

An analysis of controls on fire activity in boreal Canada: comparing models built with different temporal resolutions

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Abstract. Fire regimes of the Canadian boreal forest are driven by certain environmental factors that are highly variable from year to year (e.g., temperature, precipitation) and others that are relatively stable (e.g., land cover, topography). Studies examining the relative influence of these environmental drivers on fire activity suggest that models making explicit use of interannual variability appear to better capture years of climate extremes, whereas those using a temporal average of all available years highlight the importance of land-cover variables. It has been suggested that fire models built at different temporal resolutions may provide a complementary understanding of controls on fire regimes, but this claim has not been tested explicitly with parallel data and modeling approaches. We addressed this issue by building two models of area burned for the period 1980–2010 using 14 explanatory variables to describe ignitions, vegetation, climate, and topography. We built one model at an annual resolution, with climate and some land-cover variables being updated annually, and the other model using 31-year fire “climatology” based on averaged variables. Despite substantial differences in the variables’ contributions to the two models, their predictions were broadly similar, which suggests coherence between the spatial patterns of annually varying climate extremes and long-term climate normals. Where the models’ predictions diverged, discrepancies between the annual and averaged models could be attributed to specific explanatory variables. For instance, annually updating land cover allowed us to identify a possible negative feedback between flammable biomass and fire activity. These results show that building models at more than one temporal resolution affords a deeper understanding of controls on fire activity in boreal Canada than can be achieved by examining a single model. However, in terms of spatial predictions, the additional effort required to build annual models of fire activity may not always be warranted in this study area. From a management and policy standpoint, this key finding should boost confidence in models that incorporate climatic normals, thereby providing a stronger foundation on which to make decisions on adaptation and mitigation strategies for future fire activity.

Key words: area burned; Canadian boreal forest; climate; ignitions; regression modeling; temporal scale; vegetation; wildfire; zero-inflated models.

INTRODUCTION

The boreal forest is the world’s most northerly fire-driven biome, where landscapes are sculpted by large, high-intensity fires that occur episodically (Conard and Ivanova 1997, Burton et al. 2008). Fire histories suggest

that almost all of the North American boreal forest has burned at some point since vegetation became established after the last glaciation (18 000 to 6000 years before present [BP]). However, rates of burning are far from uniform across the boreal forest: Some areas experience fire-return intervals that barely leave time for trees to reach reproductive age, whereas other areas have been fire-free for a millennium or more (Payette et al. 1989, Bergeron 1991, Stocks et al. 2002, Kasischke and Turetsky 2006). Numerous studies of the wildfire–environment relationship have attempted to explain this

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large-scale variation in fire activity (Girardin and Sauchyn 2008, Balshi et al. 2009, Parisien et al. 2011a, Boulanger et al. 2013). Although the results of these studies share similarities with respect to the environmental drivers of fire activity, each paints a slightly different picture of the controls on boreal fire regimes. This divergence is partly due to data being gathered at different temporal and spatial scales, which makes it difficult to compare the role of particular environmental variables in fire activity across the studies.

In the North American boreal forest, where there is usually ample flammable biomass, the occurrence of hot, dry, and windy conditions largely determines when and where fires will burn (Beverly and Martell 2005, Macias Fauria and Johnson 2008, Abatzoglou and Kolden 2011). In fact, this biome is often cited as one in which fire regimes are weather dependent, rather than fuel limited (Meyn et al. 2007, Krawchuk and Moritz 2011). As such, a sensible way to model patterns of fire activity is to explicitly link annual or monthly area burned to the environmental drivers that capture the extremes in fire-conductive weather conditions (Littell et al. 2009, Preisler et al. 2009). However, models that incorporate this temporal variability are typically based on large spatial units, thereby sacrificing spatial variation to the detriment of temporal resolution. In addition, because of the acknowledged importance of weather and climate, and because land cover is relatively static from year to year on a regional level, most models of annually varying boreal fire activity have omitted non-climatic factors (Flannigan et al. 2005, Balshi et al. 2009). As a result, these “annual models” may downplay the role that land cover, ignitions, and topography play in governing fire activity.

There is reason to believe that, at least in some parts of the North American boreal forest, non-climatic factors have a strong influence on fire activity (Parisien et al. 2011a, Gralewicz et al. 2012). For example, fires ignite and burn more frequently in some forest types than in others (Cumming 2001, Krawchuk et al. 2006). Similarly, old-growth forest stands are usually found on islands or on the periphery of large natural fuel breaks such as lakes, where they are shielded from incoming fires (Heinselman 1973, Cyr et al. 2005). To investigate the influence of various climatic and non-climatic factors on fire activity, a number of “distribution” models (Franklin 2010) have been used to model fire activity over the long term (e.g., decades; Krawchuk et al. 2009, Parisien and Moritz 2009, Renard et al. 2012). Because short-term climatic fluctuations are folded into climate normals, such “averaged models” sacrifice temporal variability to focus exclusively on relatively stable spatial patterns of environmental controls. However, because the differences between annual and averaged models have never been examined systematically, it is unknown to what degree this assumption holds true.

A prerequisite to sound environmental management of the Canadian boreal forest is the ability to accurately

model and predict fire activity. The development of robust models allows us to probe the large-scale controls of fire, and further our understanding of this ecosystem process. This is particularly important in northern biomes, where the rates of current and projected change in climate (some of the fastest in the world) may lead to dramatic changes in fire regime (Flannigan et al. 2005, Moritz et al. 2012). These changes will, in turn, affect the ecology of the boreal forest, as well as its carbon dynamics (Chapin et al. 2000). Whereas fire activity is subject to great interannual variability (Burton et al. 2008, Metsaranta 2010), fire–climate–vegetation interactions of the boreal forest vary over long timescales (Carcaillet et al. 2001, Higuera et al. 2009). We thus need to assess and compare variability at more than one temporal scale in order to improve decision-making in forest and fire management. In this study, we present a framework that will help us determine if model outcomes are contingent on the temporal scale of study and, if so, what environmental factors drive short- and long-term variability in fire activity.

The overall aim of this study was to determine whether two types of wildfire probability models (annual and averaged) yield a complementary understanding of the drivers of fire activity in Canada’s boreal forest. The specific objectives were (1) to compare the predictive ability of annual and averaged models of fire activity, (2) to identify the most important environmental factors in each model, (3) to compare the spatial patterns in predicted fire activity between models, and (4) to examine the factors responsible for discrepancies between predictions from the annual and averaged models. To conduct this study, we created annual and averaged models of fire activity for the period 1980–2010 using a suite of explanatory variables describing ignitions, vegetation, climate, and topography. In the annual model, we included the values of dependent and explanatory variables for each of the 31 years from 1980 to 2010; in the averaged model, the dependent and explanatory variables consisted of averages for the 31-year period. To allow for comparison, we used parallel data and modeling approaches for the two model types.

MATERIALS AND METHODS

Study area

The study area is composed of the ecozones of Canada falling within the boreal biome (total area 5 581 096 km²) as defined by the Ecological Stratification Working Group 1995 (Fig. 1). The climate in the study area is characterized by relatively short, warm summers and long, cold winters. There is a broad gradient of decreasing annual mean temperature from south to north and a gradient of decreasing moisture from east to west. The climate can be regarded as strongly continental, with a wide range in temperature throughout the year, but areas close to the coasts do have a maritime influence. The study area covers three major geological zones: the boreal shield (a flat to undulating expanse of

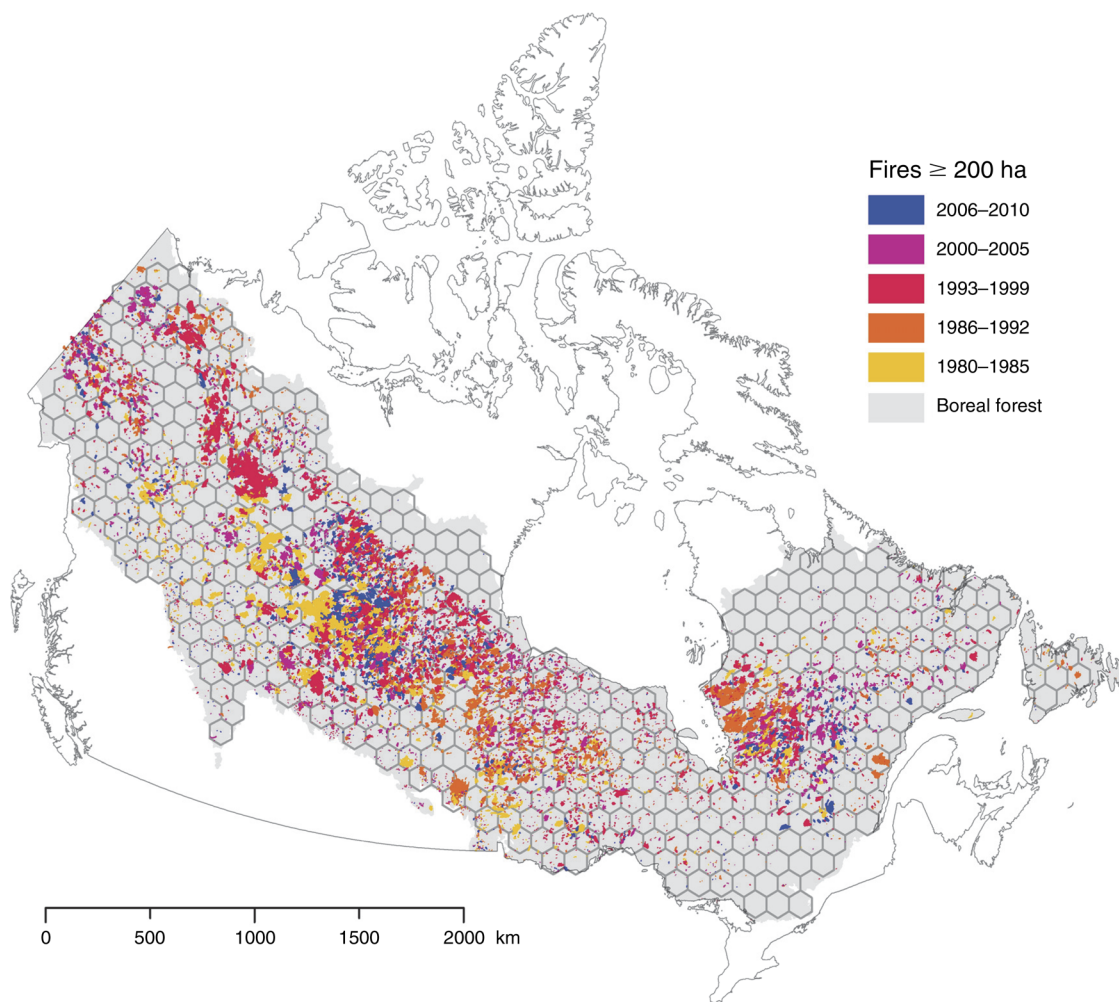


FIG. 1. The boreal forest of Canada (in gray) and fires of at least 200 ha for the period 1980–2010. The hexels on which the data are aggregated are shown outlined in dark gray.

granite and gneiss extending across the study area), the boreal plain (a fairly flat area of deep, marine sediment found in the western half of the study area, south of the boreal shield), and the boreal cordillera (a mountainous area with heavy faulting found in the westernmost part of the study area). Numerous wetlands, peatlands, and lakes are found throughout the landscape.

The dominant coniferous tree species of the study area are white spruce (*Picea glauca*), black spruce (*Picea mariana*), jack pine (*Pinus banksiana*), and lodgepole pine (*Pinus contorta*), whereas the dominant deciduous trees are of the genus *Populus* (*Populus tremuloides*, *Populus balsamifera*). Coniferous and deciduous trees can be found together throughout the study area, but the coniferous fraction generally increases northward. The mix of upland and lowland vegetation types, in conjunction with the numerous permanent landscape features (e.g., bodies of water, exposed rock), creates complex landscape mosaics that influence fire ignition and spread. In general, coniferous forests are more

flammable than deciduous forests in terms of spread rates and fire intensity. Fire is actively suppressed in the southern part of the boreal forest, but the extent of suppression has fluctuated through time and space across the study area according to shifting fire policies and the degree of anthropogenic land use. Human influence, which consists mainly of urban development, agriculture, forest harvesting, and mining, occur mainly along the southern fringe of the study area.

Data sources and selection of variables

We built annual and averaged regression models of fire activity, expressed as annual area burned (AAB), using a suite of explanatory variables describing ignitions, vegetation, climate, and topography for the period 1980–2010. In the annual model, all climate and some vegetation variables were temporally dynamic and were therefore updated annually, whereas variables for which an annual resolution was not available (e.g., ignition density) or irrelevant (e.g., topography) re-

mained temporally static and were held constant. In the averaged model, the dependent and explanatory variables consisted of averages for the 31-year period. We processed model variables using an Albers equal-area conic projection at 1-km resolution, and then averaged them within each 10 000-km² hexagonal pixel (hexels). At the subcontinental spatial extent, studies have shown that this resolution represents a good compromise between capturing sufficient environmental complexity and avoiding too much loss of information due to averaging (Archibald et al. 2009, Balshi et al. 2009, Parisien et al. 2011a). However, we cannot discount the possibility that using a finer spatial scale may reveal different results. For a hexel to be included in the analysis, at least 80% of its area had to fall within the boundaries of the study area, and data were computed only within the boundaries of the study area. A total of 525 hexels were included in the study (Fig. 1).

To ensure that the annual and averaged fire probability models were fully comparable, it was crucial that they incorporate similar explanatory variables. We based our variable-selection decisions on both objective analysis and previous studies of fire occurrence in the North American boreal forest. In addition, we screened potential variables from an initial larger set on the basis of complementarity and ability to describe annual and long-term patterns of area burned. The first step of our variable-selection process was thus to cross-correlate all explanatory variables (Pearson correlations) to identify which variables were correlated above a threshold of $|r| = 0.6$. In parallel, the fit of AAB for both annual and averaged forms was evaluated for each explanatory variable using a self-fitting generalized additive model with a distribution from the negative binomial family (Wood 2006). From each group of correlated variables, we selected one variable on the basis of how well it predicted AAB for both model types. In general, the choice of variable was obvious because some variables performed better than others for both annual and averaged area burned data; where this was not the case, we relied on previous studies to help guide our choice. This filtering resulted in 14 explanatory variables for consideration in building the model (Table 1; Appendix A), which are described in the following sections.

Fire.—We obtained burned areas in Canada for the period 1980–2010 from the Canadian Forest Service National Fire Database (Parisien et al. 2006). We excluded wildfires <200 ha because these fires are subject to inconsistent reporting over time and space. Our data set consisted of 12 228 fires and 108 933 935 ha burned within the boreal forest (Fig. 1). The source fire atlas is largely comprehensive for the study period, but there were some known gaps for northern Ontario and Labrador, where few fires have been reported over the 1980–1994 period. We filled some of the data gaps for these areas and added occasional missing fires that occurred in other remote areas for the years 1995–2010 using coarse-resolution SPOT-Vegetation burned area

maps derived from Hotspot and normalized difference vegetation index differencing synergy (Fraser et al. 2000). Although fires that occurred from 1980 to 1994 are undoubtedly missing in those two areas, we assumed that they would represent a relatively low percentage of the overall area burned, especially given their low propensity for burning compared to other parts of the study areas. Finally, unburned islands were not mapped for many of the fire perimeters in the database, but errors of this type were not expected to greatly affect estimates of area burned at the spatial scale of this study.

We compiled AAB, which was the dependent variable for both the annual and averaged models, from the previously described fire atlas data. For the annual model, we compiled AAB by hexel for each year of the study period. The total number of data points for the annual model was, therefore, 16 275 (525 hexels \times 31 years). As with AAB, each temporally dynamic variable had one value per hexel per year, whereas temporally static variables had the same value for every year. For the averaged model, we calculated the AAB within each hexel for the 31-year period, for a total of 525 data points (one per hexel). Although the annual model had a substantially larger sample size than the averaged model, every data point contained less information with respect to area burned because of the high proportion of zeros (69.2%).

Ignitions.—We used two temporally static variables to describe patterns of ignitions across the study area. We used the density of lightning strikes from the National Aeronautics and Space Administration Global Hydrology and Climate Centre (Christian et al. 2003) for the period 1995–2005 as a proxy for lightning-caused ignitions (Ltg_Dens). This data set covered only 11 years of data and it was not possible to get annual data for our study period. However, because there is ample lightning activity in Canada, we assumed that this period adequately depicted spatial patterns in lightning activity. We used the human footprint variable (Hum-Foot), which was created by the Wildlife Conservation Society through its “Last of the Wild” project (Sander-son et al. 2002), as a proxy for patterns of human-caused ignitions. In concept, the influence of humans can be both positive (more fire) and negative (less fire) on fire activity. Specifically, people living and working in wildlands may cause more ignitions; by contrast, greater access to the forest by people can lead to more effective fire suppression (Syphard et al. 2007). We also initially considered road density as a variable, but because it was highly correlated with the HumFoot variable at the spatial scale of our study it was not included in the model building.

Climate.—A large number of temporally dynamic climate variables were examined as potentially useful explanatory variables. All of these variables were computed for the period 1980–2010 from Environment Canada daily weather station observations (data avail-

TABLE 1. Variables used to model annual area burned (AAB) in the boreal forest of Canada, 1980–2010.

Variable name†	Description (units; status)	Units	Status‡	Mean (range)§
Fire (dependent)				
AAB	annual area burned by fires ≥ 200 ha	ha	dynamic	4552 (1083–14 666)
Ignitions				
Ltg_Dens	annual density of lightning strikes per unit area, for 1995–2005	no. strikes·km ⁻² ·yr ⁻¹	static	1.36 (na)
HumFoot	human footprint, an index of human influence for the year 2005	dimensionless, 0 = lowest, 100 = highest	static	3.80 (na)
Vegetation				
Conif_Pct	land cover of coniferous forest	%	dynamic	43.1 (41.1–45.6)
Wetland_Pct	land cover of wetlands	%	static	18.6 (na)
Nonfuel_Pct	land cover of nonfuel (e.g., exposed rock, open water, glaciers, recent burn)	%	dynamic	28.5 (25.8–30.9)
Water_Pct	land cover of permanent bodies of water	%	static	9.8 (na)
Climate				
MaxTempWarmest	maximum noon temperature of the warmest month	°C	dynamic	21.7 (19.6–23.1)
TempRange	temperature annual range	°C	dynamic	51.2 (45.2–58.1)
Wind90	annual 90th percentile value of wind speed	km/h	dynamic	19.5 (15.9–26.7)
StartGrow	start of the annual growing period	day of year	dynamic	137.1 (125.6–147.0)
CMI	annual climate moisture index (precipitation minus potential evapotranspiration)	mm	dynamic	27.5 (21.0–35.8)
ISI99	annual 99th percentile value of the Initial Spread Index, a CFFDRS¶ index of ease of fire spread	dimensionless	dynamic	14.8 (10.7–25.9)
FWI90	annual 90th percentile value of the Fire Weather Index, a CFFDRS index of fire severity	dimensionless	dynamic	16.7 (12.9–23.0)
Topography				
SurfArea_Ratio	ratio of surface to area, an index of topographic roughness	dimensionless, 1 = flat	static	1.0025 (na)

† Unless stated otherwise, all variables were computed for the period 1980–2010.

‡ Dynamic variables vary from year to year; static variables do not vary over time.

§ The mean represents the average of all hexels among all years; the range shows the minimum and maximum annual values averaged for all hexels (except where “na” is indicated [not applicable]).

¶ CFFDRS is the Canadian Forest Fire Danger Rating System.

able online).⁸ Annual means were calculated for use in the annual model, and these were averaged across all years for the averaged model. The initial set of about 100 variables was composed of various permutations of temperature- and moisture-related measures, as well as the fuel moisture codes and fire behavior indices of the Canadian Forest Fire Weather Index (FWI) System (Van Wagner 1987) for the 80th, 90th, 95th, and 99th percentiles. High levels of correlation among variables allowed us to reduce the climate variable set to a handful of complementary variables.

Seven variables were ultimately selected as metrics relevant to interannual variability and long-term averages in climate. Two aspects of temperature were included as explanatory variables: the maximum temperature of the warmest month (MaxTempWarmest) and the intra-annual monthly variability, expressed as the range in annual temperature (TempRange), which is a measure of continentality. A related variable, Start-

Grow, described the date on which the growing season began, as defined by mean daily temperature of at least 5°C for five consecutive days (McKenney et al. 2011). Wind conditions were described by the 90th percentile of the wind speed variable (Wind90). Two components of the FWI System were included as climate variables: the 99th percentile of the Initial Spread Index (ISI99) and the 90th percentile of the Fire Weather Index (FWI90). The ISI is a measure of the ease of potential fire spread, whereas the FWI is an index of potential fire intensity. Percentile values of wind, ISI, and FWI were calculated from daily observations for the period from 15 May to 15 August, which is when >90% of fires occurred in the study area (Parisien et al. 2011a). We constrained the calculation period to avoid having a confounding factor between the length of the growing season, which is substantially longer at southern latitudes, and other fire climate variables. The final climate variable, the climate moisture index (CMI), is an annual measure of drought conditions that is computed monthly from 1 September to 31 August. In western Canada, the zero CMI isopleth

⁸ <http://climate.weather.gc.ca/>

corresponds to the interface between aspen parkland and boreal forest (Hogg 1994).

Vegetation.—Two temporally dynamic variables were used to characterize the land cover of the study area. Percent conifer cover (Conif_Pct) and percent nonfuel (Nonfuel_Pct) were derived from a time series of five land-cover maps (for the years 1985, 1990, 1995, 2000, and 2005) based on advanced high-resolution radiometer data (Latifovic and Pouliot 2005). The nonfuel variable consisted of the land-cover classes in which fire spread is rare and included urban and agricultural areas, areas of sparse vegetation (including recent burns), and permanent water bodies. The percent deciduous cover was a meaningful variable in the study area, but it was strongly negatively correlated with Conif_Pct and was therefore excluded. Conif_Pct and Nonfuel_Pct were updated annually as described in Appendix B. In short, the five land-cover maps, in conjunction with the annual mapped fire perimeters, were used to annually update the Conif_Pct and Nonfuel_Pct variables. This process assumed that burned areas in the boreal forest do not generally re-burn for a few years (Schimmel and Granström 1997).

We used two additional land-cover variables, both temporally static, to build our fire probability models. The proportion of permanent water bodies, Water_Pct, was computed using the Canada-wide 1-km water fraction (National Topographic Data Base maps; Fernandes et al. 2001). Although open water is included in the Nonfuel_Pct variable, Water_Pct was not strongly correlated with this variable. The percent of wetland cover, Wetland_Pct, was also included as an explanatory variable; this variable was uncorrelated with the Water_Pct variable. The information for this variable was derived from a data set representing polygons of percent wetland cover (Tarnocai et al. 2011) by applying an area-weighted mean of each polygon intersecting the hexels of this study.

Topography.—A single temporally static variable, the surface/area ratio (SurfArea_Ratio), was used to describe topography in our study area. This variable has been found to correlate with fire activity (Stambaugh and Guyette 2008) and was calculated using Canada3D data produced by the Centre for Topographic Information (Natural Resources Canada 2001). Computation was performed at the native 1-km² resolution. SurfArea_Ratio is an index of topographic roughness that captures the effects of slope on fire behavior; it may also be a proxy for other factors, such as fragmentation and difficult-to-characterize microclimates. Because of the coarse spatial scale of analysis, the effect of topographic variables such as aspect and topographic position (i.e., ridge vs. valley bottom) was diminished. In fact, correlations between area burned and aspect (cosine-transformed) and a topographic position index were very low ($r = 0.05$ and 0.02 , respectively). These variables were thus not considered further.

Statistical modeling

Model building.—We used generalized linear models to construct annual and averaged models of AAB as a function of the explanatory variables. The AAB variable, expressed as number of hectares burned, was considered as count data to which a square root transformation was applied, to homogenize the variability in model residuals. Because we were not projecting our models to different geographical areas or different time periods, we did not aim for high generalizability (i.e., parsimony) and instead focused on predictive power. We used a relatively large number of explanatory variables having low correlations with one another. However, as determined through an assessment of Akaike information criterion (AIC) values for single-variable deletions, explanatory variables that weakened the model (i.e., $\Delta\text{AIC} < 0$) were removed.

Several considerations were required to build the most appropriate annual and averaged models (Appendix C). First, we evaluated quadratic terms if the bivariate relationships between AAB and an explanatory variable indicated a “humped” relationship; we subsequently removed these quadratic terms if they were unimportant in the final multi-variable model (i.e., $\Delta\text{AIC} < 2$). Next, we explored interactions between pairs of variables and opted to add two, $\text{MaxTempWarmest} \times \text{CMI}$ and $\text{MaxTempWarmest} \times \text{StartGrow}$, which capture the coincident conditions of extreme temperature with drought and length of the fire season, respectively. The fit of both annual and averaged models benefited substantially from the addition of these interaction terms (i.e., $\Delta\text{AIC} > 2$). Lastly, in the model-building phase, both annual and averaged models used distributions from the negative binomial family; we also evaluated distributions from the Poisson and quasi-Poisson families, but both of these exhibited overdispersion (residual deviance much larger than the residual degrees of freedom) in both model types.

Annual model.—In the annual model, the AAB was zero inflated. That is, the proportion of data points that had a value of zero was higher than that predicted by the Poisson distribution. This phenomenon stems from the fact that, each year, there are many more hexels that do not experience fires (69.2% in our data set) than hexels that do. As such, the annual model used the zero-inflated negative binomial (ZINB) technique from the *pscl* package in R (Zeileis et al. 2008). Zero-inflated models are “mixtures” that combine two sub-model types: The first predicting the occurrence on the basis of presence or absence (1 or 0), and the second being a count model, which uses abundance values but not the zero points. We retained quadratic terms for Conif_Pct and Nonfuel_Pct in the presence-absence sub-model and for FWI90, MaxTempWarmest, StartGrow, and Nonfuel_Pct in the count sub-model. We removed ISI99 and Ltg_Dens because they weakened the model. In addition, because there was spatial autocorrelation in model residuals when we used all samples, as determined

with a correlogram, we built models from a subset of 2500 (out of 16275) randomly sampled data points across all years; this represented the largest number of randomly sampled points that did not generate spatially autocorrelated model residuals. At the same time, using a subset of points for building models avoids overfitting. We generated 100 subset models and averaged their predictions to generate an ensemble model to limit the stochasticity of model outcomes caused by random subsampling of the data (Parisien et al. 2011a).

Averaged model.—The averaged model was built using negative binomial regressions from the MASS package in R (Venables and Ripley 2002). We retained two quadratic terms, for FWI90 and Nonfuel_Pct, because they substantially improved the model. Wind90 and Ltg_Dens were shown to weaken the model and were therefore removed. An analysis showed that autocorrelation existed in residuals of the averaged model; using 100 subsets of 200 data points (out of 525) was deemed adequate to fix this problem.

Evaluation of models and importance of variables.—We used two metrics to evaluate the predictive ability of the annual and averaged models. The first metric consisted of binning the observed counts in AAB (i.e., hectares burned) and assessing the proportion of the predicted counts that fell into the wrong bin (Lambert 1992). The second metric consisted of examining the correlation between observed and predicted counts. We evaluated the model built from each of the 100 subsets against the full data set.

The contribution of each explanatory variable to each model was evaluated by measuring the relative increase in AIC when each variable of interest was removed from the full model. The relative contribution of each variable, expressed as a percentage, consisted of the proportion of change in AIC attributed to each variable deletion relative to the total change in AIC for every variable. In addition, we examined the relationships between a few selected explanatory variables and the modeled AAB for the annual and averaged models by plotting the response of each variable when all other variables are held constant at their mean values (hereafter, “partial dependence plots”).

Spatial comparison of annual and averaged models.—We mapped predictions from the annual and averaged models and identified discrepancies among the predictions. The annual and averaged models both produced an estimate of mean AAB over the 31-year period, but the manner in which they obtained the estimate differed. The predictions from the averaged model had the same form as that of the dependent variable (31-year averages), whereas those from the annual model consisted of means of predicted area burned of each modeled year. As such, the negative binomial and ZINB modeling techniques produced predictions that differed sufficiently in their range to limit our ability to compare the model outputs. We therefore opted to scale and zero-center the model predictions. Although applying this

adjustment resulted in the loss of the absolute predicted values of AAB, it enabled the comparison of spatial patterns, which remained intact. The metric used to compare the annual and averaged models was the absolute change, whereby the scaled probability value of each hexel from the averaged model was subtracted from that of the annual model.

A separate exercise was undertaken to determine which explanatory variables were most responsible for the differences in predictions from the annual and averaged models. This analysis should be considered exploratory, rather than predictive. Using the rpart package in R (Therneau et al. 2013), we built regression trees of the absolute difference in fire probability between the annual and averaged models. In addition to the explanatory variables used in the averaged model, we included variables measuring the standard deviation of dynamic variables (calculated on a per-hexel basis) to account for interannual variability. The combination of explanatory variables that made up each terminal branch was mapped. The number of branches of the tree was determined as a function of the variance explained and the relevance of mapped patterns.

We opted to use a regression tree for exploring the differences between the predictions of the annual and averaged models because it provides a visual representation of fairly complex combinations of environmental factors. However, predictions of a regression tree are not as robust as those of more sophisticated tree techniques (e.g., boosted regression tree [BRT], random forest [RF]). Unfortunately, because many trees are built using BRT and RF, the results cannot be visualized like those of a regression tree. To test whether the regression tree approach was acceptable for the purpose of this analysis, we carried out parallel analysis using BRT and RF. These tests revealed that, in this case, the most sophisticated methods pointed to largely the same conclusions as those of the regression tree.

RESULTS

Evaluation of models and importance of variables

Both annual and averaged fire probability models performed well when we used negative binomial and ZINB regressions, respectively, with the selected set of explanatory variables. Compared with the observed data used to build the models, the annual model over-predicted AAB, by about 2% on average, in hexels with the lowest class of area burned (0–49 binned square root (sqrt) of the annual area burned [ha]); over-predicted AAB, by about 5% on average, in the intermediate class (50–99 sqrt[ha]); and predicted AAB fairly accurately in classes with large area burned (≥ 100 sqrt[ha]) (Fig. 2). The averaged model under-predicted AAB, by about 4% on average, in hexels with the lowest class of area burned (0–24 sqrt[ha]); over-predicted AAB, by about 7% on average, in the intermediate class (50–74 sqrt[ha]); and predicted AAB fairly accurately in classes with large area burned (≥ 75 sqrt[ha]) (Fig. 2). The overall

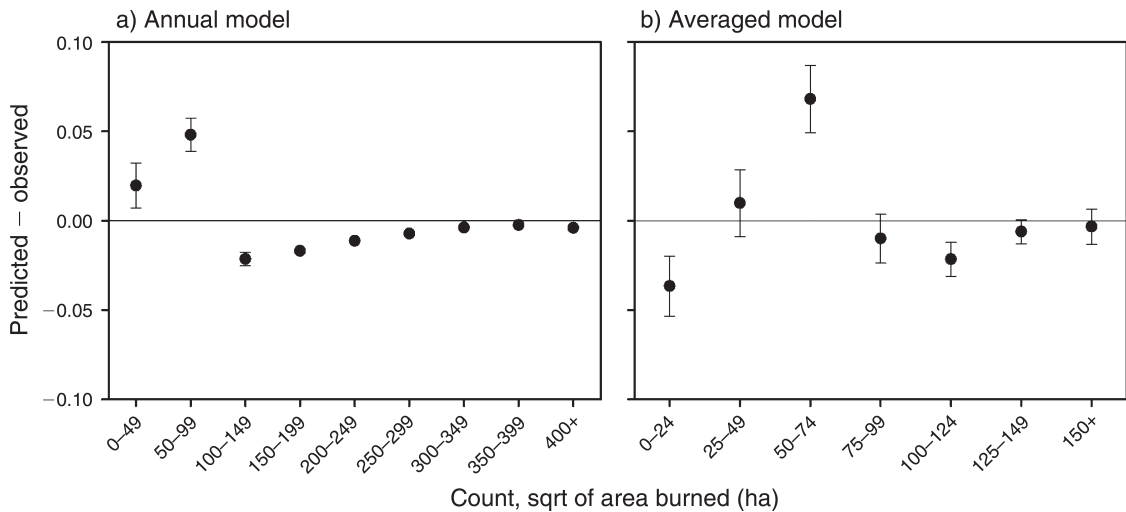


FIG. 2. Assessment of the prediction accuracy of the (a) annual and (b) averaged models. The x-axis represents the binned square root (sqrt) of the annual area burned. The y-axis represents the mean proportion (\pm SD) of misclassification of the model prediction relative to the observed values for each x-axis bin. The results were computed from 100 model subsets.

correlations between predicted and observed values were 0.754 and 0.803 for the annual and averaged models, respectively.

We found similarities and differences among contributions of the explanatory variables to the annual and averaged models (Fig. 3). MaxTempWarmest, Nonfuel_Pct, and CMI were important in both model types. Conif_Pct and FWI90 were dominant in the annual model, but not the averaged model, whereas StartGrow was highly important in the averaged model but not the annual model. Because it would be somewhat redundant

to evaluate the contributions of variables for both main effects and interactions (Venables and Ripley 2002), only the main effects are reported here. However, when we ignored the main effects and focused on interactions, we found that the MaxTempWarmest \times CMI and MaxTempWarmest \times StartGrow interactions were both very important in the averaged model (contributions of 17.1% and 45.1%, respectively); the MaxTempWarmest \times CMI interaction was also important in the annual model (9.7%), but the MaxTempWarmest \times StartGrow interaction was not (1.5%).

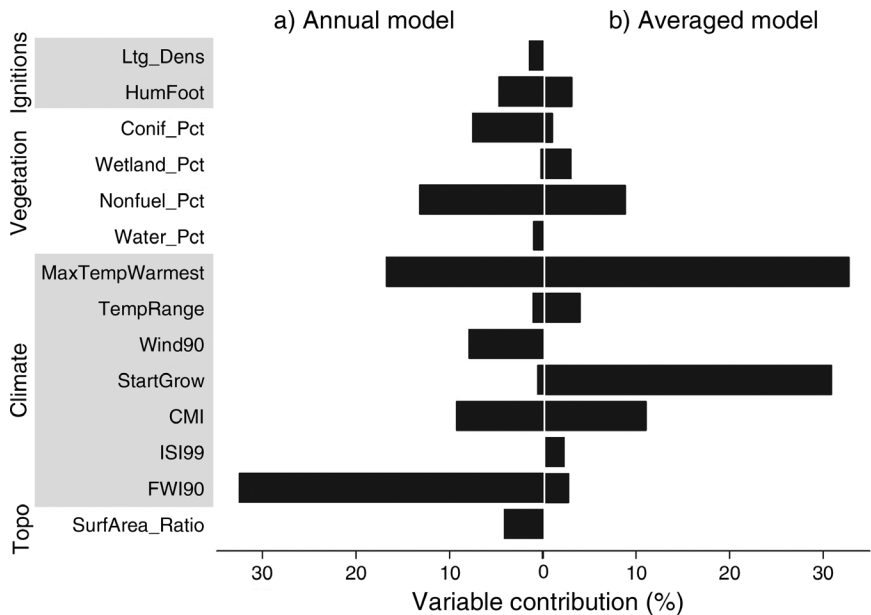


FIG. 3. The percentage contribution of each explanatory variable to the (a) annual and (b) averaged models, averaged for the 100 model subsets. See Table 1 for descriptions of variables; Topo stands for topography.

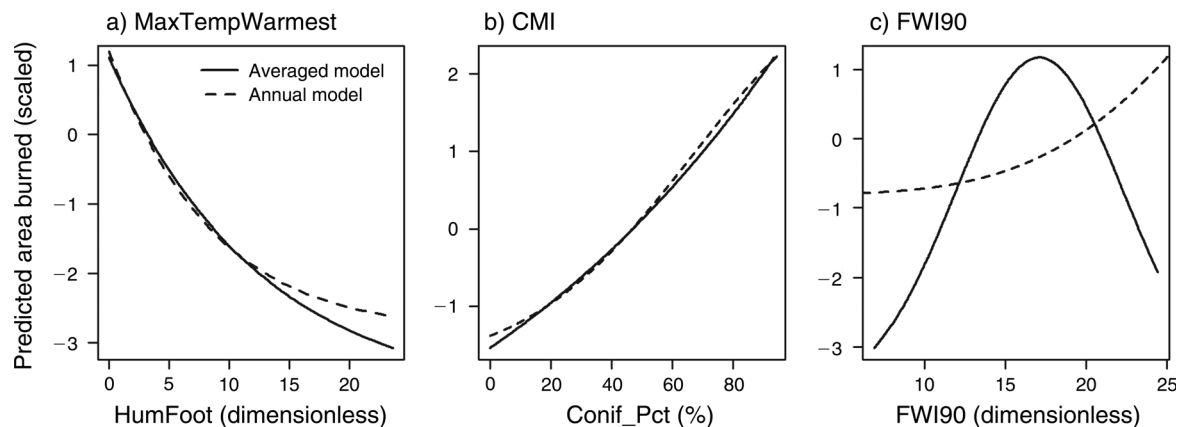


FIG. 4. Bivariate relationship between predicted annual area burned and three explanatory variables: (a) MaxTempWarmest, (b) CMI, and (c) FWI90. See Table 1 for descriptions of the variables. The y-axis values consist of the scaled predictions from the annual model and the averaged model.

The partial dependence plots of the predicted AAB and HumFoot, Conif_Pct, and FWI90 also showed both similarities and divergence between the annual and averaged models (Fig. 4). The $AAB \times HumFoot$ and $AAB \times Conif_Pct$ relationships were similar for the two model types. In contrast, the response of AAB to FWI90 differed substantially between the annual and averaged models: AAB was predicted to increase somewhat monotonically with this variable in the annual model, whereas the response was unimodal in the averaged model. For the annual model, the predicted AAB was also proportionally higher at lower levels of FWI90.

Spatial comparison of annual and averaged models

Spatial patterns in predicted AAB (scaled) from the annual and averaged fire probability models (Fig. 5a, b) were broadly similar across the study area, but varied substantially within some regions. Both models depicted essentially the same core area of highest AAB, which was a mid-latitude area spanning the middle longitudes of the study area and extending to its northwestern end. However, there was less agreement among models at the periphery of this core of high AAB (Fig. 5c). In general, higher values for the annual models dominated the western part of the study area, whereas higher values for the averaged model dominated the central and eastern parts of the study area. Areas of positive or negative change were generally clustered and covered large tracts of the study area. An exploration of model residuals (observed – predicted) showed that, on average, the annual model performed better where there were high observed values of area burned, whereas the averaged model generally performed better for low values of area burned (Appendix D).

The regression tree analysis (Fig. 6) showed that showed that differences in values of absolute change (Fig. 5c) were related to some of the explanatory variables. Therefore, as modelled, some combinations of environmental conditions yielded higher predictions

of fire activity in one model type than in the other. The full (unpruned) regression tree explained 65% of the variance, but it was too complex and over-fitted to be useful. A trimmed model, with eight terminal branches, was deemed more useful for presentation and still explained 47% of the variance. The top-splitting variable was CMI, whereas the second set of nodes used Conif_Pct and Conif_Pct_var, which is a measure of interannual variability in the Conif_Pct variable. Other important splitting variables at the third and fourth level were MaxTempWarmest, StartGrow, FWI90, and Surf-Area_Ratio. The environmental conditions described by the terminal nodes were strongly spatially coherent with the main clusters of positive and negative change in predicted fire probability between the annual and averaged models (compare Fig. 5c and map in Fig. 6).

DISCUSSION

Temporal resolution and environmental factors driving fire activity in boreal Canada

Issues related to temporal resolution are central to understanding ecological processes in general (Jentsch et al. 2007, Thompson et al. 2013). The fire regimes of boreal North America, like most other fire regimes around the world, are controlled by environmental factors that vary as a function of temporal scale ranging from days to centuries (Whitlock et al. 2010). As a result, some authors have suggested that models built using short-term (e.g., annual) variables and those built with averaged long-term (e.g., multi-decadal) variables likely provide complementary information (Moritz et al. 2012, Boulanger et al. 2013). The results of this study appear to confirm this intuition and allow us to identify where, and to some extent why, some of these differences occur. Even though our results were broadly coherent with those reported in the literature, the fact that non-climatic factors (i.e., ignitions, land cover, and topography) were roughly as influential in the averaged models of fire activity as they were in the annual models

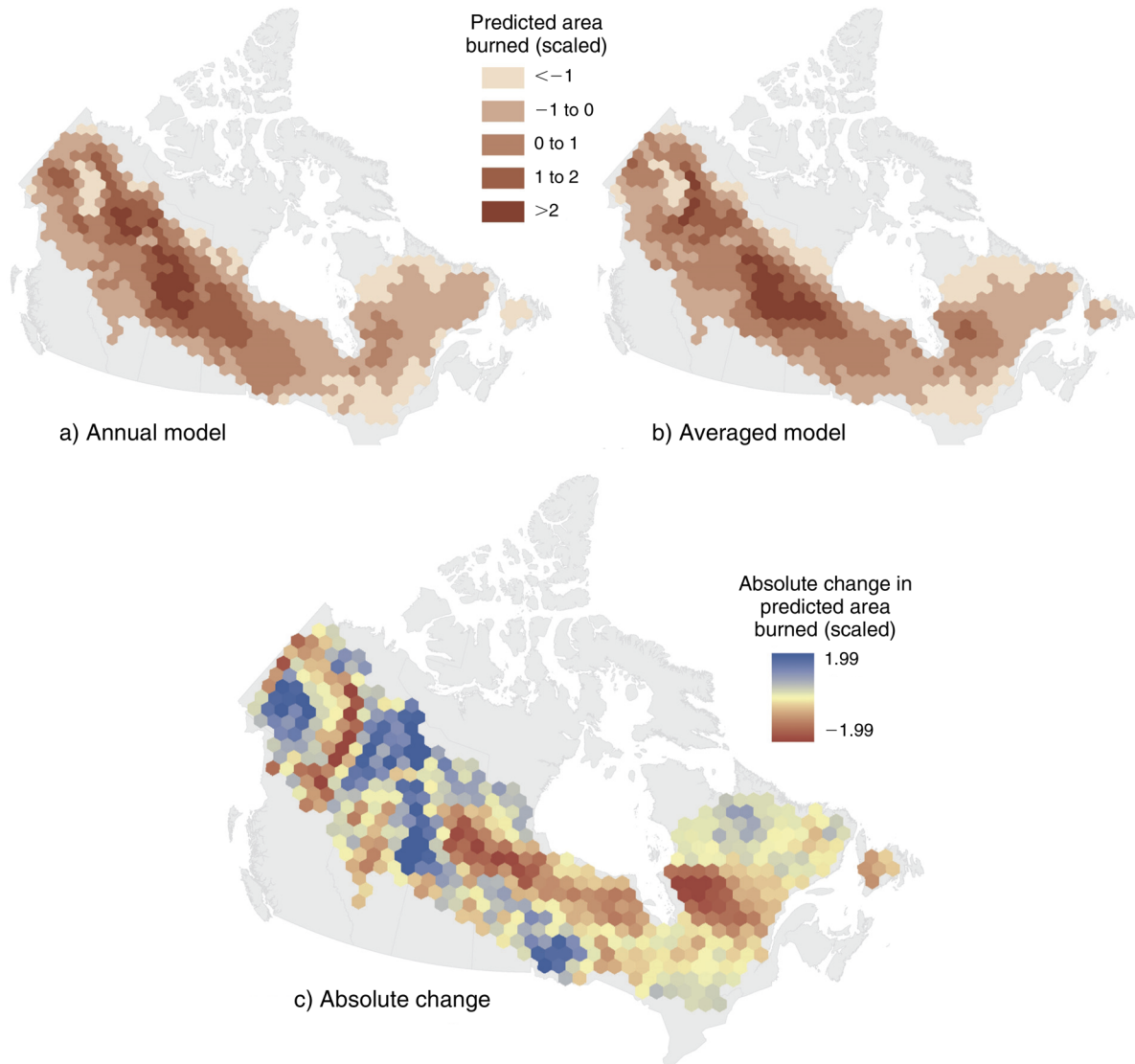


FIG. 5. Predicted fire probability for the (a) annual and (b) averaged models, averaged for the 100 model subsets. Values were scaled and centered for the purpose of comparison. The (c) absolute change from the annual to the averaged model is also shown; positive hexels (blue) indicate a higher fire probability in the annual model than in the averaged model, whereas negative hexels (red) represent a lower fire probability in the annual model.

countered our expectations. Conversely, variables characterizing climate performed equally well in the annual and averaged models, but ostensibly characterized different aspects of the fire environment.

This study provides further support that, across large geographical areas, wildfire patterns are controlled by combinations of conditions capturing potential fire-conducive weather, flammable biomass, and an ignition source (Krawchuk et al. 2009, Parisien and Moritz 2009). Our study reiterates the importance of extreme weather and climate across the boreal forest as a primary control on area burned, as observed in previous studies (Flannigan et al. 2005, Girardin et al. 2006, Balshi et al. 2009); however, it also shows that weather

and climate on their own cannot explain all of the variation in fire activity in boreal Canada, regardless of the temporal scale of study. Bradstock (2010) proposed a conceptual model whereby four environmental “switches” (biomass, availability to burn, spread, and ignition) must be turned on for a fire to happen. In fire regimes that are limited exclusively by weather (i.e., not limited by fuel availability), the biomass switch is always turned “on.” Some researchers have assumed that this is the case for the boreal forest, but our results suggest that this assumption may not always hold true due to the importance of the conifer and nonfuel percentages, both of which largely vary from year to year as a function of fire activity, in the annual model.

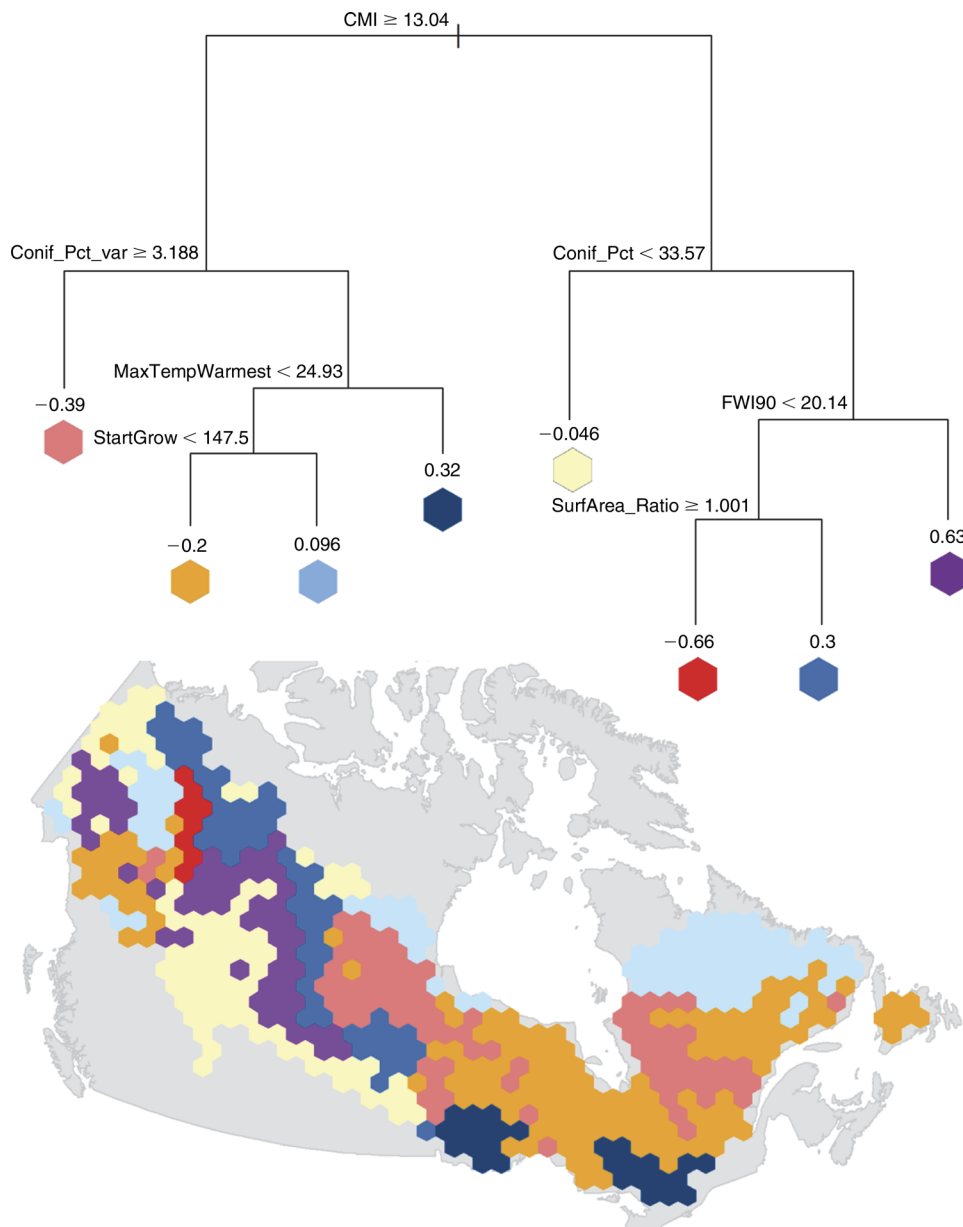


FIG. 6. Regression tree model of the absolute difference in fire probability between the annual and averaged model, as shown in Fig. 5c. The explanatory variables used are those of the averaged model, as well as additional variables representing the interannual variability (standard deviation among years) in the dynamic variables (e.g., *Conif_Pct_var*). Branch length is proportional to the importance of the splitting variable. The left branch is followed when the logical condition is true. The values of the end branches represent the mean absolute difference in fire probability; each end branch is color coded and mapped on the study area.

One surprising outcome of this study was that, even at the fairly coarse spatial scale of study, the interannual changes in land cover resulting from fires modified predictions of area burned. The combined contribution of the *Conif_Pct* and *Nonfuel_Pct* (20.7%), which are dynamic in the annual model is considerably higher than that of the averaged model (9.9%), where these variables are static. This suggests that in the annual model, for a given hexel, fire is sometimes limited by lack of available fuel, even though weather conditions may be suitable.

This observation lends credence to the idea of a feedback mechanism in the boreal forest, whereby high fire activity in some years decreases the potential for fire for a number of subsequent years (Higuera et al. 2009, Johnstone et al. 2010, Krawchuk and Cumming 2011). This said, the annual model likely still understates the importance of dynamic vegetation given the somewhat coarse method used for annually updating the vegetation and that, given their size, only a small fraction of a hexel will burn in any given year. Landscape-scale

studies show that at a fine spatial resolution fuels can be the dominant control on spatial fire probability (Parisien et al. 2011b).

Although this study focused on the effect of temporal scale, it must be acknowledged that the results are partly a function of the spatial scale of study. Whereas some variables may be fairly scale independent, others (notably those describing “bottom-up” controls; e.g., fuels, topography, and ignitions) are strongly dependent of the spatial scale of observation (Parks et al. 2011, Liu et al. 2013). The rather coarse spatial resolution used for this study (10 000 km²) is appropriate for the subcontinent extents, but invariably masks fine-scale relationships. This is the case, for instance, with topography. Variables such as aspect and topographic position, which influence patterns of area burned in mountainous parts of the boreal forest (Kasischke et al. 2002), are uncorrelated to area burned at the spatial scale of our study. It must be noted, however, that most of the Canadian boreal forest is rather flat.

Fire probability models built at different temporal resolutions effectively measure different aspects of the fire environment (Abatzoglou and Kolden 2011). In the annual model, area burned is strongly related to FWI90, the 90th percentile of the Fire Weather Index, which is a strong predictor of fire activity in Canada that is used operationally (Flannigan and Harrington 1988). Our results thus support those of Drever et al. (2008), who showed that measures designed to predict fire risk were the best predictors of interannual patterns of area burned and that the fire response increased monotonically with these measures. By contrast, areas experiencing the most frequent fire-conducive conditions over a long period, as depicted in the averaged model, did not correspond to the areas of highest fire activity in boreal Canada because these tend to support less flammable (i.e., deciduous) vegetation (Hogg 1994). Annual and long-term measures are therefore complementary: The annual resolution depicts patterns in fire danger, whereas long-term climate captures both fire danger and patterns of flammable biomass (Pausas and Paula 2012). The length of the growing season and the potential for drought, which were two of the top contributors to the averaged model, also exert this dual effect on long-term fire activity, but they interact mainly with maximum temperature (Krawchuk et al. 2009, Moritz et al. 2012). In fact, our results strongly support those of Ali et al. (2012), who showed that the combination of high temperatures and an early start to the growing season yields appreciably higher area burned in the eastern boreal forest of Canada.

Although patterns of fire ignitions are highly variable across the boreal forest in Canada (Boulanger et al. 2012), the contribution of ignitions to fire activity, as measured in this study, was minimal compared with those of climate and vegetation. This difference was partly due to the unavailability of annually updated data; for instance, patterns for lightning might have had

a stronger relation to area burned if high-quality data at an annual resolution had been available for analysis (Nash and Johnson 1996, Parks et al. 2012). Similarly, human activities appear to affect annual and long-term patterns of area burned in the North American boreal forest, but their effect is comparatively weak. Our results are coherent with those of Graliewicz et al. (2012) in Canada, who observed a decreasing relationship between area burned and human activity, but somewhat counter to the humped relationship observed by Calef et al. (2008) in Alaska. Admittedly, the anthropogenic effect on area burned was not fully captured by the human footprint metric. Given the rate at which humans are changing the boreal forest, it is imperative to gain a better understanding of their role in fire regimes. However, this is a complex issue: Even though projected climates will be generally more favorable to fire ignitions (Wotton et al. 2010), a strong human presence appears to limit fire activity through direct attack or land-use change (Cumming 2005, Martell and Sun 2008). Parisien et al. (2012), referring to the conterminous United States, and Stephens et al. (2007), referring specifically to California, have suggested that humans may have had an overall dampening effect on area burned over the past century. However, the net influence of humans on area burned in Canada is still unknown.

Modeling considerations

It might be asked whether the annual or the averaged modeling approach is most appropriate for modeling fire activity over time in Canada and other fire-driven biomes. Ultimately, the decision as to which temporal resolution is best should depend on the specific objectives of the study, the data sets available, and the sensitivities of fire to temporally dynamic vs. temporally static conditions. If the aim is to examine interannual variability or to forecast individual years, the annual model is most appropriate; however, if the aim is to define the envelope of conditions in which area burned and flammable biomass reside, it may be preferable to use the averaged model. Regardless, both types of fire–environment models developed in this study performed similarly well and can be considered good predictors of fire activity over the 31-year period. However, from a practical standpoint, it is much more difficult to generate models with high temporal resolution; therefore, if time or resources are constrained, it may be preferable to use the averaged modeling approach.

Despite broad similarities in predicted fire probabilities, there were some regional differences between the annual and averaged model outcomes. These differences could be largely explained by patterns in climate and vegetation, as shown in the regression tree of Fig. 6. The tree's first node splits the study area with respect to the moisture gradient (i.e., the Climate Moisture Index [CMI]). However, the moisture gradient alone is not enough to describe the discrepancies in predicted fire probability between models: areas of higher predictions

for the annual model (positive values in Fig. 6) and the averaged model (negative values) are best described by combinations of environmental variables. In the moister ($\text{CMI} \geq 13$) part of the study area, predicted fire probabilities from the averaged model were generally higher than those of the annual model in areas of greater year-to-year variability in conifer cover. This supports the idea that, in the annual model, fire activity in a given year responds negatively to the relative depletion of fuels. In the drier part of the study area ($\text{CMI} < 13$), predicted fire probabilities from the annual and averaged models are fairly similar in areas where there is a low conifer cover ($\text{Conif_Pct} < 34\%$). In contrast, where the conifer cover is high, the annual model predictions are considerably higher than those of the averaged model, but only in the areas that experience extreme values of fire danger (FWI90). This is coherent with our interpretation that fire activity in the annual model more effectively tracks climate extremes than in the averaged model.

Although vegetation has historically not been part of annual (or monthly) statistical models of fire activity in boreal North America, our results show that, when used in conjunction with climate, annually updated land-cover information improves the prediction of fire activity. Admittedly, updating land cover for individual years across a large area is tedious and often impossible because of lack of data. As a result, previous researchers have used static fuel data in their interannual models (Drever et al. 2008) or have simply omitted land cover in favor of a focus on climate (Flannigan et al. 2005, Balshi et al. 2009). Climate-only models are, of course, highly pertinent in strongly weather-limited biomes such as the boreal forest; however, they cannot account for potential negative feedback between area burned and probability of re-burning (e.g., Moritz et al. 2009), an issue that still has not been fully explored in the boreal forest. For example, Westerling et al. (2011) showed that, in Yellowstone National Park, the future fire activity predicted by climate-only models far exceeded the capacity of the current suite of conifer species to persist on the landscape. Although they concluded that vegetation species would change in response to climatic shifts, they also acknowledged that a reduction in biomass due to fire was likely to create a feedback mechanism that would dampen fire activity.

As in any modeling exercise, the results of this study were contingent upon inaccuracies in the data, the modeling assumptions, and limitations of the modeling techniques. The statistical models built in this study performed well, but some of the discrepancies between their outputs may have been due to lack of fit. In addition, despite attempts to do so, we were unable to directly compare predicted estimates between the annual and averaged models. Given that the data were not of the same form (i.e., annual vs. averaged) and given that the different techniques scaled the predicted probability in different ways, it is not entirely surprising that the

model predictions had different (though overlapping) ranges or predictions. There were five static variables for both the annual and averaged models, which meant that the annual models were not fully “annualized.” As such, their interannual variability was captured solely by the climate variables and some of the vegetation variables. However, with the possible exception of lightning, these variables simply do not vary much from year to year (e.g., percentage wetland). Furthermore, relatively speaking, these static variables were not found to be strong determinants of fire activity in Canada and, except for percent wetland, they performed less well in the averaged model than in the annual model.

Relevance to environmental management and policy

In this study, we found that predicted patterns of fire activity were similar for models using different temporal resolutions. The reason for this similarity is that the spatial patterns of annual extremes in climate are similar to those of the climate averages. The climate averages for the 1980–2010 time period were indeed highly correlated to the extremes in climate, as defined by the 10th (for StartGrow) and 90th percentiles (for all other climate variables) of values calculated among all 31 years. The correlations were greater than 0.9 for all climate variables except ISI99 ($r = 0.79$), which was a weak variable in both the annual and averaged models. As such, we posit that, although there is substantial year-to-year variability of boreal forest fire (Beverly and Martell 2005) and that climate variability (and therefore extremes) may increase in the future (Salinger 2005), climate normals are likely suitable variables for modeling current and future fire activity in the Canadian boreal forest. Our results indicate that including annual climate variability does not substantially improve predictions of current fire activity over the integrated 31-year timescale. Considering that climatic variability and extremes are often invoked in studies of the distribution of species or under a changing climate (Parmesan et al. 2000, Zimmermann et al. 2009), this finding has substantial implications, given that predicting future climatic variability (e.g., Wood et al. 2002) is much more difficult than predicting climatic normals. From a management and policy standpoint, this key finding should boost confidence in models that incorporate climatic normals, thereby providing a stronger foundation on which to make decisions on adaptation and mitigation strategies for future fire activity.

CONCLUSIONS

The use of parallel data and similar modeling techniques allowed us to compare statistical fire models at two temporal resolutions, annual and multi-decadal. As for analyses performed at multiple spatial scales (Cyr et al. 2007, Parisien et al. 2011a, Parks et al. 2011), changing the temporal frame of a study does yield differences in the understanding of fire–environment relationships in the North American boreal forest, as

was reported by Costa et al. (2011) in Portugal. Although the annual and averaged models used the same raw data for both the dependent and exploratory variables, they did not characterize climate in the same fashion and, as such, were distinctive from one another. Whereas the annual model captured short-term variation in climate, the averaged model defined the envelope (i.e., distribution) within which fire-conducive conditions and flammable biomass coincides.

Although it is often impractical to build models at more than one scale, whether temporal or spatial, doing so is a step toward a deeper cross-scale understanding of fire regimes (Peters et al. 2004, Falk et al. 2007). A multi-scale understanding of fire regimes is emerging, but is not yet as well developed as for other disturbance types. For example, research over a period of more than five decades has helped to depict insect defoliator–forest dynamics in the boreal forest, where four distinct cycles have been identified (Holling 1992). Clearly, wildfire are not as strongly cyclic as some defoliating insects, but identifying the factors to which wildfires respond at multiple spatial and temporal scales will allow better prediction of their occurrence and mitigation of their impacts. Prediction and mitigation are particularly important in the North American boreal forest, where rapid and widespread development and climatic changes are likely to be accelerated in the coming decades (Leroux and Kerr 2013).

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SUPPLEMENTARY MATERIAL

Appendix A

Maps of the dependent variable (annual area burned) and the 14 explanatory variables computed from the annual means for the 1980–2010 time period ([Ecological Archives A024-080-A1](#)).

Appendix B

Decision tree describing the process of creating the temporally dynamic land-cover maps that were used to derive the Conif_Pct and Nonfuel_Pct variables used in the annual model ([Ecological Archives A024-080-A2](#)).

Appendix C

Flowchart of the general construction of the annual and averaged models ([Ecological Archives A024-080-A3](#)).

Appendix D

The model residuals (observed – predicted) for the annual and averaged models ([Ecological Archives A024-080-A4](#)).