Projected changes in fire size from daily spread potential in Canada over the 21st century

Xianli Wang¹,², Kala Studens¹, Marc-André Parisien¹, Steve W Taylor¹, Jean-Noël Candau¹, Yan Boulanger¹ and Mike D Flannigan¹

1 Great Lakes Forestry Centre, Canadian Forest Service, Natural Resources Canada, 1219 Queen Street East, Sault Ste. Marie ON P6A 2E5, Canada
2 Northern Forestry Centre, Canadian Forest Service, Natural Resources Canada, 5320-122nd Street, Edmonton AB T6H 3S5, Canada
3 Pacific Forestry Centre, Canadian Forest Service, Natural Resources Canada, 506 West Burnside Road, Victoria BC V8Z 1M5, Canada
4 Laurentian Forestry Centre, Canadian Forest Service, Natural Resources Canada, 1055 du P.E.P.S., P.O. Box 10380, Sainte-Foy, Québec QC G1V 4C7, Canada
5 Department of Renewable Resources, University of Alberta, 751 General Service Building Edmonton, AB T6G 2H1, Canada

E-mail: xianli.wang@canada.ca

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Abstract

The broad consensus indicates that climate change will cause larger and more frequent fires, resulting in a growing annual area burned (AAB) in much of Canada. Our ability to predict future changes in fire size (FS) and AAB is limited due to the uncertainty embedded in climate change models and our inability to quantify the complex interactions between the changing environment and fire activity. In this study, we introduce a new method to predict future FS and AAB across Canada over the 21st century based on fire-conducive weather and how it translates to on-the-ground fire spread (i.e. spread days). We found that the potential for an extreme fire year (99th percentile of AAB) could quadruple by the end of the century across Canada, and ≥ 10 times more common in the boreal biome. Specifically, FS and AAB may increase 20%–64% and 25%–93%, respectively, and the average fire year under the extreme climate scenario may burn ~11 Mha, which is ~4 Mha higher than the most extreme fire year in Canada’s modern history (~7 Mha). Our results demonstrate that by accounting for the strong nonlinear expansion of wildfires as a function of number of fire spread days, even conservative climate-change scenarios may yield significant increase in fire activity.

1. Introduction

Throughout much of North America, wildland fire frequency and area burned have been increasing in recent decades (e.g. Kasischke and Turetsky 2006, Dennison et al 2014, Abatzoglou and Williams 2016, Hanes et al 2019). These increases were shown to coincide with the lengthening fire season (Jolly et al 2015, Hanes et al 2019) and escalating severity of fire-conducive weather conditions (e.g. Jain et al 2017, Schoennagel et al 2017, Holden et al 2018), regardless of the ever-increasing effectiveness of fire suppression (Flannigan et al 2016). The broad consensus is that climate change will cause larger and more frequent fires over the 21st century (Wotton et al 2010, Settele et al 2014), resulting in further amplification of the annual area burned (AAB) in Canada (Flannigan et al 2005, Balshi et al 2009, Boulanger et al 2014). Climate change is projected to reshape Canada's temperate and boreal biomes (Price et al 2013) in terms of vegetation structure, pattern, and species composition (Stralberg et al 2018). Changes in vegetation will further transform Canada's fire regimes over the 21st century (Flannigan and Van Wagner 1991, Boulanger et al 2014). Changing fire regimes may be estimated using fire models that project future fire activity (e.g. Wotton et al 2010, Westerling et al 2011). Though highly informative, these correlative or process-based projections remain highly uncertain, as much remains to be learned about the mechanisms that drive future fire activity (Macias-Fauria et al 2010).

Fire size (FS) and AAB are two commonly reported fire regime statistics (e.g. Stocks et al 2002, Miller...
and Ager 2013) used to characterize fire activity. Our ability to predict future changes in these statistics, however, is limited due to the large amount of uncertainty embedded in Global Climate Models (GCMs). The inability to accurately quantify complex interactions among factors affecting fire ignition and spread (e.g., fire weather, fuels condition, topographical features, and fire suppression) makes it even more challenging (Erni et al 2018). Consequently, research on FS has mainly focused on statistical distributions (e.g., Cumming 2001, Reed and Mckelvey 2002, Schoenberg et al 2003, Cui and Pereira 2008, O’Donnell et al 2014, Hantson et al 2016, Westerling 2016, Marchal et al 2017). While there have been some attempts to predict future FS and AAB (e.g., Kitzberger et al 2017), other research has also shown that correlative approaches have a high level of uncertainty (e.g., Boulanger et al 2018). Therefore, methods that are able to capture the mechanisms by which wildfires spread are essential to improve the accuracy of FS projections and, consequently, reduce the level of uncertainty in future area burned projections based on FS (Venevsky et al 2002, Westerling et al 2011, Veraverbeke et al 2017).

A large fire may burn for weeks, or even months, until a substantial rain event or the arrival of winter limits active growth, allows for containment, or extinguishes it altogether (Latham and Rothermel 1993). Despite their relative longevity, fires burn most of their area over just a few days of high or extreme fire weather (Rothermel et al 1994); these days are termed ‘spread days’ (Podur and Wotton 2011, Wang et al 2014). The number of spread days is therefore strongly related to FS estimates because it characterizes the duration of burning (Wang et al 2016). The relationship between area burned and duration of burning is not linear; it should, theoretically, follow a power relationship (Mcarthur 1968, Van Wagner 1969, Rothermel et al 1994), given that wildfires burn as an ellipse under homogenous burning conditions (Anderson 1983, Green et al 1983).

In nature, both the flammable vegetation (i.e., fuels) and weather conditions are far from homogenous. As the direction of fire spread changes with changing wind direction, major shifts in wind direction can change the flank of the fire to the head, rapidly escalating FS. The likelihood of these rapid-expansion events increases with fire duration. Somewhat surprisingly, the relationship between fire duration (i.e., number of burning days) and FS has never been substantialized (but see Xi et al 2019). Spread days, on the other hand, have been used in fire growth modeling (Parisien et al 2005), as they are better predictors of FS than the total number of active days. Because spread days can be predicted based on fire weather potential (Wang et al 2014), establishing a relationship between FS and spread days presents a unique opportunity to project climate change effects (Wang et al 2016, 2017) on FS and, by extension, AAB. Furthermore, investigating this relationship across regions with a range of fire regimes may improve our understanding of the ‘efficiency’ of translating spread days into area burned by individual wildfires in different areas.

In this study, we test a method by which FS is derived from daily fire weather and used to project future AAB. Specifically, the objectives were to (1) develop a novel method to estimate FS and AAB based on fire-conducive weather conditions that are translated to daily fire spread potential; (2) project changes in FS and AAB from daily fire spread potential in Canada estimated under changing climate regimes, over the upcoming century. Specifically, we model the relationship between the number of spread days and FS, and use this model to predict FS distributions for both the baseline and future time periods based on the projected distributions of spread days (Wang et al 2017). These FS distributions are then used in combination with the distribution of annual number of fires (ANF) from the baseline time period to simulate current and future AAB distributions.

2. Methods

2.1. Study area

The study area encompasses the predominantly forested landmass of Canada, bounded by the shrub tundra in the north, and the extensive cultivated and urban areas developed in the south. The Western Cordillera system rises in the west and the rest of the country is relatively flat. Three major biomes, the temperate coniferous forests (west coast), the temperate broadleaf and mixed forests (east coast and Great Lakes area), and the boreal forests (central Canada and north of the two other biomes) constitute the main body of Canadian forests. In this study, we used the 16 homogeneous fire regime zones (HFRZ) (Boulanger et al 2014) as the primary analysis units (figure 1). Each HFRZ represents an area of relatively homogeneous weather, fuels, and fire regime characteristics (Boulanger et al 2014). An area north of 54°N in Ontario is excluded from Boulanger et al’s (2014) zonation because of missing fire data; as a result, this area was not considered in this analysis.

2.2. Predicting FS based on the number of spread days

The spread days of historical fires between 2001 and 2017 were extracted by combining two data sources: (1) the Canadian National Fire Database (NFDB, Canadian Forest Service 2018), which contains comprehensive records of mapped perimeters of fires
≥200 ha, and (2) Moderate Resolution Imaging Spectroradiometer (MODIS) sub-daily fire detection data (hotspots) for these large fires. Fires prior to 2001 were not considered because MODIS data are not available. Daily fire spread was assessed following Parks (2014) using both the perimeter of fires from NFDB and the MODIS hotspots. Fire progression was mapped for every burning day at a 30 m resolution by spatially interpolating MODIS fire detection data (1 km resolution) (NASA MCD14 ML product, Collection 5, Version 1). The spread vs non-spread days were determined following Wang et al. (2014; see below). Spread days are defined as days in which the spread distance exceeds 240 meters (e.g. Wang et al. 2014, 2017, Stralberg et al. 2018); this definition corresponds to daily fire progressions calculated for a nominal rate of spread of at least 1 m min⁻¹, assuming a 4 h burning period each day and circular growth (cf, Hirsch 1996). In the study area, the number of spread days for each fire between 2001 and 2017 were tallied. The distribution of spread days for each fire zone, as well as for the whole study area, was then generated. The link between fire size and number of spread days was investigated using models with different functional forms, including power law, sigmoid, and quadratic. Because the distributions of both spread days and FS were highly skewed, logarithmic transformations of each variable were also considered. A 5-fold cross validation was used to test the prediction accuracy of the models. This consisted of separating the data into five random subsets and using different combinations of the subsets to train and test the data. Upon calculating the average squared prediction error for each model, it was determined that a log-transformed power-law regression model (equation (1)) had the best predictive accuracy (figures S1 and S2 (available online at stacks.iop.org/ERL/15/104048/mmedia)). This model maintains the power-law relationship between \( x \) and \( y \), while log transforming the variables to correct for skewness. The result is a simple linear regression model of the log-transformed variables, with a fixed coefficient of two to account for the quadratic relationship.

\[
\log(y) = a + 2 \log(x) \tag{1}
\]

where \( y \) = fire size (ha), \( x \) = number of spread days for the fire, and \( a \) = rate coefficient.

We fitted the regression model to spread days and FS for each HFRZ (figures 2(A) and S1) and the whole study area (figure S2). Using the resulting regression equations, we transformed the distribution function for spread days into a distribution function for FS (figures S3 and S4). We also calculated the median ratio between fire weather potential and the actual fire spread days in order to show how much fire weather

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1NASA MCD14 ML product, Collection 5, Version 1, https://activefiremaps.fs.fed.us/gisdata.php
potential is converted into actual fire spread by HFRZ (figure 2(C)).

2.3. Simulating distributions of AAB

The area burned in a region is a compound distribution of FS and numbers of fires (Podur and Wotton 2010). AAB distributions can be approximated using a simple bootstrapping procedure if ANF and FS are independent from each other (equation (2)).

$$\text{AAB} = \sum_{i=1}^{N} X_i$$

where $N = \text{ANF}$ and $X_i = \text{size of fire } i$.

However, a Pearson’s correlation test between the size (median) and annual number of observed large fires (2001–2017) showed strong correlation ($r \geq 0.7$), indicating dependence between the variables. The AAB therefore had to be simulated from a projected joint distribution of FS and ANF, which was achieved using a copula method (Nelsen 1999; appendix I).

A copula is a multivariate distribution function that describes the dependence structure between variables and acts as a link between joint and marginal distributions (Sklar 1959, Nelsen 1999). Applying an appropriate copula to the predicted distributions of FS and ANF (marginal distributions) provides a predicted joint probability distribution between the two. Future AAB can be simulated by sampling values from this joint distribution (appendix I). It is reasonable to assume that the relationship between FS and ANF is not identical across fire zones in Canada. We fitted several types of copula to each fire zone using maximum likelihood and compared the fits using Akaike information criteria (AIC) values. This was done using the R function BiCopSelect (Schepsmeier et al 2018). We applied a log transformation to reduce the weight of extreme values (figures S5 and S6).

2.4. Projecting FS and AAB distributions with climate change

2.4.1. Generating spread day distributions with climate change

As demonstrated in Wang et al (2014), daily fire weather potential (i.e. fire conducive weather condition, the potential spread day (PSD)) can be used to model the real number of spread days (realized spread day (RSD)) for a fire. Typically, a PSD corresponds to hot, dry, and windy conditions and is more likely to result in non-negligible fire spread compared to days with less extreme weather conditions (Podur and Wotton 2011). Consequently, future daily fire weather projections can be translated to a predicted number of spread days (Wang et al 2016). The current and future spread day distribution curves for the HFRZs were generated following Wang et al (2017) (figure S7) under three GCMs and three anthropogenic forcing scenarios from those included in the fifth phase of the Coupled Model Intercomparison Project (CMIP5; Taylor et al 2012). The three levels of end-of-century radiative forcing are RCP2.6, RCP4.5, and RCP8.5 from three different GCMs, namely CanESM2, HadGEM2-ES, and CSIROMk3-6-0. These three GCMs were selected because they performed the best using a best-performance selection method similar to that described in Perkins et al (2007) (for details see Wang et al 2017). Four time periods were considered: the baseline (1981–2010), 2020s (2011–2040), 2050s (2041–2070), and 2080s (2071–2100).

The national spread day distribution curve (by HFRZ) for the baseline time period was generated by averaging the spread day distribution curves across the 16 HFRZ that were reported in Wang et al (2017), weighted by the number of fires in each HFRZ. The national spread-day distribution curves for the future time periods were created using the same technique. In total, 476 spread day distributions curves were generated ([3 GCMs × 3 scenarios × 3 time periods + 1 baseline] × [16 HFRZ + 1 All]).

2.4.2. Predicting FS and AAB distributions

FS distributions were generated for both the baseline (figures S8 and S9) and future time periods by applying the regression models fitted between FS and spread days for the HFRZ individually (figures 2(A) and S1) and nationally (figure S2).

We simulated AAB using the distributions of ANF and FS (cf Venevsky et al 2002) for both baseline (figures S10 and S11) and future time periods. The distribution of ANF was modeled based on the large fires ($\geq 200$ ha) in the NFDB (Canadian Forest Service 2018) between 1981 and 2010, the baseline time period. A kernel density curve of ANF was created for each HFRZ (figure S12) and the whole study area (figure S13) for the simulations of AAB. In this study, we assumed that the distribution of the number of fires was constant across all time periods to isolate the effect of change in FS and AAB.

To be conservative, we also simulated AAB with truncated FS distributions for each zone. Specifically, we set the probability values of FS greater than the maximum observed size to zero, and the remaining weight was shifted evenly to the rest of the distribution. This ensured that no values greater than the maximum observed FS would be sampled in the simulations of future AAB. Given that the two sets of results showed similar patterns of changes (~2%–15% among HFRZ), we did not include the results of the truncated simulations here.

2.5. Analysis

For both FS and AAB, the median ratios between the future and the baseline time periods were calculated to demonstrate the predicted future changes. A ratio of the ranges (i.e. difference between 2.5th and 97.5th percentiles) was also calculated for both FS and AAB.
to show changes in variation of both measures. The future percentile values of both FS and AAB corresponding to the 99th percentile in the baseline time period were also calculated. A future percentile value that is less than 99 indicates that a currently rare extreme fire event is expected to become more common. In these instances, the difference between the values of each future percentile and the existing 99th percentile corresponds to a 100% increase in occurrence per point. For example, a future percentile value of 98 corresponds to a 1% reduction from 99, therefore it represents a 100% increment in occurrence of such extreme fire events in the baseline time period.

In order to understand the impacts of considered factors such as time period (TP), GCM, and RCP on both FS and AAB, we performed a mixed-effect analysis of variance (ANOVA) model (Zuur et al. 2009) considering HFRZ as the random factor, and time TP (3 levels), GCM (3), and RCP (3) as fixed factors. Dependent variables include the median and range ratios between the future time periods and the baseline for both FS and AAB. All analyses were carried out in R (R Core Team 2019).

3. Results

Rate coefficients derived from the power relationships are indicators of how fast FS increases with the number of spread days. The rate coefficients among various HFRZs can be roughly grouped into four categories (figure 2(A)). HFRZs with the highest rate coefficients, which show the most efficient fire growth, are located in northeast; HFRZs with lowest rate coefficients are predominantly in the west (figure 2(B)). A south-north decreasing gradient of the rate coefficients can also be found in the boreal forests across central Canada. In comparison, the proportion of daily fire weather potential (i.e. potential spread days (PSD)) that translate into realized spread days (RSD) (figure 2(C)) showed somewhat opposite inverse spatial pattern. HFRZs with lower RSD/PSD ratios are mostly in the southern boreal and over the mountain areas in the coastal provinces. In addition, there is a general south-north increasing gradient, that is especially apparent in the boreal forests.

3.1. FS distributions

Summarized over all GCMs and RCP scenarios across the study area, FS are projected to increase over time. The baseline time period average FS was 2747 ha; this is expected to increase to 3626 ha in 2020s, 3618 ha in 2050s, and 4505 ha in 2080s. These changes are equivalent to increases of 20%, 32%, and 64%, respectively (table S1). In the extreme scenario, FS could increase by 203% by the end of the century (table S1; figure 3). Within individual HFRZs, shifts vary widely (figure 4(A)), and the changes range from 3% (NAT and SY) to 85% (SC) in 2020s, 5% (NAT) to 107% (SC) in 2050s, and 11% (NAT) to 162% (LA) in 2080s (table S1; figure 4(A)). GSL, SC, and LA exhibit the largest shifts by the end of the century. The smallest shifts occurred in NAT, EJB, and GBL (table S1; figure 4(A)), which correspond to the Western Cordillera or northeast corner of the study area. The maximum
projected shifts were substantial; 14 out of 16 HFRZs could at least double their average FS by the end of the century, and the projected FS shifts could be more than six times larger in LA and GSL (table S1; figures S14-1, S14-2, and S14-3).

Shifts in the ratio of FS range (between 0.8–2.9) are slightly greater than those in median FS (between 1.0–2.6) with climate change, and the most obvious changes are in the eastern HFRZs (figure S15). Five HFRZs including SC, IC, WS, GBL, and SY (figure S15) showed consistently lower shifts in comparison to the whole study area. The FS range shifts in central and eastern HFRZs (including WJB, LA, ET, WO, EJB, ES, LW, and NAT) are typically more pronounced (table S2; figure S15), and FS in these zones are therefore more variable. Among all HFRZs, except SY, the average FS range shifts ranged between 8% (SC)—80% (WJB) in 2020s, 22% (WS)—107% (ET) in 2050s, and 34% (SC)—185 (LA) in 2080s (table S2). FS are less variable in SY; this area showed negative changes (table S2).

3.2. AAB distribution

Averaged across three GCMs and three RCPs, AAB for the whole study area show positive shifts (figure S2) of 25%, 45%, and 93% in 2020s, 2050s, and 2080s respectively. This is equivalent to changes from a median of 2.57 Mha at the baseline time period to 3.21, 3.73, and 4.96 Mha in the three future time periods (table S3), or changes from burning 0.65% to 0.81, 0.94, and 1.25% of the Canadian forested lands (~396 Mha) annually. AAB increases are greater in GSL, LW, LA, WS, and P, which are mostly in the western part of Canada (figure 4(B)), whereas relatively smaller increases were observed mainly in eastern Canada (NAT, EJB, and ET) and the Rocky Mountain area (SY, IC, and GBL). The most substantial changes occurred in GSL and P, with the smallest shifts happening in NAT and ET. The range of changes was between 12% (NAT)—47% (GSL) in 2020s, 24% (ET)—72% (P) in 2050s, and 42% (NAT)—113% (GSL and P) in 2080s. For extreme climate change scenarios (maximum changes under RCP8.5), in comparison to the baseline-period, AAB values are more than doubled by 2080s for 15 HFRZs, five of which are more than quadrupled (table S3; figures S16-1, S16-2, and S16-3).

Overall, the spatial patterns of shifts in AAB are similar to that in FS: there are higher median shifts in western Canada and higher range shifts in central to southeastern Canada (figure 4). Magnitudes of AAB range changes over time are larger than the baseline, indicating that in the future AAB will not only become larger (figure 3; table S3), but also more variable from year to year (table S4; figure S17). Among all HFRZs, except SY, the ranges of AAB increased between 11% (ES)—186% (ET) in 2020s, 28% (WS)—228% (ET) in 2050s, and 51% (NAT)—319% (LA) in 2080s. The most substantial shift was observed in ET, LA, and WJB, whereas the lowest was in SY, which became less variable with climate change (table S4). Spatially, the lowest increases are in northeast Canada (NAT, EJB, and ES) and the Rocky Mountain range (SY, SP, GBL, and IC). The most substantial changes are consistent in central to southeastern part of the boreal forests (LA, ET, WJB, LW, and GSL) (figure S17).

3.3. Potential for extreme fire events

Averaging across three GCMs and RCPs, the percentile values of FS and AAB corresponding to the baseline’s 99th percentiles shrink below 99 (tables S5 and S6), indicating that fire events currently considered to be rare under baseline conditions are expected to become more common. By the end of the century, an extreme fire (i.e. 99th percentile in the baseline) are projected to be about 2 (SC) to 9 (WJB) times more frequent than the baseline (table S5); in addition, 99th percentile values of AAB are projected to be 3 (WS) to 23 (LA) times more frequent. SY is the exception in both cases, with only slight changes in extreme fire frequency projections and no drastic changes projected in AAB (table S6). Generally, more pronounced changes are projected to be in the boreal forests in Canada, this is especially true in AAB (table S6). Across the country, what are currently considered extreme large fires may occur 2.5 times more frequently (table S5). Moreover, extreme fire years in terms of AAB may occur 26.4 times more frequently (table S6).

Results from the mixed effect ANOVA, which was used to estimate the contributions of the three considered factors, showed that RCP and TP are the most influential factors for the shifts and variation in FS and AAB (table S8), whereas GCM contributes the least to the changes in FS and AAB. Although HadGEM2-ES model did project greater changes than the other two GCMs used in the study (figures S14 and S16), the overall projected directions of change is the same as the other two GCMs. The significant interactions between TP and RCP, which has also been reported in earlier studies (Wang et al 2016, 2017), was caused by the increasing precipitation prediction in CanESM.

4. Discussion

This study introduces a new approach that links the daily fire weather potential to FS and AAB. Although fire duration and FS are intrinsically connected (Mcarthur 1968, Van Wagner 1969, Xi et al 2019), it is more specifically the number of ‘spread days’ that determines FS. Shifts in projected FS over the current century are proportionally smaller than
those of the AAB; increases of 20%–64% in average FS over the study area may result in increases of 25%–93% in average AAB. This would only be possible when increase in FS is disproportionately higher for the large fires (i.e. the right tail of the FS distribution) (figure 3). As further evidence, we found that extreme fire events (99th percentile in FS and AAB for the baseline time period) are projected to at least double or triple, respectively, by the end of the century.

By the end of the century, the average fire year under the extreme scenario may result in ~11.00 Mha burned, which represents 2.78% of the current total forested lands in Canada and is 4.27 times greater than that of the baseline. If this extreme scenario is borne out, AAB would be 4 Mha greater than the most extreme fire year in Canadian modern history (~7.0 Mha in 1989) (Hanes et al. 2019). Even in the most conservative scenario, the overall AAB would be ~16% greater than that of the baseline by the end of the century. However, these results assume no increase in the number of fires per year. The scale of increment in AAB could further increase if fire occurrences increase by 70%–150%, as has been reported in some studies (e.g. Krawchuk et al. 2009, Wotton et al. 2010), and the extent of AAB increase would be on
Figure 4. (A) Average or median baseline fire size (FS) and mean FS shifts (median-ratios) between future time periods and the baseline summarized across all GCMs and RCPs (remaining maps). (B) Average baseline AAB and mean AAB shifts (median-ratios) between future time periods and the baseline summarized across all GCMs and RCPs.

The magnitude of projected change in FS and AAB vary greatly across the country. With respect to FS, three hotspots for change could be identified: the Northwest Territories and northern parts of the Prairie Provinces, the Rocky Mountain area, and northern Ontario (figure 4(A)). Similar patterns of change can also be found in AAB (figure 4(B)), but these projected increases, which are more concentrated in the north, are geographically widespread (i.e. covering more HFRZs). Although the median changes in AAB are somewhat greater than that in FS across the whole country, certain HFRZs show projected changes in FS that exceeded their shifts in AAB. This situation may be explained by the FS distribution for a given area: a larger proportion of small- or moderate-sized fires will yield a change in mean fire size that is greater than AAB, whereas the opposite (and the more common case) will occur if the proportion of the largest fires increases (Cui and Perera 2008).

Our results show that the rate of fire weather potential being realized into actual fire growth varies
greatly across the study area. The decreasing north-south gradient of 'burn efficiency' may partially be attributed to the high suppression success in the south (e.g. Ward et al 2001, Cumming 2005), where only fires exhibiting extreme behavior are likely to escape and grow large. These escaped fires may burn faster on average than those in the north, where many fires are not suppressed and burn for a longer time period, making it possible for them to grow large under more moderate conditions. Secondly, the longer day lengths and potentially longer burning periods during the day associated with higher latitudes may also contribute to the decreasing north-south gradient. The very high burn efficiency in northeast Canada might be explained as follows. Weather conducive to large wildfires in northeast Canada is less common (Wang et al 2014); however, given the strong dominance of coniferous fuels (considered more flammable than deciduous forests), fires can grow rapidly and become very large under the right weather conditions (Erni et al 2017). In the Rocky Mountain area, where burn efficiency is low, we speculate that the rate of fire growth changes with the altitude due to the changes in weather condition, fuel type, and slope. Fires may grow faster at lower elevation because of the more fire conducive weather condition, but detection and suppression of fires are also enhanced at lower elevations because that is where the people and resources are. With elevation increases, fuel may become a constraint and limit fires from growing in bigger size.

The relationship between spread days and FS could be modeled in two groups of nonlinear regression models: the power regression model and the sigmoidal model. To appropriately fit a sigmoidal curve, which may reflect some intrinsic limitation of the landscape (i.e. bottom-up controls such as topography and fuel availability), a range of all possible FS from observations would be necessary. Without this information, the model may 'plateau' at an artificially low FS value at the higher end of the range. As a result, it may fail to project the potential FS when environmental conditions (i.e. top-down controls from fire conducive weather) allow bigger fires to grow. Because the fire records from our study cover a relatively short period of time (30 years), we chose a power function to model the relationship between FS and number of spread days. The limitation in the power regression model, however, is that the predicted FS may become so unrealistic that it surpasses the biggest continuous fuel patch in the study area. After comparing the projected largest FS to the largest continuous fuel patches in each HFRZ, we found no instances of predicted FS exceeding available fuels, but concede that fuels can assuredly be limiting locally. By comparing the projections of AAB to those obtained from truncating the maximum FS, we were able to verify that the power-law function was not substantially over-projecting the AAB.

In this study, we successfully used a copula method to capture the correlation structure between FS and fire occurrence and create a joint distribution for simulations. Because FS and fire occurrence have a non-linear correlation structure, it is very difficult to create a universal relationship between the two. However, it is important to consider these joint fire regime parameters when projecting future fire activity because measures of fire activity are inherently linked to one another. A hotter and drier fire season may cause more fire ignitions and lead to larger fires (e.g. >200 ha), and ultimately greater AAB. Such linkages make the simulations of AAB more complicated if both FS and number of fire occurrences are modeled jointly (e.g. Venevsky et al 2002, Westerling et al 2011, Veraverbek et al 2017). As such, we believe our method provides an improved, and likely more realistic, projection of future fire activity potential in the boreal forest.

Although wind speed may be the primary meteorological factor affecting the fire growth of an individual fire, numerous studies suggest temperature is the most important variable affecting overall annual wildland fire activity, with warmer temperatures leading to increased fire activity (cf Flannigan et al 2005, 2009, Parisien et al 2011) and intensity (Wotton et al 2017) at the spatio-temporal scale of our study. Although projections in precipitation may vary across Canada, these are projected to be largely overwhelmed by substantial increases in temperature, especially in the northern part of the study area (e.g. Balshi et al 2009, Flannigan et al 2016, Zhang et al 2019). Extreme weather events such as prolonged droughts or violent surface winds are implicitly reflected in the increase of number of spread days, and eventually in fire size and AAB. The projected increase in variation of both FS and AAB (i.e. ranges) in the future is a reflection of the climate change impacts on an overall more severe fire regime (Wang et al 2015), but also on a more unpredictable nature of fire activity (e.g. Moritz et al 2012, Boulanger et al 2018). A relatively small average increase in number of spread days (i.e. FS) or AAB might not seem significant, but the increase of upper extreme fire activities might easily overwhelm the current fire management capacity (Podur and Wotton 2010). Our results also show that most changes in FS and AAB are projected to occur in the northern part of the country, where a large proportion of fires are not suppressed (Magnussen and Taylor 2012). Persistent weather extremes in the Northern Hemisphere's summer may be due to the weakening jet stream (e.g. Coumou et al 2014, Mann et al 2017). These changes have caused more frequent heat waves and prolonged droughts, which are conducive to more frequent larger fires, as shown in this study. Furthermore, research has already suggested that lightning strikes, and hence lightning-caused ignitions,
will increase with increasing temperatures (Romps et al 2014, Veraverbeke et al 2017).

Two main methodologies have been used to provide transfer functions between GCM projections and fire activity: (1) Regression type relationships between average seasonal or monthly climate or fire danger indexes and area burned (Kitzberger et al 2017, Boulanger et al 2018) or annual number of fires within a geographic unit (e.g. Krawchuk et al 2009, Wotton et al 2010, Westerling et al 2011), and (2) Process-based simulation models of ignition and fire growth processes driven by daily weather or fire danger indexes (e.g. Wang et al 2016, Riley and Loehman 2016), LANDIS (e.g. Shifley et al 2009), or dynamic global vegetation models (e.g. Thonicke et al 2001). The first method shows general trends based on annual, seasonal, or monthly varying climate variables with assumptions of static vegetation and fire suppression effects and has moderately low skill. The second family of models allows for introduction of vegetation change in simulations, and indirectly, suppression effects (e.g. Reimer et al 2019); however, it is very computationally demanding and faces the same challenge in future ecosystem projections. The methodology introduced in this study is of intermediate complexity based on relating fire activity to climate extremes (spread days), with the assumption that a large proportion of area burned is related to large fires (≥200 hectares) that are driven by extreme fire weather. By considering individual days that determine FS, the prediction models are robust and could be incorporated into more modeling approaches to potentially increase their accuracy. In addition, this new method is computationally less expensive in comparison to method (2), i.e. hours vs. months for the study area.

5. Limitations

One of the foundations of this study is the definition of a spread day during the life of a fire. Although our approach is a reasonable approximation, a one-size-fits-all approach to defining spread days, it inevitably masks some of the variability. We used a threshold of 1 m min\(^{-1}\) burning 4 h a day to classify spread days as recommended by Wang et al (2014, 2017). Our analysis showed that on the national scale, if the threshold is increased to 2 m min\(^{-1}\), the model fits slightly better. However, with this higher threshold, the number of fires with less spread days increases and more of the bigger fires become binned together as one-day fires; this eventually reduced the sample sizes for fires with more spread days. Consequently, FS and spread day regression models could not be fitted for HFRZs in the northeast of Canada because number of spread days in these areas will rarely surpass three. In response, we chose to use the lower threshold of 1 m min\(^{-1}\) to ensure models could be fitted for all HFRZs across Canada. An optimal spread day threshold may be somewhat area dependent: a higher threshold may work better for areas with active fire ignition and spread, whereas a lower value may be more appropriate for areas with less active fires; however, this remains to be fully assessed.

Other important factors such as ANF (e.g. Krawchuk et al 2009, Wotton et al 2010), changes in vegetation (Wang et al 2016, Marchal et al 2017a), and fire-vegetation feedbacks (Boulanger et al 2017, Tepley et al 2018) and correlation in AAB between HFRZ could be considered in projecting future FS and AAB distributions. This study isolated the effect of spread days on two measures of fire activity (i.e. FS and AAB), which can be further improved with better understanding of these interactions (Stralberg et al 2018). For instance, the depletion of available fuels due to recent wildfire that creates a negative feedback (Heon et al 2014) will assuredly be reinforced in scenarios of increased fire activity (Marchal et al 2019).

In this study we assume that HFRZs will remain constant over the current century and consequently relationships among fire activities (ANF, spread rate, and FS), fuel conditions, and fire management will remain constant through time. However, this assumption is not realistic and requires further investigation. Regardless, there is a strong consensus that increase in FS and AAB in the projections are highly likely to occur due to the changing climate, especially in boreal Canada (Price et al 2015, Cary et al 2017, but see Boulanger et al 2017). However, the pathway of the changes may not only vary due to the changing climate, but also due to changes in vegetation composition, which is more difficult to project (e.g. Girardin et al 2013, Terrier et al 2013). As substantial changes in forest ecosystems are projected by the end of the century (Mbogga et al 2010, Stralberg et al 2018), ANF and FS may be further modified by changing fuel in addition to the change due to climate/weather (e.g. Wotton et al 2010, Kitzberger et al 2017). Because feedback between fire activity and ecosystem composition (i.e. fuel composition) is poorly understood and largely unquantified (Marchal et al 2019), the projected AAB is increasingly uncertain with time.

6. Conclusion

This study demonstrates the importance of considering fire-conducive weather conditions, expressed as fire spread days, when explaining fire size and area burned. Specifically, we developed a simple methodology to translate spread days into area burned, which can be modeled and projected into the future. Our results show that the power-function relationship between fire size and the number of spread days holds over a large range of fire sizes and ecosystems in Canada. However, the rate of conversion varies significantly among areas due to different top-down (e.g. weather) and bottom-up (e.g. fuels, topography) controls on fire regimes. Using a copula to capture the
correlation structure between fire size and fire occurrence allowed us to create joint distributions that were used to estimate annual area burned. Because spread days have a meteorological basis, these relationships could be extended to project changes in fire size and annual area burned in a changing climate. The results showed that across Canada an extreme fire year could be four times more common by the end of the century, and more than ten times more common in the boreal biome (assuming other factors remained constant). That is, an average fire year under the extreme climate scenario may burn ~4 Mha more area than the most extreme fire year in Canada’s modern history (~7 Mha). By accounting for the strong nonlinear expansion of wildfires as a function of number of fire spread days, even conservative climate-change scenarios yield significant increases in fire activity. Adding a single additional spread day to a wildfire that is already large can—and usually does—translate into disproportionately larger growth. As such, our study provides further insights into the mechanisms by which boreal and temperate wildfires can become large and further allows us to refine our projections of fire activity in a more fire-conducive future.

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