Using Spatial Analysis to Assess Fire Vulnerability and Areas of Special Concern in Ontario, Canada

GEOG*4480 - Applied Geomatics

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Abstract

Forest fires in Ontario are projected to increase in frequency by 50% within 55 years. As the frequency increases, the serious risk already posed to human and environmental safety will only grow. This report aims to identify areas of Ontario that face the highest risk of wildfire outbreak. Here, we use Multi-Criteria Evaluation to create a model that identifies areas at risk of fire in Ontario. Our research uses vegetation health as the most important criterion, followed by mean temperature and precipitation. The combination of medium population densities and low precipitation leads to the highest risks of forest fires, which are in the north-west and south-eastern parts of the study area. These conditions are frequent during

April, when half the study area is under high risk of forest fires, whereas in August, the risk of forest fire is minimal. We found the lowest fire risks near Hudson Bay and are associated with low mean temperatures, low population densities, and high levels of precipitation. Our assessment can be used in decision-making at municipal and provincial levels to reduce the risks posed by forest fires to humans and important ecosystems, as well as help plan the distribution of resources dedicated to mitigate the risks.

Problem Context

Between 1959 and 1997, over 2 million hectares of North American forests burned due to wildfires. Unfortunately, forest fire vulnerability is expected to increase due to climate change (Splawinski et al., 2016). Wildfires can occur due to many natural causes such as lightning and human activity (Wotton et al., 2005). While controlled fires have proven to be beneficial to forest ecology, such as species that have evolved to live in forests prone to fire like the jack pine (Pinus banksiana), which require fire to release seeds within pinecones (Hutto 2008). In turn, forest fires also release years of carbon-storage which can increase atmospheric CO_2 and increase the rate of climate change (Boby et al., 2010). Many species struggle to regenerate after disturbance, unable to escape the flames (Chuvieco Salinero, 2003), which put the ecological dynamics of Ontario at risk (Poley et al., 2013).

Factors that affect the risk of wildfire are local vegetation (fuel source), temperature, human development, hydrology, and topography (Bryant and Westerling, 2014). Wildlife Urban Interface (WUI) are areas in which man-made structures are adjacent to vegetation (Pavegilo and Hardy, 2013). These areas are of special concern due to the human safety and economic risks (Thompson et al., 2011). In addition, ignitability of building materials for houses are the main cause of initiating home-loss to fires (Ager et al., 2010). Fire initiation is considered a fire ignited and expected to turn into a wildfire, as a fire ignition does not necessarily result in a wildfire (Chuvieco Salinero, 2003). With the landscape, climate, and human development constantly changing, the areas at-risk of fire in Ontario requires constant updating leading to great uncertainty of which areas require fire-preventative measures.

The identification of at-risk areas can provide information to the public on the potential impacts and can suggest new locations for fire services with access to at-risk areas to combat outbreak zones. The data can be used as a basis for decision making in management and government targeting towards environmental policy and protection of lands at risk.

Utilizing Geographic Information Systems (GIS) is essential to conduct our project. GIS provides our team with tools to design and operate a spatial risk assessment which is not feasible without GIS (Korucu, 2012). Multi-criteria Evaluation (MCE) is a technique to compare conflicting variables and their varying influence in a risk assessment. An MCE is done by evaluating criteria or factors with varying states and then their influence on the objective to rank areas by a suitability score (Carver, 1991). Using GIS to perform an MCE will allow our team to manipulate and analyze spatial data and determine areas of fire risk in Ontario.

Purpose of Research

The purpose of this research is to identify areas of high and low fire initiation risks, assess the potential intensity and ecological costs of a fire, and to inform resource managers to reduce the risk of wildfires in Ontario.

Research Objectives

1. Identify factors and variables that affect the risk of wildfires, and collect relevant data
2. Weight the factors identified in Objective 1, and integrate into a GIS model
3. Examine factor relationships and determine the level of wildfire risk across Ontario
4. Evaluate the areas of determined high risk and limitations of analysis

Study Area

Our study area as seen in Figure 1 is limited to the spatial extent of forestry data available through the Ontario Ministry of Natural Resources and Forestry (MNRF) and Natural Resources Canada (NRCan). Within this area, the objective is to determine spatially significant areas where wildfires have a higher risk of occurring. Areas of high risk will be determined by spatial analysis using criteria proven to increase risk of forest fire.

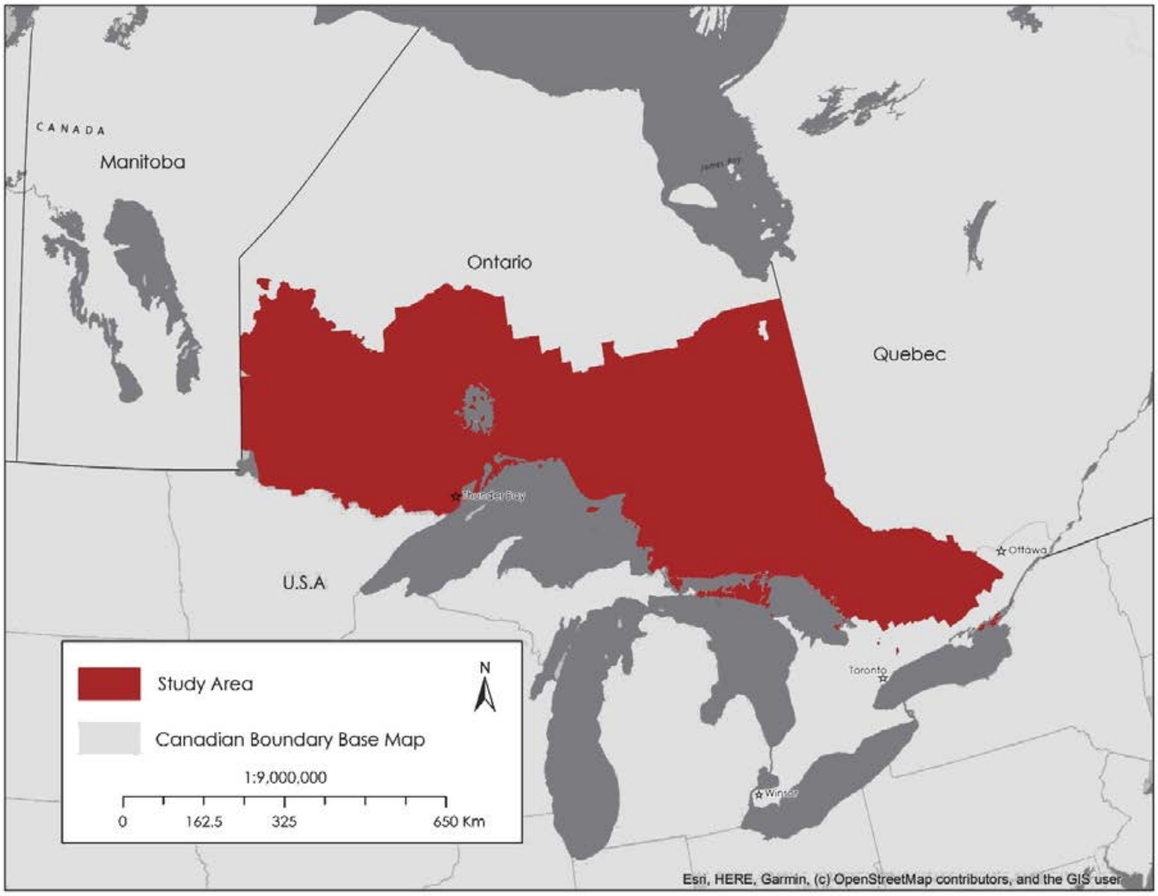

Figure 1: Image of Ontario, Canada highlighting our study area.

Research Approach

Below is our case study flow chart depicting the process of executing objective 1-4 and the data required.

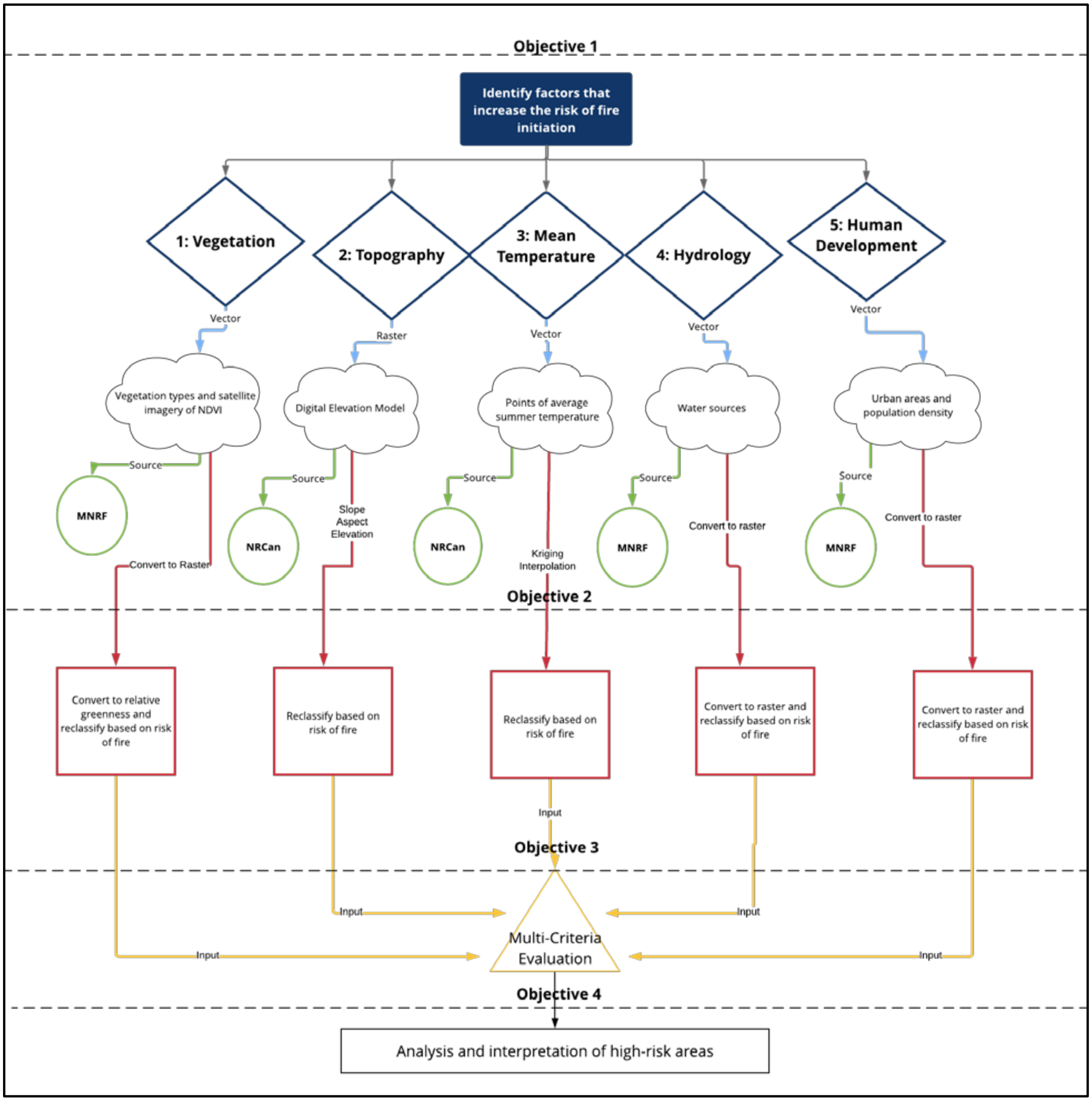

Figure 2: Requirements for executing the multi-criteria evaluations.

Objective 1: Identify factors and variables that increase the risk of wildfires

Factor 1: Vegetation (Fuel Source)

Accumulation of organic debris on forest floors can serve as a potential fuel for forest fires (Knapp et al., 2005). Since vegetation and debris type vary in the risk of fire vulnerability, we divided vegetation type into 5 classes of fire risk (extreme, very high, high, moderate, or low) listed in Table 1 below based on Pan et al., (2016).

Table 1: Vegetation type and their associated forest fire risk and weight.

Vegetation Type	Risk	Weight
Conifers	Extreme	5
Mixed, broad-leafed, shrubland	Very high	4
Grassland	High	3
Crop land	Moderate	2
All other	Low	1

Wetter vegetation is at lower risk than dry vegetation (Chuvieco Salinero, 2003). To accomplish classifying vegetation wetness, we converted NDVI (Normalized Difference Vegetation Index) to Relative Greenness (RG) using the equation below from Schneider et al., (2008):

$$RG = (NDVI - NDVI_{min}) / (NDVI_{max} - NDVI_{min})$$

We used 23 16-day NDVI rasters from MODIS satellite imagery from April to September 2019. We assessed multiple states of vegetation throughout the growing season using three RG images: the week with minimum RG, the week with maximum RG, and a calculated raster with average RG across all summer months. RG was then ranked divided into 5 classes of fire risk as shown in Table 2 below by using natural breaks of the average raster and applied these breaks to the minimum and maximum rasters. Since each raster represents different times of year, we ran three separate MCEs.

Table 2: Relative Greenness (RG) values based on NDVI rasters from MODIS data, and their associated forest fire risk and weight.

RG (%)	Risk	Weight
<14	Extreme	5
14 - 42	Very high	4
42.01 - 62	High	3
62.01 - 80	Moderate	2
80.01 - 100	Low	1

Factor 2: Topography

For the purpose of our report, topography refers to the slope, aspect, and elevation of the landscape. Elevation has an inverse relationship with fire risk as higher altitudes pose lower risk and lower altitudes have the highest risk (Eugenio et al., 2016). Slope has proved to be a major factor in fire risk, and aspect indicates the orientation to the sun, and thus the amount of solar energy received. (Yang and Jiang, 2020). Topographical parameters are included in our model by creating a Digital Elevation Model (DEM) and weighted according to Table 3 and Table 4 below. Slope and Aspect were created from this DEM.

Table 3: Slope values, obtained by calculating percentage rise over run, from the Provincial Digital Elevation Model (PDEM) of Ontario, and their associated weight and risk of forest fire.

Slope (%)	Risk	Weight
≥ 45.01	Extreme	5
35.01 - 45	Very high	4
25.01 - 35	High	3
15.01 - 25	Moderate	2
< 15	Low	1

Table 4: Aspect derived from the Provincial Digital Elevation Model (PDEM) of Ontario and their associated weight and risk of forest fire.

Aspect	Risk	Weight
N	Extreme	5
NW and W	Very high	4
NE	High	3
E	Moderate	2
S, SE, SW, and FLAT	Low	1

Factor 3: Temperature

Temperature range can significantly impact the likelihood of fire and the extent of its spread (Rodrigues et al., 2018). Increased temperatures can lead to drier, more combustible fuels through increased evaporation and transpiration. (Bryant and Westerling, 2014). Large wildfire occurrence typically increases with summer drought temperature maximums (Bryant and Westerling, 2014). Weather station point data from the MNRF was used to interpolate average temperatures across the study area using the Kriging tool in ArcGIS. Assigned weights in Table 5 below were adapted from Eugenio et al., (2016).

Table 5: Average temperatures and their associated risk of forest fire and weight.

Average Temperature (°C)	Risk	Weight
≥22	Extreme	5
20.01 - 22	Very high	4
19.01 - 20	High	3
18.01 - 19	Moderate	2
<18	Low	1

Factor 4: Hydrology

Hydrology includes precipitation and static water sources which are considered the lowest risk of fire (MNRF, 2012). Water bodies are considered as a criteria, as fires cannot occur on water bodies, therefore creating a raster with only water bodies with a weight of 0 and all other areas with a weight of 1. Areas of high precipitation and overland flow are shown to have less intense wildfires as moisture suppresses the flames (Chuvieco Salinero, 2003). We will classify the variations of hydrology according to a Standardized Precipitation Index (SPI) provided by the MNRF. The SPI evaluates the precipitation difference as a temporal index, providing information on a location’s relative wet or dry conditions (Keyantash, 2018).

Table 6: Standard Precipitation Indices (SPI) and their associated risk of forest fire and weight.

SPI	Risk	Weight
< -1.5	Extreme	5
-1.49 to -1.00	Very high	4
- 0.99 to +0.99	High	3
1.0 to 1.5	Moderate	2
> 1.5	Low	1

Factor 5: Human development

WUI are areas in which man-made structures are adjacent to vegetation posing as a fire risk (Pavegilo and Hardy, 2013). To account for this, population density presents a parabola-shaped probability, in that a medium population density poses the highest risk of fire initiation (Bryant and Westerling, 2014). We used a population vector from NRCan and converted it to a raster with risk of fire based on Miller et al., (2011).

Table 7: Population density (people per Km^2) and their associated risk of forest fire and weight.

Population Density	Risk	Weight
20 - 60	Extreme	5
60 - 80	Very high	4
5 - 20	High	3
0 - 5	Moderate	2
80 - 1028	Low	1

Lastly, we will use urban development as a criteria, in that the presence of urban areas results in no risk of fire (weight= 0) and non-urban areas results in fire possibility (weight= 1).

Objective 2: Design an MCE model based on weighted factors identified above

The factors outlined under Objective 1 are conducive to the ignition and spread of forest fires in Ontario. These factors can be weighted by their importance to these facilitating conditions. An MCE will be performed using these weighted values to determine areas of special concern through evaluating alternative factors resulting in a spatial suitability score (Carver, 1991).

Before data is weighted, it must be standardized. Data in this report will be standardized following the linear stretch method using the equations below:

Benefit factor

$$X'ij = \frac{x_{ij}-x_{min}}{x_{max}-x_{min}}$$

Cost factor

$$X'ij = 1 - \frac{x_{ij}-x_{min}}{x_{max}-x_{min}}$$

In the Heilongjiang Province in China, Yang and Jiang (2020) recently created a base reference for the weighted factors. Factors were adjusted due to the differences in variables between our studies, such as reducing anthropogenic features to 0.15 because of the lack of road data. Comparing the weighted factors lead us to creating a pairwise comparison matrix.

Table 8: Pairwise Comparison Matrix for Factor Weights of precipitation (precip), topography (topo), vegetation condition (veg), temperature (temp), and population density (pop).

	Pairwise Comparison					Individual Weights					Total Weights
	Precip	Topo	Veg	Temp	Pop	Precip	Topo	Veg	Temp	Pop	
Precip	1	2	1/2	1	2	1/5	2/10	.5/2.66	1/5	2/8.5	0.20 [0.2046]
Topo	1/2	1	1/3	1/2	1/2	½ /5	1/10	⅓ 2.66	½ /5	½ /8.5	0.10 [0.0968]
Veg	2	3	1	2	3	2/5	3/10	1/2.66	2/5	3/8.5	0.35 [0.3657]
Temp	1	2	1/2	1	2	1/5	2/10	½ /2.66	1/5	2/8.5	0.20 [0.2047]
Pop	1/2	2	1/3	1/2	1	½ /5	2/10	⅓ /2.66	½ /5	1/8.5	0.15 [0.1286]
SUM	5	10	2.66	5	8.5	1	1	1	1	1	1

Objective 3: Apply the MCE model to determine the level of wildfire risk

Through the model created above, after weights of all data are determined, the simple additive weighting equation below will be used to perform the MCE.

$$Suit = (Cn_{Lakes} * Cn_{Urban\ Areas}) * [(W_{Vegetation} * Cr_{Vegetation}) + (W_{Topography} * Cr_{Topography}) + (W_{Temp} * Cr_{Temp}) + (W_{Hydrology} * Cr_{Hydrology}) + (W_{Development} * Cr_{Development})]$$

Suit is the final value used to determine risk of forest fire in a given area. Cn are constraints given on the suitability of any area, and Cr are criteria, or factors outlined under objective 1. W refers to the weighting given to a specific criteria. The cumulative results of Objective 1 can be seen in Table 9 below.

Table 9. Ranking, weights (W), and description of factors, criteria and source of data used in the multi-criteria evaluation. (MNRF-Ontario Ministry of Natural Resources and NRCan- Natural Resources Canada).

Influence Factor or Criteria	Data Source	W	Variables	Internal W	Risk of Fire Probability	Description of Fire Probability
Precipitation	MNRF	0.20	Standardized Precipitation Index	1	5,4,3,2,1	Extreme, very high, high, moderate, low
Topographic Factors	NRCan	0.10	Slope (%) Aspect (°) Elevation (m)	0.33 0.33 0.34	1,2,3,4,5	Extreme, very high, high, moderate, low
Vegetation Condition	NRCan MODIS	0.35	Vegetation type Relative Greenness (%)	0.5 0.5	1,2,3,4,5	Low, moderate, high, very high, extreme
Temperature	NRCan	0.20	Mean summer temperature (°)	1	1,2,3,4,5	Low, moderate, high, very high, extreme
Water bodies	MNRF	C	Presence or absence of water body	1	1, 0	Criteria (Presence = 0, absence =1))
Human Impact Features	MNRF MNRF	0.15	Population Density Presence or absence of urban development	0.5 0.5	1,2,3,4,5 1,0	Extreme, very high, high, moderate, low Criteria (Fire possible=1, not possible=0)

Objective 4: Evaluate the areas of determined high risk

We expect our MCE to identify final areas of calculated risk to reflect fire risk based on the factors we analyzed. We will have three final MCE maps from the maximum, minimum, and average RG rasters. This will provide a temporal aspect of our analysis to determine when the resulting areas are of the highest risk.

Research Findings

Overall, we found our study area to range from low to extreme fire risk based on our factors and criteria. To achieve Objective 4, we will evaluate the fire risk based on each of the factors and the final MCE. First, vegetation appeared to be mostly high and very high across the study area with extreme and low patches in the far north (Figure 3). Northern Ontario seemed to be composed mostly of conifers giving it high fire risk, with patches of low risk due to bog-type vegetation.

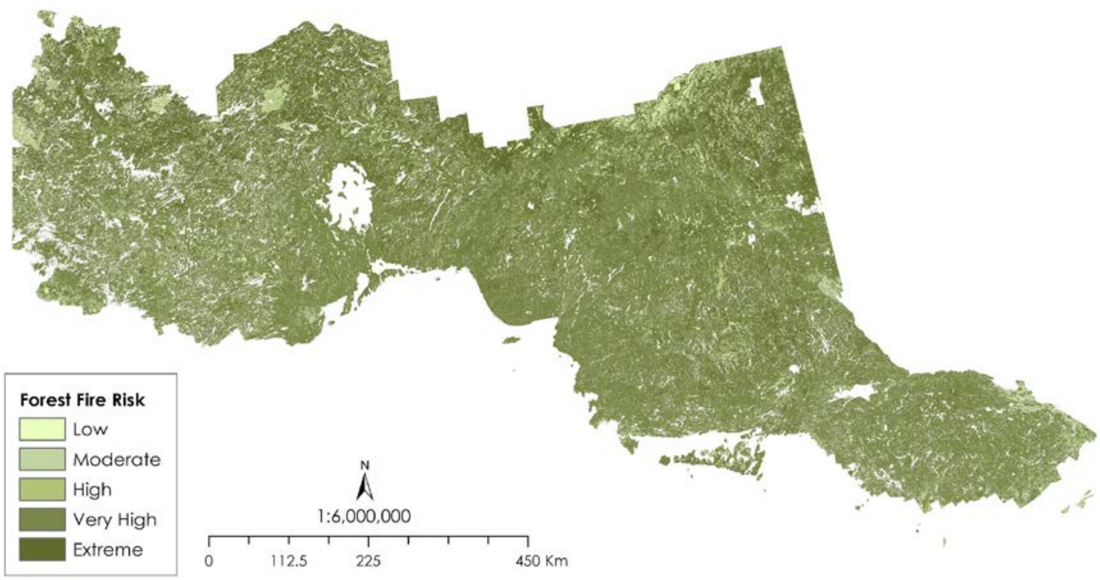

Figure 3. Resulting risk of forest fire based on vegetation types in the study area.

RG resulted in a trend as though we expected, the later in the summer, the higher the RG and therefore the lower risk of forest fire. As shown in Figure 4 in April, the majority of the province has low RG and very high risk of forest fire. This temporal analysis adds key implications to not only where in the province is at risk, but also when.

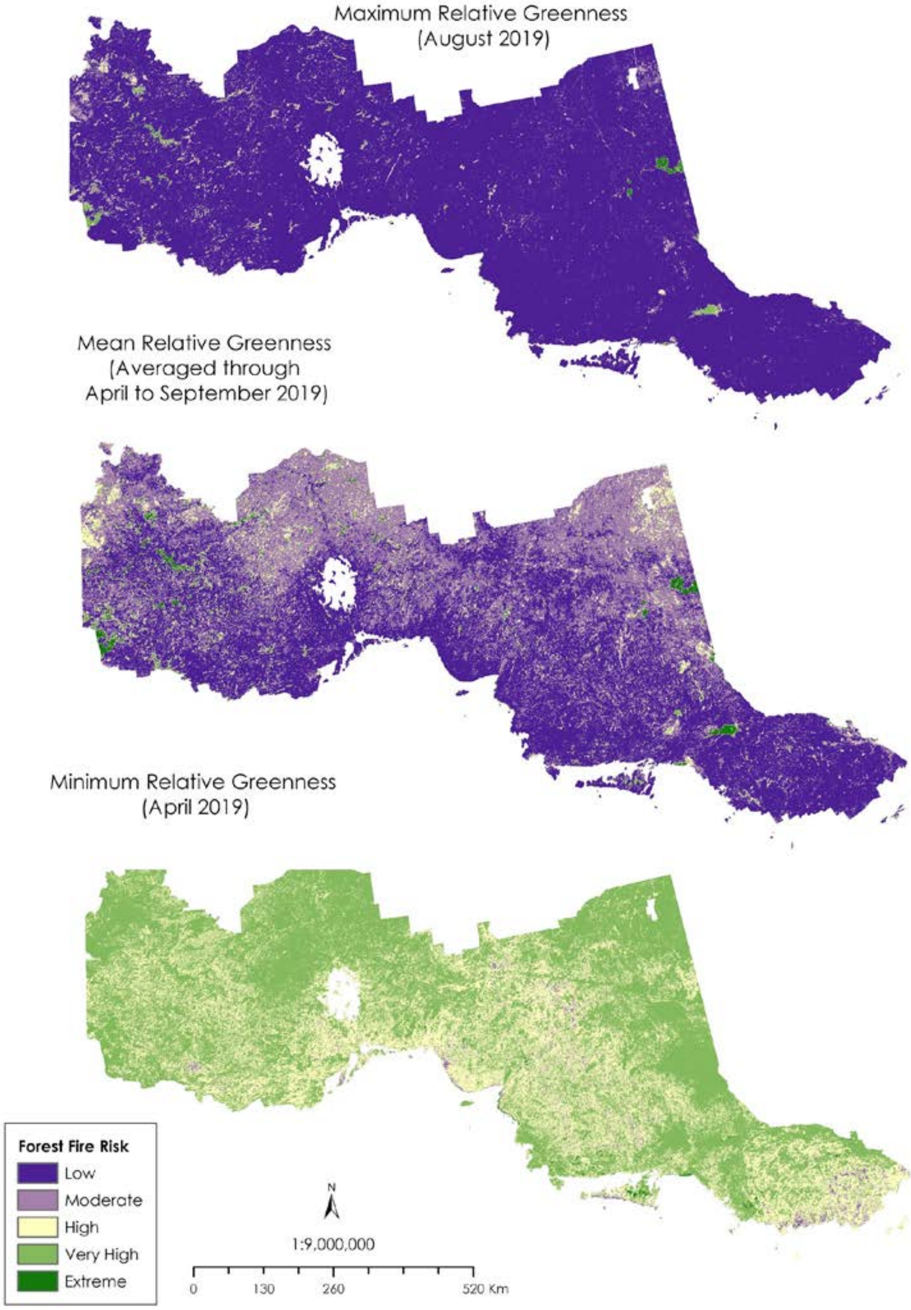

Figure 4. Resulting risk of forest fire based on Relative Greenness (RG) in the study area in April, August, and the average RGs.

Topographic features across the study area such as elevation and slope showed minimal variation. Aspect has extreme variation and the north-eastern border of the study area seems to have the highest risk. Since the topography weight is the cumulation of all three, the overall risk seems to be quite low.

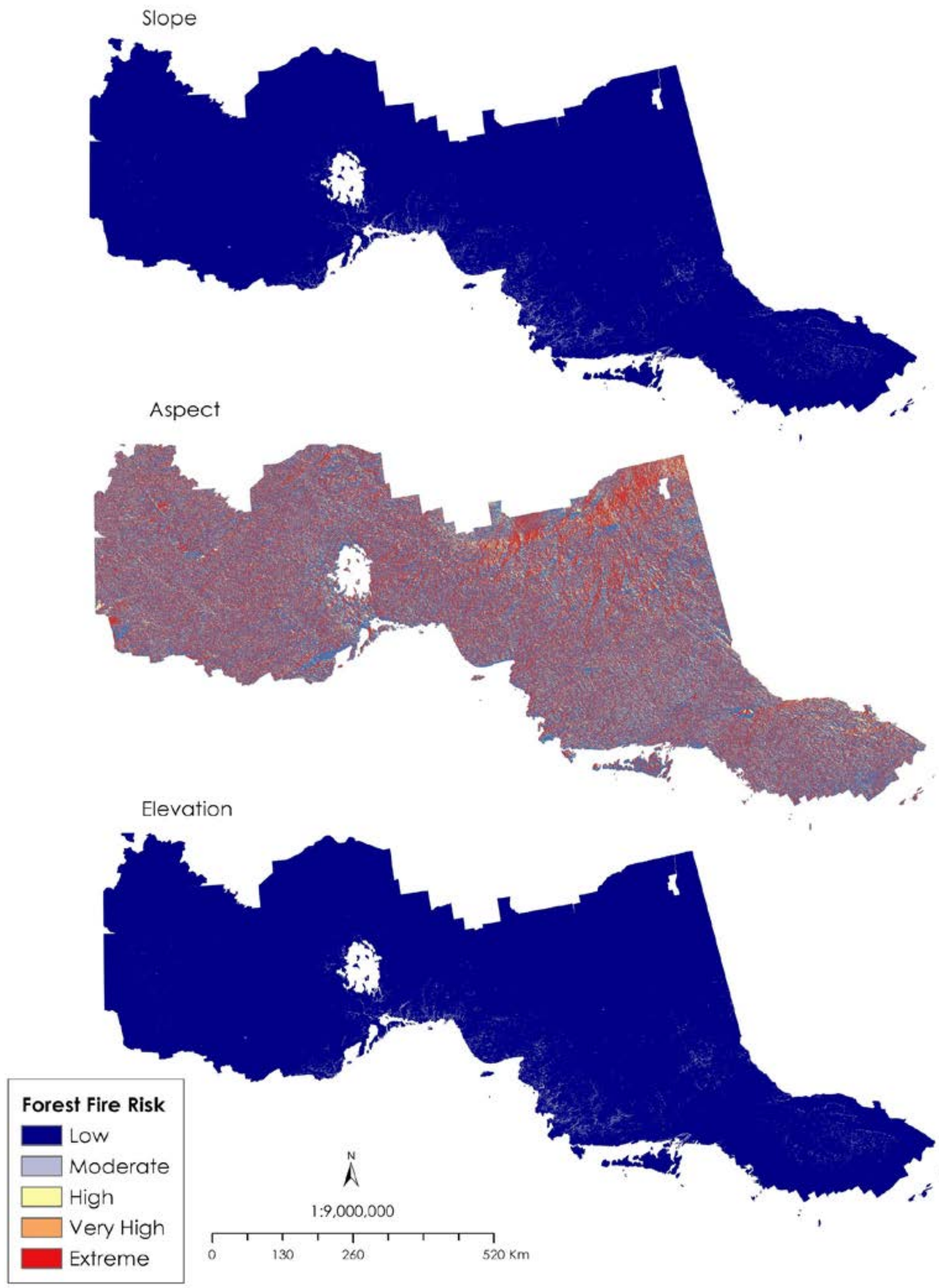

Figure 5. Resulting risk of forest fire based on slope, aspect, and elevation in the study area.

The remaining factors can be seen in Figure 10. The presence of water bodies leads to variance in temperature based on proximity. The Coastal areas of Hudson Bay areas due to higher H_2O in the environment and lower temperatures (A). Map B in Figure 10 shows higher precipitation levels present in close vicinity to larger water bodies with extreme fire risk in the center area and south arm. Map C shows areas of high forest fire risk due to population density in which most of the study area is of low risk. Lastly, Figure 10 has maps D and E of the resulting criteria of presence of water bodies and urban areas respectively, where fires cannot occur.

Figure 10. The resulting maps of the factors of temperature (A), standard precipitation index (B), and human population density (C). In addition, the resulting criteria of water bodies (D) and urban areas (E).

Across our study area, temporally we found the highest risk of forest fire to be in April of 2019 with the lowest RG in the growing season (Figure 11). Since RG represents the wetness of vegetation, it makes sense that August would have the lowest risk of forest fire. The north-west section and south-eastern tip of the study area seemed to have the highest risk of fire. This could be due to the medium population densities which have the highest risk of fire, and the lowest precipitation relative to the rest of the study area. The eastern areas that border Hudson's Bay seem to have the least risk. This could be due to the type of vegetation, lower mean temperature, high precipitation, and low population density.

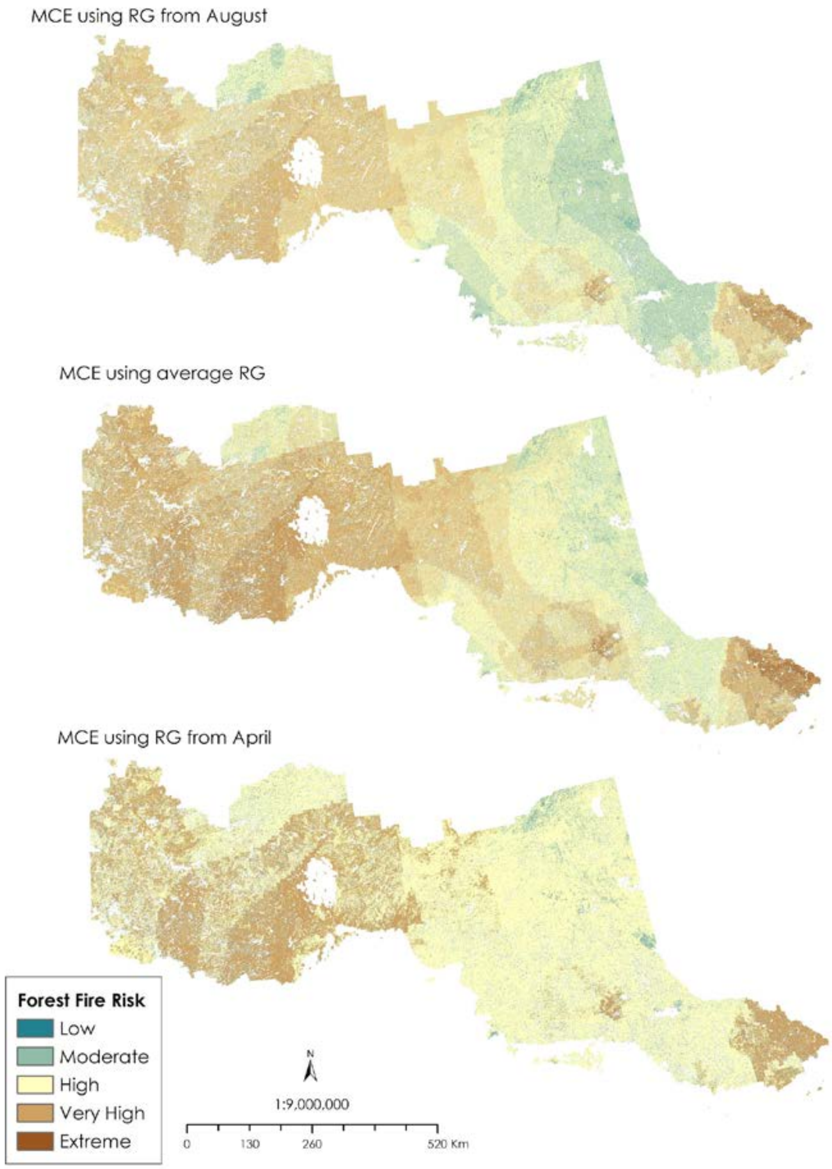

Figure 11. Resulting Multi-Criteria Evaluation maps of forest fire risk in the study area located in Ontario, Canada based on three dates with varying levels of RG.

There are multiple limitations to our analysis such as the resolution and age of our data. All data collected is from 2019, with the exception of the population density which is from 2012. This could be falsely reflecting the true risk of fire based on population density as it has increased since then. There are also factors that could influence fire ignition and spread that are not considered such as wind speed. Distance to roads was also not accounted for since the factor varies from 0-70 meters and our resolution of 250 meters is too large. Future research could endeavor to examine data with a finer resolution.

Conclusion

Our analysis of forest fire ignition criteria indicate times of growing season and areas in Ontario that have a higher risk of forest fire ignition. The resulting MCE maps indicate higher risk in April in central Ontario, and higher risk in August in Western Ontario. Based on these spatial and temporal risk assessments, recommendations can be made to residents and resource managers and prepare for times of high risk of fire.

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