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BorealFireSim: A GIS-based cellular automata model of wildfires for the boreal forest of Quebec in a climate change paradigm

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A B S T R A C T

Wildfires are the main cause of forest disturbance in the boreal forest of Canada. Climate change studies forecast important changes in fire cycles, such as increases in fire intensity, severity, and occurrence. The geographical information system (GIS) based cellular automata model, BorealFireSim, serves as a tool to identify future fire patterns in the boreal forest of Quebec, Canada. The model was calibrated using 1950–2010 climate data for the present baseline and forecasts of burning probability up to 2100 were calculated using two RCP scenarios of climate change. Results show that, with every scenario, the mean area burned will likely increase on a provincial scale, while some areas might expect decreases with a low emission scenario. Comparison with other models shows that areas forecasted to have an increase in fire likelihood, overlap with predicted areas of higher vegetation productivity. The results presented in this research aid identifying key areas for fire-dependent species in the near future.

1. Introduction

Fire is the main source of disturbance in the boreal forest of Quebec (Natural Resources Canada, 2014). Wildfires are essential for forest regrowth of tree species such as jack pine or black spruce which depend on extreme heat to reproduce, as well as for insects or bird species depending on dead trees, or snags (Bonnot et al., 2009; Nappi et al., 2003). For the last decade, fire suppression costs in Canada ranged from 500 million to 1 billion dollars per year and burned more than 2.3 million ha annually (Natural Resources Canada, 2014). Moreover, natural wildfires burning more than 200 ha account for 97% of the total area burned across Canada and represent 3% of the wildfires (Natural Resources Canada, 2014). Wildland fires are caused mainly by four factors: fuels, climate–weather, ignition agents, and people (Flannigan et al., 2009). Numerous studies have concluded that upcoming climate change will be a major driver of ecological change (Flannigan et al., 2000; IPCC, 2013). Dale et al. (2008) state how the interactions between climate, disturbances and forest systems are critical to determine climate change impacts on forests (Flannigan et al., 2000; IPCC, 2013). Among the biological impacts of climate change, variations in migration patterns of animals, increasing prevalence of wildfires and massive insect outbreaks are the most relevant (IPCC, 2013) Moreover, Mantyka-Pringle et al. (2015) demonstrated, in a study on the interplay between climate change and land-cover change, that adding climate change to land-cover change could increase the impacts of land-cover changes by up to 43% for birds and 24% for mammals. Fire frequency, size and seasonality would likely also be affected by climate change (IPCC, 2013).). Keane et al. (2008), showed that predicted future climate change will likely cause major shifts in landscape vegetation dynamics and this shift is likely to be enhanced by independent changes in biophysical conditions. Changes in fire behavior will affect forest value for wildlife habitat as well as for the industry. Additionally, fire ignition and spread depend on the amount and frequency of precipitation, the type of forest cover and different conditions, such as thunderstorms, topography and wind speed, among others; thus these variables should be included within wildfire models (Dale et al., 2001).

Modeling fire behavior and spatiotemporal patterns enable better understanding of the feedbacks and interactions occurring in forested landscapes. Fire propagation models are usually deterministic and based on linear statistics; examples of such type of models are the Canadian Wildland Fire Effects Model (CanFIRE) (De Groot, 2012). The former model is used by the Canadian Forest Service to predict the physical and ecological impacts of fires. Another widely used model is FARSITE (Finney and Andrews, 1999), a GIS-based fire growth model which is used to produce maps of fire behavior on a fire event. Even though FARSITE is extremely powerful and couples statistical decision making to GIS, this model is not meant for large scale spatiotemporal fire dynamics, but for fire spread across landscapes (Finney and Andrews, 1999). While FARSITE and other FARSITE-based models like Fire-BGC (Green et al., 1995) — a spatially-explicit fire succession model designed to investigate long-term trends in landscape pattern under historical and future fire regimes — focus on fire spread across a

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landscape. In contrast, BorealFireSim works at a provincial scale, and focuses on a long term spatiotemporal changes in wildfire patterns in the boreal forest, dealing with many fire events in space and in time (Finney and Andrews, 1999; Keane et al., 1998). Given that wildfire ignition can be caused by diverse interacting conditions, such as climate, elevation, dryness, tree species, weather, and presence of wet areas, the complex dynamics between these conditions give rise to spatial patterns of burned areas, emerging from local interactions to global scale patterns through time. The dynamic behavior of wildfire processes can be studied by complex systems theory, which takes into account non-linearity of processes and feedbacks with the environment. The term complexity is used in this research, to represent the process by which identical initial conditions in an environment will give rise to different outcomes if the experiment is repeated multiple times (Batty and Torrens, 2001). Researchers often integrate complex behaviors into simple models using stochastic and dynamic modeling approaches. Among these approaches, cellular automata (CA) models have been proven effective to reproduce non-linear processes (Wolfram, 1994).

Cellular automata are models comprising a grid of cells where each one has a finite number of states. The state of a cell is influenced by the neighboring cells via transition rules. These transitions rules are applied to each cell for a certain number of time steps. In CA models, the state of a cell can be summarized with the following equation:

$$S_{i,j}(t+1) = f\{N_{i,j}(t), S_{i,j}(t), \Delta\mathrm{T}\} \quad (1)$$

where the state (S) of a cell i,j at a time $(t+1)$ is a function of its neighborhood $N_{i,j}(t)$, and its state at the previous time $S_{i,j}(t)$ within a discrete time step ΔT. The major advantage of this approach is that instead of running simulations on the whole system with complex mathematical equations, simple rules are imposed on cells that can only interact with their neighbors. During and after the simulation, spatial patterns emerge from these local interactions between cells (Li and Magill, 2001).

The approach used in this research is a GIS-based cellular automata, which allows us to model dynamic, complex and non-linear interactions on large spatial and temporal scales. When coupled to GIS, CA models make powerful tools for simulating complex spatiotemporal phenomena such as wildfire. While most of cellular automata models represent abstract or virtual environments, adding actual georeferenced map layers lets us model complex dynamics taking into account real landscapes and that is especially why GIS-based CA models have been used in numerous fields. Examples of CA and GIS-based CA models can be found in multiple studies of dynamic processes such as land use/cover change and urban dynamics (Kocabas and Dragicevic, 2006, 2007; Rindfuss et al., 2010, Singh, 2003; Ward et al., 2000; Yeh and Li, 2003), invasive species (Bone et al., 2006; Perez and Dragicevic, 2012) and forest fires (Alexandridis et al., 2008, 2011; Yassemi et al., 2008), to cite only few of the applications. In forest fires studies, Alexandridis et al. (2011) showed the power of GIS-based cellular automata combined with meteorological data as a way to efficiently predict the evolution of fire front on forest landscapes. Alexandridis et al. (2011) also included the *spotting effect* which is a phenomenon where burning material is transported by wind to areas not adjacent to the fire front, sometimes causing the ignition of a new, independent, fire event. Even though spotting could be important for fire front evolution models, this phenomenon is not relevant on a provincial scale, where the spatial resolution does not allow these short range (100 m approximately) dynamics.

This research presents a novel GIS-based CA modeling approach named BorealFireSim, where the importance of model variables and transition rules is based on literature and on a thorough sensitivity analysis. Moreover, the BorealFireSim uses provincewide information to simulate the probability of annual forest wildfires under current and future different climate scenarios. In general, fire models consist of fire front spread models, that is, the evolution of a single fire depending on various variables, such as bush density, bush flammability and wind speed and direction (Li and Magill, 2001). Alternatively, BorealFireSim model aims to simulate probable fire patterns on a provincial scale under climate change and does not take into account fine scale fire spread behavior as much as a fire front model would.

The main goal of this study is to simulate the complexities of wildfire processes and to identify changes in their spatial patterns throughout Quebec's boreal forest. Fire spread and post-fire regrowth behavior in BorealFireSim are based on climate and environmental variables. Furthermore, after calibrating the model to reproduce current fire patterns, simulations were made using future climate data (CMIP5) for different representative concentration pathways (RCPs) (IPCC, 2013; Hijmans et al., 2005). The following manuscript is organized in five sections. The material and methods (input data, model's transition rules, model flowchart, variables, algorithms and outputs) are detailed in Section 2. The results and discussion, Section 3, show maps of burning chance, cell states after 100 years, fire risk maps and statistical analysis. Likewise, results are compared with forecasted dynamic habitat index maps for 2050 and 2080 (Nelson et al., 2014) to identify relevant areas for species conservation. Finally, conclusion is presented in Section 4.

2. Material and methods

The GIS-based CA model proposed and implemented in this paper was developed to simulate current and future wildfire spatial patterns in order to analyze the influence of future climate change scenarios in forest fire disturbances. The conceptual model representation of BorealFireSim is synthesized in a flowchart (Fig. 1) that illustrates all the model steps and algorithms with their attributes, functions and relationships. Following sub-sections explain the model behavior, variables, transition rules and the two algorithms developed to represent fire spread and forest regrowth processes, as expressed in the flowchart.

2.1. Study area

BorealFireSim was programmed to be functional on any boreal area, as long as the input data are available. However, this research focuses on the boreal forest of Quebec. The boreal forest of Quebec is the main vegetation domain in the province of Quebec, Canada, covering more than 560 000 km^2, or a third of the province area. It is composed of a 75% coniferous cover, mainly black spruce, jack pine, balsam fir, white spruce and larch (Énergie et Ressources Naturelles Québec, 2013). Wildfires are an important source of natural disturbance in the boreal region of Quebec, an average of 928 fires is recorded each year, with a total of 42.2 million ha burned since 1973 (Forêt, Faune et Parcs Québec, 2013). From 2008 to 2014, fire prevention and suppression cost the government of Quebec $677,900,000 and affected 2,705,400 ha of forest (with 1,753,900 in 2013 only), with a total of 4308 fires (MFFP, 2015). The boreal forest is very important for Quebec's economy; from 2004 to 2012, forest industry represented an average annual income of 2.24G$ (MFFP, 2015). However, forest is not only important on the economic side, but also to the animal species that form its ecosystems. Wildfires are important for species such as the black-backed woodpecker (*Picoides arcticus*), which feeds on wood-boring beetles and are directly linked to burned forests (Nappi et al., 2003).

The extent covered by BorealFireSim for this research is 45.375°N to 59.491°N to 79.757°W to 57.112°W (Fig. 2) and its spatial resolution is 4.48 × 4.48 km or ~20 km^2. The model includes the boreal forest of Quebec, as well as the forest tundra. The forest tundra was included in the model to prevent edge effects and to take into account shifts in the boreal forest northern limit with climate change.

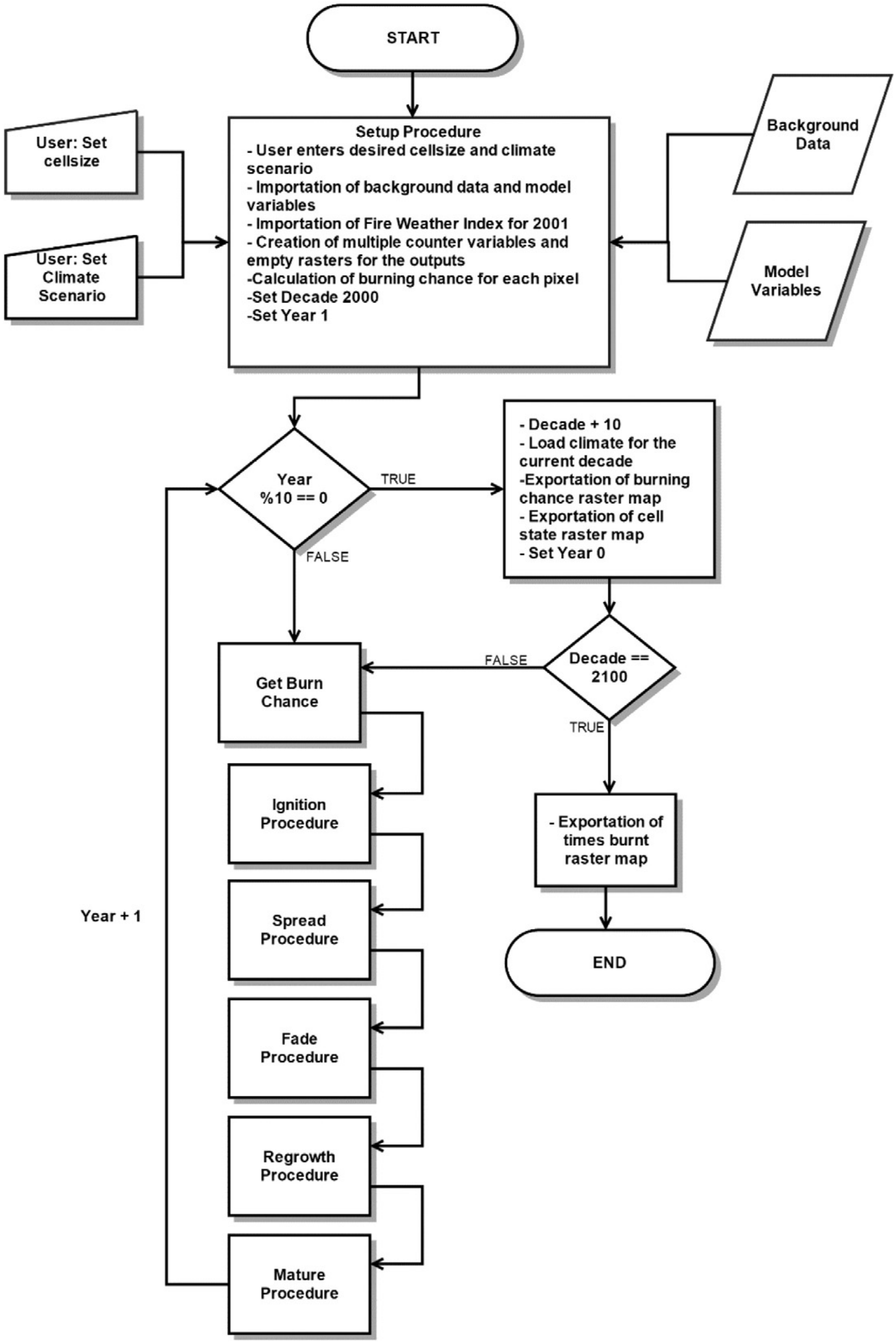

Fig. 1. Flowchart of the BorealFireSim model.

2.2. Model input data

2.2.1. Climate variables

Climate information was calculated with BioSim10, which is a software designed to assist in pest management via temperature-driven simulation models (Régnière, 2003). Even though its main purpose is the forecast of events in the seasonal biology of pests, it is a powerful software for forecasting climate information, using Environment Canada's weather stations. The only climate variable present in BorealFireSim is the Fire Weather Index (FWI) mean of the fire season, for instance from May to September. Present climate data consists of the mean for the 1981–2010 period and future values were calculated

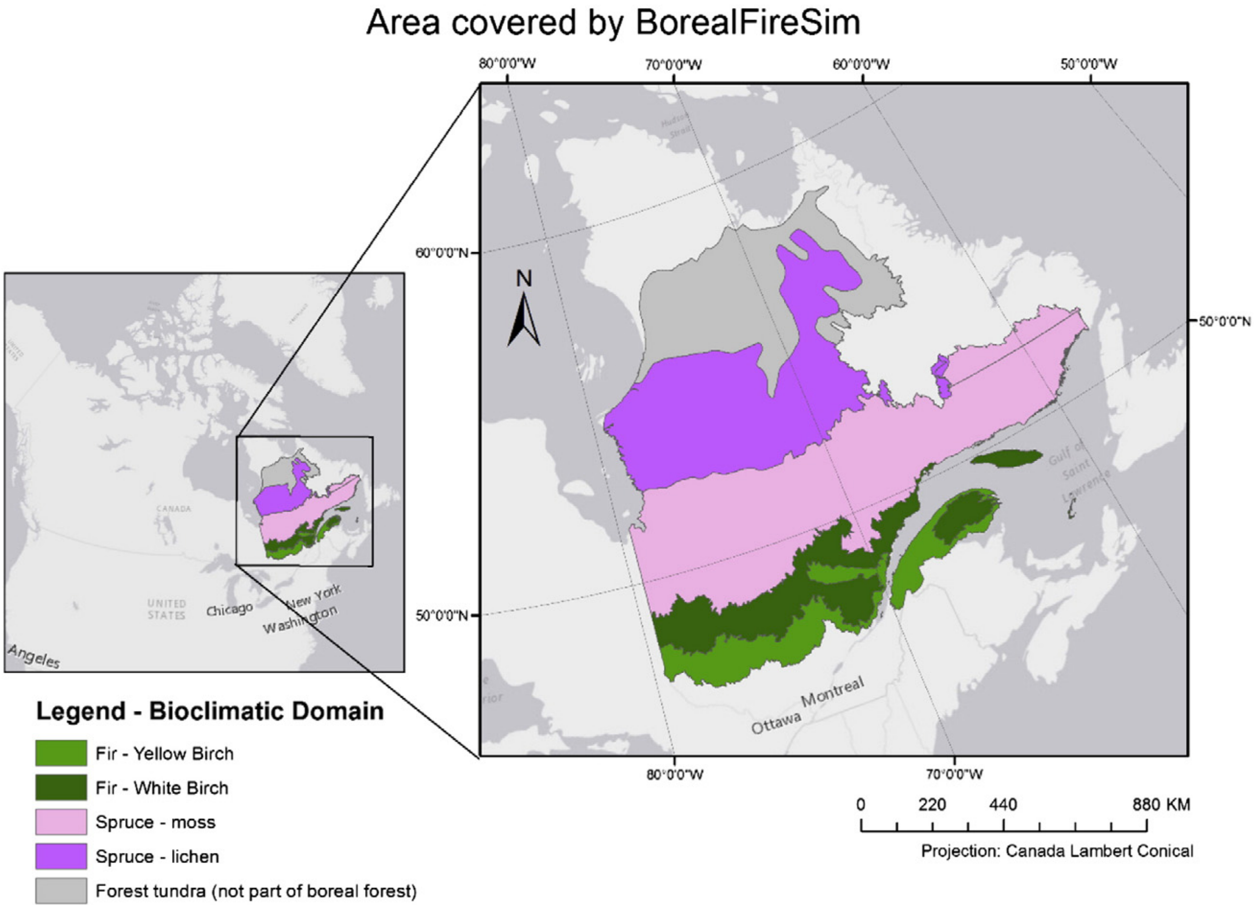

Fig. 2. The study area is located in Quebec, Canada, and comprises five bioclimatic domains. The four domains in color represent the boreal forest of Quebec and the one in gray represents the forest tundra.

with climate normals provided by OURANOS, a consortium on regional climatology and adaptation to climate change located in Montreal, Québec, which are available on the BioSim normals database (Régnière, et al., 2014). Present data consist of a 30 year average while future data extend up to 2100. This is explained by the fact that we suppose a pseudo-equilibrium between actual fire occurrences and climate. Once the link is identified between present climate and present fire risk or occurrence, we replace climate data by future climate data and see how the modeled system reacts. The model aims more at getting a better understanding of regional fire patterns than at trying to predict fire events. The FWI is an index of the fire severity and was originally conceived as a way to represent fire intensity, as defined by Byram (1959) in the equation:

$$I = HWR \tag{2}$$

where the energy output rate per unit length of fire front **I** is the combination of the heat of combustion **H**, the weight of fuel consumed per unit area **W** and the rate of advance **R** (Van Wagner, 1987). However, the FWI system developed in Canada integrates multiple components and is based on daily observations of temperature, relative humidity, wind speed and 24-hour rainfall (Natural Resources Canada, 2008). We use FWI as our only climate variable because it is calculated with many variables relevant to fires, such as wind speed, temperatures and precipitation, or Drought Code (DC). Fig. 3 shows the components of the FWI system.

Calculations of the FWI are made for each decade, between 2000 and 2100 and results are exported to raster layers using the GeoTIFF format. Climate forecasts were used for two different climate scenarios: RCP4.5 and RCP8.5 (IPCC, 2013; Régnière et al., 2014). The representative concentration pathways (RCPs) consist of the latest climate scenarios (AR5[1]), replacing the AR4-SRES[2] scenarios and are named after their radiative forcing, defined by the Intergovernmental Panel on Climate Change (IPCC) as a "cumulative measure of human emissions of greenhouse gases from all sources expressed in Watts by square meter" (IPCC, 2013). For example, concentration pathway 4.5 represents a forcing of 4.5 W/m^2 in 2100. For the purpose of clarification and further explanation on RCPs, Table 1 presents a comparison between RCPs and previous scenarios and Fig. 4 shows the different greenhouse gas emission curves.

2.2.2. Ecologic variables

Ecologic variables include species-specific variables such as mean age of stands, dominant species, percentage of wet areas, forest density and bioclimatic domain. These variables, except for the bioclimatic domains (Forêts, Faune et Parcs Québec, 2015), were extracted from the Canadian forest inventory of 2001 database, or *CanFI* (Canadian Forest Service, 2001). Stands with age over 80 years are considered as mature forest and they are more prone to fire because its multiple layers of tree heights serve as a fire ladder (Barrett et al., 2010). Dominant species are used to categorize fire-prone conifers, such as black spruces and jack pines, while giving less chance of burning to hardwoods such as birch or maple (British Columbia Forest Service, 2014). The density and type

[1] IPCC Assessment Report 5 (IPCC, 2013).

[2] Special Report on Emissions Scenarios (SRES). In AR4 most common scenarios were A2, B1 and A1B (IPCC, 2007).

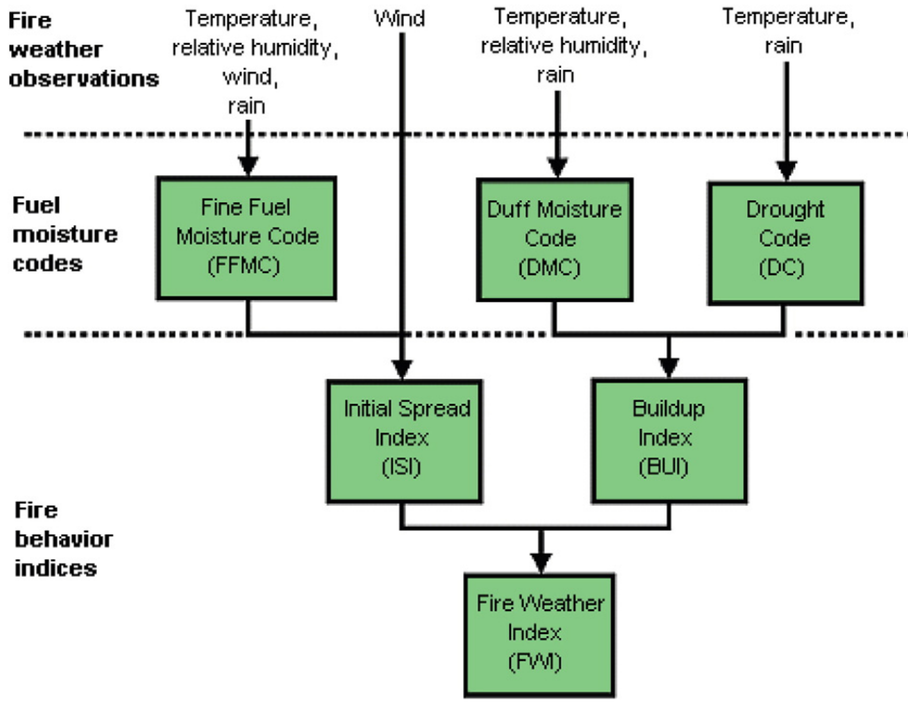

Fig. 3. Components of the Fire Weather Index (FWI). Source: Natural Resources Canada (2008).

of vegetation are the most important factors for fire spread. No matter the weather conditions, if there is no connectivity between forest patches, fire will be unable to spread, except in the presence of very strong wind (Li and Magill, 2001). Forest density layer was derived from the Canadian Forest Inventory (CanFI) of 2001 and was converted to a raster grid with values from 0 to 100 representing the percentage of every cell that is covered by forest (Canadian Forest Service, 2001). Fire has a greater chance to spread between cells of higher forest density.

2.3. Model behavior

BorealFireSim takes into account multiple predictors identified by studies on forest spread (Barrett et al., 2010; Bergeron et al., 2001), post-fire regrowth (Johnstone and Chapin III, 2006), fire ignition (Li and Magill, 2001) and on other CA-based fire models (Yassemi et al., 2008). Once the model is initialized during the setup process, roads, lakes and rivers act as background data and are turned off (given a state of 0, or null), while all other variables are considered into the model. When all the GIS layers are correctly imported, the setup ends. The user can now use the main (go) process to launch the model. The temporal resolution of BorealFireSim being one year, this means that each iteration represent one fire season. The go procedure will repeat itself until the number of iteration reaches 10. Once the number of iterations reaches 10, this means that the fire model will have run for 10 years and that the climate variables must be updated with the climate variables of the next decade. For example, the ten first iterations are made with FWI from 2000. After ten years, this variable is replaced by the forecast values for 2010, and so on, until the model reaches 2100. At the end of one decade simulation, Geotiff maps representing the risk of fire of every cell and the state of every cell are exported. Within the model each cell can have five different states: non-flammable, mature forests, burning forests, burnt forests and in regrowth. Table 2 shows the possible states and the transitions of a cell state in the BorealFireSim model. Non-flammable cells are cells that are turned off in the model and they consist of roads, rivers and lakes and cells that are not part of the study area or have *nodata* values; to summarize, these cells are non-suitable to spread the fire and therefore can never change state. Cells with a state value of 1 are cells with unburned vegetation, without discrimination to the dominant species, the density or the percentage of wet areas; hence they all have a chance of burning. These cells can either stay unburned to be ignited by lightning or by fire spreading. When a cell is burned, its state changes to 2 for the current time step and will be set to 3 at the end of the same time step. Since the temporal resolution of the model is a year, a cell that is ignited will pass from state 1 to state 2 to state 3 in the same iteration. Once a cell passes to state 3, it can either stay burned or start regrowing. Finally, cells with state 4 will eventually change to state 1 as they mature if they are not burned once again.

In every iteration, each cell evaluates its eight neighbors and the algorithms determine if the state of the cell should change. The Moore neighborhood was selected since it is more representative of real processes of fire propagation (Fig. 5).

Table 1
Analogs between new and previous climate scenarios (Snover et al., 2013).

New scenarios (RCP)	Description	Comparison with SRES scenarios	Term used in this paper
RCP 2.6	An extremely low scenario that reflects aggressive greenhouse gas reduction and sequestration efforts	No analog in previous scenarios	"Very low"
RCP 4.5	A low scenario in which greenhouse gas emission stabilizes by mid-century and falls sharply thereafter	Very close to B1 by 2100, but higher emissions at mid-century	"Low"
RCP 6.0	A medium scenario in which greenhouse gas emissions increase gradually until stabilizing in the final decades of the 21st century	Similar to A1B by 2100, but closer to B1 at mid-century	"Medium"
RCP 8.5	A high scenario that assumes continued increases in greenhouse gas emissions until the end of 21st century	Nearly identical to A1F1. The A2 scenario would be placed between RCP6.0 and RCP8.5.	"Business as Usual (BAU)"

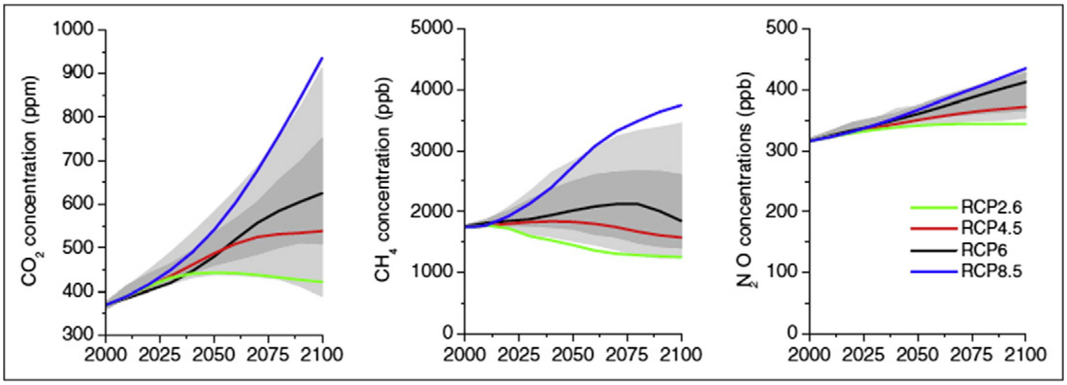

Fig. 4. Trends in the evolution of concentration of greenhouse gases for the four RCP scenarios. Left to right: carbon dioxide (CO_2), methane (CH_4) and nitrous oxides (N_2O) (Vuuren et al., 2011).

The flow of the model consists of five different actions, also called *procedures*. Every year, from 30 to 50 fires, which are the average number of fires of more than 2 km^2 burning each year in Quebec, are generated randomly throughout the landscape. Then, for every neighbor of a burning cell, the risk of fire spreading, between 0 and 1, is calculated. Each of the eight neighbors will compare its risk of spreading with a random number between 0 and 1. If the fire spreading chance is superior to the random number, the fire will spread towards that neighbor. After having spread to the neighboring patches, fire will fade and leave burnt cells. These cells can stay burned from five to fifteen years, after which they start to be in regrowth for 20 to 60 years, until they consist of mature stands. These processes are executed by five procedures called: 1) ignition, 2) spreading, 3) fading, 4) regrowth and 5) maturation, and are repeated on a yearly basis. One year is represented by an iteration of the model. After the simulation runs for an iteration, a map representing the state of the cells and representing the burning chance is exported in a raster format, and will become the input for the following iteration.

2.3.1. Algorithms

The core of the model consists of two algorithms; the fire spreading algorithm, responsible for the calculation of burning chance (BC) and the second one in charge of the regrowth chance (RC) calculation. The importance of every variable was determined using literature. The following sub-section explains the different variables and their weights in the fire spreading algorithm.

2.3.1.1. Fire spread algorithm. Every cell for every variable is given a score (Table 3). This score is then divided by the highest score of all cells, giving a value between 0 and 1, representing the probability of burn or regrowth for each cell. Table 3 shows the different scores attributed to the different variables. An initial score of 2 is given to every cell because wildfires can happen anywhere in the forest and to reduce the model sensitivity to the variables. The score of 2 was determined by running the model several times and comparing the number of fires and the number of burned square kilometers with the actual values for the boreal forest of Quebec (MFFP, 2014). A score was added to the cells dominated by black spruces or by jack pines, since these two conifer species are rich in oils and are highly flammable, while leafy vegetation is less prone to fire, because of its high foliar moisture content (Li and Magill, 2001; Drever et al., 2006). Another variable added to the model is the percentage of wet areas. Fire spreads at its fastest rate when two conditions are met: drought and high temperatures. Wet areas are less prone to fire than regular forests because of the humidity of the soil and of the vegetation. Furthermore, wet areas facilitate the formation of permafrost, keeping the soil moist and low in temperature (Barrett et al., 2010). The next variable to be included in the model is the Fire Weather Index (FWI) (Van Wagner, 1987). The FWI classes in the model represent the six danger classes defined by Van Wagner (1987), from Extreme to Very Low danger.

Finally the last variable to be added to the model is the forest density. Li and Magill (2001), identified *bush density* as the most important factor of all for CA-based fire models. The minimum density threshold for a cellular automaton with a 4-cell neighborhood, or Von Neumann neighborhood (North, East, West and South neighbors) is 59% (Resnick, 1994). Under 59% of density, the fire will not be able to spread on large areas. However, for an 8-cell neighborhood, or a Moore neighborhood, the density threshold is 41% (Li and Magill, 2001). Three classes of density were made: when the density was 0%, the burning chance was reduced to 0, when it was from 0 to 41%, the score was negative (-0.5) and when the density was higher than 41%, the score was positive (0.5). All the scores determined by the values presented in Table 3 will be combined by the Fire Spread Algorithm (FSA).

Table 2
Cell states and possible transitions.

Description	Cell state	Possible transitions
Non-flammable	0	[0] ==> [0]
Vegetation (fuel)	1	[1] ==> [1]
		[1] ==> [2]
Burning	2	[2] ==> [3]
Burned forest	3	[3] ==> [3]
		[3] ==> [4]
In regrowth	4	[4] ==> [1]

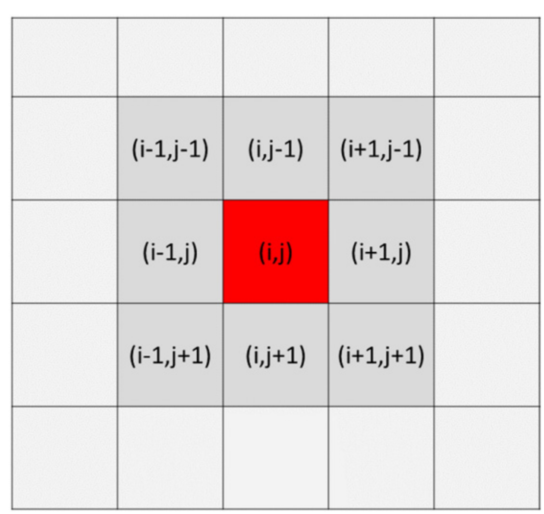

Fig. 5. Neighborhood representation used by the BorealFireSim.

Table 3
Scores given to the cells for the algorithms.

Variables	Possible values	Possible scores
Initial burn chance	Constant	2
Dominant species	Black spruce or jack pine	+0.25
% wet areas (wetlands)	[>50, >20 and ≤50]	[−1, −0.5]
Fire Weather Index	30+	Extreme (+2)
(Van Wagner, 1987)	17–29	Very high (+1)
	9–16	High (+0.5)
	5–8	Moderate (+0.25)
	2–4	Low (+0)
	0–1	Very low (−0.25)
Bush density (Li and Magill, 2001)	[0, >0 and <41, >41]	[0, −0.5, 0.5]

After all the scores are defined for a cell, a burning chance (BC) is calculated for every cell, by dividing the sum of its scores by the maximum sum reached by a cell. This gives every cell a BC from 0 to 1 representing the chance of fire spreading over it, if one of its neighbors is previously ignited. The calculation of burning chance can be summarized with the following equation:

$$\mathrm{BC}_{(i,j)} = (2 + \mathrm{DS}_{(i,j)} + \mathrm{D}_{(i,j)} + \mathrm{FWI}_{(I,j)} + \mathrm{W}_{(i,j)} / \mathrm{MbC} \quad (3)$$

where BC is calculated with a minimal chance of 1 for every cell, the dominant species score (DS), density score (D), Fire Weather Index (FWI) and wet areas score (W) divided by the maximal BC of all cells (MbC). A cell with 0.85 BC would have an 85% chance of being ignited, while a cell with 0.25 would likely be spared. At every iteration, the burning chance is calculated for every cell. Therefore, it is influenced by the state of the cell at the previous time step. If a cell has been burned in a previous step, it cannot be burned at the next step.

2.3.1.2. Regrowth algorithm. A regrowth algorithm is used to determine the timing of post-fire regrowth. This algorithm uses three values for the regrowth decision: 1) the presence of burning neighbors, 2) the presence of living neighbors and 3) the species found on the cell prior to ignition. For instance, if jack pines and black spruces were present before the fire, regrowth will be accelerated because of their serotinous and semi-serotinous cones that sprout when subject to intense heat, as fire (Barrett et al., 2010; Mansuy et al., 2012; Vasiliauskas and Chen, 2004). Regrowth chance (RC) is calculated with the following equation:

$$\mathrm{RC}_{(i,j)} = \left(\mathrm{FN}_{(i,j)} + \mathrm{LN}_{(i,j)} + \mathrm{DS}_{(i,j)}\right) / \mathrm{MrC} \quad (4)$$

where the presence of burning neighbors, the presence of living neighbors and pre-fire dominant species scores are divided by the maximal RC of all cells.

2.4. Model implementation

BorealFireSim model was programmed in NetLogo (Wilensky, 1999), a programmable modeling environment, and consists of a grid of 500 × 500 cells representing the boreal forest of Quebec. Its spatial resolution is 4.48 × 4.48 km, or ~20 km^2 and the temporal resolution is one year. A graphical user-interface (GUI) was implemented to allow users vary parameters, climate scenarios and datasets. The GUI (Fig. 6) was implemented directly in NetLogo and can be editable by the user to fit his needs. It also displays relevant information such as mean age of stands, area burned (km^2), mean BC of flammable cells, current decade and a plot of the area burned for every year. Six variables can be switched on and off by the user to choose desired parameters: the age dataset, the dominant species dataset, the density dataset, the water bodies dataset, which is a shapefile containing the major lakes and rivers, the road dataset and the wet areas dataset. In the current version, two climate scenarios can be used: low emissions (RCP45) and Business as Usual (RCP85), which correspond to RCP4.5 and RCP8.5 (Table 1).

Prior to the setup, users will define the cell size, climate scenario and the number of iterations desired. We recommend splitting the area in 500 × 500 cells, for a cell size of ~15 km^2. However, users with access to powerful computers could increase the number of cells for better results.

2.5. Model outputs

Diverse information is exported by BorealFireSim during its execution, depending on the time step. At the end of every iteration, or every year, the model writes the current year, the current decade and the number of cells and area (km^2) that has been burned during the current year to a comma separated text file (CSV). Every ten years, when the decade changes and the climate values for that decade replace the climate values of the preceding decade, the burning chance and cell state variables are both converted to a georeferenced raster dataset in *ASCII* format. Finally, at the end of the execution, when the model reaches 2100, a fire risk map is created and its values are the number of times each cell was burned. For instance, a cell that was burned twice on 100 years would have the value of 2.

To assess the stochasticity of the model, simulations with both climate scenarios were repeated 50, 100, 150 and 200 times. Since fire is ignited at a random location, two executions of the model could result in two different outputs. Moreover, since the values at time t are based on the values of $t-1$, the tiniest change in the first years could result in major differences at the final time step. By repeating the model for multiple times, we can reduce the uncertainties inherent to stochastic models.

2.6. Contrasting BorealFireSim outputs

In order to evaluate the implications of the BorealFireSim model outcomes by using future climate change scenarios, future fire likelihood maps were compared with forecasts from Nelson et al. (2014). On their study, Nelson et al. (2014) used climate data and an indirect indicator of biodiversity called dynamic habitat index (DHI) (Perez et al., 2015) to forecast, by means of random forest algorithms, future spatial distribution of vegetation productivity based on climate change conditions (Breiman, 2001). In this section we use both, the outputs from the BorealFireSim model and the outputs from Nelson et al. (2014), to visually assess the relationship of the two sets of outcomes using the same climate scenarios into the future.

Fire likelihood maps and maps from a DHI component (cumulative greenness) for 2050 and 2070 with low, medium and Business as Usual (BAU) scenarios were overlapped to compare spatial patterns. Cumulative greenness is an indication of overall vegetation productivity and the potential landscape productivity at any given location. It was expected that areas with high greenness would overlap with areas showing high fire likelihood, since both studies are based on climate variables.

3. Results and discussion

3.1. Resulting maps

For the following maps, only the simulations with 200 repetitions for the years 2010, 2050 and 2080 are displayed. However, the maps for the 50, 100 and 150 repetitions are available in supplementary materials for every decade from 2000 to 2100.

3.1.1. Burning chance

Fig. 7 shows the burning chance calculated by the spreading algorithm. These maps show that the burning chance does not change drastically, even with a high emission scenario. The areas with the

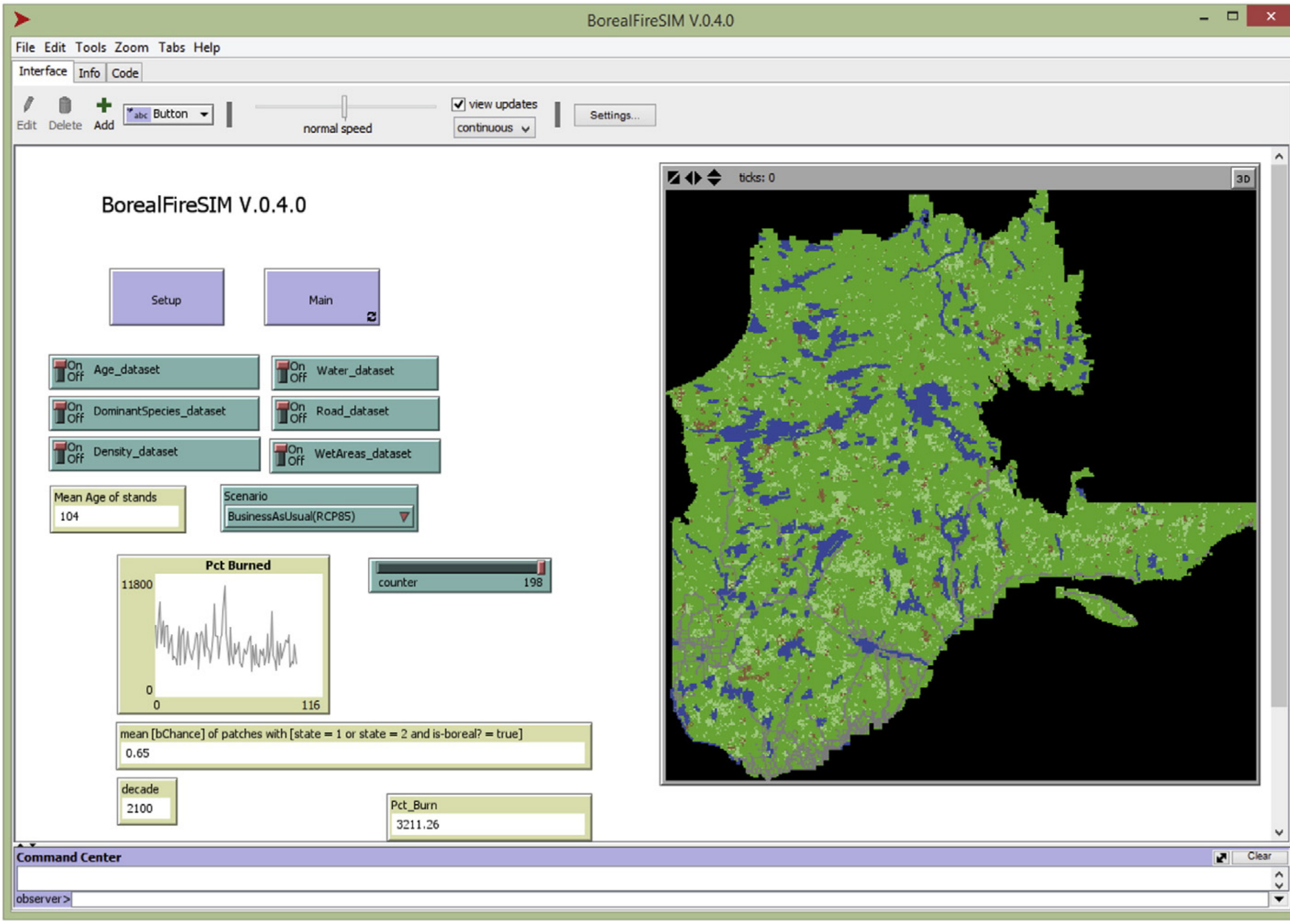

Fig. 6. Graphical user interface of BorealFireSim.

highest changes in burning chance are northwest and the center-east. Since the model is stochastic, the burning chance does not automatically drive fire events. If no fire is ignited on a cell with a high burning spread chance, there will be no fire. Since very scarce information can be retrieved from these maps, it was decided to create maps with the average state of the cells with multiple repetitions.

3.1.2. Cell state change

Fig. 8 shows the mean state of cells at years 2050 and 2080. Cells with a value near to 1 were unburned in most cases. The interesting part about the maps in Fig. 8 is the cells with values from 2 to 2.83. These cells were subject to frequent change, while cells with a value of 0 or 1 did not change state often during the hundred iterations. On these maps, it is clearly identifiable that the northeast, the east and the center areas of the province will likely experience more fires.

3.1.3. Change maps

Maps presented in Fig. 9 allow better identifying of the changes in fire risk. They represent the change in burning chance from 2010 to 2050 and from 2010 to 2080. We highlight that results for 2080 are based on results from 2010 to 2070 as well, since the model is dynamic. Areas in green are areas where the burning chance decreased, without regards to the intensity of the change, and areas in red are areas where the burning chance increased.

These maps show that with a low emission climate scenario such as the RCP4.5, continental areas are likely to expect an increase in fire spreading chance, while coastal and/or wet areas are likely to expect a decrease in fire spreading chance, because of the decrease in FWI. However, for a BAU scenario such as RCP8.5, while some areas might expect a decrease in fire spreading chance for 2050, there was either no change or an increase everywhere for 2080, except for the James Bay lowlands, which are part of the greater Hudson's Bay lowlands, the third largest wetland region and the largest peatland system on earth, with more than 50% of the surface is covered in water (Parks Canada, 2010).

3.2. Summary of the model's outputs

Fig. 10 shows the burned area per year with the RCP4.5 and RCP8.5 climate scenarios. The values are the mean values of the 50, 100, 150 and 200 repetitions. The simulations with 50 repetitions show more inter-annual variability, while simulations with 200 repetitions show less inter-annual variations.

The mean area burned with RCP45 and RCP85 are very alike. However, by taking the values and calculating the percentage of increase, we get a clearer picture of the importance of climate change on changes in fire risk. Table 4 shows the change in mean values from 2010 to 2100.

In all cases, change in area burned annually between 2010 and 2100 is more important with a Business as Usual scenario. However, burning chance is not the same in every part of the study area. In order to better represent the interprovincial climate variability, we calculated the mean burning chance of cells by bioclimatic domain for 200 repetitions of BorealFireSim for RCP4.5 and RCP8.5. Table 5 shows the mean burning chance of cells by bioclimatic domain in 2010 and 2100, as well as the percentage of increase.

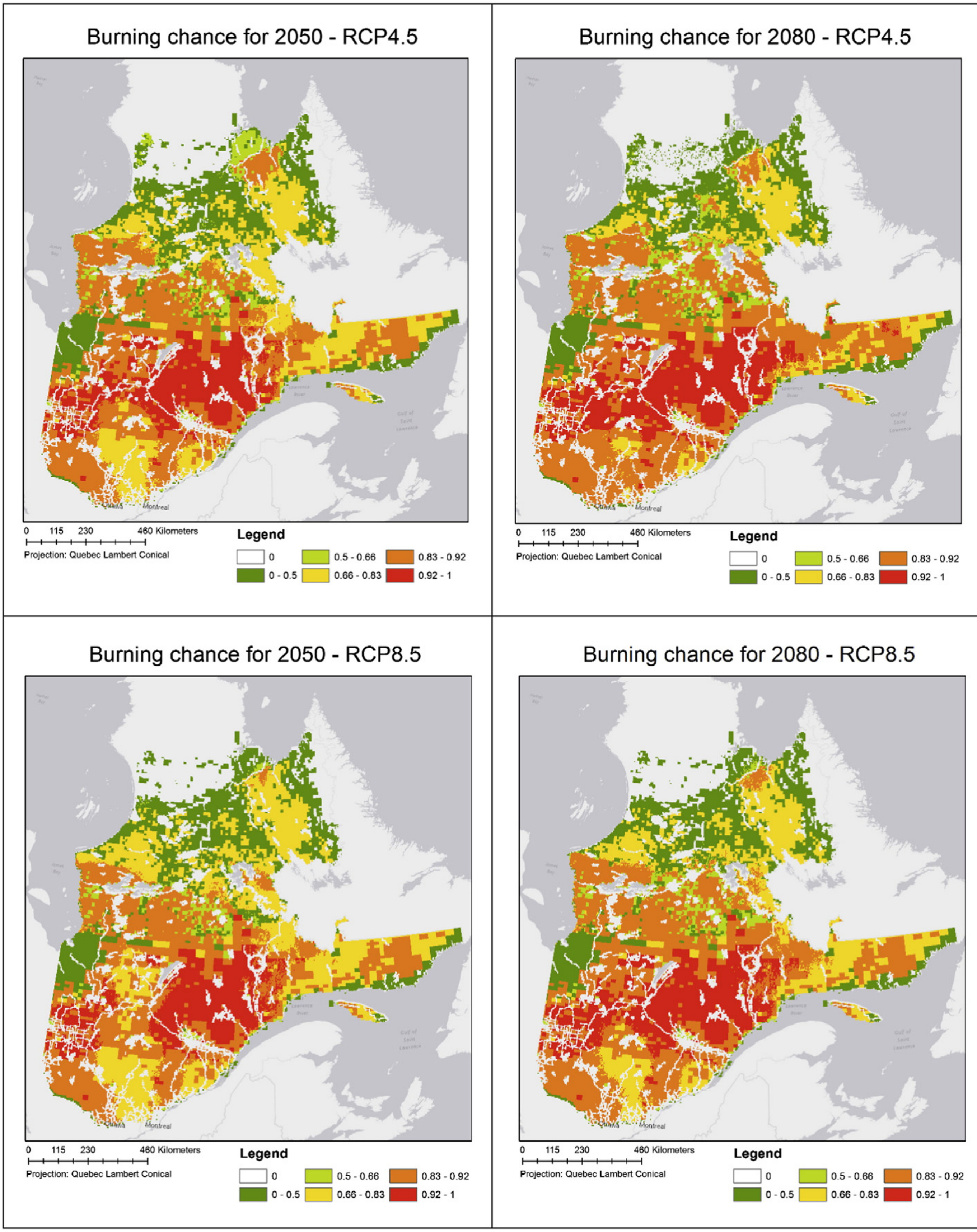

Fig. 7. Burning chance in 2050 and 2080 for the scenarios RCP4.5 and RCP8.5.

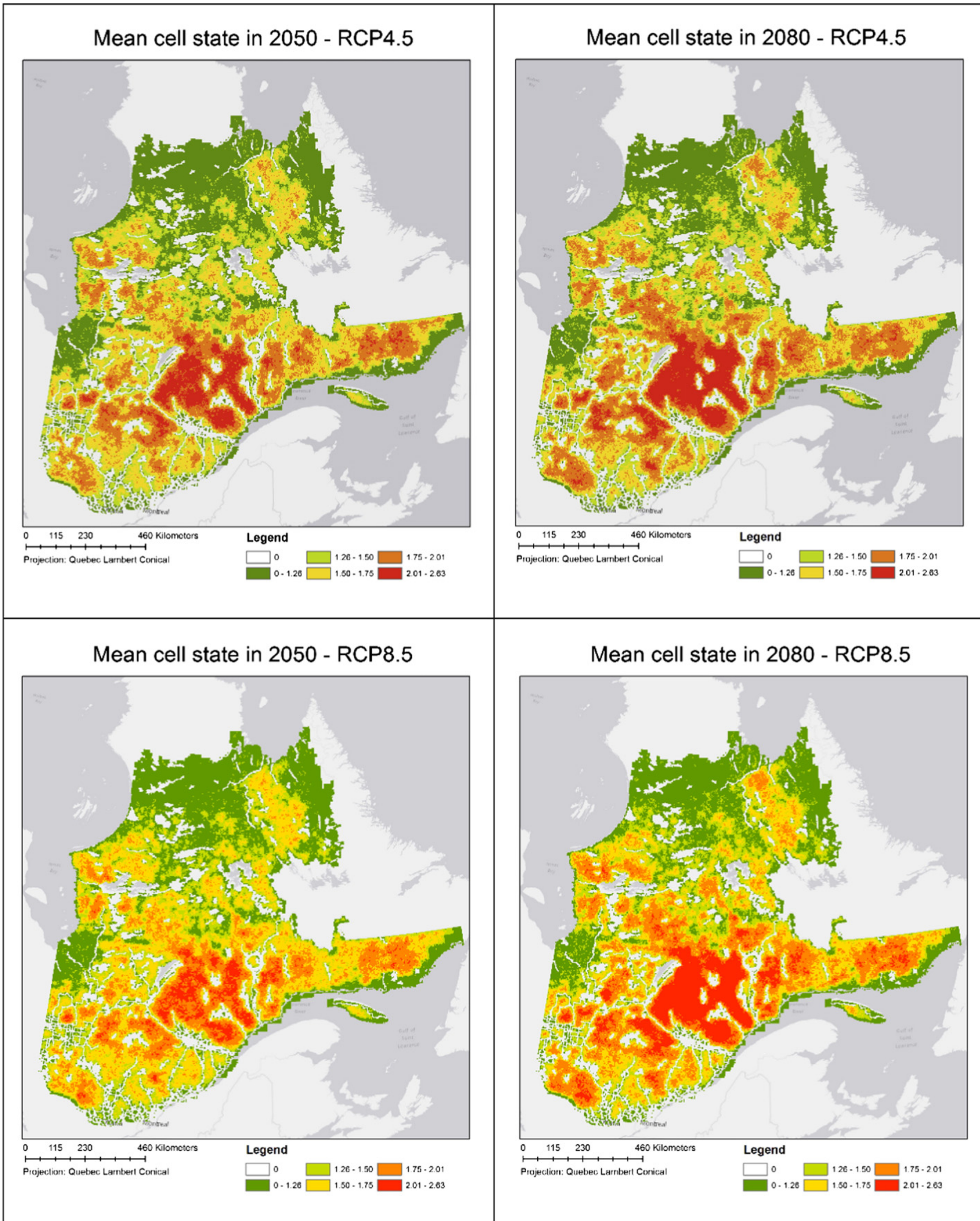

Fig. 8. Cells state after 200 repetitions.

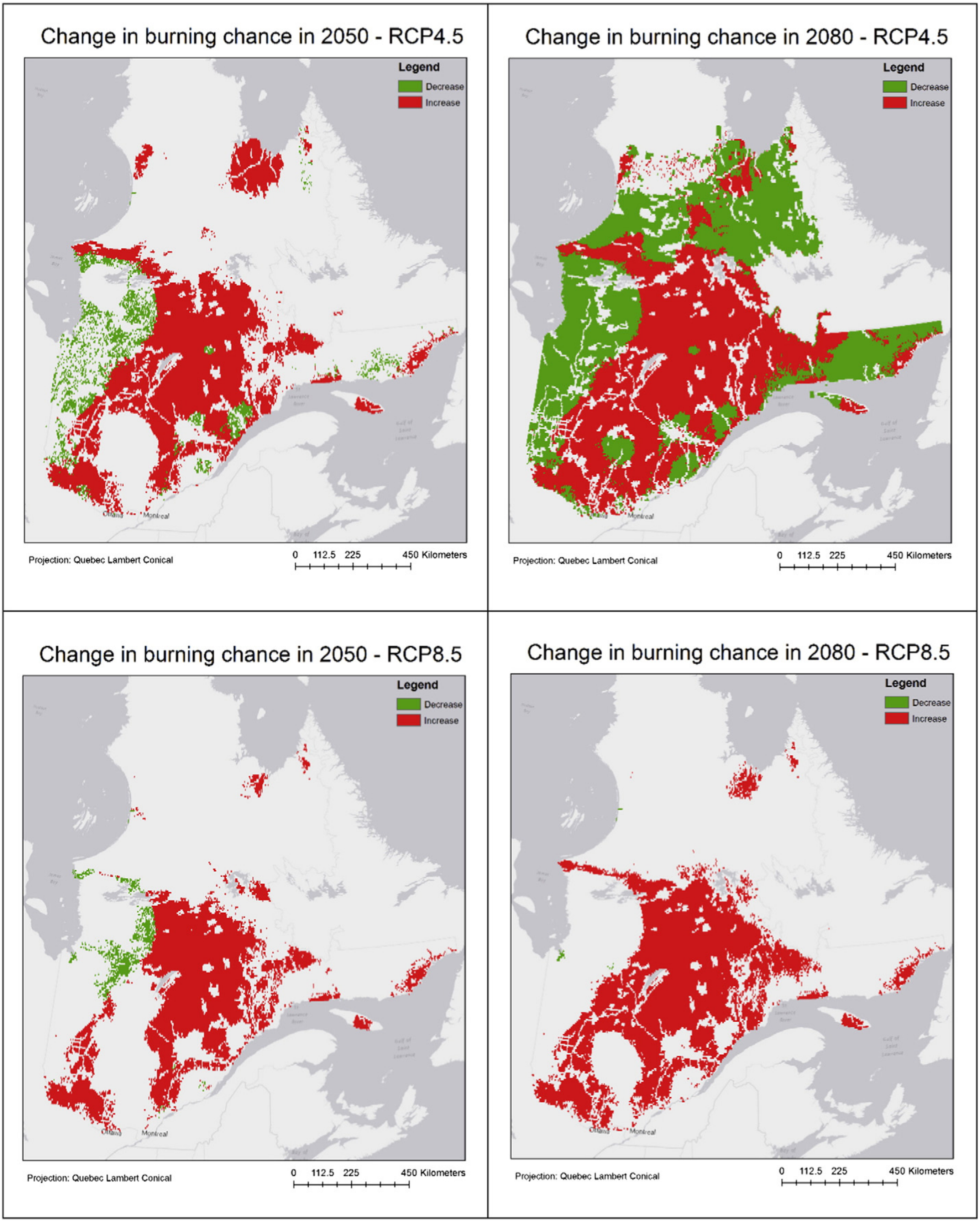

Fig. 9. Change in burning chance after 200 repetitions.

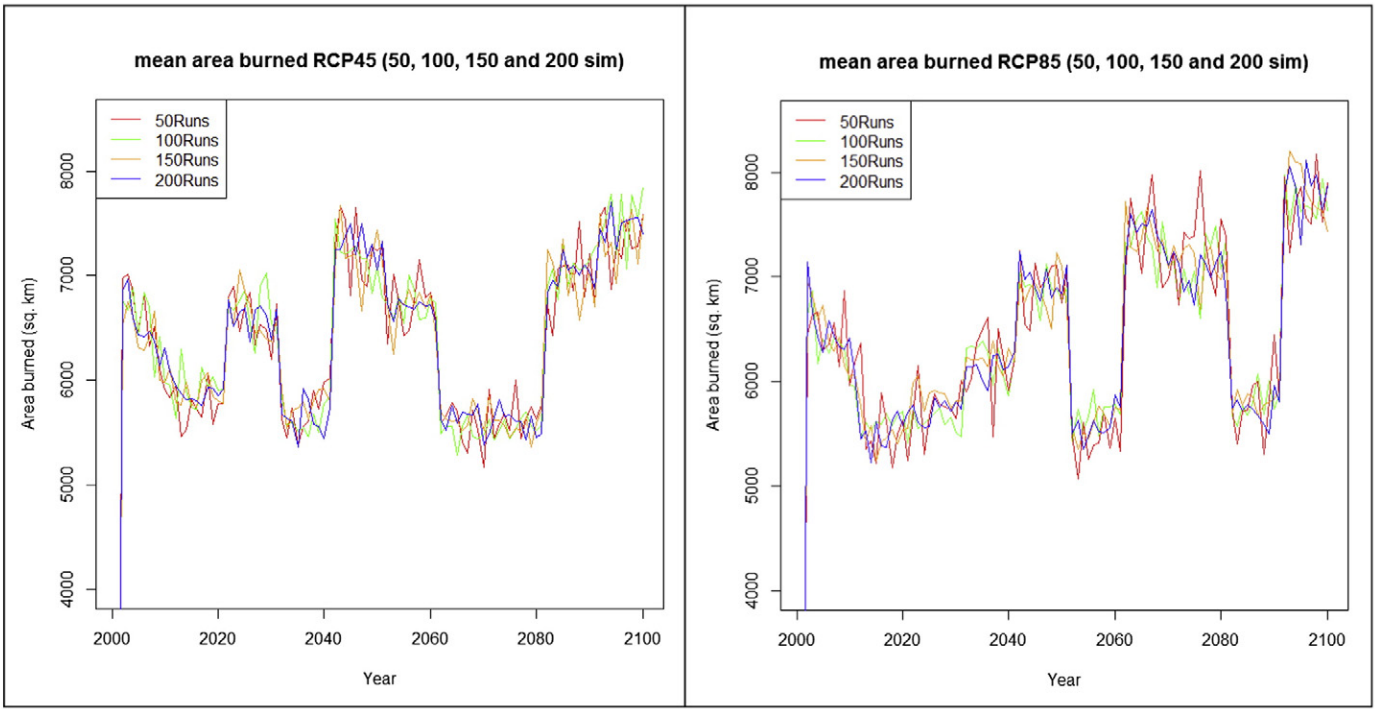

Fig. 10. BorealFireSim forecast area burned (square-km).

By comparing the change between RCP4.5 and RCP8.5, it is clear that forest tundra and, with lesser importance spruce–lichen domains will likely be more affected by climate change than the spruce–moss, fir–white birch and fir–yellow birch domains. If we compare Table 4 with Table 5, it is quite surprising that, for the entire study area, in a BAU scenario, the mean burning chance went from 0.732 to 0.771, which represents an increase of only 5.32%, however, it represented an increase of 30% in the area burned, passing from 5857 to 7627 ha. This shows that a minor increase in burning chance for the individual cells leads to major increases in the spatial patterns of fire. When burning chance is high, a small increase leads to catastrophic results. However, an increase in burning chance does not automatically lead to more fires. Forest tundra had an increase of 11.43% of mean burning chance but the values passed from 0.446 to 0.497, still being very low. In a cellular automaton, more specifically in BorealFireSim, a chance of spreading of 0.446 means that, for every neighbor of a burning cell, a random number between 0 and 5 will have to be under 0.446 for the fire to spread. The number 5 was decided during the calibration of the model. Multiple runs with different values were executed and the simulations with an interval of 0 to 5 exhibited a comparable number of fire events and of area burned annually with historical fires.

3.3. Validation process

To assess the predictive ability of BorealFireSim, simulations ($n = 200$) were overlapped by a boolean fire occurrence matrix ($0 =$ unburned, $1 =$ burned). This dataset, provided by the Ministère des Forêts, de la Faune et des Parcs du Canada (MFFP), contains every single wildfire that was reported in Quebec from 2008 to 2014 (MFFP, 2015). The validation dataset is completely independent and was not used for calibration of the model. The model was calibrated according to literature, varying the parameter weights to have an annual average of 2800 km^2 burned, with a standard deviation of 4900 km^2, being comparable with calculated annual sum of burned area in Quebec using the MFFP fire dataset. When overlapping BorealFireSim output with the MFFP boolean fire dataset, the resulting map (Fig. 11) demonstrates that BorealFireSim has very good predictive capacity for determining fire risks. Over the 52nd parallel, historical fires perfectly overlap with areas of high fire risk. However, under the 52nd parallel, there is a slight difference between forecast values and actual fires, and that is caused by

Table 4
Increase in mean area burned annually, RCP4.5 and RCP8.5.

Mean area burned annually (km^2) — RCP4.5			
n runs	2010	2100	Change (%)
50	5897.767	7291.376	23.6294347
100	5872.539	7510.123	27.8854513
150	5756.418	7301.29	26.8373839
200	5855.098	7410.082	26.5577792
Mean area burned annually (KM2) — RCP8.5			
n runs	2010	2100	Change (%)
50	5795.127	7528.929	29.9182744
100	5743.225	7529.932	31.1098207
150	5836.994	7621.494	30.5722432
200	5857.536	7627.264	30.2128403

Table 5
Increase in mean burning chance of cells.

Mean burning chance by bioclimatic domain (RCP4.5)			
Domain	2010	2100	Change (%)
Forest tundra	0.446	0.459	2.91
Spruce–lichen	0.739	0.776	5.01
Spruce–moss	0.764	0.78	2.09
Fir–white birch	0.868	0.897	3.34
Fir–yellow birch	0.844	0.878	4.03
Mean burning chance by bioclimatic domain (RCP8.5)			
Domain	2010	2100	Change (%)
Forest tundra	0.446	0.497	11.43
Spruce–lichen	0.739	0.789	6.77
Spruce–moss	0.764	0.78	2.09
Fir–white birch	0.868	0.904	4.15
Fir–yellow birch	0.844	0.885	4.86

the fact that fire suppressing activities are located under parallel 52. Statistics on the whole province and over parallel 52 were calculated. In order to validate the outcomes of BorealFireSim, the Map Comparison Toolkit (MCK) was used to calculate a fuzzy Kappa index (Visser & de Nijs, 2006). Kappa index is a widely used metric to assess the similarity between two raster layers. The Kappa index results for the comparison between the simulation outcomes of BorealFireSim and the MFFP fire dataset showed a similarity between the two maps of 88.9% for the province and 94.9% over parallel 52. However, Kappa is getting more and more criticized and another metric, the *quantity disagreement and allocation disagreement* are considered as a solution (Pontius and Millones, 2011). Being extremely minimalist, quantity disagreement and allocation disagreement rely on a contingency table for categorical variables. In the case of BorealFireSim, we reclassified the state map for 200 runs to zeros (0) and ones (1), for unburned and burned pixels respectively. This enables a comparison between BorealFireSim state map and the MFFP dataset. For unburned pixels, there is an agreement of 86% for the whole province and an agreement of 94% over parallel 52. For burned pixels, the agreement is of 50% for the whole province and 34% over parallel 52. These numbers show that BorealFireSim has power to identify areas not likely to burn, which account to 94% of the area with both the whole province and over parallel 52. Nevertheless, it is important to highlight that the difference between predicted burned cells and historical fires does not mean that BorealFireSim is wrong; it means that if there would be no anthropogenic effort to prevent and manage fires, we would likely see fire occurrences on these areas. In that sense, BorealFireSim would benefit from including a fire management sub-model.

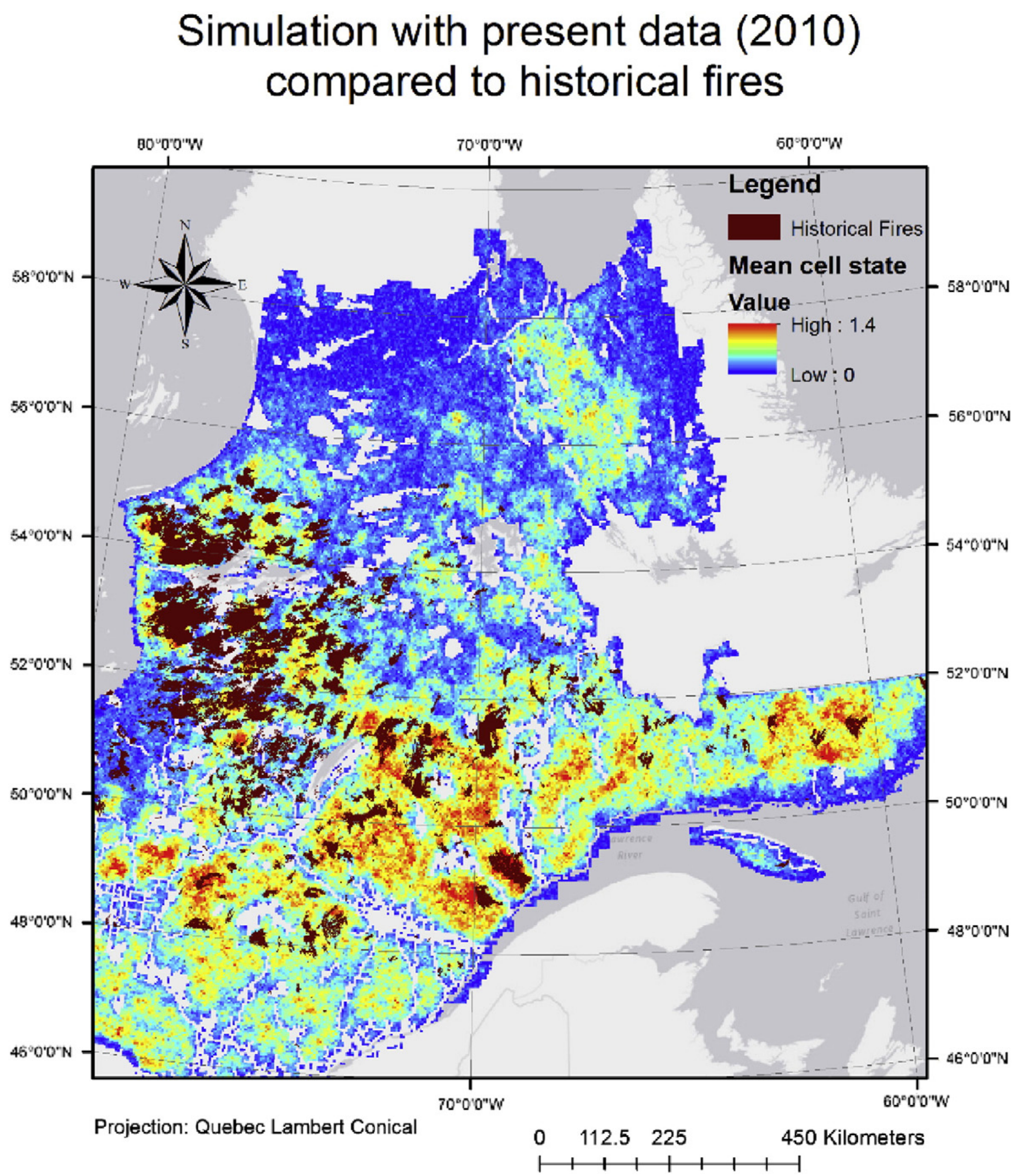

Fig. 11. Overlap of historical fires with the cell state map for present (2010).

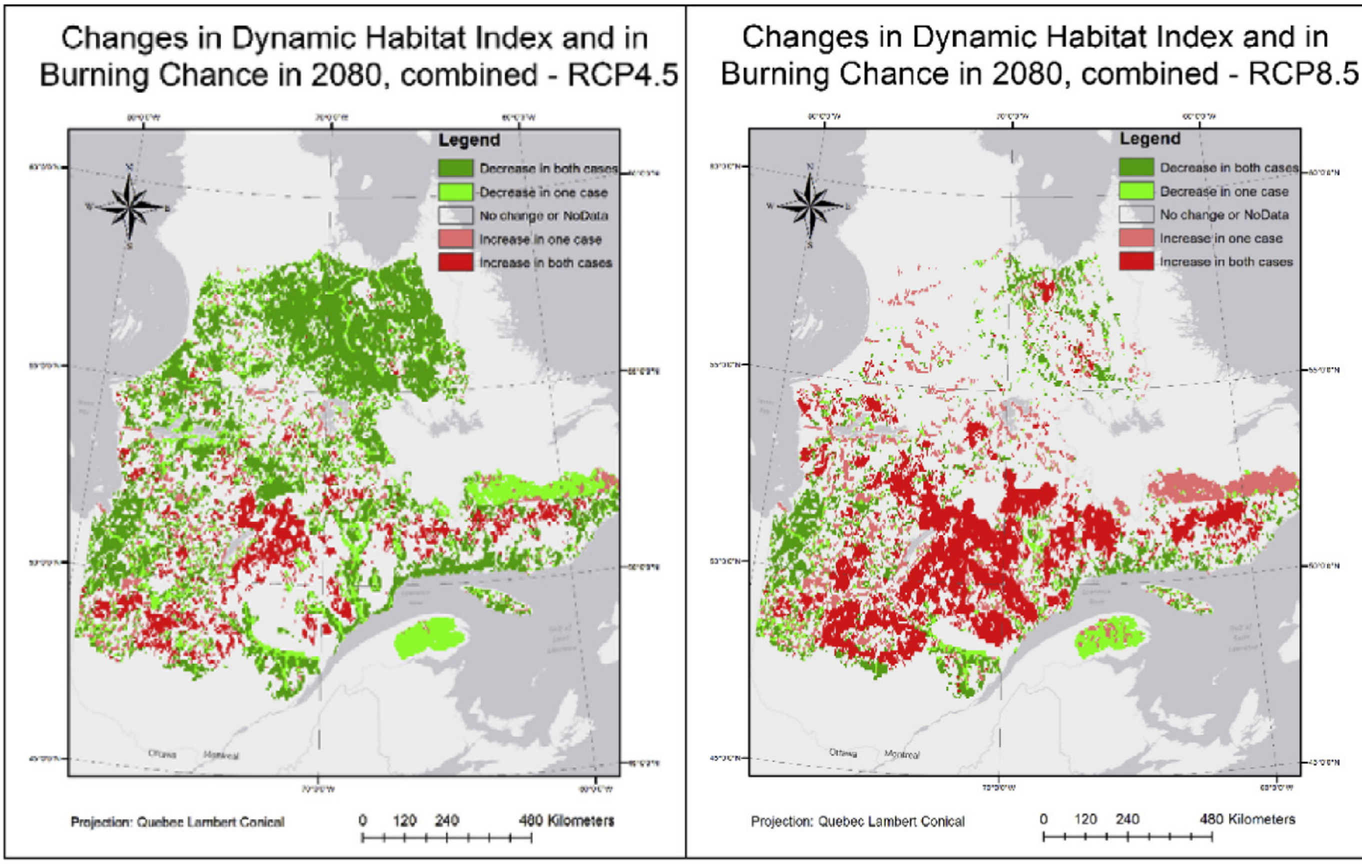

Fig. 12. Combination of DHI and burning chance forecasts for 2080.

3.4. Contrasting model outputs with DHI forecasts

The comparison between dynamic habitat index and fire spread chance helped us identify areas of good quality for fire specialist species. Dynamic habitat change was calculated by subtracting present DHI cell values to the 2080 DHI layer, for both scenarios, to get a value representing the change in DHI for each cell. The result gave the change in DHI, from -8500 to $+8500$ and the values under zero were reclassified as -1 and the values over zero, as 1. This gave binary maps of decrease/increase in DHI for 2080. For the fire spreading chance maps, results for 2080 were reclassified as follows: zeros and *nodatas* were reclassified as 0, values under 0.7 were reclassified as -1 and values over 0.7, as 1. The two variables both having values of -1, 0 and 1, we summed the layers to get values from -2 to $+2$ (Fig. 12). Calculations were made for 2080 with low emissions (RCP4.5 for the spreading chance and B1 for the DHI) and with Business as Usual (RCP8.5 for the spreading chance and A2 for the DHI).[3]

The model shows that boreal regions are more likely to burn more frequently with climate change. Comparison with vegetation productivity forecasts offers many interesting insights. Fig. 12 shows that areas with an increase in fire risks also exhibit an increase in greenness. BorealFireSim does not take into account changes in vegetation productivity. However, by comparing its results with greenness forecasts, possible feedbacks can be foreseen. On the opposite, areas with an increase in vegetation productivity do not mean an increase in fire risk, such as in wet areas and/or peatlands.

The upcoming changes in fire disturbances modeled by BorealFireSim can be used in wildlife conservation. Numerous species depend on burned forest, or snags, either for feeding or habitat. Identifying future fire patterns gives researchers foresights on the future distribution of fire dependent species, such as wood-boring beetles or bird species feeding on those beetles.

3.5. Assumptions and limitations of BorealFireSim

BorealFireSim shows that climate change will likely induce changes in spatial patterns of wildland fires, and that these changes are not homogenous. Wildfire patterns will likely variate more at higher latitudes. Changes in wildfire occurrences might facilitate regeneration accidents, meaning that succession of disturbancescan lead to a decrease in the age of stands in areas where fire risk will increase. This could give rise to feedbacks and non-linear dynamics that would require more research. Interesting dynamics could also emerge with the inclusion of timber logging and post-fire logging to wildfire dynamics. One of the limitations of BorealFireSim resides in the fact that the model does not aim to predict fire events at a given time or location. BorealFireSim aims to characterize the evolution of wildfires' spatial patterns. In that sense, Kappa and traditional statistical validation are inadequate, because complex systems models like BorealFireSim are based on stochasticity where, in the present case, 200 simulations are executed, as opposed to reality, where there is only one timeline. Modelers in complex science, and users of BorealForestSim have to keep in mind that the model is a simplified vision of reality aiming to describe and provide insights on the evolution of wildfires and should in no case be used as an intelligent decision-making tool. In the future, land-use and forestry sub-models could be added as add-ons to BorealFireSim so that fire suppression agents, in a similar manner to what was done by Alexandridis et al. (2011), could mimic Canada government efforts to extinguish fires located under parallel 52. By adding agents, BorealFireSim would benefit from more complexity and be more realistic.

[3] As shown in Table 2, RCP4.5 can be compared with B1 and RCP8.5 can be compared with A2.

4. Conclusion

This research presents a novel GIS-based CA approach to simulate wildfires under climate change conditions. BorealFireSim is a powerful model for the identification of changes in wildfire dynamics in the boreal forest of Quebec, as it is based on numerous variables and uses a cellular automata approach, making it a dynamic and stochastic model. The results from BorealFireSim serve as a first step towards integrating the complexity of fire dynamics into species distribution models (SDM). Maps of future fire patterns can be used by researchers wanting to take into account future disturbance dynamics into SDMs. The results show that, in all cases, the mean area of burned forest will likely increase with both a low emission of a high emission climate scenario, increasing by 30.2% by the end of the century with a Business as Usual (BAU) scenario. Knowing this, conservation agencies can plan their future policies by integrating forecasts from BorealFireSim and by focusing on protecting areas with higher fire risk and higher greenness, as they will be key areas for fire specialist species.

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References

Alexandridis, A., Vakalis, D., Siettos, C.I., Bafas, G.V., 2008. A cellular automata model for forest fire spread prediction: the case of the wildfire that swept through Spetses Island in 1990. Appl. Math. Comput. 204, 191–201.

Alexandridis, A., Russo, L., Vakalis, D., Bafas, G.V., Siettos, C.I., 2011. Wildland fire spread modelling using cellular automata: evolution in large-scale spatially heterogeneous environments under fire suppression tactics. Int. J. Wildland Fire 20 (5), 633–647.

Barrett, K., Kasischke, E.S., McGuire, A.D., Turetsky, M.R., Kane, E.S., 2010. Modeling fire severity in black spruce stands in the Alaskan boreal forest using spectral and non-spectral geospatial data. Remote Sens. Environ. 114, 1494–1503.

Batty, M., Torrens, P., 2001. Modeling complexity: the limits to prediction. CyberGeo: European Journal of Geography: Dossiers, 12th European Colloquium on Quantitative and Theoretical Geography, France, September 7–11 2001.

Bergeron, Y., Gauthier, S., Kafka, V., Lefort, P., Lesieur, D., 2001. Natural fire frequency for the eastern Canadian boreal forest: consequences for sustainable forestry. Can. J. for. Res. 31, 384–391.

Bone, C., Dragicevic, S., Roberts, A., 2006. A fuzzy-constrained cellular automata model of forest insect infestations. Ecol. Model. 192, 107–125.

Bonnot, T.W., Millspaugh, J.J., Rumble, M.A., 2009. Multi-scale nest-site selection by black-backed woodpeckers in outbreaks of mountain pine beetles. For. Ecol. Manag. 259, 220–228. http://dx.doi.org/10.1016/j.foreco.2009.10.021.

Breiman, L., 2001. Random forests. J. Mach. Learn. 45 (1), 5–32.

British Columbia Forest Service Wildfire Management Branch, 2014,. Fire resistant trees. http://bcwildfire.ca/Prevention/property/Landscape/fireresistantplants.htm (Last access on 27/02/2015).

Byram, G.M., 1959. Combustion of forest fuels Chapter 3 In: Davis, K.P. (Ed.), Forest Fire: Control and Use. McGraw-Hill, New York.

Parks Canada, 2010. Hudson-James Lowlands. http://www.pc.gc.ca/eng/docs/v-g/nation/sec4.aspx (Last access: 02/05/2015).

Canadian Forest Service, 2001. Canada's Forest Inventory (CanFI) 2001 for the boreal eco-region — percent forested, Quebec. http://databasin.org/datasets/a852f638bb424439a308b1aa0e8f1d6b.

Dale, V.H., Joyce, L.A., Mcnulty, S., Ronald, P., Matthew, P., 2001. Climate change and forest disturbances. Bioscience 51 (9), 723–734.

Dale, V.H., Joyce, L.A., Mcnulty, S., Neilson, R.P., Di, S., Ridge, O., Box, P.O., 2008. The interplay between climate change and forests. Bioscience 201–204.

De Groot, W., 2012. CanFIRE. Natural Resources Canada. Canadian Forest Service. Frontline Express vol. 62. Great Lakes Forestry Centre, Sault Ste. Marie, Ontario (2p).

Drever, C.R., Messier, C., Bergeron, Y., Doyon, F., 2006. Fire and canopy species composition in the Great Lakes–St. Lawrence forest of Témiscamingue, Québec. For. Ecol. Manag. 231, 27–37.

Energie et Ressources Naturelle Québec, 2013. Bref portrait de la forêt boréale au Québec. http://www.mern.gouv.qc.ca/presse/feux-grands.jsp (Online).

Finney, M.A., Andrews, P.L., 1999. FARSITE: Fire Area Simulator—a program for fire growth simulation. Fire Manag. Notes 59 (2), 13–15.

Flannigan, M.D., Krawchuk, M.A., De Groot, W.J., Wotton, B.M., Gowman, L.M., 2009. Implications of changing climate for global wildland fire. Int. J. Wildland Fire 18 (5), 483–507.

Flannigan, M.D., Stocks, B.J., Wotton, B.M., 2000. Climate change and forest fires. Sci. Total Environ. 262 (3), 221–229. http://dx.doi.org/10.1016/S0048-9697(00)00524-6.

Forêt, Faune et Parcs Québec (MFFP), 2013. Superficies affectées par les feux de forêt. http://www.mffp.gouv.qc.ca/publications/enligne/forets/criteres-indicateurs/2/213/213.asp (Online).

Forêt, Faune et Parcs Québec (MFFP), 2015. Système hiérarchique de classification écologique du territoire: niveaux du domaine bioclimatique. ESRI Shapefiles http://www.mffp.gouv.qc.ca/forets/inventaire/inventaire-systeme.jsp.

Green, K., Finney, M.A., Campbell, J., Weinstein, D., Landrum, V., 1995. Fire! Using GIS to predict fire behavior. J. For. 93 (5), 21–25.

Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.G., Jarvis, A., 2005. Very high resolution interpolated climate surfaces for global land areas. Int. J. Climatol. 25, 1965–1978.

IPCC, 2007. Climate Change 2007 : an assessment of the Intergovernmental Panel on Climate Change. Change 446 (November), 12–17. http://dx.doi.org/10.1256/004316502320517344.

Keane, R.E., Morgan, P., White, J.D., 1998. Temporal patterns of ecosystem processes on simulated landscapes in Glacier National Park, Montana, USA. Landsc. Ecol. 14 (3), 311–329.

IPCC, 2013. Summary for Policymakers. In: Stocker, T.F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Xia, Y., Bex, V., Midgley, P.M. (Eds.), Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Keane, R.E., Holsinger, L.M., Parsons, R.A., Gray, K., 2008. Climate change effects on historical range and variability of two large landscapes in western Montana, USA. For. Ecol. Manag. 254 (3), 375–389.

Kocabas, V., Dragicevic, S., 2006. Coupling Bayesian networks with GIS-based cellular automata for modeling land use change. Geogr. Inf. Sci. 217–233.

Kocabas, V., Dragicevic, S., 2007. Enhancing a GIS cellular automata model of land use change: Bayesian networks, influence diagrams and causality. Trans. GIS 11, 681–702.

Li, X., Magill, W., 2001. Modeling Fire Spread Under Environmental Influence Using a Cellular Automaton Approach. 08 pp. 1–14.

Mansuy, N., Gauthier, S., Robitaille, A., Bergeron, Y., 2012. Regional patterns of postfire canopy recovery in the northern boreal forest of Quebec: interactions between surficial deposit, climate, and fire cycle. Can. J. For. Res. 42, 1328–1343.

Mantyka-Pringle, C.S., Visconti, P., Di Marco, M., Martin, T.G., Rondinini, C., Rhodes, J.R., 2015. Climate change modifies risk of global biodiversity loss due to land-cover change. Biol. Conserv. 187, 103–111 (ISSN 0006-3207, July).

Ministère des Forêts, de la Faune et des Parcs M.F.F.P., 2014. Direction de la protection des forêts, Service de la gestion du feu et de la réglementation, 2014. Fichier des données, Données Ouvertes.

Ministère des Forêts, de la Faune et des Parcs (MFFP), 2015. Ressources et industries forestières: portrait statistique. 2015 edition.

Nappi, A., Drapeau, P., Giroux, J., Savard, J., Moore, F., 2003. Snag use by foraging black-backed woodpeckers (*Picoides arcticus*) in a recently burned eastern boreal forest. Auk 120 (2), 505–511.

Natural Resources Canada, 2008. Canadian Forest Fire Weather Index (FWI) System. http://cwfis.cfs.nrcan.gc.ca/background/summary/fwi (Last access: 11/07/2015).

Natural Resources Canada, 2014. Forest topics: fire. http://www.nrcan.gc.ca/forests/fire/13143 (Last access: 27/02/2015).

Nelson, T., Coops, N., Wulder, M., Perez, L., Fitterer, J., Powers, R., Fontana, F., 2014. Predicting climate change impacts to the Canadian boreal forest. Diversity 6, 133–157.

Perez, L., Dragicevic, S., 2012. Landscape-level simulation of forest insect disturbance: coupling swarm intelligent agents with GIS-based cellular automata model. Ecol. Model. 231, 53–64.

Perez, L., Nelson, T., Coops, N., Fontana, F., Drever, C.R., 2016. Characterization of spatial relationships between three remotely sensed indirect indicators of biodiversity and climate: a 21 year's data series review across the Canadian boreal forest. Int. J. Digital Earth http://dx.doi.org/10.1080/17538947.2015.1116623.

Pontius Jr., R.G., Millones, M., 2011. Death to Kappa: birth of quantity disagreement and allocation disagreement for accuracy assessment. Int. J. Remote Sens. 32 (15), 4407–4429.

Resnick, M., 1994. Turtles, Termites and Traffic Jams. The MIT Press, Cambridge, Massachusetts.

Rindfuss, R.R., Entwisle, B., Walsh, S.J., An, L., Badenoch, N., Brown, D.G., Deadman, P., Evans, T.P., Fox, J., Gutmann, M., Kelly, M., Linderman, M., Liu, J., George, P., Mena, C.F., Messina, J.P., Moran, E.F., Parker, D.C., Prasartkul, P., Robinson, D.T., Sawangdee, Y., Vanwey, L.K., 2010. Land Use Change: Complexity and Comparisons. 3 pp. 1–10.

Régnière, J., 2003. BioSim: Optimizing pest control efficacy in forestry, Natural Resources Canada. Canadian Forest Service, Branching Out 3. 2.

Régnière, J., Saint-Amant, R., Béchard, A., 2014. BioSIM 10: User's Manual, Laurentian Forestry Centre.

Singh, A.K., 2003. Modelling Land Use Land Cover Changes Using Cellular Automata in a Geo-spatial Environment.

Snover, A.K., Mauger, G.S., Whitely Binder, L.C., Krosby, M., Tohver, I., 2013. Climate Change Impacts and Adaptation in Washington State: Technical Summaries for Decision Makers. State of Knowledge Report prepared for the Washington State Department of Ecology. Climate Impacts Group, University of Washington, Seattle.

Van Wagner, C.E., 1987. Devleopment and Structure of the Canadian Forest Fire Weather Index System, Canadian Forestry Service, Forestry Technical Report 35.

Vasiliauskas, S., Chen, H.Y.H., 2004. Post-fire regeneration of boreal forests in northeastern Ontario. Parks Research Forum of Ontario Proceedings 2004 (2004 PRFO Proceedings).
Visser, H., de Nijs, T., 2006. The Map Comparison Kit. Environ. Model. Softw. 21, 346–358.
Vuuren, D.P., Edmonds, J., Kainuma, M., et al., 2011. The representative concentration pathways: an overview. Clim. Chang. 109 (1 and 2), 5–31.
Ward, D.P., Murray, a.T., Phinn, S.R., 2000. A stochastically constrained cellular model of urban growth. Comput. Environ. Urban. Syst. 24, 539–558.
Wilensky, U., 1999. NetLogo.http://ccl.northwestern.edu/netlogo/. Center for Connected Learning and Computer-Based Modeling. Northwestern University, Evanston, IL.
Wolfram, S., 1994. Cellular Automata and Complexity: Collected Papers. Westview Press, Champaign, IL.
Yassemi, S., Dragićević, S., Schmidt, M., 2008. Design and implementation of an integrated GIS-based cellular automata model to characterize forest fire behaviour. Ecol. Model. 210, 71–84.
Yeh, A., Li, X., 2003. Error propagation and model uncertainties of cellular automata in urban simulation with GIS. 7th Int. Conf. GeoComputation, pp. 1–16.