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Using cellular automata and multi-criteria evaluation to simulate the wildfire expansion in Prince George, British Columbia

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Abstract. Wildfires pose a critical and ongoing challenge in British Columbia, Canada, threatening human life, property, and natural ecosystems. To understand and predict the behavior of such fires, our study employs Cellular Automata (CA), a mathematical model adept at simulating complex systems through grid-based cell interactions. This model, validated by prior research, incorporates a wind propagation rule that significantly enhances the prediction of wildfire spread in the direction of prevailing winds. Research centers on a wildfire event in Prince George, utilizing CA to simulate fire dynamics influenced by various factors. The model's strength lies in its ability to represent detailed local interactions and its flexibility in scenario testing, which is instrumental in understanding model uncertainties. By simulating different fire scenarios, the study aims to grasp the complexities and potential variables affecting wildfire behavior. The research provides a foundation for decision-makers to analyze and study wildfire events, leveraging a Multi-Criteria Evaluation (MCE) Model to assess the susceptibility of cells to fire. This comprehensive approach combines CA with MCE, offering a robust framework for simulating and managing wildfire expansion in British Columbia.

Keywords: Wildfires, wildfire spread stimulation, cellular automata, multi-criteria evaluation model, management and prevention of fire.

1. Introduction

Prince George's is the largest city in the northern interior plateau region of British Columbia, surrounded by forests, mountains, and rivers. Winds, lightning, dry weather, and human activity are potential causes of wildfires.

Cellular Automata (CA) model is a mathematical model of a complex system comprising a grid of cells. Each of which is in one of a finite number of states. Cells change in discrete time based on a set of transition rules and the states of the neighboring cells0 [1]. The behavior of fire propagation is influenced by a wide range of factors, making it a highly complex phenomenon. CA models can incorporate this information into the simulation and simulate the fire spread. It allows for a detailed and accurate representation of these factors. Local interaction is essential to understand the spatial dynamic spread of wildfire. Also, the CA model provides different scenario testing that we can use this model to simulate different wildfire scenarios and understand the model uncertainty. Research studies before designed a CA wildfire simulation model using the cell with the spreading of the nearest and next-nearest neighborhoods, and each cell has four possible states [2]. Previous researchers also provided new rules and a modified model, which allows the fire to spread to non-adjacent cells. Teams found this model valuable, especially inspiring us in the neighborhood function part and the role of wind factors in wildfire propagation models. However, this model also has some uncertainties because its results are based on the probability of burning as an outcome of ensembles of runs. So, it is necessary to contact decision-makers when using this model to analyze and study other wildfire events. Previous research mentioned that multi-criteria evaluation was applied successfully to evaluate different suitability in geospatial data analysis [3]. The team practiced the previous experience and decided to make a suitability map for evaluating the cell's susceptibility.

This region's vulnerability to wildfires is exacerbated by a combination of factors, including prevalent winds, lightning strikes, dry weather, and anthropogenic influences. To confront this challenge, the research adopts a methodological fusion of Cellular Automata CA and MCE. The CA model is the foundation of the simulation effort, providing a grid-based structure that evolves through discrete time intervals guided by rules that consider the states of neighboring cells. This approach is pivotal for capturing the spatial dynamics of wildfire spread. In conjunction with CA, an MCE method is applied, enabling the assessment of diverse variables such as topography, vegetative indices, and soil moisture levels, to determine the susceptibility of various areas to wildfire. The synergistic application of these methodologies offers a refined simulation of wildfire behavior, contributing significantly to the efforts in the prediction and strategic management of wildfire incidents.

2. CA-based Methodology for Wildfires Stimulation

2.1. Study Area

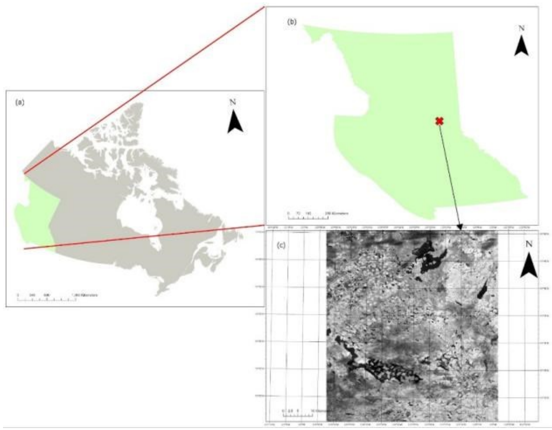

Figure 1. Map of Canada

In Fig1, (a) is a Map of Canada, where green represents the location of British Columbia (BC). (b) is a Schematic representation of BC with the location of the Prince George wildfire, where the red cross mark indicates the study area used for simulations. (c) is A zoomed area of wildfire location with grayscale. It is a 30*30 Meters Resolution Map of the Study Area

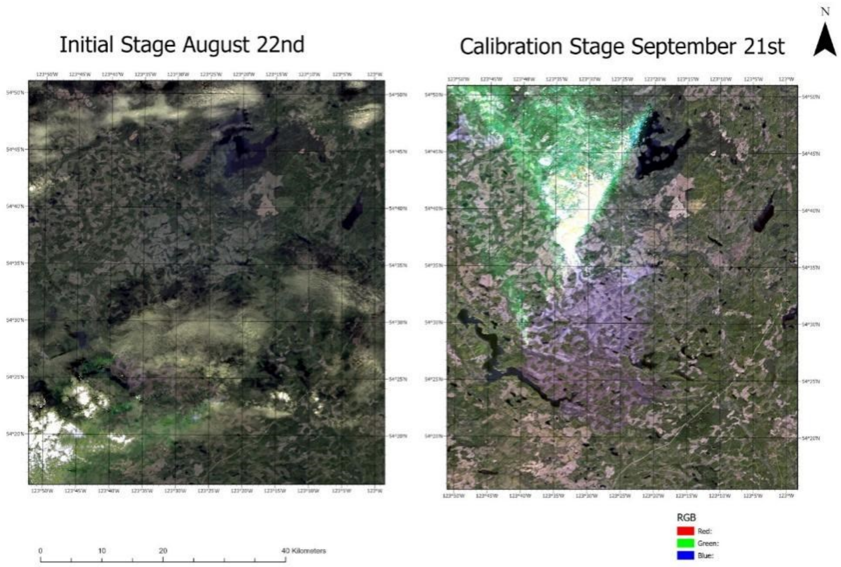

Figure 2. Initial Stage and Calibration Stage. Each image represents a different period of the study area, displayed in true color composition.

2.2. Input datasets

The study area of this model is 58.38 km × 66.39 km, which is (1946 columns × 30 m) × (2213 rows × 30 m). The temporal resolution of this study is 12 hours, separated into two stages: the initial stage is on August 21, 2023, and the calibration stage is undertaken on September 22, 2023. The satellite image and Digital Elevation Model dataset are procured from Landsat 8-9 OLI/TRS_Collection 2_Level 2, facilitated by the United States Geological Survey (USGS) with 30-meter spatial resolution. The projected coordinate system is WGS_1984_UTM_Zone_10N. Other data, including different variables used in model building, were listed in the table below (Table 1).

Table 1. Variables Involved in simulations with weights for Multi-Criteria Evaluation (MCE) Model

Variable Type	Variable Name	Code	Assigned Weights (%)
Topographic	Slope	Slope	20
	Elevation	Elevation	0
Combustible Factors	Normalized Difference Vegetation Index	NDVI	20
	Soil Moisture Index	SMI	20
	Normalized Burn Ratio	NBR	20
	Fuel Type	Fuel	20
Land Covers	Road	Road	0
	Water Body	Water	0
	Forest Biomass	Forest	0

Slope and elevation information was derived from elevation provided by the USGS [4]. Elevation was obtained from NASA Aster 30 meters DEM [5].

Combustible factors including NDVI, SMI, and NBR have all been retrieved directly[6][7], using different band combinations.

$$\text{NDVI} = \frac{(\text{NIR} - \text{RED})}{(\text{NIR} + \text{RED})} \tag{1}$$

Where NIR is Near Infrared, retrieved from [6].

$$\mathrm{NBR} = \frac{(\mathrm{NIR} - \mathrm{SWIR})}{(\mathrm{NIR} + \mathrm{SWIR})} \tag{2}$$

Where NIR is Near Infrared, SWIR is Shortwave Infrared, retrieved from (Vermote et al., 2016)[6]

$$\mathrm{SMI} = \frac{(\mathrm{LSTmax} - -\mathrm{LST})}{(\mathrm{LSTmax} - \mathrm{LSTmin})} \tag{3}$$

Where LST is Land Surface Temperature, retrieved from [7].

Fuel Type (Table 2) was manually reclassified using ArcGIS based on the burning probabilities of different vegetation types and land use from Dorain's research paper [8].

Land cover data including roads, water bodies, and forests are from the Canada Land Cover Type provided by the Canadian government.[9] Water bodies, roads, and urban build-up are considered constraints in the final suitability map, with a value of 0 at the final suitability map.

Table 2. Fuel type.

Value	Vegetation Type	Burning Probability
1	Temperate or Sub-polar needle leaf forest	0.39
2	Sub-polar taiga needle leaf forest	0.17
3	Temperate or Sub-polar shrubland	0.09
4	Temperate or Sub-polar grassland	0.02
5	Wetland	0
6	Cropland	0.13
7	Barren land	0.02
8	Urban-build up	0
9	Water	0

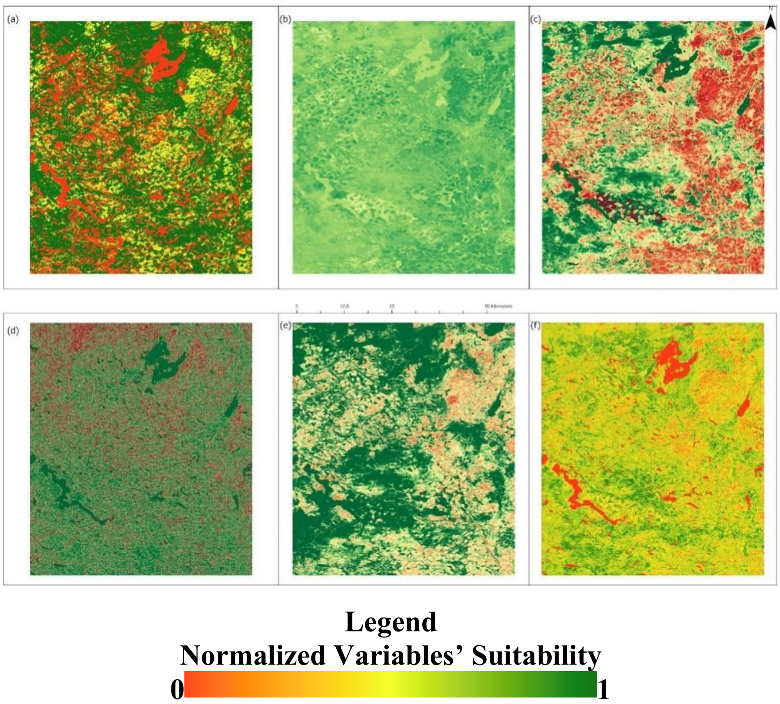

Figure 3. Normalized Raster Map of the Given Variables

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All maps are normalized from 0 to 1 in ArcGIS Pro, where 1 indicates the cell has a high susceptibility to wildfire, and 0 indicates the cell has no susceptibility to wildfire. (a) is the forest type. (b) is SM.

$$S = f(x1, x2, \dots\dots, xn) \tag{4}$$

Where S represents land suitability, and x1, x2, …, xn are the criteria affecting the suitability of the land.

In this study, MCE was involved in evaluating the susceptibility of cells. The weights of different variables are labeled in Table 1. This process involved different stages for processing the variables. (1) Normalized all the variables from the original scale to a scale of 0 to 1. (2) By using different calculating methods (e.g., linear, small), overlay each map variable. (3) Assign the weights for each variable to incorporate and get the final suitability map, as shown in Fig. 3.

2.3. Model method

The fire will propagate to 15*15 cells from the central point (Fig. 4.). Each cell is characterized by binary states, corresponding to burnt (1) and unburnt (0), with transition rules applied to the suitability map. The rules are listed below. Rule 1, "filter," states that if the center pixel in the filter kernel and its neighbors are multiplied by the values stored in the corresponding positions of the filter kernel, the resulting values are summed to arrive at a new value for the center pixel.

Rule 2, "reclass," states that after the cells are summed to a new value, after that classifying the pixel values stored in images because the values after filtering are no longer binary. According to this model, the filtered image value with a 1 to 999 interval will be reclassified to 1, and the rest will be reclassified to 0. This gives us the potential burnt cells.

Rule 3, "overlay," states that the suitability map (Fig. 2. f.) will be overlaid by multiplying with the reclassified map mentioned in rule 2. This gives us the suitability of the cells while considering that the suitability map's value will remain the same; if the same cell on the reclassified map is potentially burnt (has a value of 1), then the suitability map's value will remain the same. If the same cell on the reclassified map has a value of 0, the generated cell will have a value of 0 because this cell is not infected by wildfire.

Rule 4 states that reclassifying and overlaying the new area with the previous image to combine them by covering each other. Reclassify all cells that are over 0.65 in suitability and give them the value of 1, set the rest to 0, then overlay the new burnt area with the previous area to combine them by covering each other. This results in the map containing the old and new expansion of wildfire.

2.4. Model modifications

To more accurately simulate the wind's influence on the spread of wildfire, the model introduced modified scenarios by altering Rule 1, as specified earlier. This adjustment involved considering wind direction to encompass the impact of fire spotting.

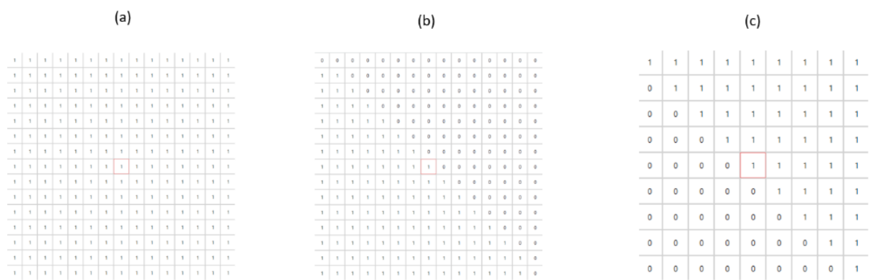

Figure 4. Neighbourhood functions.

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In Fig4, (a) is Neighborhood function for Scenario A. (b) is Neighborhood function for Scenario B. (c) is Neighborhood function for Scenario C.

3 different scenarios have been provided in this study.

Scenario A represents a 15*15 Moore neighborhood function, in which the cell will collect value from all cells in all directions. For rational, it is used for detecting how would the wildfire spread in the study area when the constrained factors are less.

Scenario B represents a 15*15 neighborhood for simulating northeast wind, in which the cell will only collect value from the southwest direction. For rationale, it is used for detecting how would overall fire-spreading trend changes in the study area when wind directions are introduced.

Scenario C represents a 9*9 neighborhood for simulating southwest wind with a relatively smaller scale in wildfire propagating. For rationale, it is used for detecting how the burnt area reduces when hazard management is involved immediately.

3. Results and discussion

Three scenarios with 180 simulated iterations were generated: the first one with the 15*15 Moore, the second with wind direction, and the last with modified fire spreading size and wind direction. Results at three selected periods are displayed in Fig.6, including the 720 hours after the real fire frontline. In this case, the Scenario B fire trend is more minor, with less noise around, and closer to the actual front line.

At 120 hours, it has a similar boundary with A. However, they are different at later periods as A has more noise points spreading to unconstrained locations. For C, the area fire spread is much smaller than the real datasets, and it has a different fire expansion direction trend because this study implements a smaller neighborhood size and makes a new approach for simulating the wind direction. By changing the parameters of the CA model, the end users can have more elements involved in each cell and have better performances for local cell interactions with variables involved. It ensures the flexibility for re-sponding to emergent scenarios in actual wildfire incidents.

Meanwhile, after the crosstab tabulation, A has an overall kappa value of 0.7062 and has a sustainable agreement with the calibration map. By contrast, Scenario B has an overall kappa value of 0.6946, which is the second highest among the three scenarios. Scenario C has the least agreement with the calibration stage because this study states the different parameters (shown in Fig.5).

Kappa Index of Agreement (KIA)

1) Using Scenario A as the reference image

Category	KIA
Unburnt	0.6313
Burnt	0.8013

1) Using Calibration Stage as the reference image

Category	KIA
Unburnt	0.8013
Burnt	0.6313

Overall Kappa: 0.7062

2) Using Scenario B as the reference image

Category	KIA
Unburnt	0.5951
Burnt	0.834

1) Using Calibration Stage as the reference image

Category	KIA
Unburnt	0.834
Burnt	0.5951

Overall Kappa: 0.6946

3) Using Scenario C as the reference image

Category	KIA
Unburnt	0.0971
Burnt	0.73

3) Using Calibration Stage as the reference image

Category	KIA
Unburnt	0.73
Burnt	0.0971

Overall Kappa: 0.1713

Figure 5. Kappa Index of Agreement.

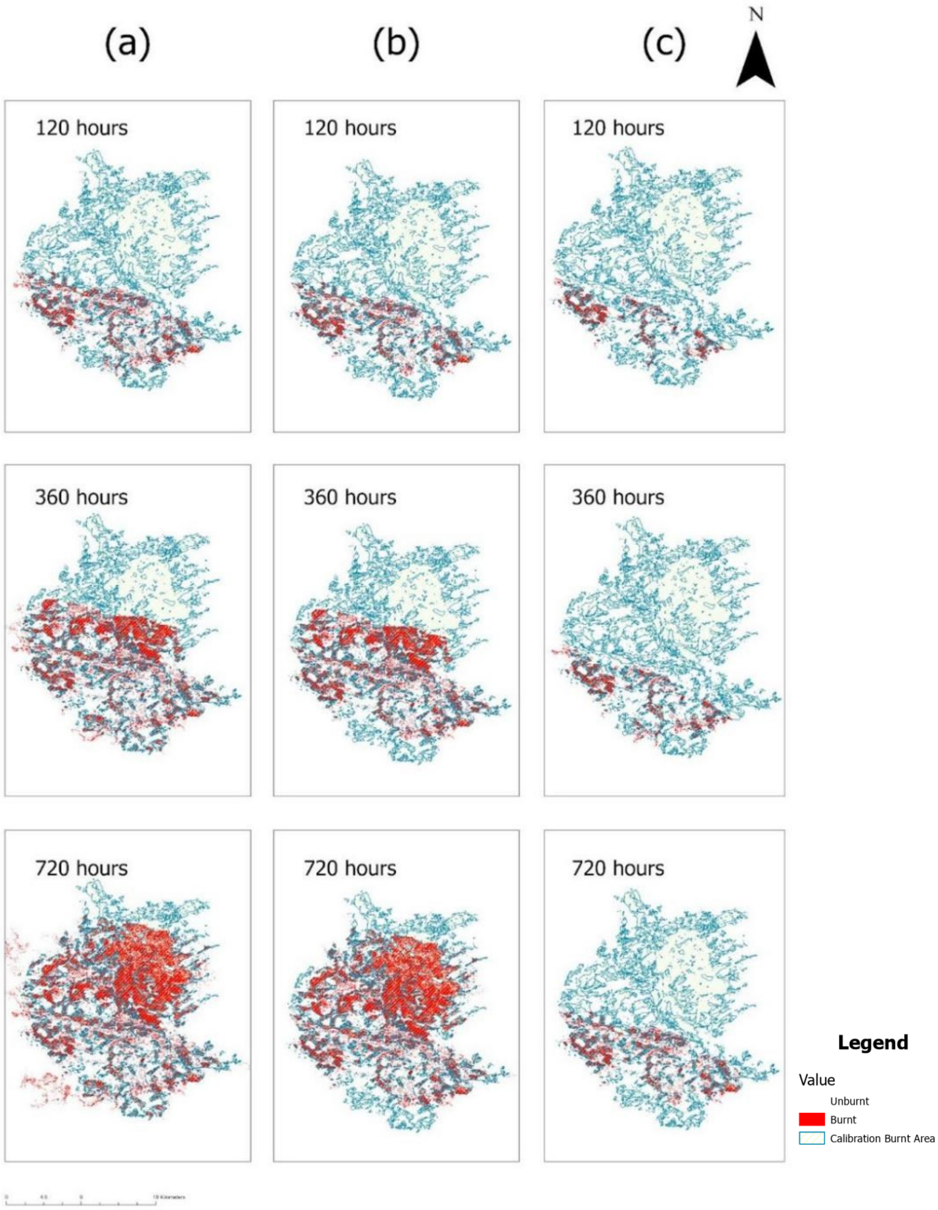

Figure 6. Simulation results

In Figure6, (a) represents simulated results under Scenarios A, (b) represents the simulated results under Scenarios B, (c) represents the simulated results under Scenarios C.

4. Conclusion

The conclusion of this study is that the efficacy of a Cellular Automata (CA) model is highlighted as a robust tool for the simulation of wildfire spread in the region of Prince George's. This model, underpinned by a suite of variables weighted according to their influence, provides a detailed suitability map for potential fire expansion. The study's innovative approach to incorporating the effects of various wind directions and human activities into the CA model significantly enhances the predictive power of the simulation. Through the comparison of three distinct scenarios, it becomes evident that wind direction plays a crucial role in the dynamic behavior of wildfires. It demonstrates the potential of Cellular Automata (CA) models in simulating wildfire spread, yet it also indicates areas for improvement and future research focus. Enhancements can be made in the precision of input data, the sophistication of modeling techniques, and the integration of real-time data. Future research may explore the use of higher-resolution satellite imagery and more granular environmental data to refine model predictions. The incorporation of live data streams from IoT sensors in forests could provide real-time adjustments to simulations, accounting for sudden changes in weather or fuel conditions.

Further development could involve machine learning algorithms that learn from past wildfire events to improve the predictive capabilities of CA models. These algorithms could identify patterns that might not be immediately apparent to human researchers, leading to more accurate risk assessments. Another promising direction is the application of ensemble modeling techniques, combining CA with other models to cover different aspects of wildfire dynamics for a comprehensive analysis.

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