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

Running head: Vegetation and topography influences on wildfires

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Table of contents summary: Use of regression models to predict average burnt areas and assess the relative influence of weather, vegetation, and topography in the distribution of wildfires in central Québec. Interactions between those factors proved important and allowed accurate predictions of burnt areas at a resolution of 350 km² and 11 years.

Abstract:

Background: It is crucial to better understand and predict how burnt areas in the boreal forest will evolve under a changing climate and landscape.

Objective: Predicting burnt areas at several spatial and temporal scales in the Quebec continuous boreal forest and comparing the influence of weather, vegetation and topographic variables by including them and their interactions in logistic regressions.

Results: At the largest spatial scale (350 km²), 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/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.

Conclusions: Vegetation and topography are important predictors of fire susceptibility, but risk factors might vary between wind- and drought-driven fire-weather.

Wider Applications: Including at least some vegetation and topographic variables in statistical models linking burnt areas to weather data can greatly improve their predictive power.

Keywords: Boreal forest, fire weather index, logistic regressions, fire susceptibility, burnt areas prediction.

1. Introduction

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

While 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 behavior (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 generalization, stating that the balance between weather, topographic and fuel variables is highly dependant upon 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 Québec 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 to 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 significant influence (Hély *et al.* 2001). In the boreal forest, conifers in particular are considered better fuel than deciduous species (Cumming 2001; Hély *et al.* 2000b). Elevation has been shown to increase the fire 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 hypothesize that the inclusion of interaction parameters between weather and non-weather variables should increase prediction accuracy.

2. Materials and methods

2.1. Study area

The study area comprised 55533 km² of eastern boreal forest in Québec (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. 1a). The study period spanned from 2000 to 2010, during which the 4 weather stations located directly in the area recorded mean annual temperatures ranging from

– 0.9 °C to 0.9 °C, and mean annual total precipitation from 529.3 mm to 620.3 mm, with 30 to 34% as snow.

The reported average historical fire cycle (last 300 years) in the region is 247 years (Bélisle *et al.* 2011), and 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.

2.2. General design

We distinguish between spatially from temporally variable data. Given the limited geographical extent of the study area, weather variables, or top-down controls, mainly vary temporally. Topographic and vegetation variables, or 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 (MRNQ) from aerial photographs taken between 1990 and 2000.

Forest inventory data were combined with forest fires larger than 0.3 ha (SOPFEU data) that occurred between 2000 and 2010 (inclusively, Fig. 1b). The original polygons were transformed into 394 361 points (or pixels) that corresponded to squares with side lengths of 374 m (approximately 14ha area). This dataset was duplicated 11 times – once for each year between 2000 and 2010. Each point was assigned a fire occurrence value (0 vs. 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). 10x10 points and 50x50 points blocks were computed, corresponding to areas of approximately 14 km² and 350 km², respectively (Fig. 2 top). Each year and block was then allocated weather variables through inverse distance weighting interpolation (see 2.4).

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.

2.3. 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), 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 since 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 Forest Fire Weather Index (FWI), which models the effect of wind and fuel moisture on fire behavior, and the Forest Fire Behavior 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:

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

where a, b and c are fuel type specific parameters in the FBP system and ISI a fire weather index (Initial Spread Index, see 2.4) 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 re-computed accordingly. The other vegetation variables were set to 0. Age increase throughout the time period was considered 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 8 neighbouring blocks. Fourteen values were computed for each variable: the base one of the block, the minimum among it and the 8 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.

2.4. Weather variables

Daily rainfall, maximum daily temperature, as well as temperature, relative humidity and wind speed measured at 1200 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. Those three moisture codes and wind speed were used to compute the Initial Spread Index (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 Fire Weather Index (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 center of the block.

2.5. Statistical analyses

2.5.1. General model structure

All statistical analyses were performed with the R software v2.15.2 (The R Foundation of Statistical Computing, 2012). The model type used in all 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. In R, it uses the general linear model (glm) 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 a 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 10x10 and 50x50 pixels blocks, respectively) were excluded from the analyses to avoid an artificial variability in the response area burnt (for 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 to each other at more than $r = 0.61$. All variables were centered and scaled so as to be confined within ± 100 with a mean of 0.

2.5.2. Weather variables 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: a) Rainfall, Humidity, Wind speed, Maximum daily temperature, b) FFMC, DMC, DC, c) ISI, BUI, and d) 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 tradeoff between accuracy and complexity, allowing the most parsimonious models to be selected (Burnham and Anderson 2002).

2.5.3. Models comparison

The global or full model was then constructed from the best set of weather variables, and adding all 9 spatial variables: RSI, Density, Age, Uneven-aged, *Cladonia* presence, Slope, Elevation, Road distance, 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 x Density, RSI x Cladonia, Density x Cladonia to test for the influence of dry lichen-covered open woodlands (hereafter named OW interactions), and RSI x Uneven, RSI x Age, Age x 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 variables influence would decrease in importance when weather conditions are more fire-prone. The threshold of 10 was the highest that could be possibly used without reducing too much the number of observations compared to the number of parameters in the model.

2.5.4. 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 than 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 one hand and predictions generated through cross-validation on the other hand. In the 10x10 pixels configuration, blocks were regrouped according to the large 50x50 pixels 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 10x10 block aggregates (1, 5 and 25 blocks, 25 10x10 blocks being the equivalent of one 50x50 block, see Fig. 2) without modifying the number of observations available to fit the model.

2.5.5. 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 combination available for vegetation values, four hypothetic 50x50 pixels blocks were chosen to run those predictions: “Black spruce” was defined as RSI = 22.3, Density = 50, Age = 60, Uneven = 0, Cladonia = 0; “Mixed spruce – deciduous” as RSI = 11.57, Density = 50, Age = 60, Uneven = 0, Cladonia = 0; “Heath” as RSI = 14.27, Density = 0, Age = 0, Uneven = 0, Cladonia = 0; and “Spruce-lichen open woodland” as RSI = 10.64, Density = 18, Age = 80, Uneven = 0, Cladonia = 0.3. These values were chosen to reflect the general vegetation type, while topographic variables were given average values: Slope = 9.9, Elevation = 1000, Roads = 23000, 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 = 23000, Water = 0. These corresponded to mean values, rounded to 0 when very low.

3. Results

3.1. Weather variables selection

The best set of weather variables differed depending on the spatial scale used: the ISI + BUI combination was best for 10x10 blocks, while the FFMC + DMC + DC was best for 50x50 blocks (Table 2). However, the ISI + BUI combination was still the second best for the 50x50 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 scales, the Temp + Humidity + Rain + Wind combination was third in order of performance, while the models using a single weather variable (the FWI) were the worst ones (Table 2).

3.2. Neighbouring effects on spatial variables

Depending on block size, the best formula to account for neighbours changed for each variable (Appendix 1). For the 10x10 pixels blocks, neighbours always had to be accounted for, and the value of the block itself was negligible for slope and *Cladonia* presence. For 50x50 pixels blocks, the influence of the block value was negligible for the distance from roads and uneven aged stands variables, but the values of neighbours were negligible for RSI and C*ladonia* presence.

3.3. 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 10x10 pixels blocks, and 66% for 50x50 pixels 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, while interactions between spatial variables were of comparatively little importance. For 10x10 pixels blocks, the most important single variables were (in decreasing order): BUI, ISI, Elevation, Water, RSI, Density, Roads, Age, Cladonia, Uneven, and Slope. For 50x50 pixels blocks, these were: BUI, ISI, RSI, Density, Water, Uneven, Elevation, Age, Slope, Cladonia, and Roads.

Sequential removing of spatial variables (in their order of importance for 10x10 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 x Spatial variables interactions remained at a similar level compared to weather variables (Appendix 3). Water presence notably became the most important spatial variable for both block sizes.

3.4. Prediction accuracy vs. 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, b and c). When the model was directly fitted on larger 50x50 pixels blocks, prediction accuracy did not appear very different from 10x10 blocks predictions aggregated on the same scale (Fig. 3 c and 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 more pronounced for the small blocks (0.65 for adjacent observations). Hence, only 50x50 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 50x50 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 10x10 blocks were equal to 0.066 for fitted values and 0.069 for predicted values. For 50x50 blocks, they were 0.036 for fitted values and 0.078 for values predicted through cross-validation.

3.5. 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 - since they not only interact with weather variables, but also among themselves. Furthermore, some spatial variable can have a positive interaction with one of the weather variables and a negative one with others (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. 6a). This was also the case for open heathlands, except under the most extreme fire weather conditions (Fig. 6a). Finally, mixed spruce-deciduous forests appeared less fire-prone (Fig. 6a). Closed spruce and open spruce-lichen woodlands seemed to burn more when ISI was high (Fig. 6b), whereas open heathlands and mixed forests were more dependant upon a high BUI (Fig. 6c).

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

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

4. Discussion

4.1. 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 (Bisquert *et al.* 2011; Chuvieco *et al.* 2009; Flannigan *et al.* 2005; Gonzalez *et al.* 2006; Krawchuk *et al.* 2006). The best performance here was obtained at the largest spatial scale (350 km²), where the model was globally able to identify high and low fire-risk areas.

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The main drawback of empirical models is the dependency upon 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 emphasized 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 being more spatially correlated, requiring further complexification 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 saw significant area burnt. Hence, removing one of these 3 years during the cross-validation drastically affected the predictive performance of the model. This is emphasized by the difference in RMSE between fitted and predicted values at this scale (0.036 vs. 0.078), which was lower if all years where used during the cross-validation (0.036 vs. 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.

4.2. Weather influence vs. vegetation and topography

Weather and spatial variables played an equivalent role explaining spatial variation in proportions of area burnt. While it would be tempting to attribute this result to the less fire-prone climate of the eastern boreal forest of Canada compared to its western counterpart, Krawchuk et al. (2006) did find similar results in Alberta, and even 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 vs. 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 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 fire weather index threshold of 10 we could use to define the subset not being all that high. While 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 since 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 one, and that some spatial variables had interaction parameters of opposite signs between the initial spread index (ISI) and the build-up index (BUI). Provided 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 favors the burning of different vegetation and topography.

Among 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 spatial variables in the model, the more 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.

4.3. 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 since 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 a better discrimination between vegetation types. Similar RSI values were thus able to correspond to either a 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 – would decrease predicted burnt areas. This is in accordance with many previous results stating the lower fire susceptibility of deciduous species compared to conifers (Bergeron *et al.* 2004; Cumming 2001; Hély *et al.* 2000b). On the other hand, 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 of 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 mixedwoods 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. 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 (Brown *et al.* 1989; Luke and McArthur 1978).

Tree density appeared to have a positive effect on fire susceptibility for coniferous stands, but a negative one 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 in contradiction with the accumulation of dead material in unmanaged forest over time (Agee 1993; Barrett *et al.* 1991; Hély *et al.* 2000a; Van Wagner 1983). On the other hand, old boreal stands tend to develop thick and moist organic layers (Crawford *et al.* 2003). This effect was weak, however, so it is also possible that mean age in 350 km² 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 one for mixedwoods. Indeed, sub-canopies 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, since 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).

5. Conclusion

Statistical models had been shown to predict burnt areas at the ecozone scale using only fire weather indices (Flannigan *et al.* 2005). The inclusion of vegetation and topographic variables in logistic regressions, and their interaction with fire weather indices, allowed such models to identify burnt areas of 350 km^2 blocks over 11 years with reasonable accuracy. Such models are limited in scope since 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 upon 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 initial spread index and build-up index 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 then how different kinds of intense fire weather (driven by wind vs. drought) would interact with topographic and vegetation features. The method itself could of course be improved upon, 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.

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Figure captions

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

Fig. 2 Maps of the two bloc sizes (top) and aggregates of the small blocs (bottom).

Fig. 3 Predicted vs. observed proportions of burnt areas of each block from 2000 to 2010 for different spatial scales: a) 10x10 pixels blocks; b) 10x10 pixels block aggregated by lines of 5 blocks; c) 10x10 pixels blocks aggregated by squares of 25 blocks; d) 50x50 pixels blocks.

Fig. 4 Maps of observed (left column) and predicted (right column) mean annual burnt areas between 2000 and 2010 for 10x10 (first line) and 50x50 blocks (second line).

Fig. 5 Predicted vs. observed proportions of burnt areas in each block for different spatial and temporal scales: a) 10x10 pixels blocks for 1 year; b) 10x10 pixels blocks for 11 years; c) 50x50 pixels blocks for 1 year; d) 50x50 pixels blocks for 11 years.

Fig. 6 Predicted burnt areas for four hypothetic 50x50 pixels blocks (see text for details) under increasing fire weather risk a) both ISI and BUI (BUI = ISI x 8); b) increasing ISI with BUI = 30; c) increasing BUI with ISI = 4.1.

Fig. 7 Predicted burnt areas of black spruce and mixed spruce – deciduous forested 50x50 blocks under increasing ISI and BUI (BUI = ISI x 8) and with varying values of vegetation variables: a) high (50% cover) vs. low (30% cover) density; b) old (70 years) vs. young (40 years) c) low (0) vs. high (0.2) proportion of uneven aged stands; d) low (0) vs. high (0.2) proportion of stands with presence of *Cladonia.*

Fig. 8 Predicted burnt areas of average 50x50 blocks with varying values of topographic variables, when either ISI increases with BUI = 30 (left column) or BUI increases with ISI = 4.1 (right column). Effect of a) Elevation; b) Slope; c) Distance to roads; d) Water body presence.

Tables

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

			Range (min-max)	
Variable	**Type**	**Unit**	**10x10 blocks**	**50x50 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)*	Weather	mm	7.34 - 141.92	7.68 - 141.46
Relative humidity (Humidity)**	Weather	%	48.72 - 68.62	48.79 - 68.36
Wind speed (Wind)***	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

* Seasonal averages of monthly totals.

** Seasonal averages of monthly minimums.

*** Seasonal averages of monthly averages.

Table 2. Model selection for weather variables. Best model has a ∆AICc of 0.

Model	AICc		∆AICc	
	10x10 blocks	**50x50 blocks**	**10x10 blocks**	**50x50 blocks**
Temp + Rain + Humidity + Wind	316287.7	201241.2	2679.03	6038.11
FFMC + DMC + DC	313952.4	195203.1	343.74	0
ISI + BUI	313608.6	197237.3	0	2034.25
FWI	324213.5	208259.3	10604.89	13056.24

Table 3. Explicative power of each variable and group of variables (higher ∆AICc means more important variable, see text for details).

Model	AICc		∆AICc	
	10x10 blocks	**50x50 blocks**	**10x10 blocks**	**50x50 blocks**
Global	193607.1	79147.18	0	0
No Weather	309400.7	193322.55	115793.60	114175.37
No Spatial	300359.3	192201.43	106752.18	113054.25
No Vegetation	248058.2	125193.59	54451.10	46046.41
No Topography	253674.2	116873.44	60067.06	37726.26
No Weather x Spatial	253772.8	142492.83	60165.72	63345.65
No OW interactions	196450.2	-*	2843.10	-*
No Structure interactions	194034.9	86418.54	427.82	7271.36
No ISI	242337.7	130824.68	48730.59	51677.50
No BUI	255902.0	147172.67	62294.88	68025.48
No RSI	207408.6	92841.21	13801.53	13694.03
No Density	206740.7	89826.08	13133.59	10678.89
No Uneven	195515.7	88235.99	1908.56	9088.81
No Cladonia	196817.8	82065.96	3210.70	2918.78
No Age	197292.5	86381.88	3685.42	7234.70
No Slope	193975.0	86079.78	367.92	6932.60
No Elevation	214154.5	87276.64	20547.35	8129.46
No Water	209824.8	89453.30	16217.65	10306.12
No Roads	200018.2	79876.28	6411.13	729.10

* Model failed to converge.

Table 4. Explicative power of each spatial variable when they are removed sequentially from the global model.

Model	Nb of spatial variables	AICc		ΔAICc		Variable impact	
		10x10 blocks	50x50 blocks	10x10 blocks	50x50 blocks	10x10 blocks	50x50 blocks
Global	9	193607.1	79147.18	0	0	0	0
"- Slope"	8	193975.0	86079.78	367.92	6932.60	367.90	6932.60
"- Uneven"	7	196264.2	96140.2	2657.06	16993.02	2289.20	10060.42
"- Cladonia"	6	199804.0	99660.45	6196.87	20513.27	3539.80	3520.25
"- Age"	5	204763.7	103338.99	11156.62	24191.81	4959.70	3678.54
"- Road"	4	219050.2	113692.14	25443.14	34544.96	14286.50	10353.15
"- Density"	3	239374.4	129112.15	45767.29	49964.97	20324.20	15420.01
"- RSI"	2	272289.5	149877.52	78682.39	70730.34	32915.10	20765.37
"- Water"	1	273507.1	150322.95	79899.96	71175.76	1217.60	445.43
"- Elevation"	0	309400.7	193322.55	115793.60	114175.37	35893.60	42999.60

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

Variable	Formula or weight of block value if weighted mean	
	10x10 blocks	50x50 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	
	10x10 blocks	50x50 blocks	10x10 blocks	50x50 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 x ISI	-2.666e-03	4.387e-02	**0.000324**	**<2e-16**
RSI x Density	2.471e-02	2.000e-02	**<2e-16**	**<2e-16**
RSI x Uneven	1.040e-01	6.584e+00	**2.67e-07**	**<2e-16**
RSI x Cladonia	-2.819e-01	3.765e+00	**8.69e-12**	**<2e-16**
RSI x Age	-4.017e-03	-2.869e-02	**<2e-16**	**<2e-16**
Density x Cladonia	-1.868e-01	-9.348e-01	**<2e-16**	**<2e-16**
Uneven x Age	2.294e-02	2.372e-01	**<2e-16**	**<2e-16**
Slope x ISI	6.283e-02	8.812e-02	**<2e-16**	**<2e-16**
Density x ISI	1.600e-02	3.193e-03	**9.09e-15**	0.0645
RSI x ISI	2.050e-01	2.498e-01	**<2e-16**	**<2e-16**
Road x ISI	1.171e-02	7.278e-06	**<2e-16**	**3.08e-15**
Elevation x ISI	-4.752e-04	2.853e-03	0.117883	**<2e-16**
Water x ISI	2.892e+00	1.955e+01	**<2e-16**	**<2e-16**
Uneven x ISI	2.692e+00	1.161e+01	**<2e-16**	**<2e-16**
Cladonia x ISI	7.395e+00	8.979e+00	**<2e-16**	**<2e-16**
Age x ISI	-1.412e-02	8.673e-03	**<2e-16**	**<2e-16**
Slope x BUI	9.502e-04	2.692e-03	**2.84e-05**	**1.12e-10**
Density x BUI	-2.682e-03	1.224e-03	**<2e-16**	**<2e-16**
RSI x BUI	-1.192e-02	-1.954e-02	**<2e-16**	**<2e-16**
Road x BUI	-1.649e-03	-8.712e-07	**<2e-16**	**<2e-16**
Elevation x BUI	1.768e-03	2.646e-04	**<2e-16**	**<2e-16**
Water x BUI	-1.858e-01	-5.499e-01	**<2e-16**	**<2e-16**
Uneven x BUI	6.800e-02	4.642e-01	**<2e-16**	**<2e-16**
Cladonia x BUI	-1.896e-02	-3.291e-01	**0.002347**	**<2e-16**
Age x 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		ΔAICc	
Model	**10x10 blocks**	**50x50 blocks**	**10x10 blocks**	**50x50 blocks**
Global	72955.97	31072.73	0	0
No Weather	113170.86	91837.13	40214.89	60764.40
No Spatial	98987.45	59285.17	26031.47	28212.43
No Vegetation	102678.04	63559.60	29722.07	32486.87
No Topography	85493.85	57335.17	12537.87	26262.44
No Weather x Spatial	89399.23	56717.80	16443.25	25645.07
No OW interactions	73387.53	33826.51	431.55	2753.78
No Structure interactions	73167.98	31605.34	212.01	532.61
No ISI	86944.09	44353.28	13988.12	13280.55
No BUI	78655.02	40791.19	5699.04	9718.46
No RSI	79155.29	39039.09	6199.32	7966.36
No Density	79631.58	32106.14	6675.60	1033.41
No Uneven	74911.86	41572.56	1955.88	10499.83
No Cladonia	73870.40	34804.46	914.42	3731.73
No Age	76578.85	34362.41	3622.88	3289.68
No Slope	73118.28	40144.99	162.30	9072.26
No Elevation	74751.79	34177.16	1795.81	3104.43
No Water	81779.58	44329.80	8823.61	13257.07
No Roads	74165.30	32773.85	1209.33	1701.12

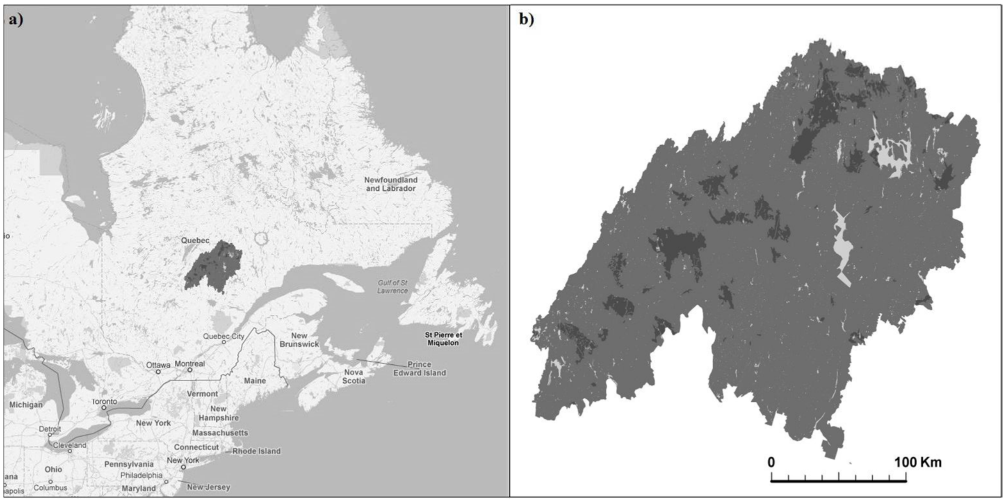

Figure 1
408x202mm (96 x 96 DPI)

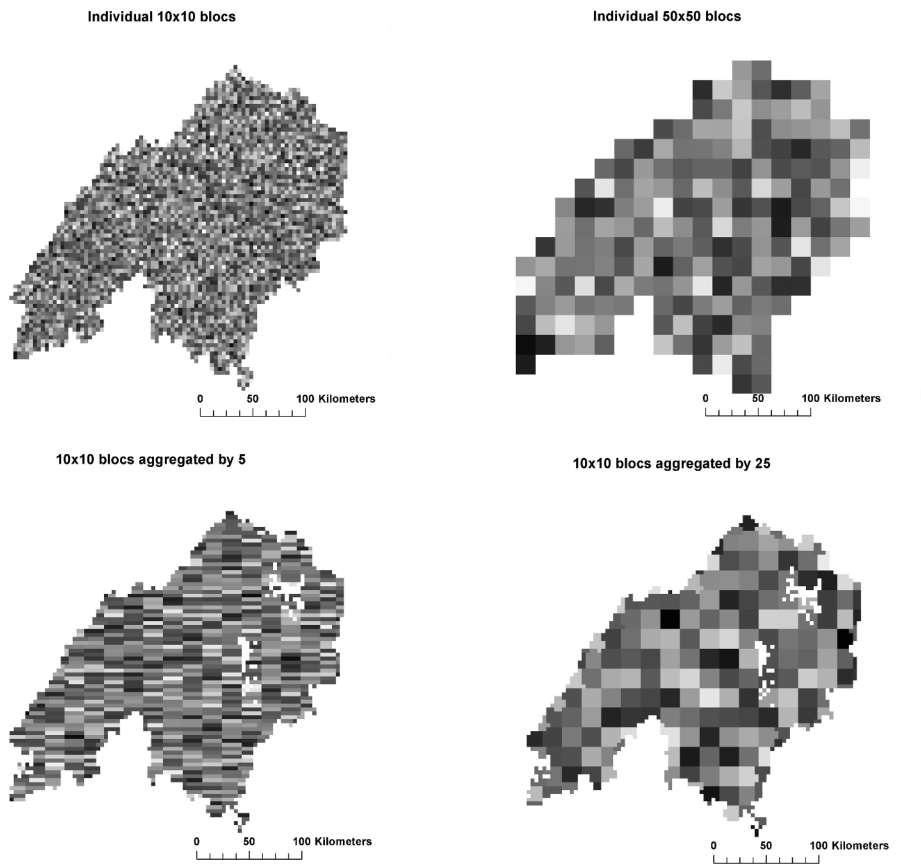

Figure 2
378x348mm (300 x 300 DPI)

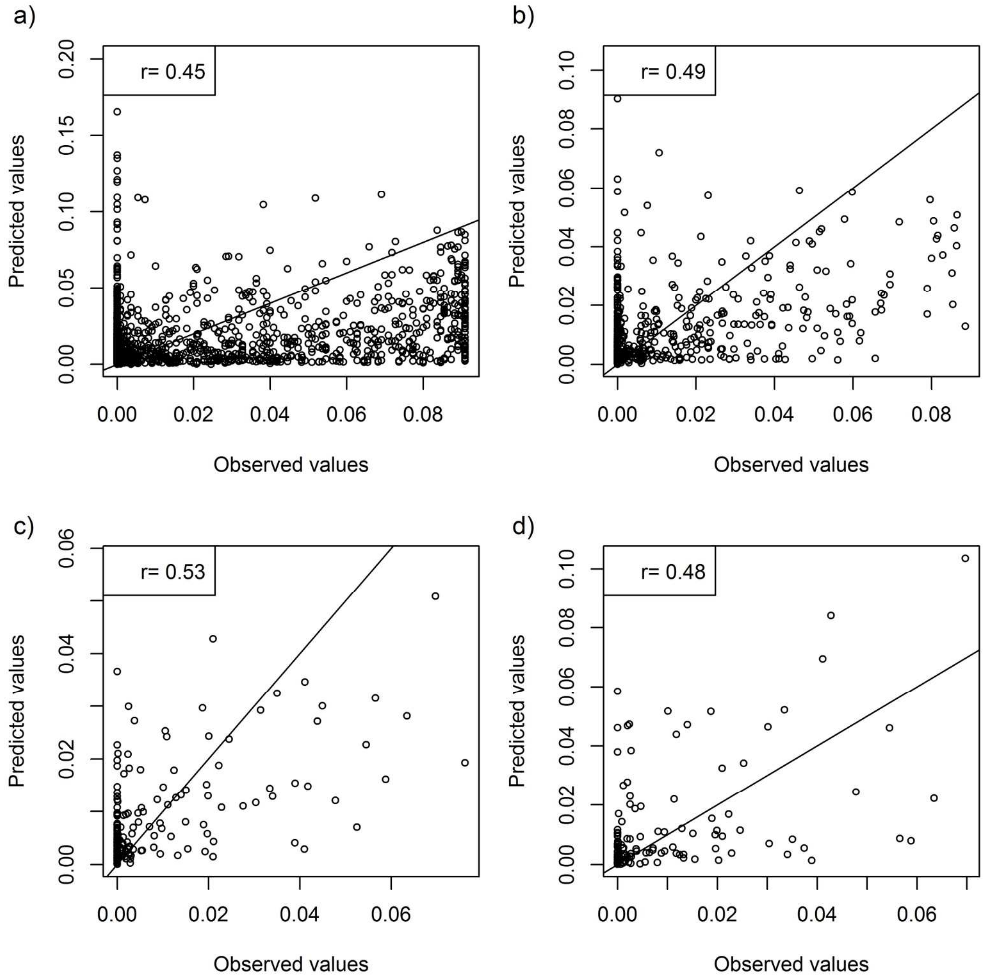

Figure 3
169x169mm (300 x 300 DPI)

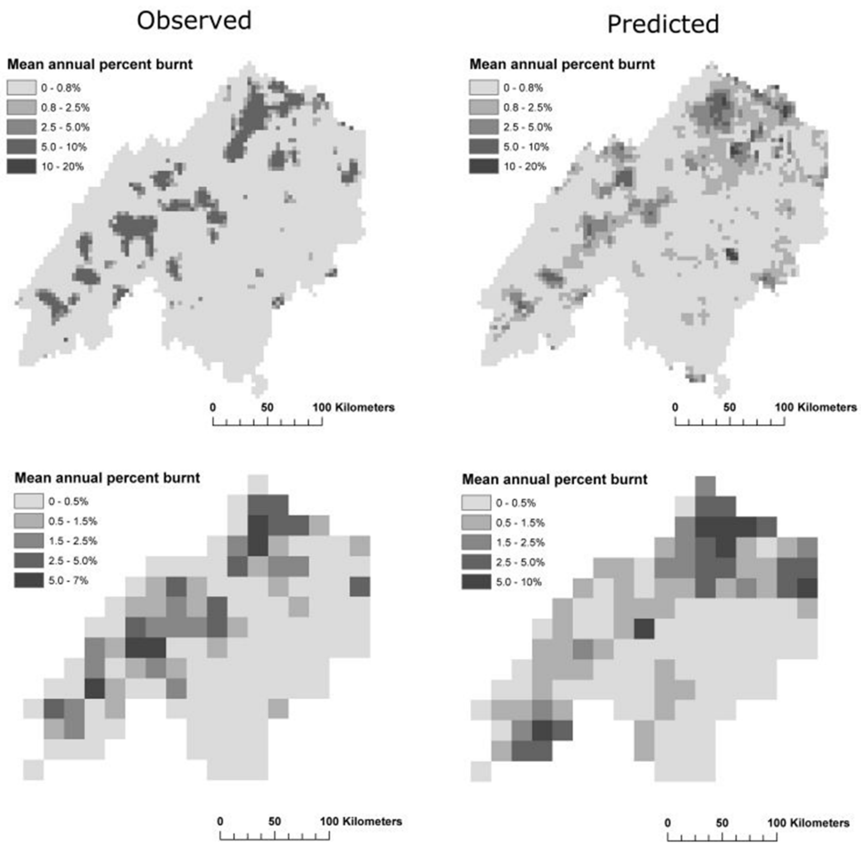

Figure 4
303x284mm (72 x 72 DPI)

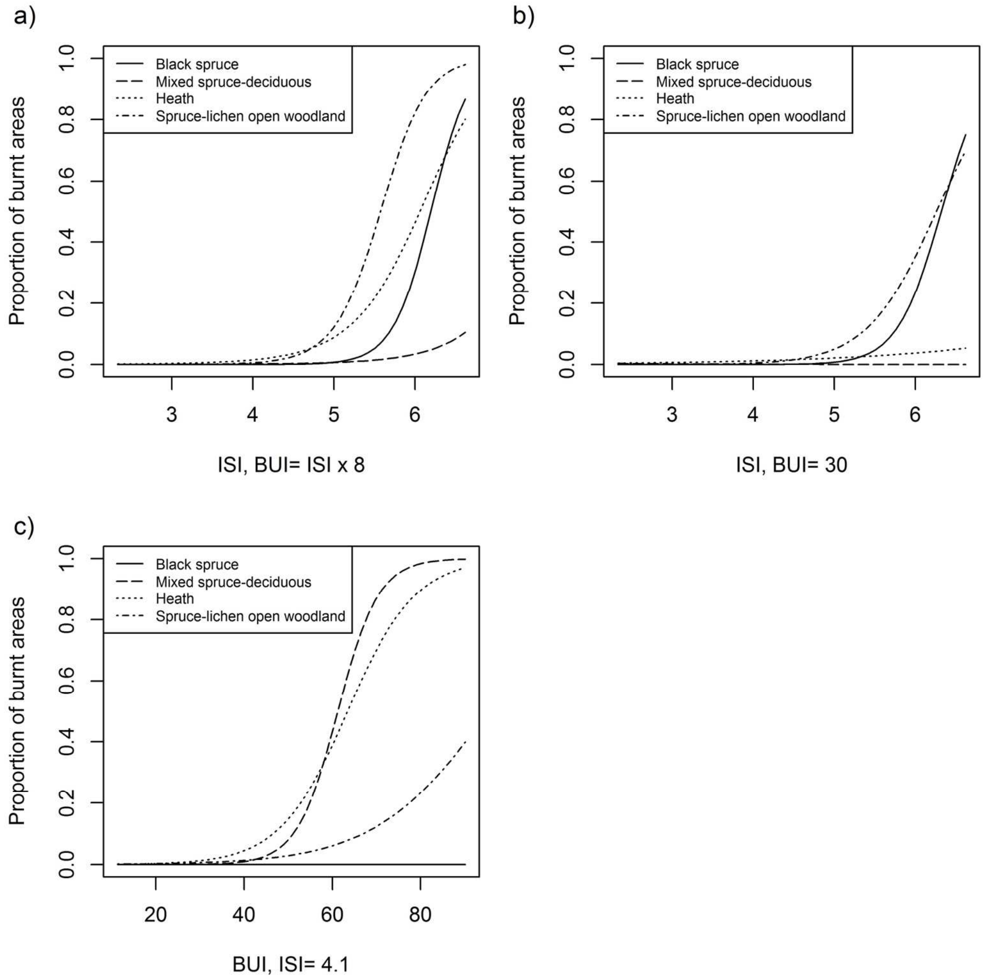

Figure 5
169x169mm (300 x 300 DPI)

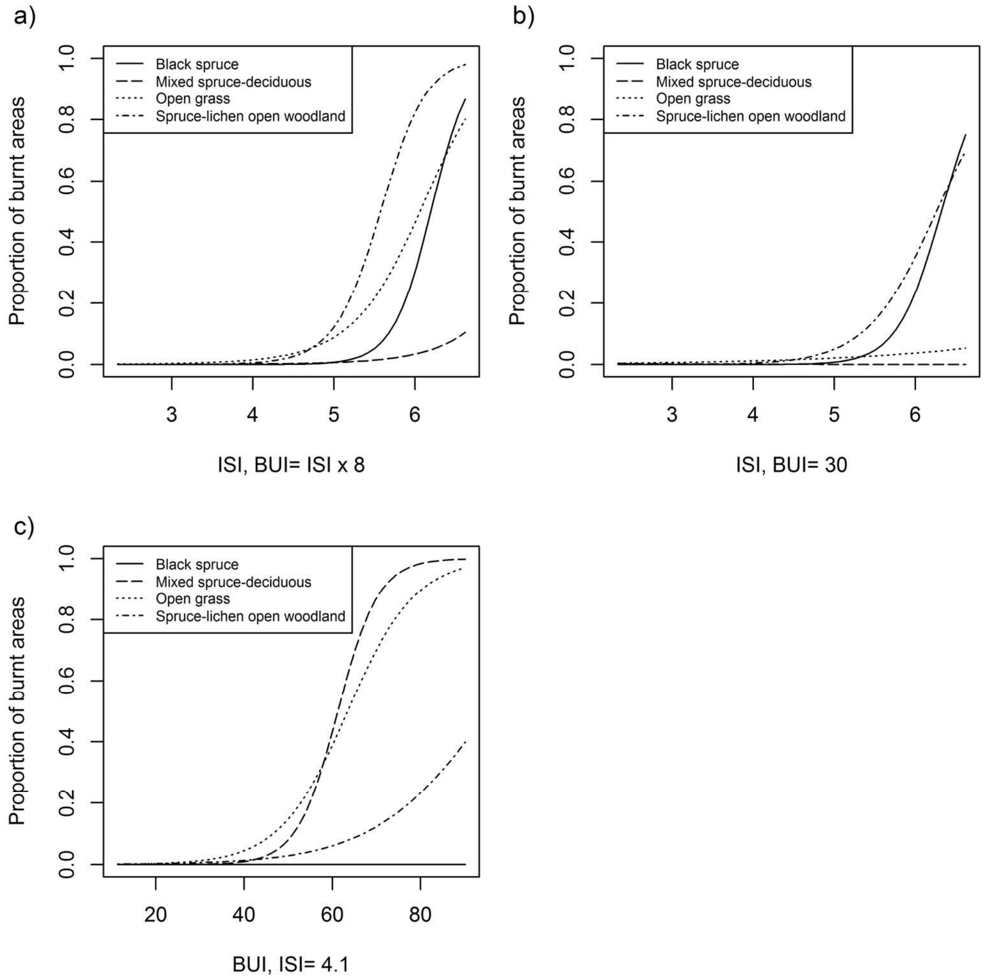

Figure 6
169x169mm (300 x 300 DPI)

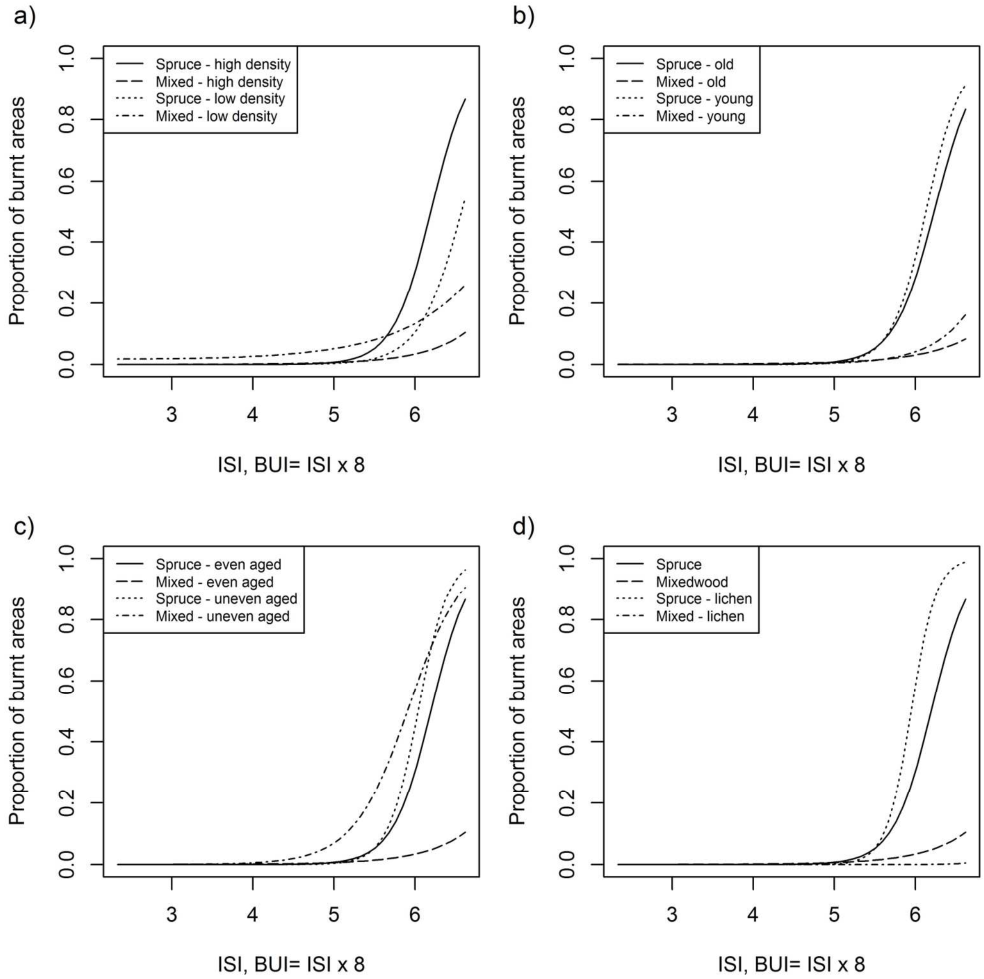

Figure 7
169x169mm (300 x 300 DPI)

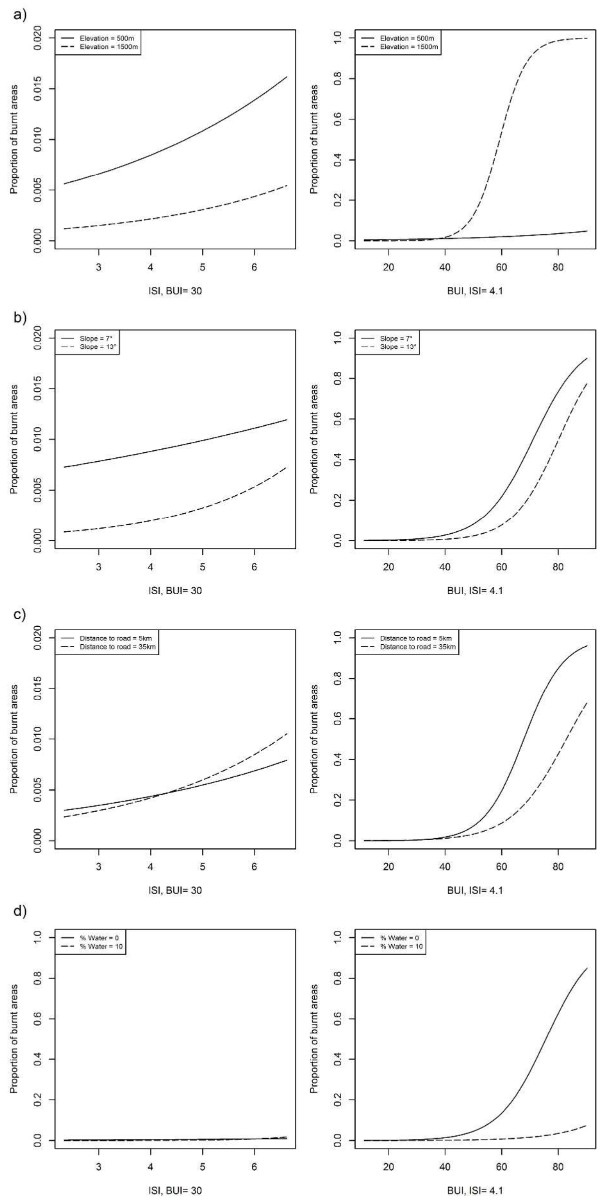

Figure 8
338x677mm (300 x 300 DPI)