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Short- and long-term wildfire threat when adapting infrastructure for wildlife conservation in the boreal forest

Ecological Applications

Appendix S1: Development of Burn-P3 inputs

Wildfire seasonality and causality

To capture variability in fire regime characteristics, namely seasonality, causality, and frequency of ignitions, we stratified our study area into four fire zones, based on the fire regime and zonation analysis for Quebec produced by Bouchard et al. (unpublished manuscript) (Fig. S1). We further described seasonal wildfire patterns by stratifying fire weather into spring (1 April - 21 May) and summer (22 May - 30 September) seasons. Seasonality was determined through an exploration of the historic timing of ignitions by fire zone and cause (human vs. lightning). The beginning of spring and end of summer were defined by the historical average onset and conclusion of ignitions that escaped initial attack and suppression efforts by SOPFEU and grew larger than the minimum fire size setting in Burn-P3 (Fig. S2), described further below. Historical ignitions exceeding our minimum fire size begin in April and typically do not extend past September. It should be noted that such ignitions in April and September are rare in this study area; we opted to retain these months within the wildfire season to acknowledge projected lengthening of the wildfire season in the future (Flannigan et al. 2013). The transition date between spring and summer corresponds to the average time of green-up, that is, the timing when deciduous trees and shrubby vegetation begin to leaf out, thereby influencing fuel moisture and wildfire behavior (Fig. S3). As such, fuel types including deciduous components were set to “leaf” for any wildfire simulated for the summer season. Percentage of grass curing (i.e., the amount of dead or dried grass) was also affected by seasonality, with 70% curing in the spring and 55% curing in the summer.

Ignition locations within each iteration were stratified by fire zone, cause, and season based on historical ignitions from 1980-2017 (taken from the Canadian National Fire Database; Canadian Forest Service 2019) that grew larger than 25 ha (n = 184 ignitions in our study area). We used 25 ha as the minimum fire size for fires retained by the software. Though smaller fires do have the potential to affect the caribou corridor area, fires larger than 25 ha account for more than 99% of the total area burned within the study area (Fig. S4). As such, the use of a 25-ha threshold represented a sensible modeling shortcut and a way to balance a degree of realism against the additional simulation time required to model smaller fires on fine-scale spatial inputs. The distribution of ignitions by season, cause and zone was held constant through all scenarios due to inherent difficulty in projecting changes to these factors for future time periods.
Figure S1: Spatial wildfire regime characteristics showing the distribution of wildfire ignition (fires ≥ 25 ha) a) size, b) casualty, and c) seasonality within the study area’s fire zones.
Figure S2: Temporal wildfire regime characteristics (fires ≥ 25 ha) graphed biweekly by fire zone including a) number of fires and b) total area burned. Graphs present statistics between 1980 and 2017.
Figure S3: Average green-up timing from 2013-2016 a) spatially and b) as a distribution of average timing within each wildfire zone.

Figure S4: Percent of the total area burned within the study area from wildfires from 1980-2017 equal to or less than a given fire size, partitioned by wildfire cause. Historical fires smaller than our minimum fire size (< 25 ha) contributed to <0.7% of the total area burned in this 1980-2017 time frame.
**Topography and wind grids**

The direct influence of topography on wildfire spread (i.e., wind vectoring) was modeled through the inclusion of a digital elevation model (DEM) (USGS, SRTM), while the indirect influence of topography on wind speed and direction (i.e., channeling) was modified by wind grids produced by WindNinja, version 3.5.2, software (Forthofer et al. 2014). These wind grids consist of continuous values describing how wind speed and direction are changed due to topographic characteristics, such as slope and aspect. Topography will have different effects on wind depending on the wind direction (e.g., winds will behave differently if blowing cross slope vs. up or downslope); as such, wind grids are built for eight wind directions (N, NE, E, SE, S, SW, W, NW) with a specific grid enabled based on the wind direction selected by Burn-P3 for a day of burning from the fire weather list. If, for example, Burn-P3 selects a fire weather entry with a westerly wind blowing at 10 km/h, the “W” wind speed and wind direction grid will be selected; the wind speed and wind direction grids will then modify that selected direction and speed as a function of the underlying topography (Natural Resources Canada 2017).

**Ignition grids**

We developed a logistic regression model to relate the spatial variability of human- and lightning-caused ignitions to factors affecting their likelihood, following the methods used by Wang et al. (2016). The product of this process, called an ignition grid, provides a variable surface of ignition probability used by Burn-P3 when selecting the location of ignitions. Given the scarcity of ignitions in spring (Fig. S2A), we did not further subdivide ignition grids by season. Three explanatory variables, elevation, topographic position index, and solar radiation, were explored in the development of both human and lightning ignition grids. For the human ignition grids, we additionally examined the influence of the distance to and density of linear features, the distance from established population centres, and the density of anthropogenic points (such as vacation properties and industrial infrastructure). For the lightning ignition grids, we also examined the effect of historical lightning strike density, as recorded by Environment and Climate Change Canada’s Canadian Lightning Detection Network (CLDN). As in Wang et al. (2016), our response variable consisted of the location of all historical ignitions (1980-2017) producing fires greater than or equal to our minimum fire size of 25 ha and 500 randomly selected points in which ignitions were absent. The best prediction of human ignitions was achieved using elevation and a 3rd order polynomial of distance to linear features. Lightning ignitions were best described by elevation accompanied by a quadratic term. Predictive accuracy of models was assessed using the cross-validation function of the DAAG package in R (Maindonald and Braun 2020).
Depending on the severity of the fire season, few or many ignitions may escape suppression efforts. To mirror this inter-annual variability in escaped ignitions, we fitted a lognormal distribution to the historical number of ignitions per year leading to fires ≥ 25 ha. The number of ignitions attempted by Burn-P3 in each iteration for the observed scenario was then drawn from this distribution. To validate the Burn-P3 outputs, we adjusted this distribution to ensure the total number of large fires and area burned per fire season paralleled the range of historic conditions.

To project the number of ignitions per iteration to each future climate scenario, we fit a regression model relating the annual number of historical ignitions ≥ 25 ha with historical daily weather data summarized from 29 weather station locations from within the study area. We subset the weather and ignitions data to all values after 1994. Weather station distribution before this year was concentrated in the southern portion of the study area and thus not representative of weather conditions driving ignition behavior across our landscape. We averaged fire weather variables (temperature, relative humidity, wind speed, precipitation, and the six fire weather index, or FWI, system indices; Lawson and Armitage 2008) by the length of the fire season and by each fire season month (May-September), broadly following the methods of Wang et al. (2016) and Stralberg et al. (2018). Following a review of the literature describing variables important to wildfire ignition and escape, we investigated the potential predictive value of other variables, such as the number of days exceeding 95th percentile conditions for the initial spread index (ISI), fine fuel moisture code (FFMC), and duff moisture code (DMC) (Podur and Wotton 2011) as well as the number of days exceeding the criteria for what we considered a potential spread event day (i.e., number of days in which FWI exceeded 13 and DMC exceeded 20). We examined the bivariate relationship between all variables and the annual number of ignitions and proceeded in model selection with those variables with the highest deviance explained, removing highly correlated
variables (Pearson correlation coefficient >0.7) to reduce problems associated with collinearity (Dormann et al. 2013). We found that a Poisson regression model fit to this data was overdispersed, and opted to correct this with a negative binomial model (Zuur et al. 2013). Of the variables examined, a model including the mean wildfire season wind speed and total number of days in June in which the DMC exceeded 20 best balanced the number of predictor variables used, and overall predictor ability, as judged by Akaike Information Criterion corrected for smaller sample sizes (AICc) (Burnham and Anderson 2002). Regression coefficients are provided in Table S1.

Table S1: Negative binomial regression coefficients for model used to project annual number of fires (≥ 25 ha. n = 184)

|         | β     | Standard Error | P     |
|---------|-------|----------------|-------|
| (Intercept) | -6.615 | 2.902          | 0.0226 |
| June number days, DMC ≥ 20 | 0.165  | 0.059          | 0.0048 |
| Mean wind speed | 0.425  | 0.178          | 0.0171 |

(Dispersion parameter for Negative Binomial(1.3739) family taken to be 1)
Null deviance: 41.50496 on 23 degrees of freedom
Residual deviance: 23.99103 on 21 degrees of freedom

The observed historical maximum annual ignitions included one year (1996) with an unusually high number of ignitions; that year exceeded the maximum predicted annual number of ignitions of any of the regression models. To acknowledge that extreme years, such as this, are likely to occur again, we opted to allow this historical precedent to extend into the simulated distributions by truncating the lognormal distributions at this historical maximum value, rather than the predicted maximum value. Distributions of annual ignitions for each climate scenario and time period are provided in Figure S6.

![Figure S6: Distributions of annual ignitions for each climate scenario and time step over the 20,000 iterations in each scenario](image-url)
Spread event days

We used the methods of Wang et al. (2014) to create distributions of potential and realized spread for each climate and time period combination. As in Wang et al. (2014), wildfire spread potential was derived from climate and truncated to a more realistic, “realized” spread, through use of a link function. Although wildfires can be active for long periods (weeks to months), they typically have a much-reduced duration in which weather conditions are conducive to significant fire spread (Wang et al. 2014). We generated this distribution of “potential spread event days” based on the frequency distribution of consecutive fire-conducive days for both observed and simulated weather inputs. This distribution of potential wildfire spread is broader than that of realized spread, the number of actual days a wildfire actively spreads. This is due to factors such as the timing of ignition in relation to a series of conducive weather days and the effect of wildfire suppression (Podur and Wotton 2011). To account for this difference in the observed scenario, we adjusted the potential spread distribution until simulated wildfire sizes and total area burned best aligned with historical observations. We tested a range of maximum spread days for this distribution and found that a maximum of 10 days produced the most accurate outputs. For the simulated baseline spread day distributions, we calculated the linear relationship between baseline, weather-based potential spread, and observed, realized spread separately for both RCP 4.5 and RCP 8.5, again as in Wang et al. (2014) and Wang et al. (2017). We then used these linear relationships as a “link” to convert potential spread to realized spread for all scenarios using simulated weather. We allowed simulated fires to burn for a variable distribution of 5 or 6 hours for each day of spread, equivalent to a third of the total number of daylight hours during the peak of the fire season, based on comparisons of fire size distributions produced by this and other time periods. Figure S7 presents the distribution of spread days used in Burn-P3.

Figure S7: Distributions of spread days by climate scenario and time period
Daily fire weather conditions associated with fire growth for the observed scenario were taken from 29 spatially representative weather stations from the period 1980-2019. We stratified weather station locations into two weather zones to capture differences in climatic conditions within the study area, broadly following fire zone and Quebec biogeoclimatic zone boundaries to identify areas of generally more coastal or continental climates. Fire weather conditions input to Burn-P3 represent severe conditions under which fires are anticipated to ignite, spread, and escape initial attack suppression efforts (Parisien et al. 2005). We determined that average weather conditions for our study region during days of FWI ≥ 13 would lead to head fire intensity likely to pose a challenge to suppression efforts (>4,000 kW/m) in the study area’s dominant fuel type, C-2 (boreal spruce). We used only fire weather for days in which the FWI exceeded this threshold as the weather input driving wildfire growth and spread in all scenarios.

For the baseline, mid-, and late-century scenarios, we stochastically generated daily fire weather for 30-year periods (1991-2020, 2041-2070, and 2071-2100, respectively) using BioSIM v11 (Régnière and Saint-Amant 2014) for these same station locations. Two sets of weather data were simulated in BioSim, one for Burn-P3 simulations, and the other for LANDIS fuel simulations. We projected weather using the Canadian Earth System Model v2 and used the ANUSPLIN method to downscale climate projection to a 10 km resolution (hereafter 10 km ANUSPLIN cells). For Burn-P3 simulations, future monthly normals at each weather station were directly assessed from changes observed between the 1981-2010 period and future projections in the 10km ANUSPLIN cells with a weather station. BioSIM projected daily maximum and minimum temperatures (C), precipitation (mm), mean daily relative humidity, and wind speed by matching georeferenced sources of weather data (here the 10 km ANUSPLIN cells) to spatially georeferenced points (the weather station), adjusting the weather data for differences in latitude, longitude, and elevation using spatial regression. Future climate variables for each weather station were calculated from 30 BioSIM simulations considered as single-year replicates. For LANDIS simulations, we calculated and corrected for elevation monthly climate variables for 1981-2100 using the ANUSPLIN dataset for ten points randomly located in each landtype of the simulated area. For both the Burn-P3 and LANDIS sets of weather data, we produced simulations for both RCP 4.5 and RCP 8.5. Baseline and observed fire weather data were compared to ensure simulated weather realistically described observed historical weather patterns.

Fuels

Vegetation in Burn-P3 is simplified and expressed using the Canadian Fire Behavior Prediction (FBP) System fuel types. These fuel types typify fire behavior for specific vegetation types, dependent on topographic and weather conditions, rather than describing the actual composition of vegetation. Fuels for the current time period (observed and baseline scenarios) were provided and classified from ecoforestry polygons by SOPEFU according to a ground-truthed ruleset; these were provided at 100 m resolution and subsequently resampled to 500 m to match the resolution of inputs used in Burn-P3. We surveyed the region by helicopter to confirm that fuel types properly represented existing vegetation and made two generalized changes to the original grid. First, a large wildfire perimeter from the 2018 season close to the caribou corridor was converted to M-1 C25 (boreal leafless mixedwood, with 25% conifer) to describe likely fuel conditions (and
associated fire behavior) in the timeframe within which the Micoua-Saguenay line is anticipated to be operational. Second, the 1991 fire perimeter neighbouring the corridor contained pixels classified as grass or vegetated non-fuel. Much of this burned area has poorly regenerated; we assessed the areas classified as grass or vegetated non-fuel and determined that these pixels tended to contain patchy distributions of small trees intermixed within dominant, open shrub. We recategorized these pixels to M-1 C25, a fuel type more conducive to fire spread, following our on-site assessment, based on a desire to not underestimate potential ignition and spread within the immediate proximity of the line. Future fuels were projected from these initial vegetative conditions in LANDIS-II v. 6.2 (Scheller et al. 2007); details are provided in Appendix S2.

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