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Vegetation and topography interact with weather to drive the spatial distribution of wildfires in the eastern boreal forest of Canada

Xavier Cavard[A,C], *Jean-François Boucher*[A] *and Yves Bergeron*[B]

[A]Université du Québec à Chicoutimi, Département des Sciences Fondamentales, 555 Boulevard de l'Université, Chicoutimi, Québec, G7H 2B1, Canada.
[B]NSERC-UQAT-UQAM Industrial Chair in Sustainable Forest Management, Université du Québec en Abitibi-Témiscamingue, 445 Boulevard de l'Université, Rouyn-Noranda, Québec, J9X 4E5, Canada.
[C]Corresponding author. Email: xavier.cavard@uqat.ca

Abstract. It is crucial to better understand and predict how burnt areas in the boreal forest will evolve under a changing climate and landscape. The objective of the present study was to predict burnt areas at several spatial and temporal scales in the Quebec continuous boreal forest and to compare the influence of weather, vegetation and topographic variables by including them and their interactions in logistic regressions. At the largest spatial scale (350 km^2), the best model explained 66% of the data variability and was able to predict burnt areas with reasonable accuracy for 11 years ($r = 0.48$). Weather and vegetation or topographic variables had an equivalent importance, though no single vegetation or topographic variable was mandatory to the model performance. Interactions between weather and non-weather variables largely improved the model, particularly when several weather indices were used, as the sign of the interaction with a non-weather variable could differ between weather indices. Vegetation and topography are therefore important predictors of fire susceptibility, but risk factors may vary between wind- and drought-driven fire weather. Including at least some vegetation and topographic variables in statistical models linking burnt areas to weather data can greatly improve their predictive power.

Additional keywords: burnt areas prediction, fire susceptibility, fire weather index, logistic regressions.

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Introduction

Wildfires are a natural phenomenon that shape the boreal forest (Rowe and Scotter 1973). Given the strong impact that they have on the boreal forest carbon balance (Conard *et al.* 2002; Balshi *et al.* 2007; Bond-Lamberty *et al.* 2007), their effect is not only local but also global as they may positively contribute to climate change feedback (Flannigan *et al.* 2005; Amiro *et al.* 2009). Improving their predictability under a changing climate and on an evolving landscape is thus of utmost importance.

Although wildfires are by definition stochastic events that cannot be predicted individually, some success has been achieved at larger scales using empirical data and statistical models; weather variables in particular have proven to be strong predictors of burnt areas (Flannigan *et al.* 2005), fire occurrence (Preisler *et al.* 2008) and fire behaviour (Hély *et al.* 2001). The link between dry weather episodes and wildfire activity is indeed so strong that it led some scholars to assume that other variables like fuel and topographic characteristics would comparatively be unimportant (Bessie and Johnson 1995; Flannigan and Wotton 2001). However, Agee (1997) has put the so-called weather hypothesis into perspective and warned against generalisation, stating that the balance between weather, topographic and fuel variables is highly dependent on the study area. Indeed, Bessie and Johnson (1995) explained the stronger effect of weather over fuel by the fact that weather variables manifested more variation than fuels in their western subalpine dataset. It is thus entirely possible that in areas with generally wetter climate, such as the eastern boreal forest of Canada, the influence of weather variables may be less predominant. This is illustrated by the fact that components of the Canadian Fire Weather Index (FWI) System explain 33% of the variance of the provincial area burned monthly in western Canada but only 12% in eastern Canada (Harrington *et al.* 1983). The pattern is probably more complex though, as in Quebec alone the variance explained by such weather indices can range from 42% in the south to 62% in the northernmost part of the province, compared with 50–60% in the prairies (Flannigan *et al.* 2005).

Even when weather is the main driver of fire behaviour, forest composition and structure can have a significant influence (Hély *et al.* 2001). In the boreal forest, conifers in particular are considered better fuel than deciduous species (Hély *et al.* 2000*b*; Cumming 2001). Elevation has been shown to increase the fire

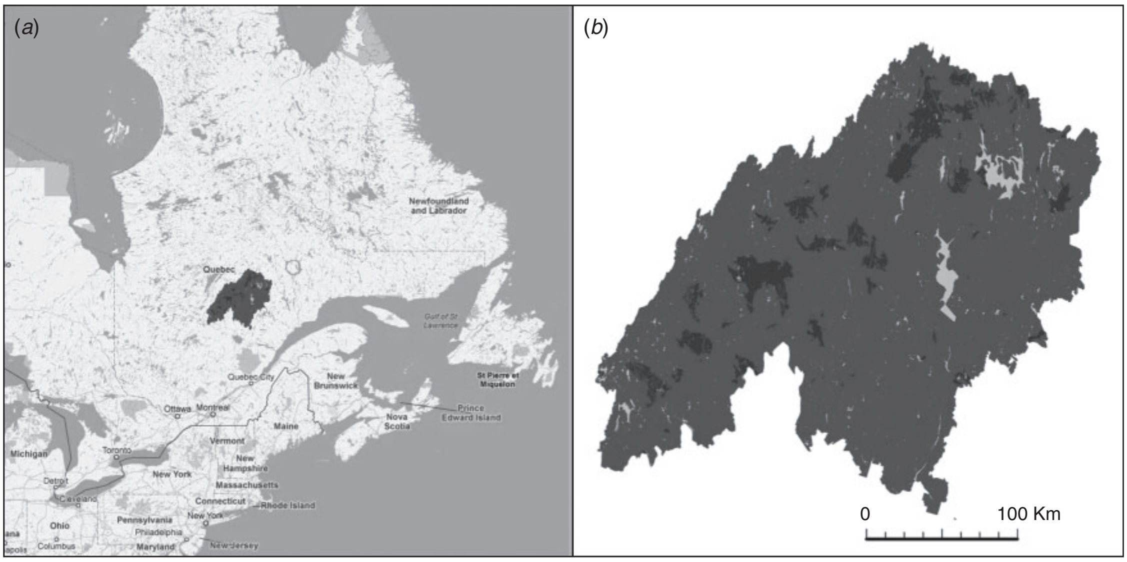

Fig. 1. Study area (*a*) within Quebec and (*b*) detail. Lighter areas correspond to water coverage, darker areas to burnt areas between 2000 and 2010.

return interval (McKenzie *et al.* 2000). However, reputed effects of fuel and topography have been contradictory. For instance, topographic roughness has been shown to increase fire return interval (Stambaugh and Guyette 2008) but also large fire occurrences (Dickson *et al.* 2006). Increasing stand density has also been reported as having both positive (Perry *et al.* 2004) and negative (Tanskanen *et al.* 2005) effects on fire susceptibility. It is unclear whether those apparent contradictions stem from differences in study area or methodology but, as mentioned above, it is likely that interactions with climate lead to different effects of non-weather variables. However, their inclusion in fire prediction models appears necessary to take into account spatial variability in fire spread on finer scales than that allowed by weather alone (Mansuy *et al.* 2010).

The present work aims at identifying the respective weights of weather, topographic and fuel variables on burnt areas in the eastern Canadian boreal forest, using logistic regression models. Different spatial and temporal scales are used in order to find the best compromise between prediction accuracy and precision. We hypothesise that the inclusion of interaction parameters between weather and non-weather variables should increase prediction accuracy.

Materials and methods

Study area

The study area comprised 55 533 km^2 of eastern boreal forest in Quebec (Canada), in the spruce–moss bioclimatic domain. It is mostly uninhabited (limiting anthropogenic impact on fire ignition and suppression) and covers four forest management units of the Saguenay-Lac-Saint-Jean region, spanning approximately from 48°39′N to 51°28′N and from 69°49′W to 74°25′W (Fig. 1*a*). The study period spanned 2000–2010, during which the four weather stations located directly in the area recorded mean annual temperatures ranging from – 0.9 to 0.9°C, and mean annual total precipitation from 529.3 to 620.3 mm, with 30–34% as snow.

The reported average historical fire cycle (last 300 years) in the region is 247 years (Bélisle *et al.* 2011), varying spatially between 128 and 1343 years since 1940 (Mansuy *et al.* 2010). Almost 10% of the study area has burnt during the 11 years of the study period, meaning fire activity has been more intense during this period than what has been historically recorded.

General design

We distinguish between spatially variable and temporally variable data. Given the limited geographical extent of the study area, weather variables (top-down controls) mainly vary temporally. Topographic and vegetation variables (bottom-up controls) vary across space but mostly stay the same from year to year, and are hereafter referred to as spatial variables. Most of these spatial variables were derived from the third forest inventory conducted by the Quebec Ministry of Natural Resources from aerial photographs taken between 1990 and 2000.

Forest inventory data were combined for forest fires larger than 0.3 ha (Société de protection des forêts contre le feu (SOPFEU) data) that occurred between 2000 and 2010 inclusive (Fig. 1*b*). The original polygons were transformed into 394 361 points (or pixels) that corresponded to squares with side lengths of 374 m (~14 ha area). This dataset was duplicated 11 times – once for each year between 2000 and 2010. Each point was assigned a fire occurrence value (0 *v.* 1) for each year. No point had burnt more than once during the study period.

For each year, points were pooled into blocks of various sizes, the value of each spatial variable in a block being the average of the values of the points that composed it (only numerical variables were used). 10×10 points and 50×50 points blocks were computed, corresponding to areas of ~14 km^2 and 350 km^2 respectively (Fig. 2 top). Each year and block were then allocated weather variables through inverse distance weighting interpolation (see section *Weather variables*).

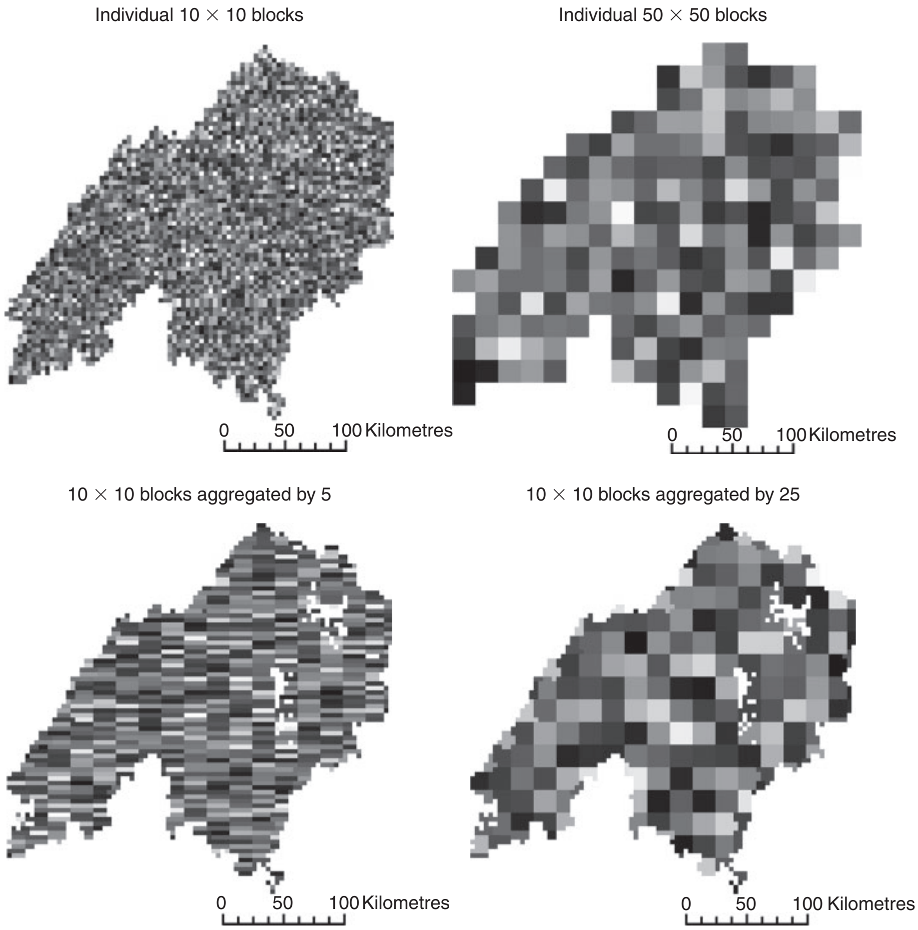

Fig. 2. Maps of the two block sizes (top) and aggregates of the small blocks (bottom).

Each block had its own set of spatial variables, and was replicated 11 times with different weather and burnt area values for each year (Table 1 gives a list of all variables and their ranges). The burnt areas we used here as a response variable were integrative of both ignition and fire spread.

Spatial variables

The following variables were retained from forest inventory data: slope (for the impact of topography on fire spread), stand density (higher fuel concentration), canopy age (as older stands may accumulate woody debris), uneven-aged stands (a binary variable, smaller trees being able to act as ladders for fire to reach the canopy), *Cladonia* presence (also a binary variable, necessary to take into account the potential effect of spruce–lichen open woodlands in the study area) and water body presence (binary, vegetation variables for water points were set to 0). Elevation and distance from main roads (which we qualified as a topographic variable as at our temporal scale these roads were fixed in the landscape) were also added to the dataset, elevation for its microclimatic effect and road distance to account for anthropogenic influences. Each pixel was also attributed a fuel type according to the Canadian Wildland Fire Information System (Pelletier *et al.* 2009). This system is composed of two subsystems: the FWI, which models the effect of wind and fuel moisture on fire behaviour, and the Forest Fire Behaviour Prediction (FBP), which estimates potential head fire spread rate, fuel consumption and fire intensity. The initial rate of spread (RSI) from the FBP subsystem was chosen as an integrative numerical variable representing fuel types. It is defined as the head fire spread rate on level terrain under equilibrium conditions (Forestry Canada Fire Danger Group 1992). The general equation for RSI is as follows:

$$\mathrm{RSI} = a \times [1 - e^{(-b \times \mathrm{ISI})}]^c$$

where a, b and c are fuel type-specific parameters in the FBP system and ISI is the Initial Spread Index (see section *Weather variables*). A fixed value of ISI was chosen in order to keep vegetation and weather variables separate. As the differences in RSI across fuel types tend to increase as ISI becomes higher, the chosen ISI was 15, which is in the high range of the daily values recorded in the area during the study period. This allowed the computed RSI values to discriminate between fuel types as best as possible.

When a fire had occurred in a previous year, the fuel type of the corresponding points was changed to open, and the RSI recomputed accordingly. The other vegetation variables were set to 0. Age increase throughout the time period was considered

Table 1. List of variables used in the analyses
Values given for weather variables are seasonal averages of monthly maximums (see text for details)

Variable	Type	Unit	Range (min–max)	
			10 × 10 blocks	50 × 50 blocks
Rate of Spread Index (RSI)	Vegetation	NA	0–22.06	5.32–19.45
Tree density (Density)	Vegetation	% cover	0–72.92	5.56–55.49
Uneven-aged stand (Uneven)	Vegetation	Binary	0–0.79	0–0.37
Cladonia presence (*Cladonia*)	Vegetation	Binary	0–0.67	0–0.27
Canopy age (Age)	Vegetation	Years	0–125.60	9.38–102.38
Slope (Slope)	Topography	°	0–23.33	2.44–16.07
Elevation (Elevation)	Topography	m	328.8–2021.5	484.2–1692.4
Water body presence (Water)	Topography	Binary	0–1	0.02–0.63
Distance from main roads (Roads)	Topography	m	606.2–123739.6	2050.0–115518.0
Temperature (Temp)	Weather	°C	22.09–32.06	22.42–31.73
Rainfall (Rain)[A]	Weather	mm	7.34–141.92	7.68–141.46
Relative humidity (Humidity)[B]	Weather	%	48.72–68.62	48.79–68.36
Wind speed (Wind)[C]	Weather	km/h	4.03–14.57	4.20–14.55
Fine Fuel Moisture Code (FFMC)	Weather	NA	75.31–85.91	75.77–85–73
Duff Moisture Code (DMC)	Weather	NA	6.85–62.81	7.17–62.37
Drought Code (DC)	Weather	NA	69.09–478.07	69.79–470.17
Initial Spread Index (ISI)	Weather	NA	2.30–6.76	2.32–6.62
Build-up Index (BUI)	Weather	NA	10.76–90.74	11.29–90.15
Fire Weather Index (FWI)	Weather	NA	2.39–16.31	2.53–16.11

[A]Seasonal averages of monthly totals. [B]Seasonal averages of monthly minimums. [C]Seasonal averages of monthly averages.

to be negligible given the lack of resolution of age classes in forest inventory data.

Even though our analyses were aspatial in nature, it was necessary to account for neighbouring effects. To this end, each spatial variable was also given alternative values taking into account the values of that variable in the eight neighbouring blocks. Fourteen values were computed for each variable: the base value of the block, the minimum among it and the eight neighbours, the maximum, and the weighted mean of the target block and its neighbours, the possible weights of the target block being 0, 1, 2, 3, 4, 5, 8, 16, 24, 32 and 40.

Weather variables

Daily rainfall, maximum daily temperature, as well as temperature, relative humidity and wind speed measured at 1200 local standard time (LST) were obtained from 19 weather stations located in and around the study area, from 2000 to 2010. Those data were used to compute the components of the Canadian Forest Weather Index System (Van Wagner 1987). The first-level components (computed directly from the aforementioned weather variables) are the Fine Fuel Moisture Code (FFMC), the Duff Moisture Code (DMC) and the Drought Code (DC). These codes represent the fuel moisture of litter-fine fuels, loosely compacted surface organic matter-medium fuels and deep-layer compacted organic matter-large logs respectively. These three moisture codes and wind speed were used to compute the ISI and the Build-up Index (BUI), the first representing rate of spread without fuel-quantity influence and the second the total fuel available to a fire. Finally, the ISI and BUI were combined to compute the FWI, representing potential fire intensity as energy output rate per unit length of fire front. Those daily values were transformed into annual values in four different ways. First, either monthly averages or monthly maximums were computed. Then, for each of these cases, the average or maximum of monthly values during the fire season (from May to September in our case) were used. Graphical examinations of the relationships between weather variables and observed burnt areas showed no great differences between the different means of calculation, but a slight advantage to the seasonal average of monthly maximums, which were thus used in all analyses for most weather variables. For each year, each block was attributed values for all of these variables using the 12 nearest weather stations (out of 19) and inverse distance weighting interpolation, the distance to a station being determined from the centre of the block.

Statistical analyses

General model structure

All statistical analyses were performed using R software v2.15.2 (The R Foundation of Statistical Computing, http://cran.r-project.org/). The model type used in all of the analyses described below predicted annually burnt area within a block through success/trial logistic regression. It is similar to regular logistic regression, using binomial distribution, but the response variable is not binary, it is a proportion – in our case, the proportion of burnt pixels in a block. R uses the general linear model function with the syntax family = binomial, and weights = total number of pixels in a block. The dependant variable was calculated as the number of burnt pixels in a block for 1 year divided by the total number of pixels in the same block (or 'weight'). Although this kind of analysis accounts for different block sizes, blocks with less than 80% of the maximum amount of pixels (100 or 2500 for 10 × 10- and 50 × 50-pixel blocks respectively) were excluded from the analyses to avoid an artificial variability in the response area burnt (as it is more likely that a smaller block burns entirely). This had the advantage of removing blocks on the edge of the map, whose neighbours were partly unknown. No pair of spatial variables were correlated with each other at more than $r = 0.61$. All variables were centred and scaled so as to be confined within ± 100 with a mean of 0.

Weather variable selection

A first set of simple models was designed in order to select the proper weather variables. The different levels from the FWI components are derived from one another and are thus redundant, correlated and mutually exclusive in a model. Hence, one set of weather variables had to be selected among the following combinations: (1) rainfall, humidity, wind speed and maximum daily temperature; (2) FFMC, DMC and DC; (3) ISI and BUI; and (4) FWI. Four models were fitted using each of these combinations as independent variables. Those four models were compared using the corrected Akaike Information Criterion (AICc), which is a relative measure of goodness of fit (lower AICc values meaning better fit) but also takes into account the trade off between accuracy and complexity, allowing the most parsimonious models to be selected (Burnham and Anderson 2002).

Model comparison

The global or full model was then constructed from the best set of weather variables, and adding all nine spatial variables: RSI, density, age, uneven-aged, *Cladonia* presence, slope, elevation, road distance and water presence. Interactions between all spatial variables and each weather variable were also included to test our main hypothesis, as well as pairwise interactions among the selected weather variables. The following interactions among spatial variables were also added: RSI $\times$ density, RSI $\times$ *Cladonia* and density $\times$ *Cladonia* to test for the influence of dry lichen-covered open woodlands, and RSI $\times$ uneven, RSI $\times$ age, age $\times$ uneven to test for the influence of vertical structure (hereafter named structure interactions). The 18 different versions of each spatial variable (giving more or less weight to neighbouring blocks) were tested successively and the ones providing the best fit according to AICc in the global model were kept. AICc was then used to assess the relative importance of all variables, groups of variables and interactions. For each variable, one model was built from which this variable and all associated interactions were excluded. ΔAICc relative to the global model (the best one in our case) provided a measure of the importance of the excluded variable. The same was done for groups of variables (weather, vegetation and topography) and their interactions.

A subset of the dataset with only relatively high yearly FWI values ($>$10) was also used in order to identify any potential breakpoint after which the effects of spatial variables would change, and whether spatial variable influence would decrease in importance when weather conditions are more fire-prone. The threshold of 10 was the highest that could be used without reducing too much the number of observations compared with the number of parameters in the model.

Model validation

In order to assess the performance of the model outside of the data used to calibrate it, predictions were generated through cross-validation. Yearly burnt areas of each block were predicted by a model that was fitted on all observations, excluding those stemming from the same block or the same year as the one to be predicted (jackknife method). Root Mean Square Errors (RMSE) between observed and predicted values were computed with values fitted by the model on the one hand and predictions generated through cross-validation on the other hand. In the 10×10-pixel configuration, blocks were regrouped according to the large 50×50-pixel block they were in, and the 25 small blocks thus regrouped were excluded from the model that predicted burnt areas in each of them. This allowed us to assess prediction accuracy on various sizes of 10×10 block aggregates (1, 5 and 25 blocks, 25 10×10 blocks being the equivalent of one 50×50 block, see Fig. 2) without modifying the number of observations available to fit the model.

Individual effects of variables

To help assess the effects of individual vegetation variables, predictions were computed with an increase in BUI (ISI being fixed to an average value), ISI (BUI being fixed to an average value) or both. When both ISI and BUI were increased, a ratio of BUI/ISI = 8 was chosen, which allowed ISI and BUI to reach their median and 3rd quartile values together (highest BUI values were considerably rarer than ISI ones). Given the multiplicity of combinations available for vegetation values, four hypothetical 50×50-pixel blocks were chosen to run those predictions: 'black spruce' was defined as RSI = 22.3, density = 50, age = 60, uneven = 0 and *Cladonia* = 0; 'mixed spruce – deciduous' as RSI = 11.57, density = 50, age = 60, uneven = 0 and *Cladonia* = 0; 'heath' as RSI = 14.27, density = 0, age = 0, uneven = 0 and *Cladonia* = 0; and 'spruce–lichen open woodland' as RSI = 10.64, density = 18, age = 80, uneven = 0 and *Cladonia* = 0.3. These values were chosen to reflect the general vegetation type, whereas topographic variables were given average values: slope = 9.9, elevation = 1000, roads = 23 000, except for water presence, which was set to 0. The 'black spruce' and 'mixed' staples were then kept to test the effect of density, age, uneven and *Cladonia*. Values for those variables were chosen so that they would be as different as possible while remaining within the 1st and 3rd quartiles of their distribution. The same principle was applied to test for the effects of topographic variables, values of variables other than the one shown in that case being: RSI = 15, density = 30, age = 60, uneven = 0, *Cladonia* = 0, slope = 9.9, elevation = 1000, roads = 23 000 and water = 0. These corresponded to mean values, rounded to 0 when very low.

Results

Weather variables selection

The best set of weather variables differed depending on the spatial scale used: the ISI + BUI combination was best for 10×10 blocks, whereas the FFMC + DMC + DC combination was best for 50×50 blocks (Table 2). However, the ISI + BUI combination was still second best for the 50×50 scale. In order to avoid burdening the model with too many parameters (as each weather variable interacts with each spatial variable) and to facilitate comparisons between spatial scales, the ISI + BUI set of weather variables was chosen for both scales. For both spatial

Table 2. Model selection for weather variables
The best model has a difference in corrected Akaike Information Criterion (AICc) of 0

Model	AICc		ΔAICc	
	10 × 10 blocks	50 × 50 blocks	10 × 10 blocks	50 × 50 blocks
Temperature + Rain + Humidity + Wind	316 287.7	201 241.2	2679.03	6038.11
FFMC + DMC + DC	313 952.4	195 203.1	343.74	0
ISI + BUI	313 608.6	197 237.3	0	2034.25
FWI	324 213.5	208 259.3	10 604.89	13 056.24

Table 3. Explicative power of each variable and group of variables
A higher difference in corrected Akaike Information Criterion (AICc) means a more important variable, see text for details

Model	AICc		ΔAICc	
	10 × 10 blocks	50 × 50 blocks	10 × 10 blocks	50 × 50 blocks
Global	193 607.1	79 147.18	0	0
No Weather	309 400.7	193 322.55	115 793.60	114 175.37
No Spatial	300 359.3	192 201.43	106 752.18	113 054.25
No Vegetation	248 058.2	125 193.59	54 451.10	46 046.41
No Topography	253 674.2	116 873.44	60 067.06	37 726.26
No Weather × Spatial	253 772.8	142 492.83	60 165.72	63 345.65
No Open woodlands interactions	196 450.2	–[A]	28 43.10	–[A]
No Structure interactions	194 034.9	86 418.54	427.82	7271.36
No ISI	242 337.7	130 824.68	48 730.59	51 677.50
No BUI	255 902.0	147 172.67	62 294.88	68 025.48
No RSI	207 408.6	92 841.21	13 801.53	13 694.03
No Density	206 740.7	89 826.08	13 133.59	10 678.89
No Uneven	195 515.7	88 235.99	1908.56	9088.81
No *Cladonia*	196 817.8	82 065.96	3210.70	2918.78
No Age	197 292.5	86 381.88	3685.42	7234.70
No Slope	193 975.0	86 079.78	367.92	6932.60
No Elevation	214 154.5	87 276.64	20 547.35	8129.46
No Water	209 824.8	89 453.30	16 217.65	10 306.12
No Roads	200 018.2	79 876.28	6411.13	729.10

[A]Model failed to converge.

scales, the Temperature + Humidity + Rain + Wind combination was third in order of performance, whereas the models using a single weather variable (the FWI) were the worst ones (Table 2).

Neighbouring effects on spatial variables

Depending on block size, the best formula to account for neighbours changed for each variable (Appendix 1). For the 10 × 10-pixel blocks, neighbours always had to be accounted for, and the value of the block itself was negligible for slope and *Cladonia* presence. For 50 × 50-pixel blocks, the influence of the block value was negligible for the distance from roads and uneven-aged stand variables, but the values of neighbours were negligible for RSI and C*ladonia* presence.

Explanatory power of variables

A large majority of the global model parameters had a statistically significant effect for both block sizes (Appendix 2). The global model accounted for 45% of the total deviance of the dataset for 10 × 10-pixel blocks, and 66% for 50 × 50-pixel blocks. By ΔAICc, removal of all weather or spatial variables had an equivalent effect on model performance, and removal of interactions between weather and spatial variables had a negative effect equivalent to removing either ISI or BUI (Table 3). Removal of vegetation or topographic variable groups had a similar impact, whereas interactions between spatial variables were of comparatively little importance. For 10 × 10-pixel blocks, the most important single variables were (in decreasing order): BUI, ISI, elevation, water, RSI, density, roads, age, *Cladonia*, uneven and slope. For 50 × 50-pixel blocks, these were: BUI, ISI, RSI, density, water, uneven, elevation, age, slope, *Cladonia* and roads.

Sequential removal of spatial variables (in their order of importance for 10 × 10 blocks) showed that globally, the effect of removing a given spatial variable increased when other spatial variables had already been removed, with the notable exception of water presence, for both block sizes (Table 4).

When a subset of the dataset in drier conditions (FWI > 10) was used, the impact of spatial variables decreased to half that of weather variables, but total weather × spatial variable interactions remained at a similar level compared with weather variables (Appendix 3). Water presence notably became the most important spatial variable for both block sizes.

Table 4. Explicative power of each spatial variable when they are removed sequentially from the global model
AICc, corrected Akaike Information Criterion

Model	No. of spatial variables	AICc		ΔAICc		Variable impact	
		10 × 10 blocks	50 × 50 blocks	10 × 10 blocks	50 × 50 blocks	10 × 10 blocks	50 × 50 blocks
Global	9	193 607.1	79 147.18	0	0	0	0
'–Slope'	8	193 975.0	86 079.78	367.92	6932.60	367.90	6932.60
'–Uneven'	7	196 264.2	96 140.2	2657.06	16 993.02	2289.20	10 060.42
'–*Cladonia*'	6	199 804.0	99 660.45	6196.87	20 513.27	3539.80	3520.25
'–Age'	5	204 763.7	103 338.99	11 156.62	24 191.81	4959.70	3678.54
'–Road'	4	219 050.2	113 692.14	25 443.14	34 544.96	14 286.50	10 353.15
'–Density'	3	239 374.4	129 112.15	45 767.29	49 964.97	20 324.20	15 420.01
'–RSI'	2	272 289.5	149 877.52	78 682.39	70 730.34	32 915.10	20 765.37
'–Water'	1	273 507.1	150 322.95	79 899.96	71 175.76	1217.60	445.43
'–Elevation'	0	309 400.7	193 322.55	115 793.60	114 175.37	35 893.60	42 999.60

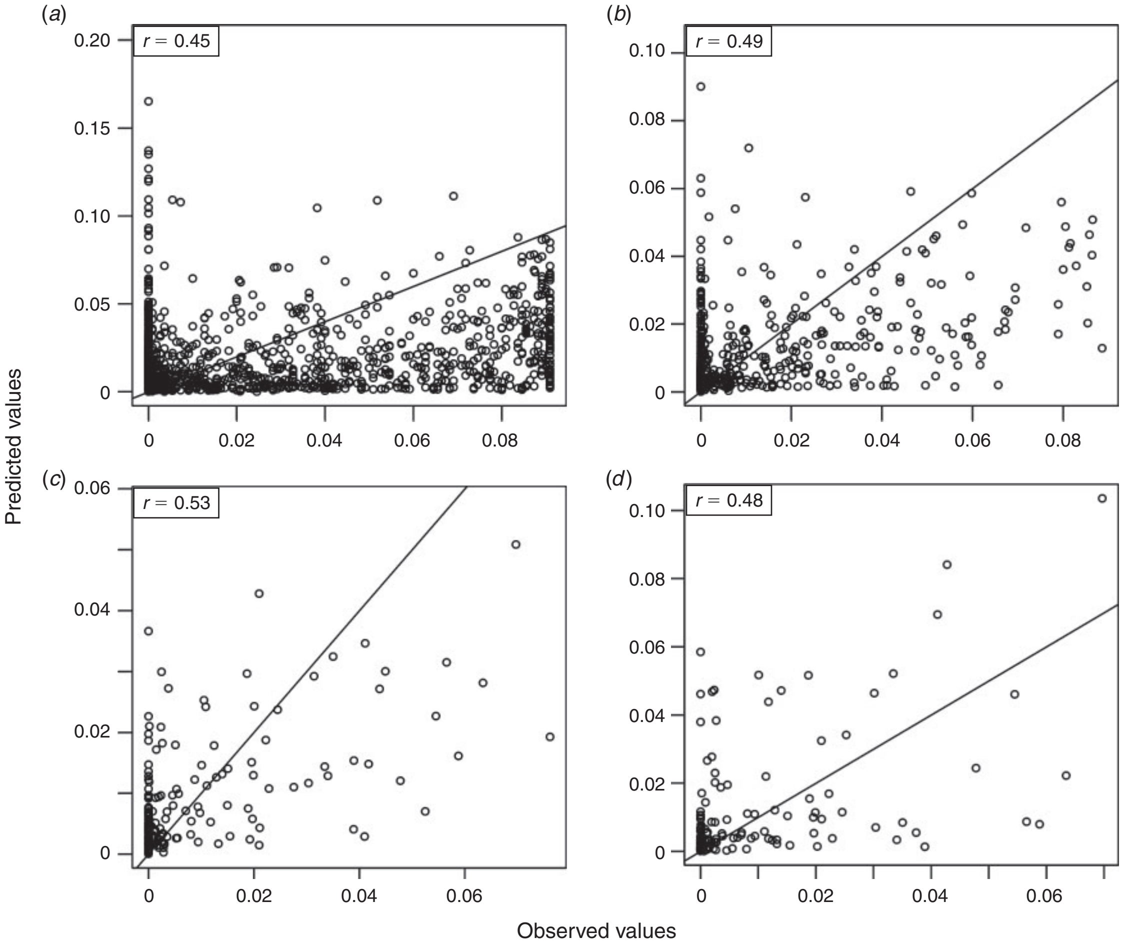

Fig. 3. Predicted *v.* observed proportions of burnt areas of each block from 2000 to 2010 for different spatial scales: (*a*) 10 × 10-pixel blocks; (*b*) 10 × 10-pixel block aggregated by lines of five blocks; (*c*) 10 × 10-pixel blocks aggregated by squares of 25 blocks; and (*d*) 50 × 50-pixel blocks.

Prediction accuracy v. precision

Correspondence between observed and predicted burnt proportions was poor for the smallest blocks, but increased by aggregating predictions on larger spatial scales (Fig. 3*a–c*). When the model was directly fitted on larger 50 × 50-pixel blocks, prediction accuracy did not appear very different from the 10 × 10 block predictions aggregated on the same scale (Fig. 3*c–d*). Furthermore, whereas autocorrelation of the model residuals did not appear to be a problem for the largest blocks (equal to 0.2 for adjacent observations), it was much

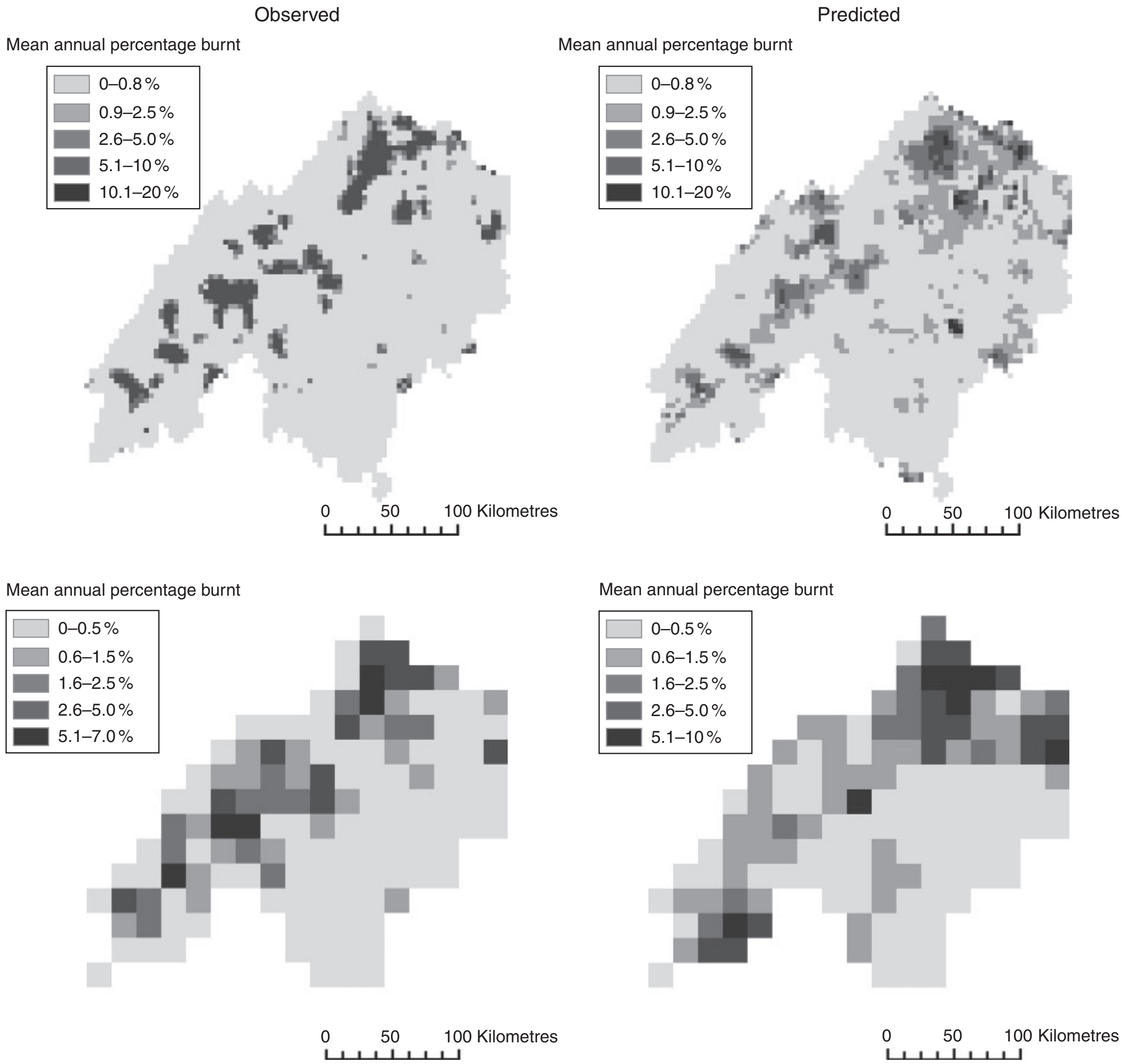

Fig. 4. Maps of observed (left column) and predicted (right column) mean annual burnt areas between 2000 and 2010 for 10 × 10 (first line) and 50 × 50 blocks (second line).

more pronounced for the small blocks (0.65 for adjacent observations). Hence, only 50 × 50 blocks were used for later predictions (Fig. 4) and analyses, given the lower amount of processing they required. Different temporal scales appeared to greatly affect prediction accuracy for 50 × 50 blocks, with extremely poor correspondence between yearly observed and predicted burnt areas, but average accuracy when predictions were pooled over 11 years (Fig. 5). RMSE for 10 × 10 blocks were equal to 0.066 for fitted values and 0.069 for predicted values. For 50 × 50 blocks, RMSE were 0.036 for fitted values and 0.078 for values predicted through cross validation.

Individual effects of variables

Given the large number of interactions in the global model, the effect of one given variable is difficult to assess, especially when vegetation variables are involved, as they not only interact with weather variables but also among themselves. Furthermore, some spatial variables can have a positive interaction with one of the weather variables and a negative interaction with other variables (Appendix 2), meaning that the same spatial variable can have a positive or a negative effect on predicted burnt areas depending on the BUI/ISI ratio.

According to the model, spruce–lichen open woodlands were more fire prone than closed spruce forests (Fig. 6*a*). This was also the case for open heathlands, except under the most extreme fire weather conditions (Fig. 6*a*). Finally, mixed spruce–deciduous forests appeared less fire prone (Fig. 6*a*). Closed spruce and open spruce–lichen woodlands seemed to burn more when ISI was high (Fig. 6*b*), whereas open heathlands and mixed forests were more dependent on a high BUI (Fig. 6*c*).

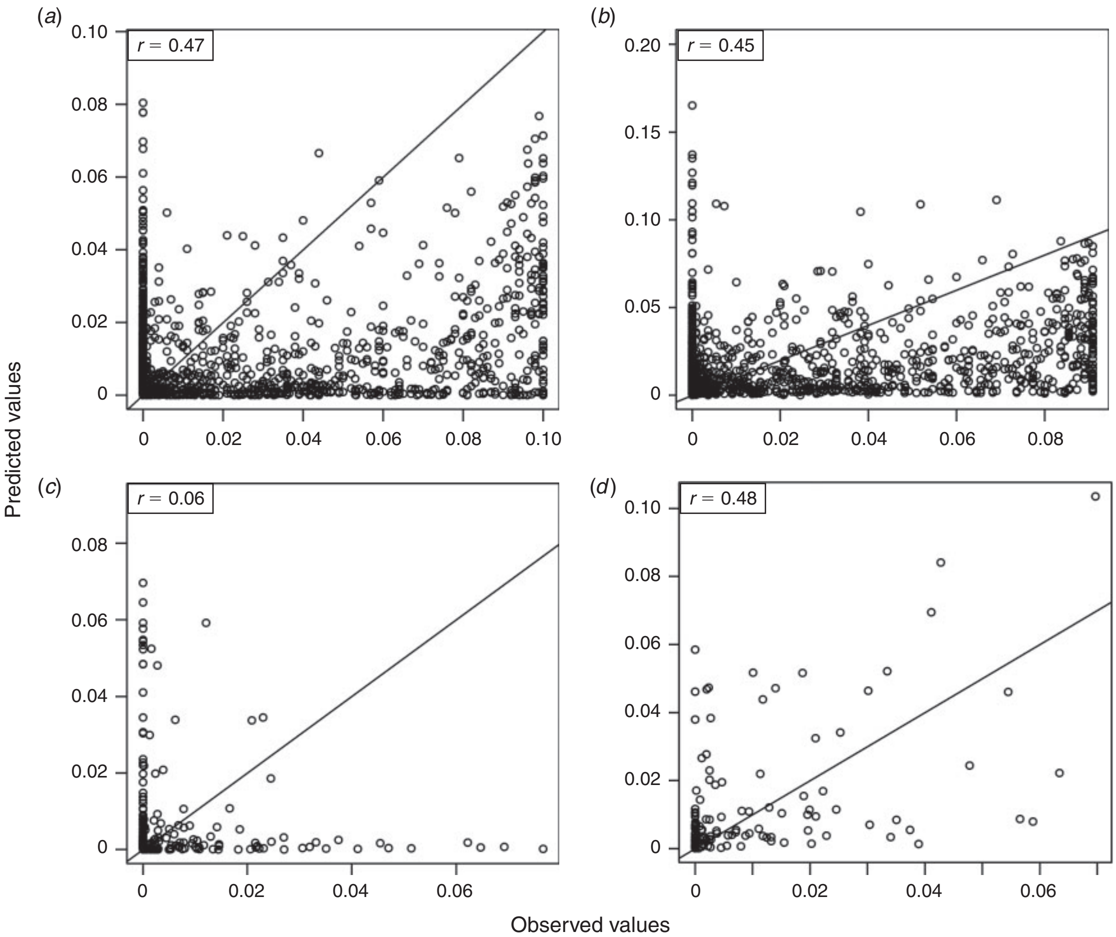

Fig. 5. Predicted *v.* observed proportions of burnt areas in each block for different spatial and temporal scales: (*a*) 10×10-pixel blocks for 1 year; (*b*) 10×10-pixels blocks for 11 years; (*c*) 50×50-pixel blocks for 1 year; and (*d*) 50×50-pixel blocks for 11 years.

The stem density effect on burnt area predictions was highly dependent on RSI values: it was positive on spruce stands (high RSI) but negative on mixed stands (low RSI; Fig. 7*a*). Age had a slight negative effect in both cases (Fig. 7*b*). Uneven-aged stands, in contrast, had a slight positive effect on predicted burnt areas in spruce stands and a large positive effect in mixed stands (Fig. 7*c*). *Cladonia* presence had a positive effect on predictions when RSI was high, but a negative effect when RSI was lower (Fig. 7*d*).

Elevation had a negative effect on predictions with increasing ISI but a positive effect with increasing BUI (Fig. 8*a*). Slope had a negative effect in both cases (Fig. 8*b*). Distance from main roads had a positive effect under high ISI but a negative effect under high BUI (Fig. 8*c*). Finally, the effect of water body presence was negative overall but positive when ISI was near its maximum (Fig. 8*d*).

Discussion

Model performance and scales

It has previously been established that regression models such as those used here can achieve acceptable levels of prediction accuracy on burnt areas or fire occurrence (Flannigan *et al.* 2005; Gonzalez *et al.* 2006; Krawchuk *et al.* 2006; Chuvieco *et al.* 2009; Bisquert *et al.* 2011). The best performance here was obtained at the largest spatial scale (350 km^2), where the model was globally able to identify high and low fire-risk areas.

The main drawback of empirical models is the dependency on the dataset used to build the model. It is not expected that the parameters calibrated for a specific region would allow for good prediction in an entirely different area. However, our methodology should still perform well if applied, for instance, to predict future burnt areas under a changing climate in a region where terrain features and past fire activity are known, or to test the effects of moderate changes in vegetation features.

The effect of spatial scales on prediction accuracy was unsurprising given the nature of the method we used. Even though wildfire spread is also controlled by finer-scale processes (Cyr *et al.* 2007; Falk *et al.* 2007), our smallest blocks did not reach the size at which such processes may have become apparent (Parks *et al.* 2011). Hence, our method is more adapted to a coarse spatial resolution. This is emphasised by the fact that taking surrounding blocks into account for the values of most spatial variables improved model performance even at the 350 km^2-block scale. Besides the required computing power and lower accuracy, the smaller blocks also had the drawback of

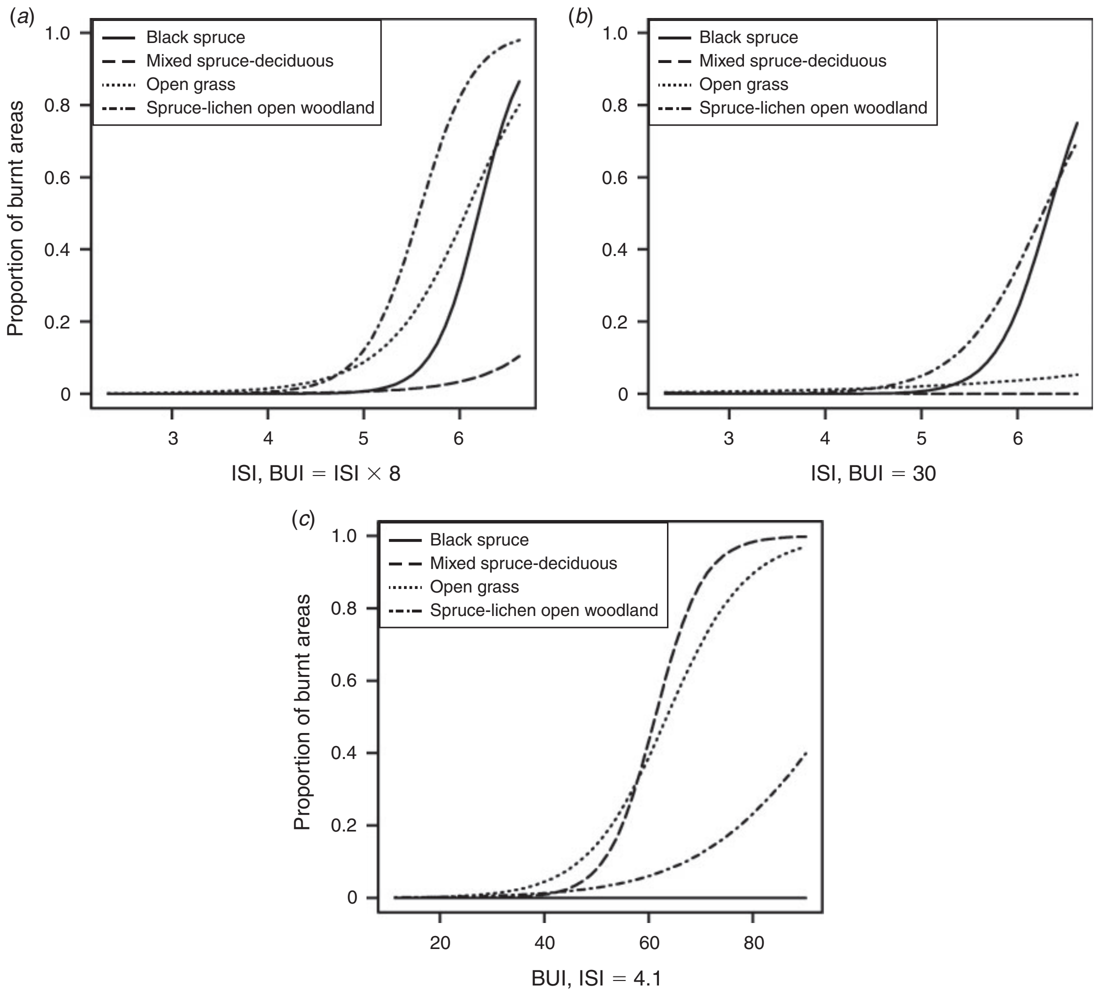

Fig. 6. Predicted burnt areas for four hypothetical 50 × 50-pixel blocks (see text for details) under increasing fire weather risk: (*a*) both Initial Spread Index (ISI) and Build-up Index (BUI) (BUI = ISI × 8); (*b*) increasing ISI with BUI = 30; and (*c*) increasing BUI with ISI = 4.1.

being more spatially correlated, requiring further complexity of the model to take the spatial structure into account. The very low accuracy of the model when predicting yearly burnt areas on the largest blocks may be explained by the fact that among the 11 years of the study period, only 3 years saw significant areas burnt. Hence, removing one of these 3 years during the cross-validation drastically affected the predictive performance of the model. This is emphasised by the difference in RMSE between fitted and predicted values at this scale (0.036 *v.* 0.078), which was lower if all years where used during the cross-validation (0.036 *v.* 0.051, not shown). This effect was fortunately offset by aggregating predictions on a larger temporal scale, probably because it averaged weather variations and put more emphasis on the blocks that were generally more susceptible to fire, due to their vegetation and topographic characteristics. It is unclear though why such an effect was not apparent for the smallest blocks. In any case, this result shows that the model may be greatly improved by adding more fire years in the dataset, provided those and the corresponding vegetation data are available. In addition, aggregating predictions over a time period much longer than 11 years might also produce significantly more accurate predictions.

Weather influence v. vegetation and topography

Weather and spatial variables played an equivalent role in explaining the spatial variation in proportions of area burnt. Although it would be tempting to attribute this result to the less fire-prone climate of the eastern boreal forest of Canada compared with its western counterpart, Krawchuk *et al.* (2006) did find similar results in Alberta, and observed that the influence of forest composition was even stronger with more severe fire weather. Other studies have shown the importance of vegetation (Parisien *et al.* 2011) and topography (Kennedy and McKenzie 2010) in explaining the spatial distribution of wildfires. Thus, forest and topographic heterogeneity *v.* homogeneity would be the main factor influencing the balance between top-down and bottom-up controls in a landscape, explaining the lack of vegetation effect in some studies (Bessie and Johnson 1995). Although our results from a more fire-prone subset of the data

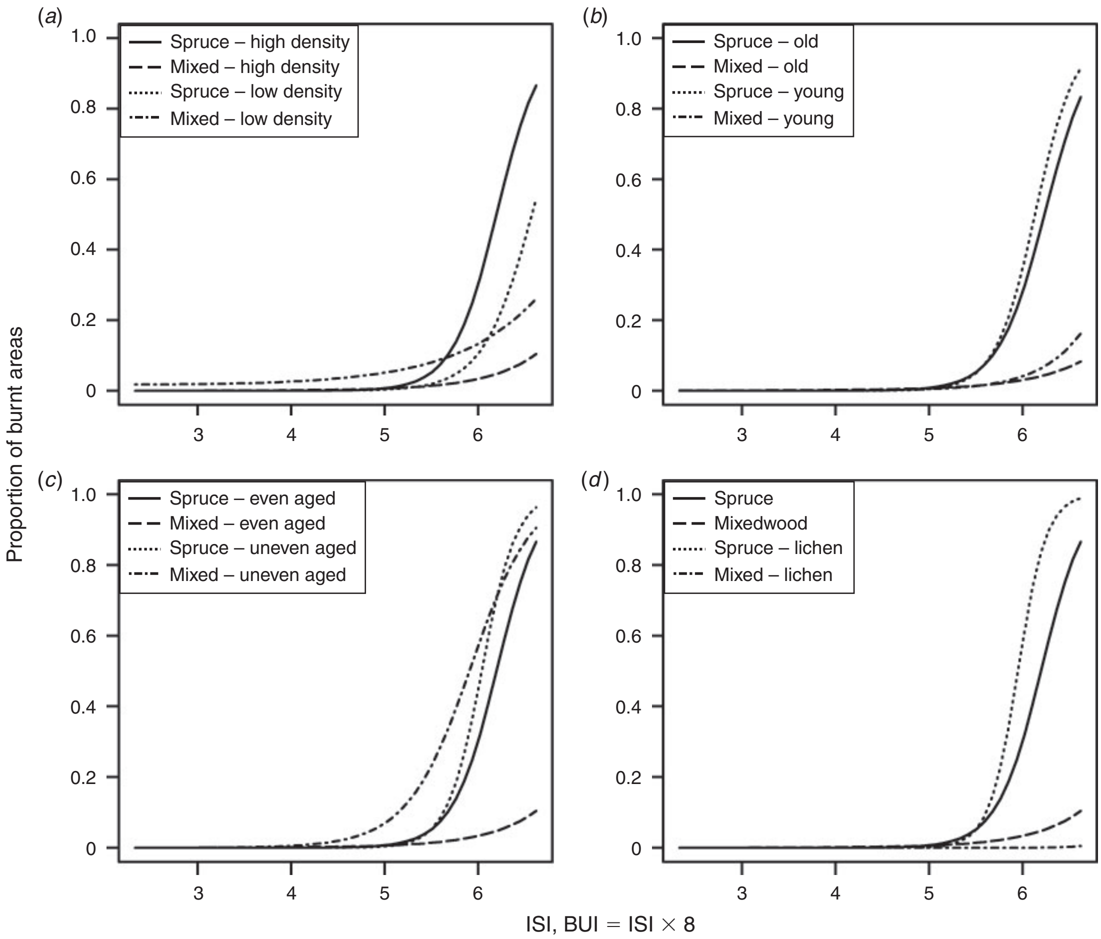

Fig. 7. Predicted burnt areas of black spruce and mixed spruce – deciduous forested 50 × 50 blocks under increasing Initial Spread Index (ISI) and Build-up Index (BUI) (BUI = ISI × 8) and with varying values of vegetation variables: (*a*) high (50% cover) *v.* low (30% cover) density; (*b*) old (70 years) *v.* young (40 years); (*c*) low (0) *v.* high (0.2) proportion of uneven-aged stands; and (*d*) low (0) *v.* high (0.2) proportion of stands with presence of *Cladonia.*

still suggest a decreased influence of non-weather variables under more intense fire weather, there were too few episodes of such intense fire weather in our study area to really proceed to such analyses – the FWI threshold of 10 that we used to define the subset not being all that high. Although we are unable to shed any conclusive light on this issue, we have been able to show the importance of interactions between weather and spatial variables, which is as expected as terrain and vegetation features are insignificant to fire risk without suitable weather. Even more interesting is the fact that several weather variables always performed better than a single weather variable, and that some spatial variables had interaction parameters of opposite signs between the ISI and the BUI. Provided that this is not merely an artefact of the model, it could suggest that ‘intense fire weather’ can actually encompass varied meteorological conditions, each of which favours the burning of different vegetation and topography.

Among the spatial variables, none was individually as important as ISI or BUI were to the model goodness of fit. Sequential removal of spatial variables showed that the fewer the number of spatial variables in the model, the more statistical weight each one had. This redundancy between spatial variables means that none of them was essential to the method we used, and thus that it could probably be replicated elsewhere with similar success, with whatever vegetation and topographic data are available. Water presence is the notable exception, in that it was mostly useless to the model when most other spatial variables had already been removed.

Effects of individual spatial variables

Every spatial variable in our model interacted significantly with both ISI and BUI, and vegetation variables showed interactions among themselves. Their effects must thus be understood in relation to those other variables. This is particularly true for RSI, which interacted with all of the other vegetation variables. This was necessary as a given RSI value can represent different vegetation types – spruce–lichen forest, heathlands and mixed forests can all have similar RSI values, for instance. By combining RSI with other variables, particularly tree density, we hoped to allow for better discrimination between vegetation types. Similar RSI values were thus able to correspond to either a

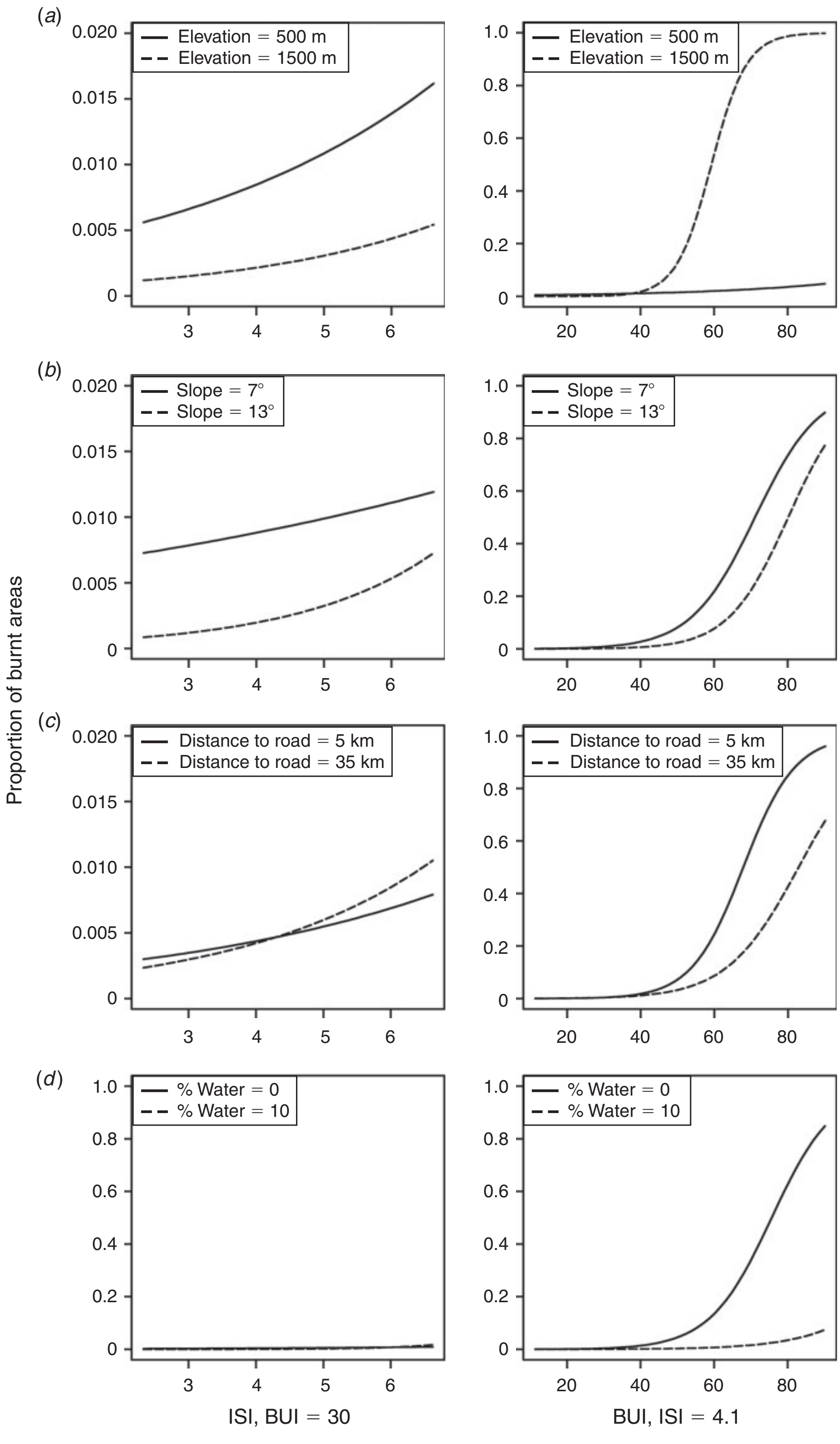

Fig. 8. Predicted burnt areas of average 50 × 50 blocks with varying values of topographic variables, when either Initial Spread Index (ISI) increases with Build-up Index (BUI) = 30 (left column) or BUI increases with ISI = 4.1 (right column). Effects of: (*a*) elevation; (*b*) slope; (*c*) distance to roads; and (*d*) water body presence.

mixed spruce–deciduous forest or a spruce–lichen open woodland, with contrasting model predictions. It appeared that for high densities, a lower RSI – corresponding to an increased proportion of deciduous forest – would decrease predicted burnt areas. This is in accordance with many previous results stating the lower fire susceptibility of deciduous species compared with conifers (Hély *et al.* 2000*b*; Cumming 2001; Bergeron *et al.* 2004). In contrast, very low densities combined with medium or low RSI (heath and spruce–lichen woodland) led to a higher proportion of predicted burnt areas for ISI values below 6. The fact that open forest stands would require less-intense fire weather than closed-canopy forests in order to burn is not surprising as the burnt areas being predicted here were the result of fire ignition and spread, not fire intensity or severity; hence, the flammability was arguably of more importance than the amount of fuel. Closed canopies can create a shady and moist microclimate that decreases ignition success (Tanskanen *et al.* 2005). However, this doesn't explain why coniferous stands relied on a high ISI to burn and mixed woods depended on a high BUI. High BUI values are associated with prolonged droughts and late-summer conditions, and thus to the 'leaf-out' period of deciduous trees, which is assumed to decrease rate of spread (Forestry Canada Fire Danger Group 1992). Thus, a contrary result was expected. The dependence of open heathlands on high BUI values is easier to explain as the flammability of such fuel heavily relies on its degree of curing, which is dependent on rainfall (Luke and McArthur 1978; Brown *et al.* 1989).

Tree density appeared to have a positive effect on fire susceptibility for coniferous stands, but a negative effect when RSI was lower (such as from the inclusion of broadleaved species), suggesting that higher fuel availability increased susceptibility to fire only when it was easily flammable. More surprisingly, upper canopy age had a negative effect on fire susceptibility in both cases, which is contradictory to the accumulation of dead material in unmanaged forest over time (Van Wagner 1983; Barrett *et al.* 1991; Agee 1993; Hély *et al.* 2000*a*). However, old boreal stands tend to develop thick and moist organic layers (Crawford *et al.* 2003). This effect was weak, so it is also possible that mean age in 350-km^2 blocks did not vary enough to detect a proper influence of canopy age. Of more importance was the proportion of uneven-aged stands in a block, which had a slight positive effect in the case of coniferous stands but a much greater effect for mixed woods. Indeed, subcanopies in mixed deciduous–coniferous stands of the eastern boreal forest are generally composed of late-successional conifers (Bergeron 2000; Chen and Popadiouk 2002), which may act as a bridge for a surface fire to reach the canopy (Van Wagner 1977) and will greatly increase the flammability of mixed stands. The model also attributed a positive impact on fire susceptibility to the presence of *Cladonia*-type lichens, which have been classified as fuels of intermediate flammability (Sylvester and Wein 1981), but only in coniferous stands. The negative impact of lichens in spruce–deciduous mixed stands may have no physical meaning, as lichens were seldom found in such forests in our dataset.

Including several weather variables and their interactions led to some interesting behaviour from our model, such as the contrasting effects of elevation and distance from main roads on fire susceptibility, depending on which weather index was dominating. Nothing proves at this stage that the inversion of the effect of spatial variables with changing weather variables values is not a mere artefact from the model construction. These could however lead to interesting hypotheses to be investigated in future studies, such as risk factors not being the same when strong winds are frequent but only fine fuels would be dried (high ISI and medium BUI, a situation more common in spring and early summer) or when strong winds are infrequent but prolonged drought would have increased the range of flammable fuels (high BUI and medium ISI, more common from mid- to late summer in our dataset).

Conclusion

Statistical models had been shown to predict burnt areas at the ecozone scale using only FWI (Flannigan *et al.* 2005). The inclusion of vegetation and topographic variables in logistic regressions, and their interaction with FWI, allowed such models to identify burnt areas of 350-km^2 blocks over 11 years with reasonable accuracy. Such models are limited in scope as their performance decreases dramatically when they are forced to extrapolate outside the range of the data that were used to build them, but the method is flexible enough that it could be used on other large areas for which some degree of topographic, vegetation and possibly anthropogenic characteristics are known. The large scale on which it operates means its primary use may be in determining future evolution of burnt areas when both climate and vegetation cover evolve.

Examination of the model behaviour could lead to several interesting research avenues, if only to confirm the impact of individual variables. Most notably, the balance between ISI and BUI affecting the influence of some variables is worth investigating further, in order to determine whether this has any real physical grounding and, if it has, how different kinds of intense fire weather (driven by wind *v.* drought) would interact with topographic and vegetation features. The method itself could of course be improved, especially by looking for a better balance between precision and accuracy, refining the way the neighbouring effects are taken into account, and using datasets expanded over space or time.

Acknowledgements

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Appendix 1. Best formula to account for neighbours, for each spatial variable

Variable	Formula or weight of block value if weighted mean 10 × 10 blocks	50 × 50 blocks
Rate of Spread Index (RSI)	2	Block value
Tree density (Density)	Minimum value	16
Uneven aged stand (Uneven)	Maximum value	0
Cladonia presence (*Cladonia*)	0	Block value
Canopy age (Age)	Minimum value	Minimum value
Slope (Slope)	0	8
Elevation (Elevation)	4	3
Water body presence (Water)	16	8
Distance from main roads (Roads)	Maximum value	0

Appendix 2. Parameter estimates of the global model

Parameter	Estimate		*P*-value	
	10 × 10 blocks	50 × 50 blocks	10 × 10 blocks	50 × 50 blocks
RSI	−2.313e−01	−2.549e−01	<2e−16	<2e−16
Slope	−8.871e−02	−4.494e−01	<2e−16	<2e−16
Density	−1.123e−01	−1.075e−01	<2e−16	<2e−16
Road	6.269e−03	−8.516e−06	<2e−16	1.68e−11
Elevation	−1.126e−02	−4.726e−03	<2e−16	<2e−16
Water	−1.097e+01	−3.210e+01	<2e−16	<2e−16
Uneven	−3.295e+00	−3.602e+00	<2e−16	2.63e−12
Cladonia	−4.136e+00	−6.490e+00	<2e−16	<2e−16
Age	2.063e−02	−1.725e−02	<2e−16	<2e−16
BUI	9.221e−02	1.122e−01	<2e−16	<2e−16
ISI	1.711e+00	2.249e+00	<2e−16	<2e−16
BUI × ISI	−2.666e−03	4.387e−02	0.000324	<2e−16
RSI × Density	2.471e−02	2.000e−02	<2e−16	<2e−16
RSI × Uneven	1.040e−01	6.584e+00	2.67e−07	<2e−16
RSI × *Cladonia*	−2.819e−01	3.765e+00	8.69e−12	<2e−16
RSI × Age	−4.017e−03	−2.869e−02	<2e−16	<2e−16
Density × *Cladonia*	−1.868e−01	−9.348e−01	<2e−16	<2e−16
Uneven × Age	2.294e−02	2.372e−01	<2e−16	<2e−16
Slope × ISI	6.283e−02	8.812e−02	<2e−16	<2e−16
Density × ISI	1.600e−02	3.193e−03	9.09e−15	0.0645
RSI × ISI	2.050e−01	2.498e−01	<2e−16	<2e−16
Road × ISI	1.171e−02	7.278e−06	<2e−16	3.08e−15
Elevation × ISI	−4.752e−04	2.853e−03	0.117883	<2e−16
Water × ISI	2.892e+00	1.955e+01	<2e−16	<2e−16
Uneven × ISI	2.692e+00	1.161e+01	<2e−16	<2e−16
Cladonia × ISI	7.395e+00	8.979e+00	<2e−16	<2e−16
Age × ISI	−1.412e−02	8.673e−03	<2e−16	<2e−16
Slope × BUI	9.502e−04	2.692e−03	2.84e−05	1.12e−10
Density × BUI	−2.682e−03	1.224e−03	<2e−16	<2e−16
RSI × BUI	−1.192e−02	−1.954e−02	<2e−16	<2e−16
Road × BUI	−1.649e−03	−8.712e−07	<2e−16	<2e−16
Elevation × BUI	1.768e−03	2.646e−04	<2e−16	<2e−16
Water × BUI	−1.858e−01	−5.499e−01	<2e−16	<2e−16
Uneven × BUI	6.800e−02	4.642e−01	<2e−16	<2e−16
Cladonia × BUI	−1.896e−02	−3.291e−01	0.002347	<2e−16
Age × BUI	1.290e−03	−1.093e−03	<2e−16	<2e−16

Appendix 3. Explicative power of each variable and group of variables when FWI >10 (higher ΔAICc means more important variable, see text for details)

AICc, corrected Akaike Information Criterion

Model	AICc		ΔAICc	
	10 × 10 blocks	50 × 50 blocks	10 × 10 blocks	50 × 50 blocks
Global	72 955.97	31 072.73	0	0
No Weather	113 170.86	91 837.13	40 214.89	60 764.40
No Spatial	98 987.45	59 285.17	26 031.47	28 212.43
No Vegetation	102 678.04	63 559.60	29 722.07	32 486.87
No Topography	85 493.85	57 335.17	12 537.87	26 262.44
No Weather × Spatial	89 399.23	56 717.80	16 443.25	25 645.07
No Open woodlands interactions	73 387.53	33 826.51	431.55	2753.78
No Structure interactions	73 167.98	31 605.34	212.01	532.61
No ISI	86 944.09	44 353.28	13 988.12	13 280.55
No BUI	78 655.02	40 791.19	5699.04	9718.46
No RSI	79 155.29	39 039.09	6199.32	7966.36
No Density	79 631.58	32 106.14	6675.60	1033.41
No Uneven	74 911.86	41 572.56	1955.88	10 499.83
No *Cladonia*	73 870.40	34 804.46	914.42	3731.73
No Age	76 578.85	34 362.41	3622.88	3289.68
No Slope	73 118.28	40 144.99	162.30	9072.26
No Elevation	74 751.79	34 177.16	1795.81	3104.43
No Water	81 779.58	44 329.80	8823.61	13 257.07
No Roads	74 165.30	32 773.85	1209.33	1701.12