

Integrating Explainable Machine Learning and Classification methods for Wildland Fire Danger Mapping

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Abstract

In the context of contemporary wildland fire management, accurately understanding and predicting fire danger is fundamental to ensuring public safety and optimizing the allocation of suppression resources. Geospatial data combined with machine learning provides an effective framework for analyzing the complex interactions between weather patterns and site characteristics, thereby identifying conditions associated with elevated wildfire danger. Machine learning encompasses a range of algorithms developed to detect patterns in data. This study integrates a Random Forest model with Recursive Feature Elimination and Cross Validation (RFECV) and three classification methods to generate wildland fire danger maps. To address the opacity inherent in machine learning models, SHapley Additive exPlanations (SHAP) were utilized to quantify the marginal contribution of each variable to the predicted distance from fire. Given the critical role of classification in mapping outcomes, we evaluated the relative effectiveness of several classification methods, including Natural Breaks (NB), Geometrical Interval (GI), and Standard Deviation (STDI). The results indicate that the GI approach most effectively aligns high-risk classes with observed fire patterns. Assessing the sensitivity of wildland fire danger mapping across the three classification methods demonstrates both consistency and uncertainty in the resulting fire danger maps. Overall, the comparative results highlight the robustness of the proposed machine learning based framework for producing spatially explicit fire danger maps.

1. Introduction

The boreal forest constitutes a critical natural resource, offering essential ecological, economic, social, and cultural benefits to human societies by safeguarding nearly half of the world's remaining natural and near-natural forests. Boreal forest is a crucial component of the Earth's ecosystem, but is regularly altered by wildfires (Liang et al., 2019), which contains roughly one-third (30%) of the world's forest region (Girona et al., 2023). Rising global temperatures are expected to exacerbate wildfire regimes, leading to more frequent, severe, and expansive fire events (Wang et al., 2022). In Canadian boreal forests, the annual area burned varies significantly; on average, 8,000 fires consume approximately 2 million hectares of forest nationwide each year (Shorohova et al., 2023). The shift toward warmer and drier conditions under climate change highlights the critical need to better understand Canadian wildland fire regimes. In Ontario, wildfires threaten infrastructure, timber supplies, and human safety. Fire danger refers to the combined influence of static and dynamic environmental variables that collectively determine ignition probability, potential spread rate, suppression difficulty, and overall fire impact. Identifying high danger zones is crucial for implementing mitigation strategies that reduce fire-related damages. Wildland fire danger assessment has evolved through various paradigms, including traditional empirical and physics-based approaches, as well as modern frameworks leveraging remote sensing data and machine learning methods. However, limitations of using physics-based simulators in wildland fire modeling from low predictive accuracy, localized bias, and the complexity of implementation due to extensive expert rules, making wildland fire danger mapping challenging (Jain et al., 2020). In contrast, Machine Learning (ML) algorithms offer an effective alternative by directly learning complex patterns from large datasets without requiring explicit expert rules. ML consists of a set of algorithmic techniques and software tools that enable machines to analyze data and uncover hidden

patterns, facilitating the transition from raw data to actionable predictive insights (Alkhatib et al., 2023). This data-driven approach is essential for evaluating the 'fire danger' environment, where the convergence of static and dynamic elements determines the ultimate complexity of fire control and impact. However, developing reliable danger maps requires not only high-performing algorithms, but also detailed methods for classifying and visualizing risk levels. Consequently, this research focuses on optimizing the transition from raw model outputs to actionable spatial data. In the past decade, various ML algorithms have been successfully developed and widely applied to generate wildfire danger, risk and susceptibility maps, demonstrating considerable efficacy in predicting natural disasters. Yel et al. (2026) employed several machine learning models to generate susceptibility maps with seventeen topographic, meteorological, stand-related, and anthropogenic factors. The RF and GBM models identified areas of very high fire susceptibility, both achieved an accuracy of 0.98. In another study, Thies (2025) employed an RF algorithm with a set of meteorological, topographic, and land-cover predictors to identify dominant wildfire drivers and generate monthly wildland fire susceptibility maps. Their model achieved 89% accuracy and identified surface air pressure, elevation, vegetation condition, and proximity to urban areas as the most influential factors. Moreover, Durlević et al. (2026) applied several artificial intelligence techniques, including RF, XGBoost, Deep Neural Network (DNN), and Kolmogorov–Arnold Networks (KAN), to predict wildfire occurrence across southeastern regions using 11 natural and anthropogenic criteria. Their results showed that RF with an AUC of 90.7% achieved the highest predictive performance among the models. Recent research emphasizes that both model selection and data classification are critical for accurate hazard mapping. Huan et al., (2012) evaluated several classification techniques, including equal interval, Geometric Interval (GI), Natural Break (NB), and quantile methods for groundwater vulnerability mapping. This outcome showed that

high-risk classes were more successfully matched with real contamination patterns using the GI approach.

This study integrates a Random Forest model with Recursive Feature Elimination and Cross-Validation (RFECV) with three classification methods to generate wildland fire danger maps. The critical role of the classification method in wildland fire danger mapping motivated us to evaluate and compare the effectiveness of various classification methods, including NB, GI, and Standard Deviation Interval (STDI).

2. Study area

Our study area is Ontario's Managed Forest (MF), located between approximately 97° W and 70° W longitude and 45° N and 51° N latitude, covering about 39 Mha (Figure 1). A 2024 report from the Government of Ontario indicated that the province recorded more than 470 wildfires that year, burning nearly 90,000 ha, with most fires caused by either human activity or lightning.

3. Data and Method

Our study includes 413 fire incidents from 2000 to 2023 as the historical fire dataset. The study uses a historical fire dataset including 413 fire incidents between 2000 and 2023. These data were obtained from the Land Information Ontario (LIO) digital data warehouse, maintained by the Ministry of Natural Resources (MNR). The dataset includes both fire occurrence records and non-fire samples. Water bodies and fire-disturbed areas were excluded from candidate points to generate non-fire samples. Two primary challenges associated with wildfire historical data are class imbalance and the presence of false 'no-fire' records (Bjånes et al., 2021). To mitigate these issues, the number of non-fire samples was balanced with fire samples, with dates assigned to match the temporal distribution of recorded fire events. Spatial independence was maintained using a grid-based allocation approach combined with a 100 m minimum-distance constraint, which removed samples sharing the same date in close proximity. This procedure minimized spatial autocorrelation and ensured that the machine-learning models were trained on a representative and unbiased landscape sample.



Figure 1. Ontario's boreal Managed Forest is the extent of our study area.

It is split into 87% for training and 13% for validation. All records, including fire-occurrence and non-fire samples from 2021, were used to validate the model as unseen data. We computed and analyzed 42 key static and dynamic variables for this dataset. The static variables: distance from roads, railways, settlements, rivers, and water bodies. We also incorporate topographic features such as elevation, slope angle, slope aspect, planform curvature, profile curvature, hillshade index, tangential curvature, Topographic Wetness Index (TWI – Equation 1), flow direction, and flow accumulation, derived from the NASA Digital Elevation Model (NASADEM).

$$TWI = \ln (\alpha / \tan \beta) \quad (1)$$

Here, α represents the cumulative upslope drainage area for a specific pixel, while $\tan \beta$ indicates the slope angle at that pixel. To capture these dynamic environmental conditions, several environmental variables were incorporated into the modelling framework, such as Global Vegetation Moisture Index (GVMI), Normalized Burned Ratio (NBR), Normalized Dry Matter Index (NDMI), normalized difference vegetation index (NDVI), and Normalized Difference Water Index (NDWI) derived from MODIS satellite products and Leaf Area Index (LAI) and surface albedo from ERA5 land. NDVI is calculated from equation (2) (Rouse et al., 1974):

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad (2)$$

GVMI can be calculated from equation (3) (Ceccato, et al., 2002):

$$GVMI = \frac{(NIR + 0.1) - (SWIR + 0.2)}{(NIR + 0.1) + (SWIR + 0.2)} \quad (3)$$

Wang et al. (2013) proposed NDMI is a dry-matter spectral index designed to estimate vegetation dry-matter content using wavelengths sensitive to leaf biochemical compounds around 1722 nm (Equation 4).

$$NDMI = \frac{NIR - SWIR}{NIR + SWIR} \quad (4)$$

NDWI was introduced by (Gao, 1996) to estimate vegetation liquid water content using near-infrared (NIR) and shortwave infrared (SWIR) reflectance data (Equation 5).

$$NDWI = \frac{GREEN - NIR}{GREEN + NIR} \quad (5)$$

Burned vegetation does not reflect much within the NIR due to reduced leaf cover, which the NBR index is based on this fact, but it reflects a significant amount of SWIR radiation due to its low moisture content (Costa-Saura et al., 2022) shown in Equation (6) (Key and Benson, 1999):

$$NBR = \frac{NIR - SWIR2}{NIR + SWIR2} \quad (6)$$

Additionally we include key meteorological parameters obtained from the ERA5 land reanalysis dataset like Surface Albedo, total precipitation, air temperature measured at 2 m above the ground, total evaporation, dew point temperature at 2 m, canopy evaporation, surface skin temperature, evaporation from bare soil, soil temperature (level 1), soil temperature (level 2), surface atmospheric pressure, skin reservoir water content, volumetric

soil moisture (layer 1), volumetric soil moisture (layer 2), surface latent heat flux, net solar radiation, net thermal radiation, downward solar radiation, downward thermal radiation, surface sensible heat flux, wind (north-south), wind (east-west). Soil layers and level 1 and 2 correspond to depths of 0–7 cm and 7–28 cm, respectively. ECMWF produced the ERA5 reanalysis within the Copernicus Climate Change Service (C3S) in early 2019 (Hersbach et al., 2020).

This study employs an RF and RFECV to identify the most influential predictors for wildland fire danger mapping. Despite RFECV procedure optimises the feature set through a systematic removal of less significant variables, yet it fails to clearly explain the link between predictors and the target variable. SHapley Additive explanations (SHAP) were employed to improve transparency in the model's decision-making process. SHAP is based on coalitional game theory that allocates an importance value to each feature for a particular prediction and facilitating the deconstruction of the model output into distinct feature contributions. This study employed a SHAP dependence plots was to analyze non-linear correlations and interaction effects among the highest-ranked variables such as Volumetric Soil Moisture and Leaf Area Index. This method quantifies the marginal effect of these variables on projected fire hazard that ensures that the resultant fire danger maps are grounded in physically significant environmental thresholds rather than merely statistical correlations. Random forests consist of numerous decision trees, each formed from a randomly generated vector separately selected from a uniform distribution across all trees in the ensemble (Breiman, 2001). To improve the predictive performance of the Random Forest model, we used Recursive Feature Elimination with Cross-Validation (RFECV). RFECV is a wrapper-based feature selection approach that iteratively removes the least important predictors while simultaneously validating model performance through cross-validation (Guyon et al., 2002).

The predictors include environmental, climatic, topographic, and anthropogenic factors. A total of 88% of the dataset (278 fire and 556 non-fire samples) was used for model training and validation, with the remaining 12% reserved for independent performance testing. Finally, the trained model was used to generate initial wildland fire danger. Finally, three classification methods are employed to classify the generated map, including Natural Break (NB), Geometric Interval (GI), and Standard Deviation Interval (STDI). The Jenks Natural Breaks algorithm, commonly applied in fire risk assessment, reduces variance within classes and increases variance between classes to establish distinct risk categories (Özcan et al., 2025). The effectiveness of the framework's performance and classification method was evaluated using the number of fire and no-fire samples in each fire danger class for every classification method, along with accuracy metrics. To evaluate the effectiveness of the proposed framework and the resulting classification methods in generating a wildland fire danger map, several performance metrics were utilized, including accuracy, recall, precision, sensitivity, geometric mean, and quality. These metrics, which are commonly used to evaluate the quality of the classification models, provided a comprehensive validation of the framework's ability to correctly identify high-risk fire zones while minimizing false positives. The formulas representing these metrics are shown in the following equations (7) to (12)

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \quad (7)$$

$$\text{Precision} = TP / (TP + FP) \quad (8)$$

$$\text{Recall} = TP / (TP + FN) \quad (9)$$

$$\text{Specificity} = TN / (TN + FP) \quad (10)$$

$$\text{Geometric mean} = \sqrt{\text{Sensitivity} + \text{Specificity}} \quad (11)$$

$$\text{Quality} = TP / (TP + FP + FN) \quad (12)$$

where:

True Positive (TP): The model correctly predicts a very high or high risk fire zone and wildland fires actually occurred in that area.

True Negative (TN): The model correctly predicts a very or low risk area and no wildland fire occurred in that area.

False Positive (FP): The model predicts a very high or high risk zone, but no wildland fire occurred in that area.

False Negative (FN): The model predicts very low or low risk, but wildland fires occurred at that location.

To determine how the results of the classification methods differ on the final vulnerability mapping, we performed a pixel-by-pixel comparison across all three frameworks. We calculated the average percentages of pixels for which all three classification methods assigned the same class (Triple Agreement), for which two of the three methods agreed (Partial Agreement). Also, we calculated the average percentage of pixels that all three methods classified as different classes (Total Disagreement). This analysis facilitates an assessment of the sensitivity of wildland fire danger mapping across various classification methods.

4. Results

After correlation pruning and applying RFECV, fourteen key features were selected for inclusion in the training model. The selected features are presented in Figure 2. The generated fire danger map for 2021 (test data), produced using the Random Forest model, was classified into five risk categories ranging from *very low* to *very high*. The wildland fire danger map generated for 4 July 2021 using the RF model and GE, NB, and STDI classification method is presented in Figure 7-9. To better understand the complex relationships among environmental factors, we presented the interactions within the wildland fire danger model using SHAP values in Figure 3-Figure 6. In these visualizations, the vertical axis represents the SHAP value, indicating the change in predicted fire proximity relative to the model's base value.

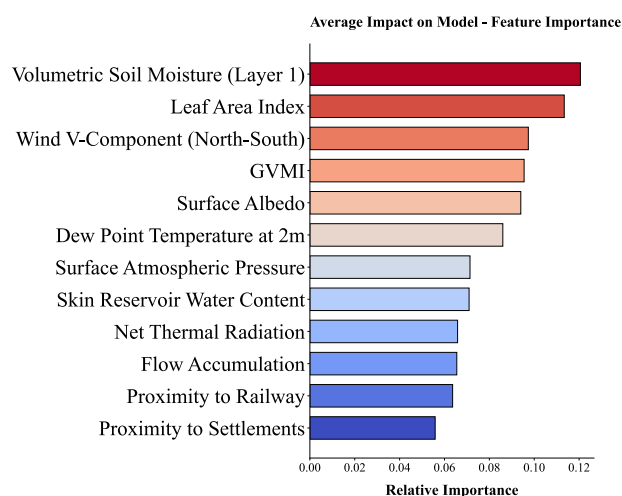


Figure 2. Feature importance values from the RF model.

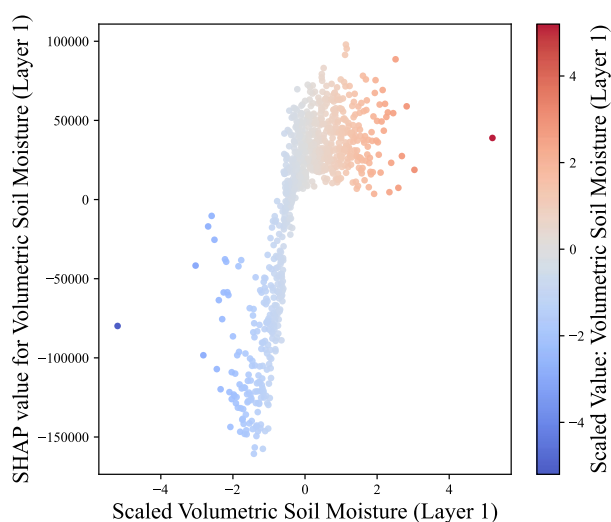


Figure 3. SHAP dependence plot for Volumetric Soil Moisture (Layer 1) in the wildland fire danger model. The vertical axis represents the marginal impact (SHAP value) on fire danger, while the color gradient indicates the scaled intensity of soil moisture. The sharp upward trend from scaled values of -2 to 0 suggests a critical threshold where increasing soil moisture significantly increases the model's predicted fire danger output.

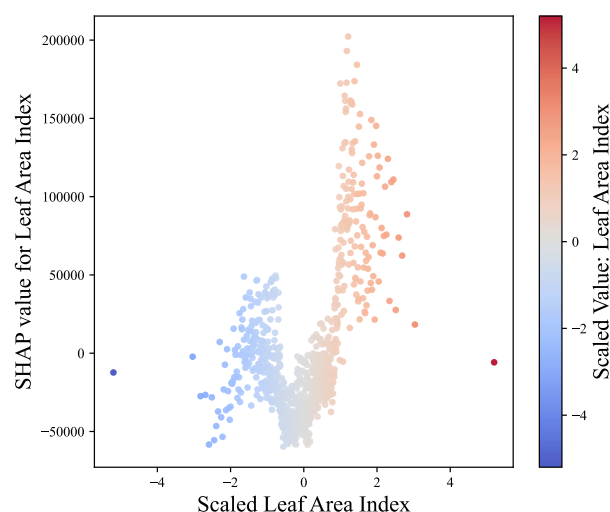


Figure 4. The SHAP dependence plot illustrates the non-linear effect of Leaf Area Index on wildland fire danger predictions. This visualization reveals the functional relationship between vegetation density and the model's danger assessment. The vertical spread of points at identical LAI values reflects interactions with additional environmental variables within the RF model.

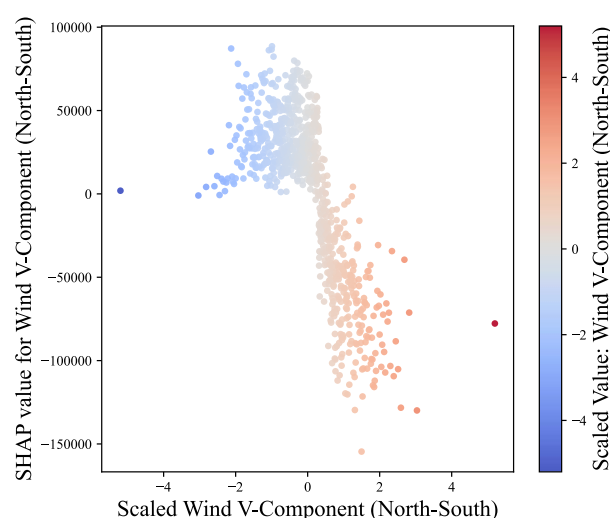


Figure 5. The SHAP dependence plot for the Wind V-Component (North-South) illustrates the influence of north-south wind vectors on predicted fire hazard. The observed downward shift in SHAP values at higher positive scaled values suggests that certain wind orientations serve as negative drivers, thereby reducing the predicted fire danger for those cases within the study area.

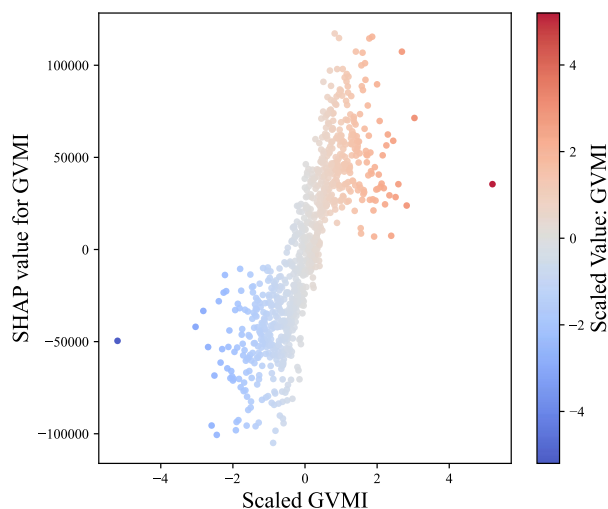


Figure 6. The SHAP dependence plot for the Global Vegetation Moisture Index illustrates the marginal effect of vegetation water content on fire danger predictions. The observed [positive/negative] trend as GVMI values increase demonstrates the model's sensitivity to fuel moisture levels. The vertical spread of SHAP values at similar GVMI levels indicates interactions with other biophysical variables within the Random Forest framework.

Table 1 presents the pixel-level agreement analysis among the classification methods, including the percentages of triple agreement, partial agreement, and total disagreement. The quantitative performance and sensitivity analysis of the classification methods used for wildland fire danger mapping are presented in Table 2. This dual assessment quantifies both the statistical accuracy of the models and the spatial variation within the framework, highlighting how different classification approaches affect the final wildland fire danger distribution.

Table 1. Pixel-level agreement analysis between Classification Methods.

	Average Percentage (%)
Triple Agreement	21.50
Partial Agreement	71.17
Total Disagreement	7.55

Table 2. Quantitative performance evaluation of various classification methods used for wildland fire danger mapping.

	NB	GI	STDI
Accuracy	0.52	0.57	0.43
Recall	0.87	0.93	0.94
Precision	0.42	0.45	0.39
Specificity	0.32	0.36	0.14
Geometric mean	0.61	0.65	0.60
Quality	0.40	0.44	0.38

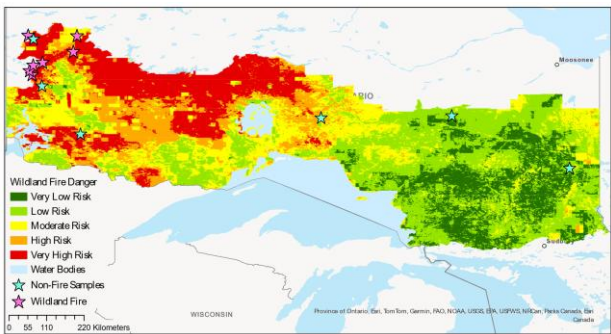


Figure 7. Generated wildland fire danger map using geometric intervals for 4 July 2021.

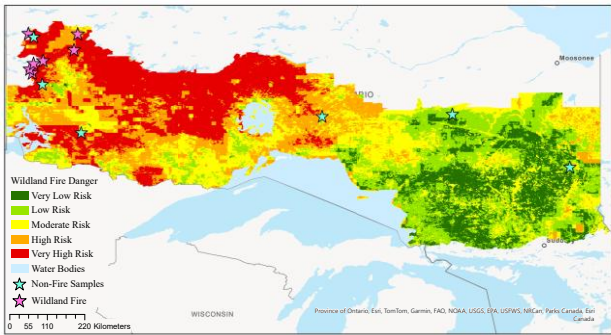


Figure 8. Generated wildland fire danger map using Natural Break for 4 July 2021.

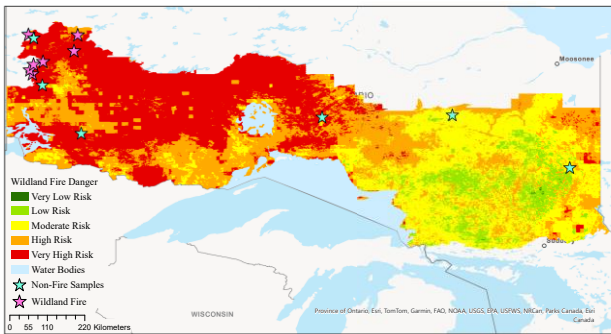


Figure 9. Generated wildland fire danger map Standard Deviation Interval for 4 July 2021.

5. Discussion

Following RFECV model optimization, the relative importance of the remaining predictors was quantified to identify the primary drivers of wildland fire danger. Volumetric Soil Moisture (Layer 1) was identified as the most influential variable, consistently ranking highest in importance. This result suggests that soil moisture levels are the most critical factor for estimating the distance to fire occurrence. LAI and the Wind V-Component (North-South), representing vegetation and atmospheric drivers, ranked second and third, respectively. The importance of LAI emphasizes the role of fuel density, while the significance of the Wind V-Component demonstrates the effect of atmospheric orientation on localized fire danger. Other factors, including the GVMI and Proximity to Settlements, were of moderate importance. These variables provide essential contextual information that enhances the model's predictive accuracy in areas characterized by specific vegetation types or patterns of

human activity, although they are less influential than soil moisture.

Figure 3 demonstrates that when scaled Volumetric Soil Moisture falls below -1 , SHAP values remain consistently negative, reaching values as low as $-150,000$. These results indicate that low soil moisture substantially decreases the predicted distance to a fire compared to the model's average prediction, thereby signifying increased wildland fire danger. As moisture levels approach the mean (scaled value 0), SHAP values increase sharply. At higher moisture levels, the predicted fire distance increases, suggesting a threshold at which greater moisture is associated with fires occurring at greater distances. Figure 4 LAI and Figure 6 GVMI illustrate that as vegetation density and canopy moisture increase, SHAP values generally shift toward positive ranges. In these cases, higher vegetation metrics are associated with an increased predicted distance from a fire. In Figure 5, the relationship for the Wind V-Component reveals higher positive scaled values correspond to a distinct downward shift in SHAP values. This pattern indicates that certain north-south wind orientations act as drivers, reducing the predicted distance to a fire and thereby making those areas more susceptible to nearby fire incidents.

An evaluation of wildland fire danger mapping sensitivity across three classification methods reveals both consistent patterns and areas of uncertainty in the resulting fire danger. Triple agreement was maintained over 21.50% of the study area, as indicated by the sensitivity analysis, suggesting stable classification zones. In contrast, 71.17% of the landscape showed partial agreement, indicating that most pixels are sensitive to various classification methods. Total disagreement across the three classification methods was minimal, accounting for only 7.55% of the study area, which reinforces the overall reliability of the predictive framework.

Considering partial agreement and total disagreement highlights a widespread sensitivity to classification breaks, underscoring the need to select a robust method such as Geometrical Interval to minimize potential mapping errors. The GI approach presented is the most accurate spatial representation of wildland fire danger, as shown in Table 2. Compared to NB or STDI, GI more accurately matches very high risk and high risk classes to real historical wildland fires and optimizes predictive quality by controlling the skewed distribution of the Random Forest output. This confirms that selecting a statistically appropriate classification framework is as critical as choosing the machine learning algorithm itself. Similar results were found by Huan et al. (2012) in groundwater vulnerability mapping, where the Geometrical Interval (GI) method outperformed traditional grading approaches by minimizing within-class variance and more effectively accommodating skewed data distributions. They evaluated several classification techniques, including equal interval, geometrical interval, natural breaks, and quantile methods for groundwater vulnerability mapping. This outcome showed that high-risk classes were more successfully matched with real contamination patterns using the GI approach.

The proposed random forest (RF)-based wildfire danger index provides a spatially explicit, data-driven evaluation of wildfire risk, thereby enhancing Ontario's current operational fire-danger rating systems. The RF framework integrates meteorological, topographic, vegetation, and anthropogenic variables to capture complex nonlinear interactions that influence fire occurrence. This approach differs from operational systems such as the Canadian Forest Fire Weather Index (FWI), which are primarily weather-based and designed for short-term ignition and fire behavior forecasting. The model also represents underlying fuel conditions that modulate the effects of daily weather fluctuations by incorporating static and slowly changing factors such as topography, LAI, and the GVMI. This comprehensive integration

improves the spatial characterization of wildfire danger beyond the capabilities of weather-driven indices alone.

6. Conclusion

The majority of fire incidents were successfully identified by both the GI and STDI approaches. However, STDI showed lower precision, indicating a higher rate of false alarms. On the other hand, GI performed best in terms of overall quality, geometric mean, accuracy, and sensitivity. Overall, the GI classifier provided the most consistent and well-balanced performance and reliable predictions across all evaluation metrics. The accuracy of wildfire danger maps depends on both the selected conditioning factors, the training machine learning model, and the adopted classification technique. The variables and methodological approach used in this study provide practical insights for wildfire danger assessment and decision-making by forest managers and emergency response agencies. Furthermore, the proposed framework can serve as a transferable reference for researchers and land management authorities in other regions seeking to develop wildfire danger assessments that account for local environmental conditions and fire dynamics.

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