

Article

SHAP-Based Identification of Grassland Fire Danger Thresholds and Temporal Transferability Validation: A Case Study of the Eastern Steppe in Mongolia

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Abstract

Based on the eXtreme Gradient Boosting (XGBoost) model and SHapley Additive exPlanations (SHAP) dependence plots, this study identified the fire-risk thresholds of the Normalized Difference Vegetation Index (NDVI) and the Dead Fuel Index (DFI), and analyzed their interaction using SHAP interaction values. The results showed that the suitable NDVI range was 0.1555–0.1943, and values outside this range were unfavorable. $DFI \geq 15.4008$ was identified as a critical threshold, above which the probability of fire occurrence increased significantly, making it the dominant condition for fire occurrence. The interaction analysis showed that NDVI mainly exerted a positive regulatory effect on DFI, but the overall interaction strength was relatively weak. Comparison of threshold effectiveness showed that the single DFI threshold achieved the highest recall, reaching 98.57%, and was suitable for large-scale early warning. The combined threshold ($0.1555 \leq NDVI \leq 0.1943$ and $DFI \geq 15.4008$) achieved the highest precision of 63.33%, but its recall was only 47.78%, indicating a relatively high missed-fire risk. Independent validation using 2022 samples showed that the high-risk area defined by $DFI \geq 15.4008$ covered 96.49% of fire points, with a precision of 63.91%, an F1 score of 76.90%, and an accuracy of 71.00%. Overall, the single DFI threshold has good temporal transferability and can serve as a fire-risk monitoring indicator.

Keywords: grassland fire; Eastern Mongolia; NDVI; DFI; SHAP; fire hazard threshold



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1. Introduction

Mongolia is located in the arid and semi-arid regions of Asia, with grasslands accounting for more than 70% of its total land area. Dornod, Sukhbaatar, and Hentii provinces in eastern Mongolia are located in the transition zone between typical steppe and forest

steppe. These areas are characterized by dry and windy conditions in spring and substantial accumulation of dry grass in autumn, making them among the most fire-prone regions in Mongolia [1–3]. In recent years, with climate warming and intensified extreme drought, fire activity across the Mongolian Plateau has increased, posing serious threats to regional ecological security, livestock production, and biodiversity conservation. Its cross-border spread also has extensive impacts on Inner Mongolia, China, and Siberia, Russia [4–6]. However, existing studies have mainly focused on ranking the importance of fire-driving factors or predicting fire risk [7–9], while relatively limited attention has been paid to the risk thresholds of environmental factors and their underlying mechanisms.

As a boundary point at which fire risk undergoes a qualitative change, the identification of critical thresholds is essential for fire risk early warning [10]. Once such a threshold is exceeded, the probability of fire may increase sharply, and this pronounced turning point can provide a clear basis for early warning [11]. Threshold identification can reveal nonlinear responses and quantify critical ranges of increasing risk, thereby providing a scientific basis for fire risk classification, early warning, and prevention and control decisions [7]. Existing methods for identifying critical thresholds of fire risk mainly include statistical distribution methods, receiver operating characteristic (ROC) curve methods, and machine-learning-based explainability methods.

The first method is a quantile method based on the distribution of historical fire points. This method uses historical fire samples as the basis and statistically analyzes the value distributions of environmental factors such as air temperature, relative humidity, and wind speed before fire occurrence, thereby determining the threshold ranges. These factors are selected because they are closely related to the level of fire risk. The underlying premise of this method is that the values of environmental factors corresponding to fire points reflect the range of favorable conditions for fire occurrence [12]. Specifically, the actual values of environmental factors corresponding to historical fire points are first extracted to construct frequency distributions. Statistical measures such as percentiles, histogram peaks, or confidence intervals are then used to characterize their central tendency and dispersion. Finally, threshold ranges are determined accordingly, such as using the 5th–95th percentiles or the mean $\pm$ 1.96 standard deviations as suitable ranges. For example, CHAO Lumen et al. (2023) determined Dead Fuel Index (DFI) threshold ranges of 14–26 for meadow steppe and 12–26 for typical steppe based on the frequency distribution of DFI values in burned pixels [13]. However, thresholds derived from the DFI distribution of burned pixels mainly reflect the environmental range in areas where fires occurred and cannot directly determine whether a given DFI level can effectively distinguish between fire and non-fire conditions.

The second method determines thresholds by plotting ROC curves and selecting the cutoff point with the highest Youden Index (Sensitivity + Specificity – 1) as the threshold [14]. The principle is to evaluate all possible cutoff points and calculate the sensitivity and specificity at each point. A higher Youden Index indicates stronger discrimination between positive and negative samples. For example, Guo et al. [15] used logistic regression and random forest models to predict human-caused fires in forests in northern China and determined the optimal probability thresholds using ROC curves and the Youden Index. The results showed that the prediction accuracy of the random forest model was 70.1%, higher than the 60.8% achieved by the logistic regression model, and that distance to railways, distance to residential areas, forest type, and distance to roads were key factors affecting human-caused fire occurrence. However, such studies mainly focus on human-caused fires, with their driving factors primarily consisting of human activity variables. The eastern grasslands of Mongolia are sparsely populated, and lightning-caused fires occur frequently, making fire occurrence more dependent on meteorological conditions and

the amount and dryness of fuels. The advantages of the ROC curve and Youden index lie in incorporating comparisons between fire and non-fire samples and directly optimizing misclassification rates. However, their thresholds only reflect the optimal overall discrimination performance, making it difficult to reflect the marginal effects and directions of fire occurrence, and they cannot capture the promoting or inhibiting effects of features on fire occurrence across different value ranges.

In recent years, with the development of machine learning and explainable artificial intelligence, increasing attention has been paid to identifying risk thresholds of fire-driving factors, constituting the third approach, namely, machine-learning-based explainability methods. These methods use partial dependence plots (PDPs) or SHapley Additive exPlanations (SHAP) dependence plots to identify turning points in the nonlinear responses of factors to model predictions [16]. Methods such as Random Forest, eXtreme Gradient Boosting (XGBoost, implemented in Python 3.9.21), and SHAP (SHapley Additive exPlanations) have been applied to investigate the driving mechanisms of fire risk. These approaches can not only evaluate the importance of variables with relatively high accuracy but also identify key threshold ranges where the probability of fire occurrence changes substantially [17,18]. For example, SHAP dependence plot analyses have shown that fire occurrence probability increases substantially when land surface temperature, solar radiation, or atmospheric dryness reaches specific levels [19]. Vegetation cover, precipitation conditions, and fuel conditions have also exhibited significant nonlinear threshold effects [7,20]. Compared with traditional empirical threshold methods, SHAP can explain the direction and magnitude of the contributions of fire-driving factors and effectively identify key risk thresholds at which fire risk shifts from low to high [19], thereby partly addressing the limitations of traditional threshold methods in explaining underlying mechanisms. However, existing studies have mainly used machine learning and SHAP methods to identify the effects and threshold responses of meteorological, topographic, and vegetation factors, with research primarily focusing on forest ecosystems or fire risk assessment at the global scale [21,22]. Relatively little attention has been paid to hazardous thresholds associated with grassland fuels [23]. In particular, in the eastern Mongolian Plateau, systematic identification of key environmental thresholds based on long-term fire data remains limited, and the seasonal mechanisms and critical response characteristics are not yet well understood [24].

Previous studies have shown that fuel conditions, meteorological conditions, and topographic factors all have important effects on fire occurrence [25–27], among which fuel conditions and meteorological conditions exhibit significant fire response thresholds [28,29]. Fuel is the material basis for fire occurrence, and its quantity and dryness directly determine whether a fire can occur and persist [30]. Meteorological conditions regulate fire occurrence by affecting fuel moisture content and the combustion environment; for example, high temperatures, low humidity, and strong winds can reduce fuel moisture content and promote fire spread [31,32]. Topography affects local hydrothermal conditions and wind field structure through slope, aspect, and elevation, thereby influencing fuel dryness and fire spread direction [33]. Therefore, fire risk is the result of the combined effects of fixed factors such as topography and fuels and variable factors such as meteorological parameters. Grassland fires in eastern Mongolia mainly occur in spring (April–May). During this period, precipitation is low, the air is dry, and wind speeds are relatively high, resulting in frequent fires [1,34]. Under similar seasonal conditions, meteorological conditions are relatively stable, and the influence of seasonal-scale meteorological variations is reduced, making the role of fuel conditions in fire occurrence more prominent. Normalized Difference Vegetation Index (NDVI) can reflect vegetation cover and the potential availability of fuel [35,36], while DFI can characterize the dryness and potential flammability of dead fuels [13]. The two variables describe the fire environment from two dimensions, namely

fuel quantity and dead-fuel dryness, and can therefore effectively characterize pre-fire environmental conditions. Fire occurrence requires the simultaneous presence of fuels, fuel reaching a flammable state, and an ignition source [37,38]. Considering only vegetation cover or only fuel dryness is insufficient to comprehensively characterize the conditions required for fire occurrence, and the two variables are complementary. Therefore, this study focuses on the spring period (April–May) and selects NDVI and DFI as the representative factors [39,40].

Based on this, the eastern three provinces of Mongolia were selected as the study area. The MCD64A1 burned area product for April–May from 2012 to 2022 was used, combined with VIIRS active fire data to extract burned pixels, and an equal number of unburned pixels were generated. On this basis, an XGBoost model based on NDVI and DFI was constructed, and the Optuna framework was employed for hyperparameter optimization. Subsequently, SHAP dependence plots were used to identify the fire-risk thresholds of NDVI and DFI, while SHAP interaction values were used to analyze their interaction, thereby exploring the nonlinear risk response characteristics and combined relationship between NDVI and DFI. Meanwhile, independent fire event samples were selected to conduct threshold effectiveness analysis and temporal transferability validation, in order to evaluate the applicability of the identified thresholds across different fire events and years (Figure 1). This study aims to reveal the key environmental conditions and threshold mechanisms underlying grassland fire occurrence in eastern Mongolia, providing a scientific basis for grassland fire risk assessment and the development of early-warning indicators.

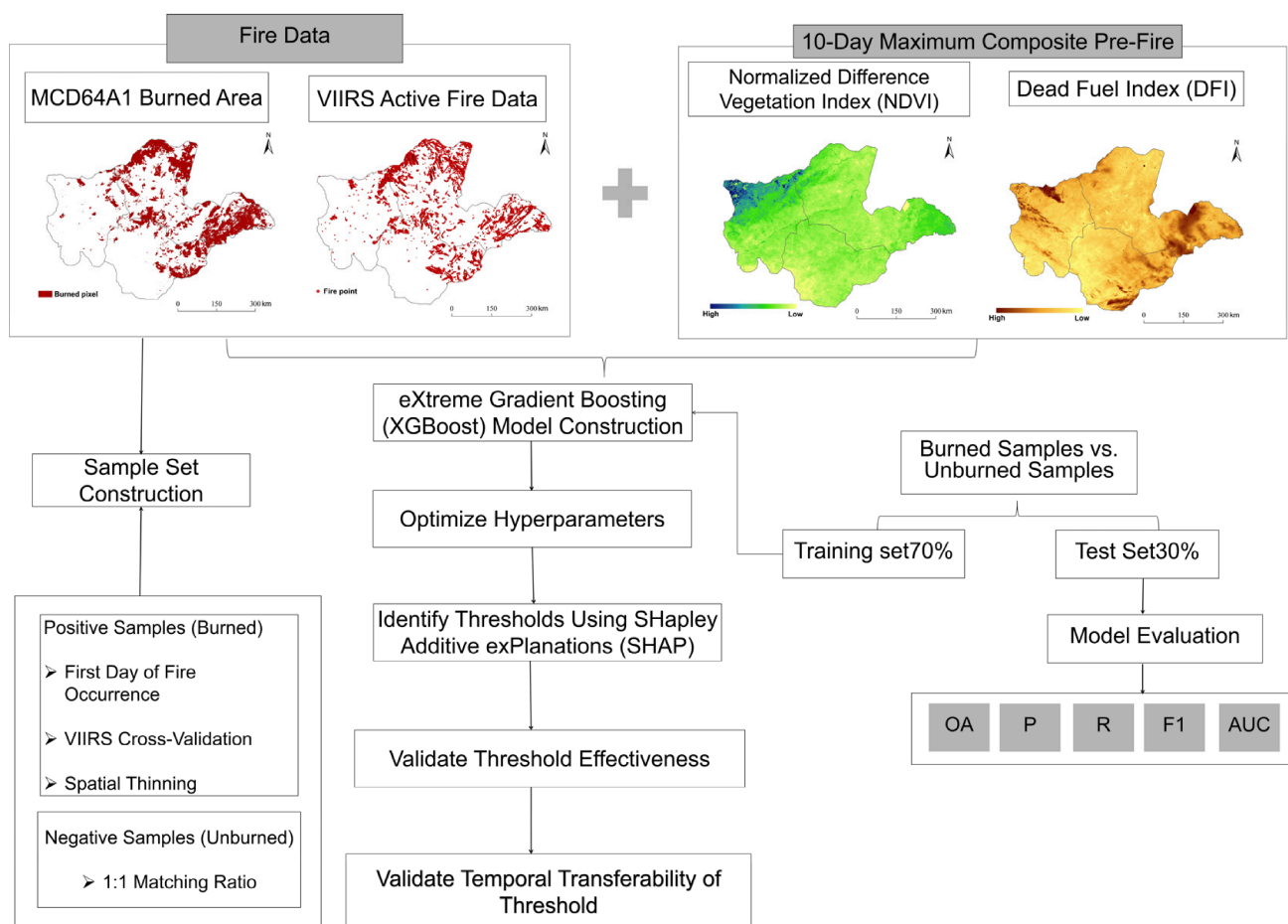


Figure 1. Technical workflow of the study.

2. Materials and Methods

2.1. Overview of the Study Area

The study area is shown in Figure 2 and covers Dornod, Sukhbaatar, and Hentii provinces in eastern Mongolia. The region is located in the temperate steppe zone of Eurasia and lies within the forest steppe transition zone of the eastern Mongolian Plateau. It has a temperate continental climate, with an annual mean precipitation of 200 to 300 mm, which decreases from north to south. Spring is characterized by rapid warming, low precipitation, and frequent strong winds, making it a period of frequent fire occurrence. From 2012 to 2022, fires in the three eastern provinces of Mongolia (Dornod, Sukhbaatar, and Hentii) were mainly concentrated in spring (April–May), with the burned area accounting for more than 70% of the total annual burned area in the three provinces [13,41]. The region has historically experienced frequent fires and remains highly susceptible to wildfires. Therefore, identifying critical fire hazard thresholds is important for improving regional fire early warning and prevention and control capabilities. At the same time, vegetation in the study area shows a clear transition from forest steppe in the north to typical steppe and desert steppe in the south. This distinct transition in vegetation types results in significant spatial differences in fuel quantity and the dryness of dead fuels, providing an ideal study area for investigating the effects of NDVI and DFI on fire occurrence and their threshold mechanisms.

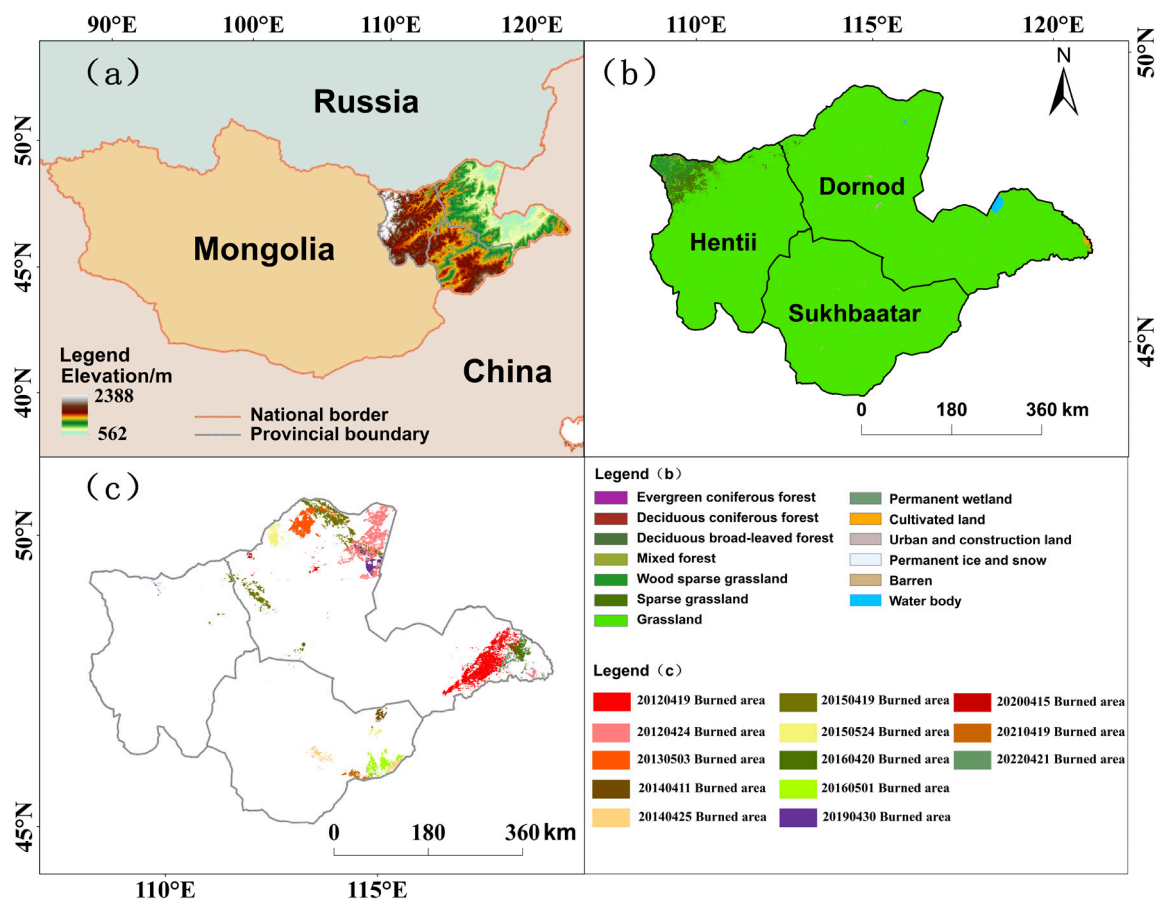


Figure 2. Overview of the study area: (a) geographic location and elevation of the study area; (b) administrative divisions and land cover of the study area; (c) distribution of burned areas from 2012 to 2022.

2.2. Data Sources and Preprocessing

2.2.1. Burned Area Data

The MCD64A1 Version 6.1 burned area product was obtained from NASA EOSDIS LP DAAC [42]. The product has a spatial resolution of 500 m and a monthly temporal resolution, covering the period from 2012 to 2022, and was used to extract fire samples. It provides the spatial distribution of burned areas and the corresponding burn dates. Pixel values represent the Julian day of burning (1 to 366), while 0 indicates unburned areas. First, the data format and projection were standardized in ArcGIS Pro 3.0.2 (WGS84/UTM Zone 48N). The data were then clipped to the study area, and annual burned area datasets were generated for extracting fire samples and determining the fire occurrence dates.

2.2.2. VIIRS Active Fire Data

This study also used the VIIRS-SNPP active fire product (VNP14IMG1) obtained from the Fire Information for Resource Management System (FIRMS) of the National Aeronautics and Space Administration (NASA) [43]. The product has a spatial resolution of 375 m and a daily temporal resolution, covering the period from 2012 to 2022. Active fire points within the study area were extracted, and low confidence fire points (confidence < 30%) were removed. The processed VIIRS active fire points were then matched spatially and temporally with the MCD64A1 burned area data, and overlapping pixels were selected as fire samples.

2.2.3. Calculation of NDVI and DFI

NDVI was obtained from MOD13A1 and DFI from MOD09A1, with both datasets accessed through Google Earth Engine (GEE) at a spatial resolution of 500 m. NDVI and DFI images corresponding to the fire occurrence dates were used to extract the factor values for burned and unburned pixels. To characterize the fuel conditions before fire occurrence and reduce the effects of clouds, fog, and other factors, the maximum values of NDVI and DFI during the 10 days preceding the fire occurrence date were composited and used as feature variables for model input.

The calculation formula for NDVI is as follows:

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

where *NIR* represents the surface reflectance of the near-infrared band, and *RED* represents the surface reflectance of the red band.

The calculation formula for DFI is as follows:

$$DFI = 100 \times \left(1 - \frac{SWIR2}{SWIR1} \right) \times \frac{Red}{NIR} \quad (2)$$

where *SWIR1*, *SWIR2*, *Red*, and *NIR* represent shortwave infrared band 1, shortwave infrared band 2, red band, and near-infrared band of the MODIS sensor (Raytheon Santa Barbara Remote Sensing, Goleta, CA, USA), respectively. Previous studies have shown that DFI can effectively characterize the dryness of dead fuels in grassland areas and has good application value in grassland fire monitoring and risk assessment [13,44,45].

2.3. Research Methods

2.3.1. Sample Construction Strategy

Using burned pixels as the analysis units, the study data consisted of 13 periods of MCD64A1 burned area products for April–May from 2012 to 2022 (Figure 2c). First, burned pixels were extracted from the MCD64A1 burned area products for April–May from 2012 to 2022, and the burned pixels from the first day of fire occurrence were then selected, resulting in 13 periods of fire event data. On this basis, the fire samples from 2012 to 2021 were used to identify the fire-risk thresholds of NDVI and DFI, and the fire data from 19 April 2012 were selected from these samples for threshold effectiveness analysis. Meanwhile, the fire data from 21 April 2022 were selected from the 2022 fire samples as an independent-year sample for temporal transferability validation. The burned pixels from the first day of fire occurrence were selected to avoid interference from fire spread with the response relationships of local environmental factors, thereby enabling more accurate identification of critical conditions. Subsequently, the VIIRS active fire data were used for spatiotemporal cross validation. If a corresponding active fire record was found within 2 days before or after the fire occurrence date and within a 500 m range of the pixel, the pixel was considered a high confidence fire sample. Spatial thinning was then performed to reduce the influence of spatial autocorrelation. Finally, the selected burned pixels were used as positive samples.

Negative samples were constructed using a spatiotemporal matching strategy. Pixels where no fire occurred on the same dates as the fire events were selected within the study area, and pixels located within 2 km of burned pixels were removed. The final negative samples were combined with the positive samples to form a balanced dataset with a 1:1 ratio.

2.3.2. XGBoost Model Construction and Hyperparameter Optimization

XGBoost (Extreme Gradient Boosting) is an ensemble learning algorithm based on the gradient boosting framework. It iteratively adds decision trees to fit the residuals predicted by the previous tree, thereby gradually improving model performance. Compared with traditional gradient boosting methods, XGBoost introduces L1 and L2 regularization terms to control model complexity and reduce overfitting. It also uses second order derivative information to accelerate loss function optimization and has built in parallel computing capabilities to improve training efficiency [46]. The algorithm has a strong ability to fit nonlinear coupling relationships among features and can effectively capture the complex response between NDVI, DFI, and fire occurrence, providing the model basis for subsequent SHAP analysis.

In this study, NDVI and DFI were used as input features to construct a binary classification model for fire occurrence. Before modeling, the samples were randomly divided into training and test sets at a ratio of 7:3. The training set was used for model training, while the test set was used for performance evaluation. Model performance was comprehensively evaluated using accuracy, precision, recall, F1 score, and AUC to determine whether the model accuracy met the requirements for threshold analysis. To obtain optimal performance, the Optuna framework (version 3.6.1) was used to optimize the XGBoost hyperparameters, with the objective of maximizing the mean AUC obtained from 5 fold stratified cross validation [47–49]. The search space included parameters such as learning_rate, max_depth, subsample, reg_alpha, reg_lambda, min_child_weight, and gamma. During the optimization process, the TPE sampler was used for Bayesian optimization, combined with MedianPruner to terminate inefficient trials early. A total of 1000 trials were conducted, and the parameter combination with the highest cross validation AUC was finally selected.

2.3.3. SHAP Hazard Threshold Identification

The XGBoost model provides high prediction accuracy but has limited interpretability. SHAP is based on Shapley values and can decompose prediction results into the additive contributions of individual features [50–52]. It satisfies local accuracy and consistency while quantifying the marginal contribution and direction of NDVI and DFI to the probability of fire occurrence. Therefore, the SHAP method was used to analyze the nonlinear relationships between NDVI, DFI, and fire occurrence. A positive SHAP value indicates that the variable promotes fire occurrence, whereas a negative value indicates that it does not support fire occurrence. Based on this, SHAP dependence plots were generated to further analyze the marginal effects of changes in variable values on fire occurrence probability. The turning point where the SHAP value changes from negative to positive was defined as the hazard threshold, representing the critical value at which the feature changes from inhibiting fire occurrence to promoting fire occurrence. If multiple turning points were present, promoting and inhibiting intervals were divided according to the trend of SHAP value changes [53]. Considering that the SHAP zero point depends on the 1:1 sampling ratio of positive and negative samples, this study further employed the bootstrap resampling method to estimate the uncertainty of the identified thresholds and evaluate their robustness. Specifically, the original samples were resampled with replacement 100 times. After each resampling, the SHAP dependence relationship was recalculated and the corresponding fire-risk threshold was extracted. Finally, the 2.5th and 97.5th percentiles of the threshold distribution were used as the 95% confidence interval. The point estimate of the threshold was taken as the intersection between the SHAP dependence fitted line based on the full sample and $\text{SHAP} = 0$. A narrow confidence interval indicates that the threshold is insensitive to the sampling ratio and has good robustness. Compared with the quantile method that relies only on the distribution of fire points, this approach incorporates information from both fire and non-fire points.

The single feature threshold has an implicit assumption that the threshold is not affected by other features [52]. However, if two features interact with each other, the threshold of one feature may change with the value of the other feature [54]. Therefore, this study further calculated the SHAP interaction values between NDVI and DFI to quantify their interaction. SHAP interaction values indicate how the contribution of one feature to the prediction results changes with the value of another feature: if the interaction value is close to 0, the effects of the two features are relatively independent; if the interaction value deviates significantly from 0, the two features have an interaction, and the single-feature threshold needs to be used in combination with the other feature. Accordingly, it can be determined whether the fire-risk thresholds of NDVI and DFI are independent and whether a combined threshold needs to be constructed for fire-risk discrimination. If the interaction is weak, the single-feature threshold can be used independently; if the interaction is strong, the two features need to be combined to construct a combined threshold to improve the discrimination capability [48].

2.3.4. Threshold Validation

To evaluate the ability of the NDVI and DFI thresholds to characterize fire environments, this study used a Confusion Matrix to validate the threshold identification results. According to the correspondence between the threshold based classification results and the actual sample classes, the samples were divided into four categories: true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) [55]. Based on these categories, precision, recall, accuracy, and F1 score were used to comprehensively

evaluate model performance and threshold identification performance [56]. The calculation formulas are as follows:

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

$$Recall = \frac{TP}{TP + FN} \quad (5)$$

$$F_1 = \frac{2 \times Precision \times Recall}{(Precision + Recall)} \quad (6)$$

where Precision represents the proportion of actual fire samples among the samples identified as fire; Accuracy represents the overall proportion of correctly classified samples; Recall represents the proportion of fire samples that are correctly identified; and the F1 score considers both Precision and Recall and can effectively evaluate the overall performance of the identification results.

For the validation of the NDVI and DFI hazard thresholds, the distribution of samples from 2012 to 2021 inside and outside the hazard thresholds was first statistically analyzed, and the actual fire occurrence rates in the two zones were calculated separately to evaluate threshold effectiveness. The independent samples from 2022 were then used to validate the temporal transferability of the hazard thresholds and assess their stability across different years. If the proportion of fire occurrences in the high risk zone is significantly higher than that in the low risk zone, the threshold is considered capable of effectively distinguishing between fire and non-fire environments and meeting the requirements for early warning applications.

3. Results

3.1. XGBoost Model Performance

On the training set, this study employed the Optuna framework to optimize the hyperparameters of XGBoost. Finally, with a combination of `learning_rate = 0.0470`, `max_depth = 6`, `subsample = 0.9783`, `reg_alpha = 0.0443`, `reg_lambda = 0.5810`, `min_child_weight = 1`, and `gamma = 0.0348`, the model achieved the highest mean AUC of 0.7867 in 5-fold cross-validation. Subsequently, the test set was used to evaluate the model accuracy (Figure 3). The results showed that the overall accuracy (Accuracy) was 0.7159, and the AUC was 0.783 (Figure 3). Regarding the identification results of burned samples, the Precision, Recall, and F1 score of the model were 0.68, 0.83, and 0.74, respectively. Among these, the Recall reached 0.83, indicating that the model was able to identify the vast majority of burned samples and had a strong ability to capture fire occurrence. However, the relatively low Precision of 0.68 indicated a relatively high number of false positives. In comparison, the Precision, Recall, and F1 score for unburned samples were 0.78, 0.60, and 0.68, respectively. The Precision was higher than that for burned samples, indicating that the model produced fewer false positives when predicting no fire. Overall, the model maintained good classification performance and was able to support subsequent SHAP dependence plot analysis and fire-risk threshold identification.

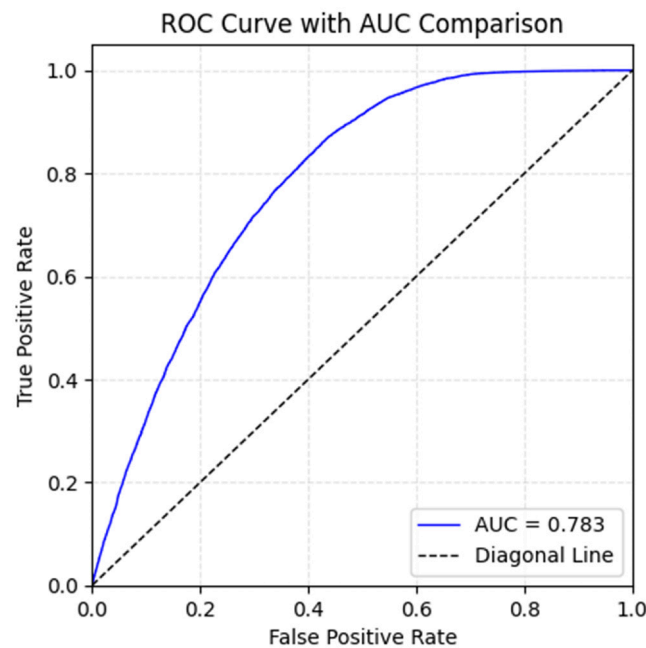


Figure 3. AUC performance of the XGBoost model.

3.2. NDVI and DFI Hazard Threshold Identification

To identify the fire-risk thresholds of NDVI and DFI and evaluate their robustness, SHAP dependence plots of the two variables were generated, and bootstrap resampling was used to estimate the uncertainty of the thresholds (Figure 4). The results showed that the fire-risk threshold of DFI was 15.4008 (95% CI: 15.3668–15.4221); the lower limit of the fire-risk threshold of NDVI was 0.1555 (95% CI: 0.1554–0.1557), and the upper limit was 0.1943 (95% CI: 0.1939–0.1946). The confidence intervals of all thresholds were relatively narrow, indicating that the fire-risk thresholds identified based on SHAP had good robustness and were insensitive to the sampling ratio.

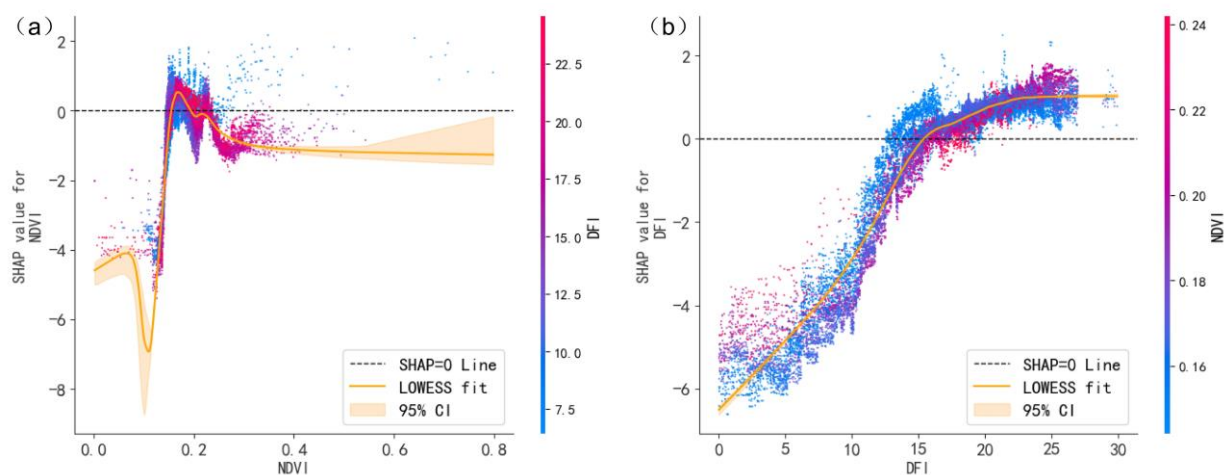


Figure 4. SHAP dependence plots of the NDVI and the DFI: (a) NDVI; (b) DFI.

As shown in the SHAP dependence plot (Figure 4a), the effect of NDVI on fire occurrence was not monotonically increasing. Under high DFI conditions, the SHAP values were also low when NDVI was low. Although dry fuels were present under these conditions, insufficient vegetation cover made it difficult to support fire occurrence. When NDVI was within 0.1555–0.1943, the SHAP values increased significantly, and the probability of fire occurrence was highest. When NDVI exceeded 0.1943, the SHAP values became

negative, indicating that excessively high NDVI instead inhibited fire occurrence. Therefore, NDVI had a suitable range, and both excessively high and excessively low NDVI values were unfavorable for fire occurrence. The analysis using DFI as the horizontal axis further showed (Figure 4b) that $DFI = 15.4008$ was a critical point. When DFI was below 15.4008, the SHAP values were negative regardless of the NDVI level, indicating that fire occurrence was inhibited. When DFI exceeded 15.4008, the SHAP values changed from negative to positive and increased rapidly, and the probability of fire occurrence increased significantly. This threshold effect was stable in spring (April–May), indicating that when the dryness of dead fuels exceeded the critical level, fire risk increased significantly. Comparison under different NDVI conditions further showed that the SHAP values were higher under high NDVI conditions, indicating that the promoting effect of NDVI on DFI had a positive regulatory effect; under low NDVI conditions, although the SHAP values remained positive, they decreased significantly, indicating that insufficient vegetation cover weakened the promoting effect of DFI. Overall, DFI exceeding 15.4008 was the dominant condition for an increase in fire probability; NDVI regulated the strength of its promoting effect, and the effect of NDVI had a suitable range of 0.1555–0.1943. Together, the two variables determined the risk level of fire occurrence.

To quantify the interaction between NDVI and DFI, this study calculated their SHAP interaction values (Figure 5a) and used them to determine whether the interaction was significant. The interaction values were mainly concentrated at NDVI values of approximately 0.15–0.25, with both positive and negative interactions occurring. Statistical tests showed that the interaction was significantly non-zero, with a mean absolute interaction value of 0.233. Among them, there were 21,927 samples with positive interactions, with a mean value of 0.212; there were 16,037 samples with negative interactions, with a mean value of -0.261 , and the t -statistic was 7.168, which was greater than 2. Within the range of NDVI 0.1555–0.1943 and $DFI \geq 15.4008$ (Figure 5b), there were 17,258 samples, accounting for 45.46% of the total samples. The mean interaction value within this range was 0.115, and positive interactions accounted for 78.52%. Compared with the overall results, the interaction direction within this range was consistent, but the strength was weaker, indicating that NDVI mainly exerted a slight positive regulatory effect on DFI rather than a decisive effect. The results showed that although NDVI and DFI had a statistically significant interaction, the overall interaction strength was relatively weak. Accordingly, this study used $0.1555 \leq NDVI \leq 0.1943$ and $DFI \geq 15.4008$ as the combined threshold and further compared it with the single thresholds of NDVI and DFI.

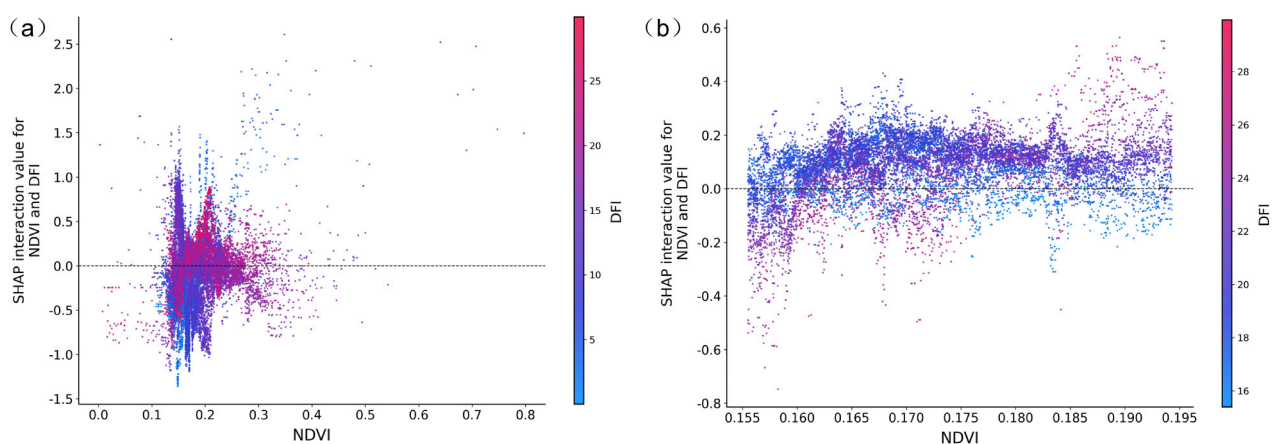


Figure 5. SHAP interaction plots of NDVI and DFI: (a) Full sample; (b) NDVI 0.1555–0.1943 range.

3.3. Threshold Effectiveness Analysis

To test the discrimination ability of each threshold, the burned and unburned samples from 19 April 2012 were used as the test set. The DFI single threshold, NDVI single threshold, and NDVI-DFI combined threshold were respectively used as criteria to analyze the distribution characteristics of burned and unburned samples inside and outside each fire-risk threshold.

From the confusion matrix and evaluation metrics (Table 1), the three threshold groups showed different strengths in fire identification. The DFI single threshold had the highest recall, reaching 98.57%. This indicates that it could cover almost all fire points, with very few missed detections. Its precision was 58.46%, indicating that a relatively large number of non-fire points were included within the identified conditions. The NDVI single threshold showed moderate performance. Its recall was 48.80%, and its precision was 51.84%. Both were lower than those of the DFI single threshold. Using only the NDVI range to determine fire risk had limited capability. For the combined threshold, its precision was the highest, reaching 63.33%, which was approximately 4.87 percentage points higher than that of the DFI single threshold. This indicates that when both $DFI \geq 15.4008$ and $0.1555 \leq NDVI \leq 0.1943$ were satisfied, classifying a point as a fire point was more reliable. However, its F1 score and accuracy were only 54.46% and 60.10%, respectively, both lower than those of the DFI single threshold. More importantly, its recall was only 47.78%, approximately 50.79 percentage points lower than that of the DFI single threshold. This means that more than half of the fire points would be missed. For fire-risk identification, such a high rate of missed detections is difficult to accept. Overall, the combined threshold had slightly higher precision, but its recall was too low, and the risk of missed detections was prominent. Therefore, it was not suitable as the primary criterion for fire-risk discrimination. In contrast, the DFI single threshold was more stable. It had the best recall, F1 score, and accuracy. It could cover the vast majority of fire points with a relatively low missed-detection rate. This is consistent with the practical requirement of fire early warning for stronger control of missed detections. Therefore, the DFI single threshold was subsequently adopted as the criterion for fire-risk discrimination, and temporal transferability validation was conducted to test its stability and generalization capability across fire events in different years.

Table 1. Validation results of the effectiveness of NDVI, DFI, and combined fire-risk thresholds (19 April 2012).

Evaluation Metrics	NDVI Risk-Promoting Interval ($0.1555 \leq NDVI \leq 0.1943$)	DFI Threshold (≥ 15.4008)	Combined Threshold ($0.1555 \leq NDVI \leq 0.1943$ and $DFI \geq 15.4008$)
TP	9120	18,419	8929
FP	8472	13,088	5170
TN	10,215	5599	13,517
FN	9567	268	9758
Recall	48.80%	98.57%	47.78%
Precision	51.84%	58.46%	63.33%
F1 Score	50.28%	73.33%	54.46%
Accuracy	51.76%	64.28%	60.10%

Note: TP, FP, TN, and FN represent true positives, false positives, true negatives, and false negatives, respectively.

3.4. Temporal Transferability Validation of the DFI Hazard Threshold

Based on the previous threshold comparison results, the DFI single threshold with the best performance was selected and tested using the independent fire event sample from 21 April 2022. Here, $DFI \geq 15.4008$ was classified as the high-risk area, while $DFI < 15.4008$ was classified as the low-risk area. The results are shown in Figure 6 and Table 2. The

high-risk area covered 96.49% of the fire points, with only 3.51% of the fire points falling into the low-risk area, indicating few missed detections. The non-fire points were relatively evenly distributed between the high-risk and low-risk areas, accounting for 54.48% and 45.52%, respectively. Based on these results, the evaluation metrics were calculated (Table 2). The recall was 96.49%, the precision was 63.91%, the F1 score was 76.90%, and the accuracy was 71.00%. The recall reached 96.49%, indicating that this threshold could cover the vast majority of fire points with very few missed detections. This is consistent with the practical requirement of fire early warning that it is preferable to generate more false alarms than to miss fires. The precision was 63.91%, indicating that some non-fire points were still included in the high-risk area, resulting in relatively more false positives, but the overall level remained within an acceptable range. The F1 score was 76.90%, balancing recall and precision and showing good overall performance. The accuracy was 71.00%, indicating that this threshold had an acceptable overall discrimination capability between fire and non-fire points. Overall, $DFI \geq 15.4008$ maintained a stable pattern of “high recall and moderate precision” in the independent fire event in 2022 and was suitable as the primary criterion for fire-risk discrimination.

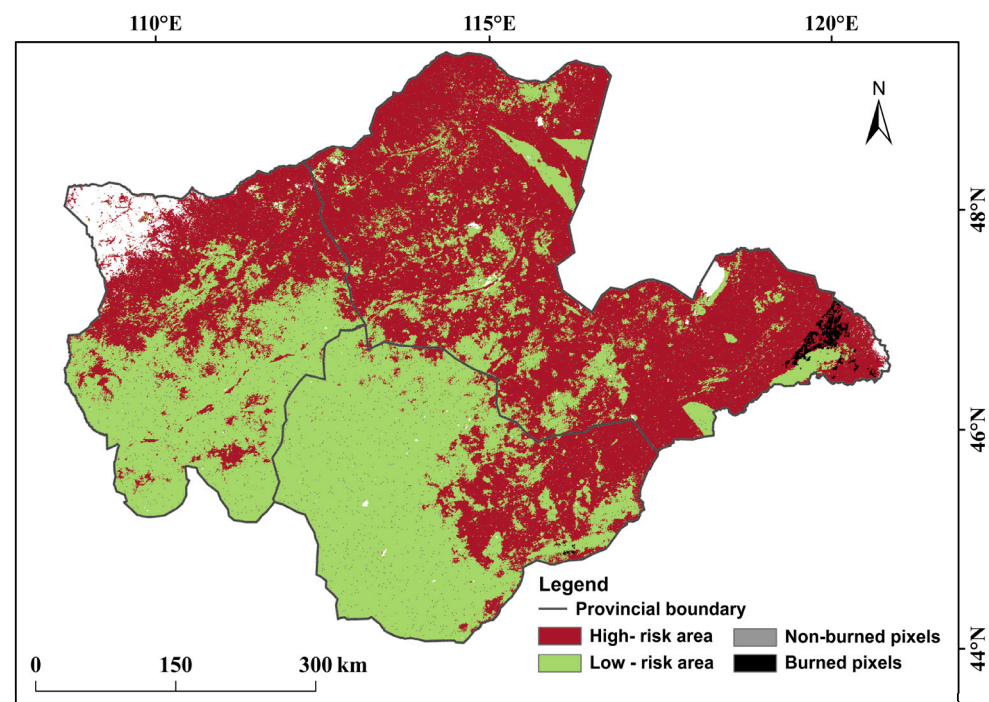


Figure 6. Validation map of the 21 April 2022 fire event.

Table 2. Temporal Transferability Validation Results of the DFI Threshold (21 April 2022).

Evaluation Metrics	DFI Threshold (≥ 15.4008)
TP	5216
FP	2945
TN	2461
FN	190
Recall	96.49%
Precision	63.91%
F1 Score	76.90%
Accuracy	71.00%

Note: TP, FP, TN, and FN represent true positives, false positives, true negatives, and false negatives, respectively.

4. Discussion

4.1. Identification and Stability Analysis of Hazard Thresholds

This study employed the XGBoost method to construct a grassland fire prediction model for eastern Mongolia using NDVI and DFI, identified the fire-risk thresholds for fire occurrence through SHAP dependence plots, and analyzed the interaction between NDVI and DFI using SHAP interaction values. The results showed that NDVI exhibited a continuous risk-promoting range rather than a single threshold. The suitable range identified in this study was 0.1555–0.1943, which was consistent with the trend reported by Li Hanyu et al. [19]. They established a European wildfire occurrence model based on variables including NDVI, LST, precipitation, and soil moisture and calculated SHAP values. The resulting dependence plot also showed that NDVI exhibited a suitable range. However, the suitable range identified in this study was substantially lower than their transition point of 0.78. This difference was mainly due to differences in the study areas: the European study covered forests, shrublands, and herbaceous vegetation, where vegetation cover was relatively high, whereas grasslands in eastern Mongolia have sparse vegetation and limited fuel loads, making fires more likely to occur at relatively low NDVI values.

In contrast, DFI exhibited a stable threshold effect during spring (April–May), with 15.4008 representing the critical threshold. This finding was consistent with the results of CHAO Lumen [13] and other scholars. Based on frequency statistics of the measured and retrieved DFI values of historical fire pixels, they found that the DFI threshold for typical grassland fire occurrence areas ranged from 12 to 26, with the highest fire occurrence rate occurring within the range of 16–18. Analysis based solely on historical fire pixels has certain limitations. In addition to historical fire pixels, this study also incorporated 1:1 non-fire pixels into the analysis, effectively reducing the misclassification rate of the threshold. The interaction analysis showed that although NDVI and DFI had a significant interaction, the interaction strength was relatively weak and was mainly positive. This weak but predominantly positive interaction suggests that vegetation conditions mainly regulate the effect of fuel dryness on fire occurrence, while DFI plays a more direct role in determining whether fuels reach a fire-prone state.

4.2. Implications for Fire Risk Monitoring and Early Warning

The DFI threshold can be used for large-scale fire-risk zoning. Exceeding the DFI risk threshold is the dominant condition for an increase in fire probability. Meanwhile, DFI can be rapidly obtained from remote sensing data, with a clear threshold and good temporal transferability, making it suitable as the primary indicator for regional fire-risk early warning. When DFI exceeds 15.4008, the corresponding area can be classified as a high-risk area. The combined NDVI and DFI threshold also has certain reference significance. The interaction analysis showed that there was a statistically significant interaction between NDVI and DFI, but the overall interaction strength was relatively weak. Within the range of NDVI 0.1555–0.1943 and $DFI \geq 15.4008$, the mean interaction value was 0.115, and positive interactions accounted for 78.52%, indicating that NDVI mainly exerted a positive regulatory effect on DFI, but the regulatory strength was limited. This range achieves a balance between the “quantity” and “dryness” of fuels: when NDVI is too low, vegetation is sparse, fuel load is insufficient, and fire spread is difficult; when NDVI is too high, vegetation cover is dense and moisture content is high, which is unfavorable for combustion [57,58]. Only when NDVI is within 0.1555–0.1943 is the fuel load moderate, continuity relatively good, and dryness relatively high, while forming a good coupling with the high-dryness conditions indicated by DFI, thereby promoting fire occurrence to some extent. The combined threshold had the highest precision, reaching 63.33%, and can be used as a reference for a high-confidence hazard criterion to reduce false alarms.

However, because its recall was only 47.78%, the risk of missed detections was prominent, and it should not be used as the primary criterion for fire-risk discrimination. It should be noted that the thresholds reflect combustion potential. $DFI \geq 15.4008$ only indicates a significant increase in the probability of fire occurrence and does not mean that a fire will necessarily occur [59]. Fire occurrence is also affected by ignition-source conditions such as human activities and lightning. Therefore, actual early warning should combine real-time meteorological conditions and information on human activities to conduct dynamic early warning. For the vast pastoral grasslands of eastern Mongolia, this method has low cost, broad spatial coverage, and rapid updating, and can provide a scientific basis for regional fire monitoring and prevention and control.

4.3. Limitations and Future Prospects

This study mainly identified hazard thresholds based on two factors, NDVI and DFI, with a focus on the effects of fuel quantity and the dryness of dead fuels on fire occurrence. The study area was limited to the grasslands of eastern Mongolia. Whether the identified hazard thresholds are applicable to other ecosystems and climatic conditions still requires further validation. Meanwhile, factors such as human activities, lightning, and short-term meteorological fluctuations have not been fully considered. In the future, human activity data, lightning data, and remote sensing data with higher spatial and temporal resolutions can be incorporated to further reveal the multiscale driving mechanisms of fire occurrence and develop a dynamic fire risk early warning system applicable to larger regions.

5. Conclusions

Based on the XGBoost model and SHAP dependence plots, this study identified the NDVI and DFI fire-risk thresholds for grassland fires in eastern Mongolia. Meanwhile, SHAP interaction values were used to analyze the interaction between NDVI and DFI, and the effectiveness of single-factor thresholds and combined thresholds was compared and analyzed. The main conclusions are as follows:

- (1) NDVI had a suitable range of 0.1555–0.1943 for fire occurrence, and both excessively high and excessively low NDVI values were unfavorable for fire occurrence. $DFI \geq 15.4008$ was a critical threshold. When DFI exceeded this value, the probability of fire occurrence increased significantly, and this threshold effect remained stable during spring (April–May). DFI was the dominant condition for an increase in fire probability, while NDVI regulated its promoting effect. However, the overall interaction between the two variables was relatively weak, and NDVI mainly played a positive regulatory role.
- (2) Comparison of threshold effectiveness showed that the DFI single threshold had the highest recall, reaching 98.57%, and was suitable for large-scale early warning. The combined threshold had the highest precision, reaching 63.33%, but its recall was only 47.78%, indicating a prominent risk of missed detections. Therefore, it was not suitable as the primary criterion and had only certain reference significance for high-confidence fire-point identification. Overall, the DFI single threshold performed best in terms of recall, F1 score, and accuracy and was more suitable as the primary condition for fire-risk discrimination.
- (3) Validation using the independent fire sample from 21 April 2022 showed that the high-risk area with $DFI \geq 15.4008$ covered 96.49% of the fire points and also contained 54.48% of the non-fire points. The precision of this threshold was 63.91%, the F1 score was 76.90%, and the accuracy was 71.00%. These results indicated that the DFI single threshold could effectively cover the vast majority of fire points and had good applicability and temporal transferability.

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Data Availability Statement: The MODIS MCD64A1 Version 6.1 burned area product used in this study is available from the NASA EOSDIS LP DAAC (<https://lpdaac.usgs.gov/>, accessed on 22 April 2026) [42]. Fire point data for eastern Mongolia are available from the NASA Fire Information Resource Management System (FIRMS) (<https://firms.modaps.eosdis.nasa.gov/download/>, accessed on 26 April 2026) [43].

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