bed characteristics (Beverly & Wotton, 2007). Therefore, our models seemed to substitute ISI with vegetation and geographic covariates (e.g., treed area coverage, deciduous species coverage, Boreal ecozone, and Montane Cordillera ecozone) for PSUF.

We further examined the relationship between large fire occurrence and environmental factors. The results indicated that the size of LCF was also influenced by ecumene covariates, in addition to fire weather, geographic, and vegetation factors. As discussed earlier, greater access and development may influence fire size in several ways: earlier detection and reporting (Narayanaraj & Wimberly, 2012), faster response time, greater suppression effort, presence of roads used as

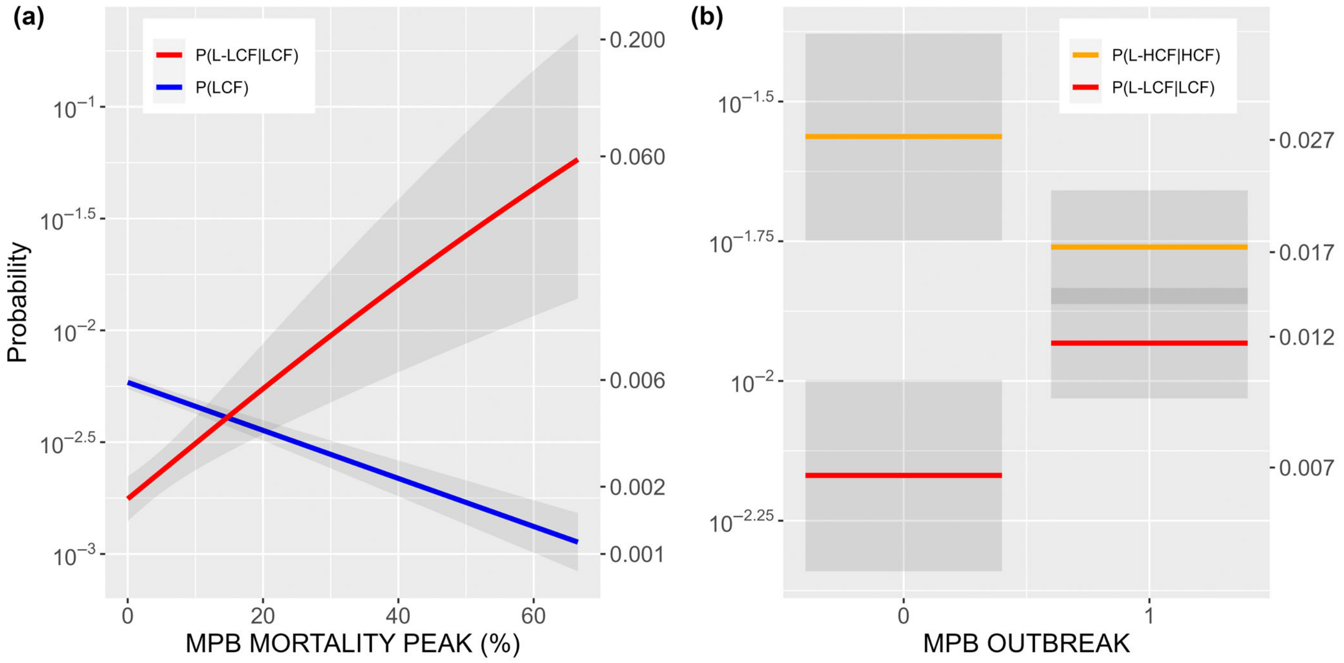

FIGURE 5 Average marginal effect of (a) MPB MORTALITY PEAK (%) and (b) MPB OUTBREAK (factor) variables on the probabilities of lightning-caused fire (LCF) occurrence, large lightning-caused fire occurrence conditional on lightning-caused fire (L-LCF|LCF) occurrence, and large human-caused fire occurrence conditional on human-caused fire (L-HCF|HCF) occurrence. The scale of *y*-axes (probabilities) is an order of magnitude. Only significant MPB variables are shown. MPB, mountain pine beetle.

firebreaks in response efforts, and fuel modification in developed areas that may retard fire growth in some cases, especially through forest harvesting (Burton et al., 2019).

Research contribution and future work

Attribution methods have recently been developed to determine the extent to which extreme environmental events are due to climate change (e.g., Fischer & Knutti, 2015; Stott et al., 2016) including wildfire in Western Canada (Kirchmeier-Young et al., 2019). However, methods are also needed to examine the complex interaction between weather, fire, and insect outbreaks or other disturbances in the context of climate change. We used a similar approach to intervention analysis to model wildfire response with weather and other factors on a daily basis for two decades before an extreme MPB outbreak in BC, and then over two subsequent decades as the outbreak developed and collapsed, updating MPB impact covariates annually. Our logistic regression and a variable ranking procedure determined the significant covariates for the fire characteristics with interpretable coefficients and relative importance and distinguished the effects of MPB-induced mortality from other environmental covariates.

There may be room to optimize the spatiotemporal scale of the sampling units as well as the modeling strategy depending on the scope of the research. While the grid-based sampling approach adopted in this study allowed us to analyze the presence–absence of daily fire occurrence in relation to the landscape-level MPB outbreak, it was done so at a coarse spatial resolution of 20 × 20 km grid cells. The coarse resolution inherently leads to the elimination of small-scale heterogeneity, while the frequent temporal coverage enhances the ability to detect landscape-level changes (Borak et al., 2000). Future research may adopt multiscale analyses including individual stand- or fire-level responses to capture the local variability in MPB severity and vegetation conditions. In that case, the selection of controls will be critical for comparison between the presence and absence of fire occurrences.

Another potential constraint on the analysis was the discretization between large and small fires (e.g., at 100 ha burned area threshold). Although this is a common practice in fire research (e.g., Fernandes et al., 2016; Ganteaume & Jappiot, 2013; Moreno et al., 2011; Podur & Martell, 2007) where the fire size is influenced by exogenous factors such as detection and response measures in addition to environmental factors, the challenge with using this approach is the loss of information and subjectivity in threshold selection (Uusitalo, 2007).

Diversifying the modeling strategies by accounting for the variability in fire size (e.g., Pareto distribution; Holmes et al., 2008; Li & Banerjee, 2021) may allow opportunities to parametrize the MPB influence on fire size without categorizing the size class.

Analysis of the effect of MPB and other insect outbreaks on fire characteristics is limited by data. The effect of insect mortality is primarily through changes in the fuel complex. Mortality surveys are often used as a proxy for forest fuel conditions instead of direct estimates of the amounts of live and dead crown fuel and surface fuel over time because this level of detail is not available in current forest fuel inventories over large spatial scales.

MPB outbreak and wildfire interactions largely occur in managed landscapes in WNA (e.g., Hart et al., 2015; Kulakowski & Veblen, 2007; Meigs et al., 2015). While we accounted for several confounding human factors, they could be eliminated because their effect and interaction with fire management and land management are not well specified. In addition to changes in fire management resources in BC over the outbreak period, salvage logging of killed timber was greatly accelerated in the mid-2000s; we were not able to account for this in our data. Recent observations suggest lower fire spread and fire severity in young plantations (Burton, 2010).

We may be able to better understand the interactions between insect outbreaks, wildfires, and climate through improved data, improved analytical methods, and a deeper understanding of the underlying processes.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Data (Woo, 2023) are available from the Borealis UVic Research Data Collection: https://doi.org/10.5683/SP3/FCVW1W.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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