International Cartographic Association
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Spatial Susceptibility Mapping of Boreal Forest Fires: Insights from Quebec's Historical and Future Trends (1980-2050)

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Abstract: Forest fires cause significant loss and damage each year, with climate change exacerbating their frequency and severity, highlighting the need for accurate susceptibility maps for effective mitigation and planning. This study integrating various environmental, ecological, and meteorological factors assesses the current and future forest fire susceptibility of Quebec's boreal forests under two climate change scenarios over the next 30 years (2021-2050). The study involved identifying factors affecting forest fires and collecting 40 years of historical forest fire data (1980-2020). Climate variables were downloaded, and the Fire Weather Index (FWI) was calculated using BioSIM software and then interpolated into raster layers in ArcGIS Pro. The data was divided into training (70%) and testing (30%) sets, with a Random Forest (RF) model trained and validated using three accuracy metrics including receiver operating characteristics-area under the curve (ROC-AUC), the figure of merit (FoM), and F1 score, achieving results of 0.895, 0.808, and 0.894, respectively. Although forest fire susceptibility maps displayed some variation over the next 30 years (2021-2050), no distinct upward or downward trend was detected. Additionally, susceptibility remained largely unchanged under both the RCP 4.5 and RCP 8.5 scenarios. The study also highlighted the key factors affecting fire susceptibility, with the FWI, live biomass, and dead biomass being the most significant, contributing 21.8%, 14.28%, and 11.35%, respectively. This study predicting fire susceptibility and providing current and future susceptibility maps offers a proactive approach to climate change preparedness and improving resource allocation and forest fire risk management.

Keywords: Geographic information systems (GIS), Climate change, Machine learning (ML), Random Forest (RF), Forest fire susceptibility mapping (FFSM).

1. Introduction

Forest fires, whether natural or human-induced, are among the most frequent natural hazards, causing significant loss of life, biodiversity, and ecosystem services globally (Khan and Eslamian 2022; Katan and Perez 2021). Forest fires impact approximately 30% of the global terrestrial surface, disrupting ecosystems and their services (Pechony and Shindell 2010). Climate change and human activities have further increased fire risks in many forested regions, intensifying the threat of wildfires and their effects on ecosystems (da Silva et al. 2018).

Regarding the Canadian National Forestry Database (Canadian National Fire Database (CNFDB) 2024), more than 8,000 fires occur annually, burning an average of over 2.1 million hectares in Canada. Additionally, there is a growing global awareness of the importance and susceptibility of Canadian boreal forests concerning future climate change (Flannigan et al. 2009). Future changes in temperature and precipitation are anticipated to alter the patterns of forest fires in boreal areas (Flannigan et al. 2001).

Although it is challenging to control forest fires naturally, forest fire susceptibility mapping (FFSM) is essential for reducing risks and preventing damage. Numerous studies on FFSM have utilized remote sensing (RS) and geographic information systems (GIS) (Faramarzi et al. 2014; Pourtaghi et al. 2015), applying techniques that vary widely in complexity and focus. These approaches are generally categorized into physics-based, multi-criteria decision analysis (MCDA), statistical, and machine learning (ML) methods. Physics-based methods use probabilistic equations related to fluid mechanics, heat transfer, and canopy combustion (Keane 1998; Sturtevant et al. 2009). These methods are generally computationally intensive and require a thorough understanding of underlying processes and comprehensive and precise datasets. MCDA is a decision-making process that assesses and compares multiple conflicting criteria to choose the most suitable option or solution, considering various factors and preferences. Some studies have implemented MCDA methods for FFSM (Eskandari 2017; Sari 2021). Given the complex structures and conflicting criteria involved in forest fires, although MCDA techniques allow solutions to be tailored to specific needs and preferences (Yu et al. 2011; Zolekar and Bhagat 2015), a major drawback of MCDA-based forest fire models is their susceptibility to bias, as they rely on expert knowledge. Statistical models are mathematical tools that analyze data relationships, identify patterns, and make predictions by quantifying relationships between independent and dependent variables based on probability and statistical theory (Chambers and Hastie 2017). Various statistical methods have been applied to FFSM including frequency ratio (FR) (Hong et al. 2017), evidential belief

Advances in Cartography and GIScience of the International Cartographic Association, 5, 20, 2025.
32nd International Cartographic Conference (ICC 2025), 17–22 August 2025, Vancouver, Canada. This contribution underwent double-blind peer review based on the full paper. https://doi.org/10.5194/ica-adv-5-20-2025 |

function (EBF) (Nami et al. 2018), and weight of evidence (WOE) (Jaafari et al. 2017). Statistical models may lack insight into physical fire processes, are sensitive to data errors, and often struggle to capture complex factor interactions. As an alternative to statistical models, ML models have recently become essential tools for hazard susceptibility mapping worldwide, proving highly effective in assessing natural hazard risks (Rihan et al. 2023). These models are widely used for spatial susceptibility assessment of various hazards, including landslides (Goetz et al. 2015), soil erosion (Mosavi et al. 2020), floods (Gharakhanlou and Perez 2023), and are frequently applied in studies on forest fire susceptibility (Sachdeva et al. 2018; Shahfahad et al. 2022; (USGS) 2024).

Boreal forests are expected to be highly sensitive to climate change, leading to changes in forest growth and species composition, which could impact forest fires through fuel dynamics (Kellomäki et al. 2005). While the direct effects of climate change on climatic factors are better understood, their influence on fire potential across larger areas is less studied. Developing a deeper understanding of how climate change affects the fire susceptibility of boreal forests is crucial for predicting future fire risks and shaping management strategies. Accordingly, this study aims to assess the fire susceptibility of Quebec's boreal forests under projected climate conditions for the next 30 years (2021-2050). To achieve this, this study employs a random forest (RF) model that (i) integrates multiple environmental, ecological, and meteorological factors, (ii) evaluates the impact of each factor on forest fire susceptibility, (iii) examines the fire susceptibility under two climate change scenarios until 2050, and consequently (iv) provides spatial maps identifying forest areas prone to fire until 2050. The specific highlight of the current study that differentiated it from preceding ones was its ability to address these concerns.

2. Materials and methodology

Figure 1 illustrates the research methodology flowchart. We began identifying and gathering a set of factors that affect forest fires following the earlier studies (Gaudreau et al. 2016; Gharakhanlou and Hooshangi 2021). Besides, historical forest fire inventory data were gathered from 1980 to 2020 (40 years). Having downloaded climate variables and calculated the Fire Weather Index (FWI) at climate stations across Quebec using BioSIM 11.8.21.5 software (Centre and Régnière 2003), FWI values were interpolated into continuous raster layers using the Kriging interpolation tool in ArcGIS Pro 3.3.0. Next, predictor values spanning 40 years were assigned to their corresponding target variable (fire event), and the data was randomly divided into training (70%) and testing (30%) datasets. The optimal values for hyperparameters were determined using 5-fold cross-validation with GridSearchCV, followed by training the RF model and validating its performance using receiver operating characteristics-area under the curve (ROC-AUC), figure of merit (FoM), and F1 score metrics. Finally, variable importance was assessed, and forest fire susceptibility was mapped under two climate scenarios for 2021–2050.

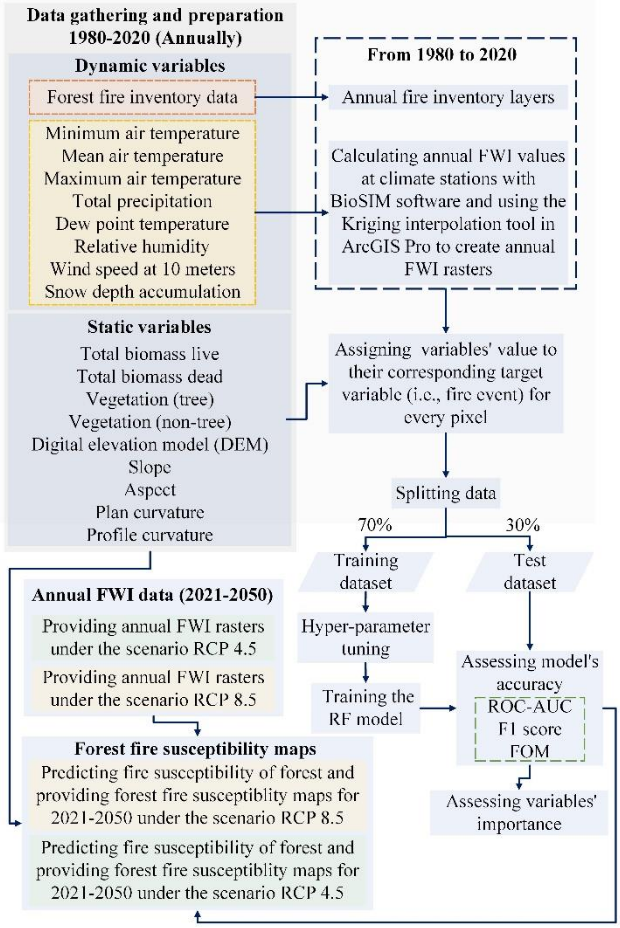

Figure 1. The flowchart of research methodology.

2.1 Study area

Over the past 40 years, Canada has averaged 7,000 wildfires annually—mainly in British Columbia and the boreal forests of Ontario, Quebec—with burned areas ranging from 0.5 to over 7 million hectares yearly (Hanes et al. 2019). This study focuses on Quebec's boreal forest (Figure 2), which spans 560,000 km²—one-third of the province—and is dominated by coniferous trees (75%) (Gaudreau et al. 2016).

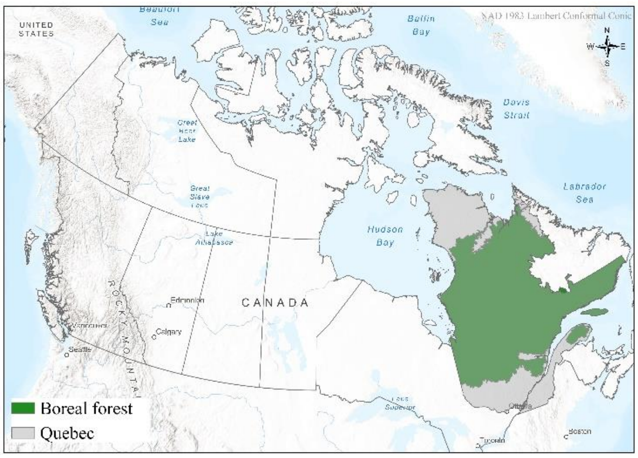

Figure 2. Quebec's boreal forest.

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2.2 Data and preprocessing of the data

This study examined several ecological, environmental, and meteorological factors that may influence forest fire spread, drawing on insights from previous research on fire propagation (Alexandridis et al. 2011; Gaudreau et al. 2016; Zheng et al. 2017; Shahfahad et al. 2022). The factors considered include elevation, slope, aspect, plan and profile curvature, FWI, and four forest attributes, such as total live and dead biomass, and two vegetation classes: tree and non-tree vegetation. Elevation influences temperature, rainfall, moisture, and wind directly, and affects vegetation and fuel moisture indirectly, making it relevant to this analysis (Tiwari et al. 2021). Terrain slope is crucial in wildfire progression as fires spread faster uphill due to the increased proximity to the ground on steeper slopes (Bar et al. 2020). Aspect was also included due to its relationship with solar radiation, as south-facing slopes receive more sunlight, resulting in higher temperatures, lower humidity, and stronger winds (Sachdeva et al. 2018). Curvature, representing topographic shape, was considered for its role in fire spread (Gupta et al. 2018). FWI describes how atmospheric conditions influence vegetation moisture content and the potential for fire ignition and spread (Di Giuseppe et al. 2018). Since FWI incorporates multiple fire-relevant climate factors—such as minimum, mean, and maximum temperature, total precipitation, dew point temperature, relative humidity, 10-meter wind speed, and snow depth accumulation—it is the only climate variable included in our investigation. Live biomass, mainly trees, serve as fuel for fires, with denser vegetation enhancing both fire intensity and spread. Dead biomass, including fallen branches and leaves, contributes to the fuel load, intensifying and prolonging fires. Trees, having higher moisture content, can help moderate fire behavior, whereas non-tree vegetation, with lower moisture content, burns more easily and rapidly. Table 1 provides an overview of all datasets used in this study, along with their respective sources.

Data	Variables	Source
Maps of Canada's forest attributes	Live biomass	Natural Resources Canada (2022)
	Dead biomass	
	Vegetation (Tree)	
	Vegetation (non-tree)	
Climate data	FWI	Centre and Régnière (2003)
Forest fire inventory data	Forest fires	Ministry of Natural Resources and Forests (2024)
1-arc second resolution SRTM-DEM	Elevation	United States Geological Survey (USGS) (2024)
	Slope	
	Aspect	
	Plan curvature	
	Profile curvature	

Table 1. Data collection along with their sources.

Data preparation was performed using ArcGIS Pro 3.3.0. The 1-arc second resolution Shuttle Radar Topography Mission Global Digital Elevation Model (SRTM-DEM) for the study area was downloaded from the Google Earth Engine (GEE) cloud platform. Subsequently, slope, aspect, and plan and profile curvature variables were derived from the DEM using Surface Spatial Analyst tools such as Slope, Aspect, and Curvature. To create continuous raster data for the FWI across the entire study area, annual FWI values were first calculated at climate stations throughout Quebec province using BioSIM 11.8.21.5 software, and then the Kriging interpolation tool was applied. To generate annual forest fire inventory layers, the Polygon to Raster tool was used. Additionally, forest attribute layers were clipped to the boundary of the study area using the Extract by Mask tool. Since the spatial resolution and projection of layers varied, we first standardized the projection and then applied resampling to achieve a consistent spatial resolution of 1 km.

2.3 Climate change scenarios

The Representative Concentration Pathways (RCPs) are climate scenarios projecting future greenhouse gas levels and their impact on global temperatures. Each RCP represents a unique emissions pathway, providing different projections for climate change. RCP2.6 assumes strong emission cuts to stabilize levels, RCP4.5 anticipates moderate emissions with eventual stabilization, and RCP8.5 (i.e., business-as-usual) represents high emissions with substantial warming due to minimal mitigation (Van Vuuren et al. 2011).

This study employed the regional climate model (RCM) to project future annual FWI values from 2021 to 2050 under RCP4.5 and RCP8.5 scenarios. RCM, built on CanRCM4, enhances data from the global CanESM2 model to generate more localized and higher-resolution climate projections (Laprise 2008). RCMs are particularly valuable for analyzing climate variability within specific regions by incorporating finer geographic details that broader global models might miss.

2.4 Random Forest (RF) model

RF is an ML model that builds multiple random decision trees by creating bootstrap samples—random subsets of the data with replacement—allowing each tree to fit independently. The final prediction is made by aggregating the predictions of all trees, a process known as bootstrap aggregation or bagging (Breiman 1996). The RF model incorporates two random processes: bootstrapping and random feature selection. Bootstrapping prevents any two trees from using the same data, which makes the model less sensitive to the original training set. Random feature selection reduces the correlation between the trees and has an additional benefit. It ensures that some trees are trained on less important features while others focus on more significant ones, leading to a more balanced set of predictions. It should be noted that the RF model was implemented in Python using the scikit-learn library and was employed within a classification framework to differentiate fire-prone from non-fire-prone classes.

32nd International Cartographic Conference (ICC 2025), 17–22 August 2025, Vancouver, Canada. This contribution underwent double-blind peer review based on the full paper. https://doi.org/10.5194/ica-adv-5-20-2025

2.5 Hyperparameter tuning

Hyperparameters in ML models play a crucial role in determining their performance. While default settings are often used, tuning these hyperparameters is essential to optimize model outcomes and improve accuracy (Gharakhanlou and Perez 2024). This study focused on tuning two hyperparameters of the RF model, specifically the number of estimators and maximum depth. Hyperparameter tuning was performed using 5-fold cross-validation and the "GridSearchCV" method to optimize these parameters. The mean test accuracy score, which measures the average accuracy of model predictions on the test dataset, was used to evaluate the impact of different hyperparameter combinations.

2.6 Model validation and performance assessment

The model's performance was evaluated using three accuracy metrics: ROC-AUC, FoM, and F1 score. The ROC curve is a graphical tool for evaluating binary classifiers by plotting the true positive rate against the false positive rate at different threshold levels (Park et al. 2004). AUC values range from 0.5 to 1, where 1 represents a perfect prediction and 0.5 indicates a random prediction (Park et al. 2004). The FoM evaluates the degree of similarity and quantifies how accurately the model's predictions align with the expected results (Gharakhanlou and Perez 2022). A higher FoM indicates improved model performance, with values ranging from 0 (indicating no overlap) to 1 (representing a perfect match). The F1 score evaluates binary classification models by balancing precision and recall. It ranges from 0 (poor performance) to 1 (perfect performance), with higher values indicating better accuracy in correctly predicting positive outcomes (Chicco and Jurman 2020).

2.7 Variables' importance assessment

This study also aimed to identify key variables affecting forest fire susceptibility. Using RF's feature importance function, the study assessed the contribution of each feature to model performance by measuring its impact across all trees in the ensemble. Features with higher average gain were considered more influential, enhancing decision-making accuracy. This analysis aids in prioritizing informative features and supports model interpretation and feature selection.

3. Results

3.1 Hyperparameter tuning

This study optimized the number of estimators and maximum depth hyperparameters of the RF model using 5-fold cross-validation and the GridSearchCV method. The results were visualized using a heatmap to display the accuracy for various settings of these two parameters (Figure 3). The optimal hyperparameter values were 500 for the number of estimators and 29 for the maximum depth, achieving an average test accuracy of 89.34%.

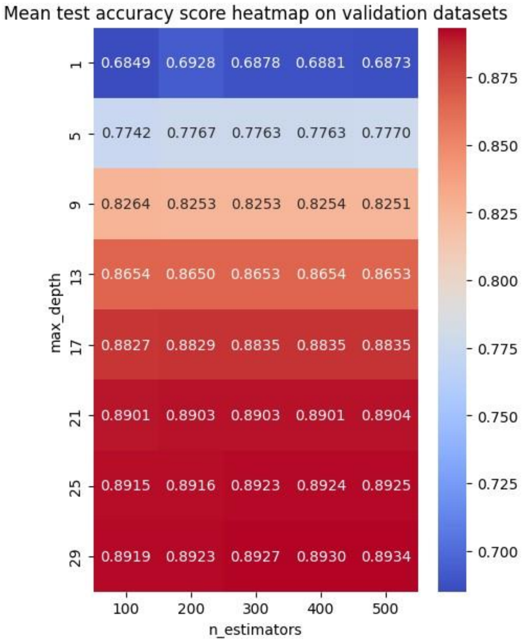

Figure 3. Mean test accuracy of the RF model on the validation dataset with different values for its two main hyperparameters.

3.2 Model validation and performance assessment

The performance of the RF model was assessed using three evaluation metrics: ROC-AUC, FoM, and F1 score. The evaluation metrics, with a ROC-AUC of 0.895, a FoM of 0.808, and an F1 score of 0.894, confirmed the RF model's strong performance in accurately identifying forest fire-prone areas.

3.3 Forest fire susceptibility maps

The primary objectives of this study were to provide forest fire susceptibility maps and evaluate the impacts of climate change on forest fire susceptibility in the study area over the next 30 years (2021-2050). Accordingly, after training and testing the RF model using data from 1980 to 2020, the FWI layer was updated annually for years 2021-2050 based on the respective scenario and then input into the model to predict annual forest fire susceptibility across the study area. The predicted susceptibility values were then classified into five categories, from very low to very high, using the natural breaks classification method in ArcGIS Pro 3.3.0. The percentage of the area within each susceptibility class was calculated over 30 years (2021-2050) for each climate scenario. Due to the minimal variations in the area percentage of susceptibility classes between the two scenarios (Figure A1. Appendix A), we only depicted the area percentage of susceptibility classes under the RCP 8.5 scenario (Figure 4), assuming current emissions trends continue. Additionally, forest fire susceptibility maps for 2030, 2040, and 2050 under the RCP 8.5 scenario were created to spatially visualize fire susceptibility across the study area (Figure 5).

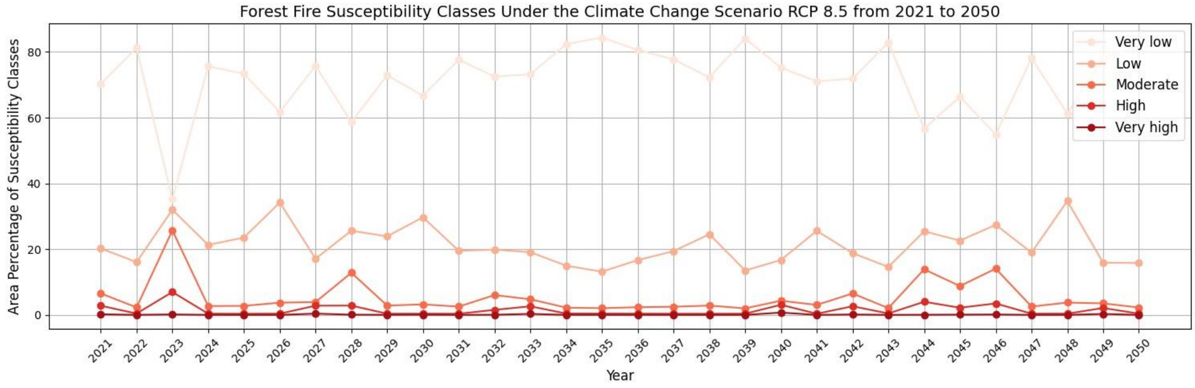

Figure 4. Area percentage of forest fire susceptibility classes from 2021 to 2050 under the RCP 8.5 scenario.

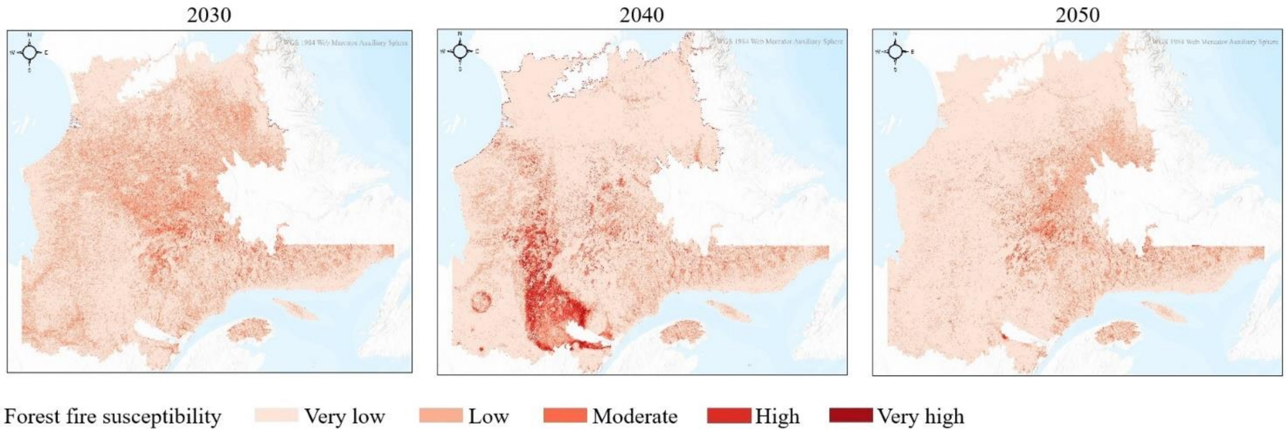

Figure 5. Forest fire susceptibility maps generated for 2030, 2040, and 2050 under the climate change scenario RCP 8.5.

The "Very Low" class dominates the landscape, reflecting consistently low fire susceptibility over the 30 years, with some fluctuations. A notable portion of the area falls under the "Low" class, which demonstrates moderate variability but remains generally stable. The "Moderate" class covers a smaller area but shows significant variability, indicating fluctuating conditions. The "High" class occupies a very limited area, displaying considerable variability and inconsistent high susceptibility. Lastly, the "Very High" class represents the smallest area, with relatively low variability, suggesting a limited yet stable very high susceptibility. This pattern suggests that forest fire susceptibility classes varied over time, potentially influenced by changes in climate. However, no clear trend was observed to indicate a general increase or decrease in susceptibility within these classes during the study period. Besides, our findings revealed minimal differences in the area percentages of susceptibility classes between the two scenarios RCP 4.5 and RCP 8.5, indicating that forest fire susceptibility classes remain relatively stable across both climate change scenarios.

3.4 Assessment of factors' importance on forest fires

The study identified key drivers of forest fire susceptibility using the RF model's feature importance analysis. Figure 6 depicts the relative importance of factors in predicting forest fire susceptibility. The feature importance analysis revealed that FWI, live biomass, and dead biomass were the top three factors affecting forest fire susceptibility, contributing 21.8%, 14.28%, and 11.35% to the prediction, respectively.

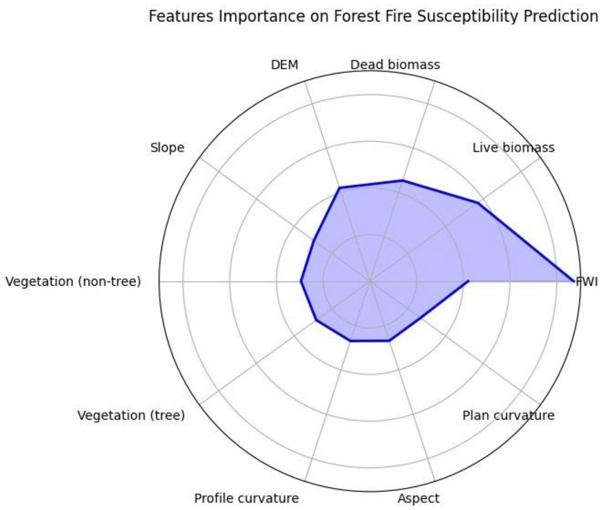

Figure 6. The relative importance of factors on forest fire susceptibility prediction.

4. Discussion

Forests are essential natural resources, critical in sustaining ecosystems (Suryabhagavan et al. 2016), and supporting habitat continuity and species diversity. However, forest fires pose the greatest threat to these ecosystems, significantly contributing to environmental transformation (Khan and Eslamian 2022). Forest fires are

 https://doi.org/10.5194/ica-adv-5-20-2025 |

a recurring issue globally, making the spatial analysis of fire events and identification of susceptibility zones crucial for enhancing prevention and prediction efforts (Tian et al. 2013), a need that has become increasingly important over the past decade (Miller and Ager 2012). Additionally, the potential impact of climate change on fire regimes (Miller and Ager 2012) underscores the need for accurate FFSM in boreal forests. Given the strong connection between fire and climate, as well as its crucial role in the lifecycle of Canada's forests (Wotton et al. 2010), this study mainly focused on investigating the impacts of climate change on forest fire susceptibility in the boreal forests of Quebec, Canada. To accomplish this, this study employed an RF model that integrated various environmental, ecological, and meteorological factors, building on the potential benefits of incorporating diverse factors to enhance the accuracy of the FFSM (Pourghasemi 2016; Sachdeva et al. 2018; Shahfahad et al. 2022).

Recent research has focused on employing more robust methodologies to create precise and accurate forest fire susceptibility maps. The remarkable accuracy and potential of ML models in FFSM have been demonstrated in prior studies (Oliveira et al. 2012; Sachdeva et al. 2018; Rihan et al. 2023). Accordingly, this study in alignment with earlier studies (Gharakhanlou and Perez 2022; Gharakhanlou and Perez 2023) demonstrated the potential of the RF model in spatial susceptibility assessment, specifically in FFSM (Oliveira et al. 2012). While earlier studies (Stocks et al. 1998; Flannigan et al. 2009; Wotton et al. 2010), emphasized a growing susceptibility of forests to fires in Canada over time, our findings showed temporal fluctuations in the susceptibility of Quebec's boreal forest to fires. Our results indicated no clear pattern suggesting a general increase or decrease in forest fire susceptibility between 2021 and 2050. Additionally, this study sought to identify the key factors influencing forest fire susceptibility. Our findings revealed that FWI, live biomass, and dead biomass were the three most influential factors in determining forest fire susceptibility, contributing 21.8%, 14.28%, and 11.35% to the prediction, respectively. Our findings aligned with previous studies (Bedia et al. 2015; Atalay et al. 2024), emphasizing the significant influence of FWI in FFSM.

5. Conclusion

Forest fires have a major impact on the structure and function of the boreal forest. Since fire ignition and spread are heavily influenced by weather, climate change is likely to significantly affect fire activity and, consequently, the structure of the boreal forest. Accordingly, this study examined the fire susceptibility of Quebec's boreal forest under two climate change scenarios (RCP 4.5 and RCP 8.5) for the next 30 years. Using an RF model, the study incorporated various environmental, ecological, and meteorological factors, achieving strong model performance (ROC-AUC of 0.895, FoM of 0.808, F1 score of 0.894). Findings revealed that fire susceptibility classes varied over time but showed no clear trend of increasing or decreasing susceptibility. Additionally, minimal differences were observed between the two climate scenarios, suggesting stability in the susceptibility of Quebec's boreal forest to fires. This study also identified key factors influencing fire susceptibility in Quebec's boreal forest, with FWI, live biomass, and dead biomass being the most significant, contributing 21.8%, 14.28%, and 11.35%, respectively.

This study by evaluating the impacts of climate change on current and future forest fires and providing forest fire susceptibility maps contributes in several manners: i) it assists in identifying fire-prone areas, allowing for the prioritization of regions that need targeted fire prevention measures, such as firebreak creation, to mitigate the risk of large fires; ii) the susceptibility maps aid in the efficient allocation of firefighting resources, ensuring vulnerable areas are properly monitored and prepared for potential fires; iii) by revealing climate-induced changes in fire risk, it supports proactive forest management practices, such as adjusting tree density or species composition to reduce fire hazards; and iv) by projecting forest fire susceptibility over the next 30 years, it assists in predicting fire trends, enabling authorities to plan more effectively for future fire seasons.

6. Appendix A. Differences in forest fire susceptibility across climate change scenarios

Figure A1 shows minimal differences in the area percentages of forest fire susceptibility classes between the RCP 4.5 and RCP 8.5 scenarios.

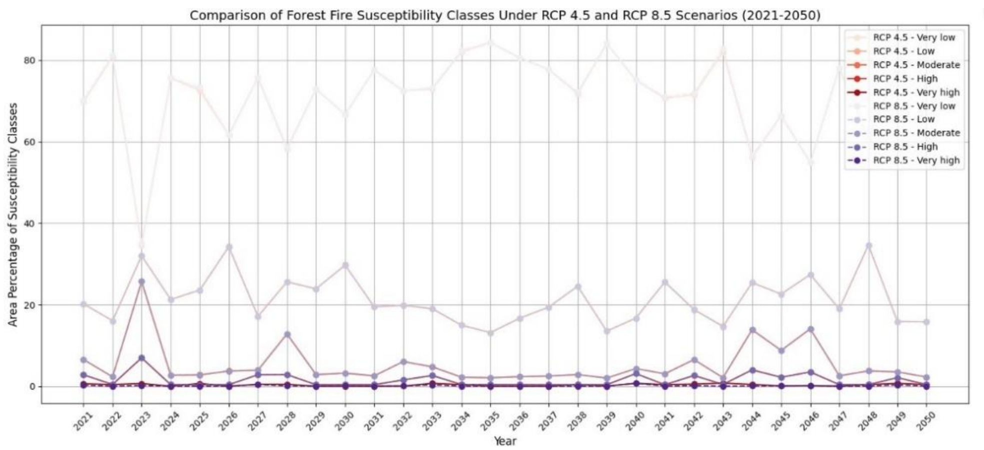

Figure A1. Differences in forest fire susceptibility across climate scenarios.

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