Mapping Wildfire Dynamics in Eastern Mongolia: Integrating Remote Sensing for Sustainable Resource Management

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Abstract. This study presents a comprehensive spatiotemporal analysis of wildfire patterns across Mongolia from January 2005 to December 2024 using satellite imagery, covering a 20-year period of observed data. The study reveals characteristics of wildfire frequency, distribution, and trends at national and provincial levels, with a focus on eastern provinces, which are the most prone to wildfires. Wildfire patch centroids were extracted and analyzed using spatial clustering techniques, kernel density estimation, and emerging hotspot analysis via space-time cube tools. Results show that while fire points are scattered across western Mongolia, the largest burned areas and most persistent hotspots are concentrated in the eastern steppe regions, particularly near borders. Temporal trend analysis revealed that spring (March-May) is the peak fire season, accounting for 62% of burned areas, followed by summer (21%) and autumn (16%). Although the total number of fires shows a decreasing trend, the intensity and extent of individual fire events remain significant, especially in 2012, 2015, and 2023. Comparative assessment with official fire incident reports from the Mongolian Statistical Information Service highlights both consistencies and discrepancies with satellite-derived data. The findings contribute to a better understanding of wildfire dynamics in Mongolia and support improved fire risk management and policy development. To assess wildfire risk and its environmental drivers, the MaxEnt model was applied using presence-only fire patch data and environmental variables such as vegetation index (NDVI), land surface temperature, precipitation (SPI), wind speed, and slope. The model results revealed that land surface temperature and wind speed were the most influential predictors of wildfire occurrence in Eastern Mongolia, indicating that dry, warm, and windy conditions significantly increase fire probability. The model results effectively delineate high-risk zones, providing valuable insights for fire prevention and management.

Keywords: Wildfire, Spatiotemporal Analysis, Eastern Mongolia, MODIS, Risk Assessment.

1 Introduction

Wildfires are a major natural hazard affecting terrestrial ecosystems, particularly in fire-prone arid regions such as Mongolia. With its vast grassland steppes, forest patches, and sharply continental climate, Mongolia is highly vulnerable to seasonal wildfires that threaten biodiversity, air quality, carbon storage, and local livelihoods [1]. The frequency, intensity, and extent of wildfires in recent decades have been shaped by both climatic variability and human activities, highlighting the need for effective wildfire monitoring and risk assessment [2, 3].

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This study conducts a comprehensive spatiotemporal analysis of wildfire patterns across all of Mongolia, providing a national overview. However, it places particular emphasis on Eastern Mongolia, focusing on the provinces of Dornod, Sukhbaatar, and Khentii, which are recognized wildfire hotspots. These regions feature steppe landscapes with patchy forests and experience frequent human-induced fires related to pasture burning, agriculture, and accidental ignitions [4]. Eastern Mongolia is especially suitable for detailed risk analysis due to its fire-prone steppe ecosystem, dry and windy climate, and frequent cross-border fires originating from neighboring Russia [5]. The region's flat grasslands, patchy forests, and seasonal land-use practices, such as pasture burning, promote rapid fire ignition and spread. Additionally, limited ground-based monitoring capacity in this region makes it an ideal case for applying satellite-based spatiotemporal analysis and wildfire risk modeling.

While official wildfire records often lack spatial detail or suffer underreporting, satellite remote sensing, especially the MODIS MCD64A1 burned area product, provides consistent, large-scale fire monitoring [6]. This research applies spatiotemporal analysis and hotspot detection using MODIS data from January 2005 to December 2024, combined with Maximum Entropy (MaxEnt) modeling to assess wildfire risk relative to environmental factors such as NDVI, land surface temperature, precipitation, wind speed, and topography. The aim is to inform targeted wildfire management and land-use policies in Mongolia. This study aims to:

- Analyze spatial and temporal wildfire patterns across Mongolia (January 2005–December 2024) using satellite data and geospatial methods.
- Identify wildfire hotspots and seasonal trends through spatial clustering and time-series analyses.
- Examine temporal wildfire dynamics specifically in Eastern Mongolia.
- Develop detailed wildfire risk maps for Eastern Mongolia using MaxEnt model.

By providing a comprehensive assessment of wildfire dynamics and environmental impacts in Mongolia, this study further supports improved wildfire monitoring and management. The results aim to highlight high-risk zones and quantify wildfire contributions to carbon emissions and storage changes, offering valuable insights for environmental policy, land-use planning, and future research.

2 Study Area

Mongolia is a landlocked country in Central Asia (46.86°N, 103.85°E) with an average elevation of 1580 m above sea level. It covers diverse landscapes from mountain ranges in the west and north to expansive steppe and desert areas in the east and south. Administratively, Mongolia is divided into 21 aimags (provinces) and over 330 soums. While this study analyzes wildfire patterns across the entire country, detailed risk modeling focuses on Eastern Mongolia (44.71°–50.82°N, 108.78°–119.98°E), covering approximately 286,200 km^2, encompassing Dornod, Sukhbaatar, and Khentii provinces. This subregion is a known wildfire hotspot due to its open terrain, abundant fine fuels, and climatic conditions that promote fire spread.

Mongolia's land cover is composed of approximately 49% grassland, 38% bare or sparsely vegetated areas, 6% tree cover, 4% moss and lichen, and 1% permanent water bodies, with the remainder consisting of shrublands, cropland, built-up areas, snow, ice, and wetland, as shown in Figure 1. Eastern Mongolia is dominated by flat grasslands (around 70%) interspersed with forest zones (around 30%). These fuel-rich grasslands enable fast-moving fires, while forest patches can support more intense burns, particularly during the dry spring and autumn seasons [7]. Additional environmental variables affecting wildfires in Eastern Mongolia are shown Figure 2.

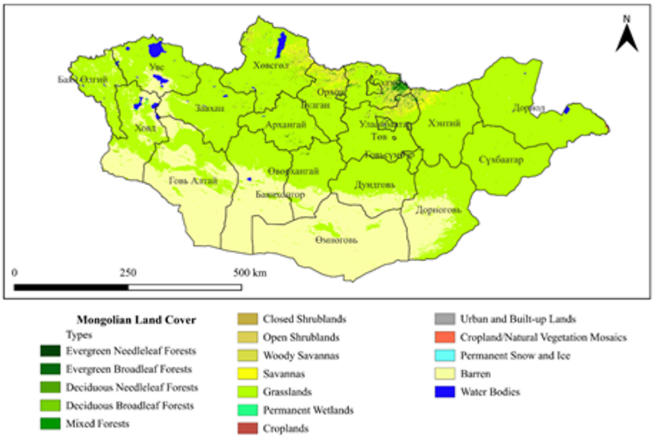

Fig. 1. Vegetation zone/Land cover pattern of Mongolia.

According to Köppen climate classification, Mongolia has a sharply continental climate with large seasonal and diurnal temperature variations and low annual precipitation. Climate types include cold desert (BWk), cold semi-arid (BSk), and subarctic (Dfc). Annual precipitation ranges from 300-400 mm in the mountainous regions (Khangai, Khentii, Khuvsgul), 150-250 mm in the steppe, 100-150 mm in the steppe-desert, and below 100 mm in the Gobi Desert. Approximately 85% of the total annual precipitation occurs between April and September, with around 50-60% falling in July and August [8]. These precipitation patterns, combined with rapid snowmelt in spring and vegetation drying in autumn, create two seasonal peaks in wildfire activity.

The annual average temperature in Mongolia varies from –22°C to 17°C, with maximum temperatures reaching up to 24°C in July and minimum temperatures dropping to about –28°C in January [9, 10]. In the mountain ranges, average temperatures range between –4°C and –8°C, while in the steppe desert region they can rise to around 2°C, and in the southern desert bordering China, averages reach approximately 6°C [11].

Eastern Mongolia shares these general climatic features but with region-specific extremes that further influence wildfire dynamics. It experiences temperate steppe conditions with cold winters (down to −27°C in January) and short, dry summers (up to 25°C). Annual average temperatures range from −4°C in the north to 4°C in the south. The combination of prolonged dry periods, strong winds, and highly flammable vegetation makes this region particularly susceptible to frequent and fast-spreading wildfires.

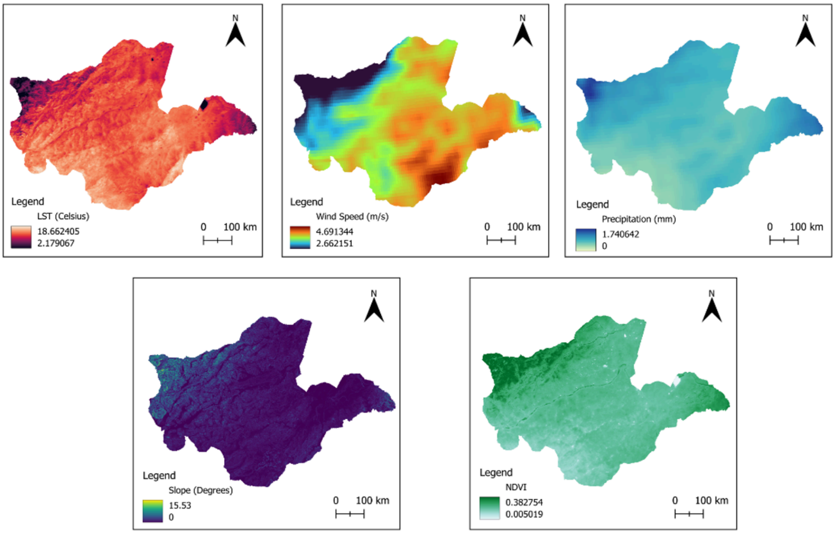

Fig. 2. Environmental variables of Eastern Mongolia.

3 Materials and Methods

3.1 Terminology clarification

In this study, wildfire patches refer to contiguous burned areas detected from satellite data with at least five connected pixels. The centroid of each patch is identified as a fire point, representing the fire location. The burned area is the total land affected by these patches. Meanwhile, fire incidents denote individual wildfire events as recorded by satellite or official sources. These terms are used consistently throughout the analysis to avoid confusion.

3.2 Data source and Processing

In this study, the wildfire pattern analysis framework proposed by Yulong Bao et al. [12] is adopted for spatiotemporal analysis of Mongolian wildfires. This method was selected because it effectively leverages long-term, satellite-based burned area products to detect fire patterns across large, remote landscapes where ground-based records are sparse or incomplete. Mongolia's vast steppe and forest–steppe ecosystems, combined with highly seasonal fire activity, require a consistent and scalable approach; the methodology by Bao et al. provides such a framework while allowing detection of both persistent and emerging wildfire hotspots.

Satellite data for this study were extracted using the Google Earth Engine (GEE) platform, with all pre-processing and analysis performed in GEE and QGIS. Wildfires were identified using the Aqua–Terra combined MCD64A1.061 MODIS Burned Area Monthly Global product (500 m resolution) provided by NASA. This dataset records burned areas along with fire dates and point coordinates. Therefore with a span of over a 20-year period (January 2005 – December 2024) is used for the analysis, offering a uniform spatial and temporal framework for interpretation compared with heterogeneous or short-term statistical datasets.

3.3 Spatial Pattern Analysis of Wildfire

Monthly fire patches in Mongolia were detected using Google Earth Engine's functions such as 'ee.Kernel.plus', and 'connected'. Patches with more than five connected pixels were retained, and their total burned area was calculated from January 2005 to December 2024. Centroids of these patches were exported as a CSV for spatiotemporal analysis.

Emerging Hot Spot Analysis was performed in ArcMap 10.8 using the Spatial Analyst toolbox. A space-time NetCDF cube was created with 3-month time steps and 10 km spatial resolution using the "Create Space Time Cube by Aggregating Points" tool. The analysis applied the Getis-Ord Gi* statistic with a 100 km spatial neighborhood and 177-month time step to classify each bin's z-score, p-value, and hotspot category. Statistically significant hotspots were identified where the z-score was greater than 1.96 and the p-value was less than 0.05, indicating a confidence level of 95%. The hotspot categories are determined by trends in z-scores and p-values over time, where persistent hotspots remain consistently significant, intensifying hotspots increase in significance, diminishing hotspots decrease, and sporadic hotspots occur irregularly without a clear pattern. Mann-Kendall trend tests were used to detect statistically significant spatial-temporal trends in hotspot dynamics.

3.4 Temporal pattern analysis of wildfire

The temporal analysis involves examining the monthly burned area (in km^2) for each year along with its trend, the seasonal percentage of wildfire occurrences, and the yearly trend over the past 20 years, all presented through various chart types. Additionally, the number of fire occurrences each month, for each year, is graphically displayed in 5-year intervals to identify the peak occurrence periods. Furthermore, satellite-based wildfire occurrence estimates are compared with open-source statistical data to validate the analysis. The statistical data is sourced from the “1212.mn” website [13], while satellite data estimates are derived from the MODIS MCD64A1.061 datasets.

3.5 MaxEnt-based fire risk analysis (modelling)

The Maximum Entropy model efficiently utilizes all available information to estimate the probability distribution of a sample. It is methodologically straightforward and requires only two datasets for implementation.

MaxEnt predicts potential fire-prone areas using two key inputs: known wildfire occurrence points (X) and environmental variables (Y), ensuring all layers share the same spatial resolution.

The model estimates the probability distribution of wildfire occurrence that maximizes entropy under known constraints, avoiding assumptions about unknown data. Conditional entropy $H(X|Y)$ is minimized during training to derive the most uniform and unbiased distribution. To reduce randomness, multiple training runs are averaged, using separate training and test datasets. Model performance is assessed using the Area Under the ROC Curve (AUC). AUC values range from 0.5 (no predictive power) to 1.0 (perfect prediction), with values above 0.7 indicating moderate to high accuracy.

MaxEnt also evaluates variable importance through percent contribution (based on model training paths) and permutation importance (based on sensitivity to variable perturbation). These complementary metrics help identify the most influential factors driving wildfire occurrence.

Among the three MaxEnt output formats are raw, logistic, and cloglog. The cloglog output is used in this study for its probabilistic interpretation of fire risk, producing values between 0 and 1 that closely approximate the actual probability of occurrence.

Based on prior analysis and recent research, five key environmental variables were selected for wildfire risk modeling: slope (topography), average monthly precipitation, average monthly land surface temperature (LST), wind speed (climate), and vegetation health (NDVI). These variables were sourced from publicly available datasets and processed using Google Earth Engine. Slope, a static variable, was derived from elevation and used as a single raster layer, while dynamic variables (LST, NDVI, precipitation, wind speed) were processed monthly by averaging values from 2005–2024 to produce one composite layer per month. Correspondingly, wildfire occurrence points were grouped by month across all years (e.g., all March events from 2005–2024) for use in MaxEnt modeling.

All raster data was converted from shapefile (SHP) to ASCII (ASC) format using QGIS 3.40.5, as MaxEnt supports only ASC and CSV formats. To ensure compatibility, all datasets were projected to the same coordinate reference system of EPSG:32648 (UTM Zone 48N, WGS84)—and standardized to a spatial resolution of 1 km.

4 Results and Discussion

4.1 Spatial clustering analysis of wildfire

Wildfire patches with more than 5 connected pixels were classified as confirmed fires, with centroids representing fire occurrences over 20 years. Between January 2005 and December 2024, wildfires affected approximately 186,182 km² (12%) of Mongolia's 1.56 million km² land area.

As it can be seen in Fig. 3a and Fig. 3b, fire points clustered in the eastern part and western Mongolia's Bayan-Ulgii province, indicating localized hotspots, but the largest burned areas are in eastern provinces such as Khentii, Dornod, and Sukhbaatar. The Gobi region showed minimal wildfire activity, and western fires were generally small and isolated.

Kernel density mapping confirms that eastern Mongolia, especially near the Russian border, is the most fire-prone area, while the northwest remains least affected as shown in Fig. 3c.

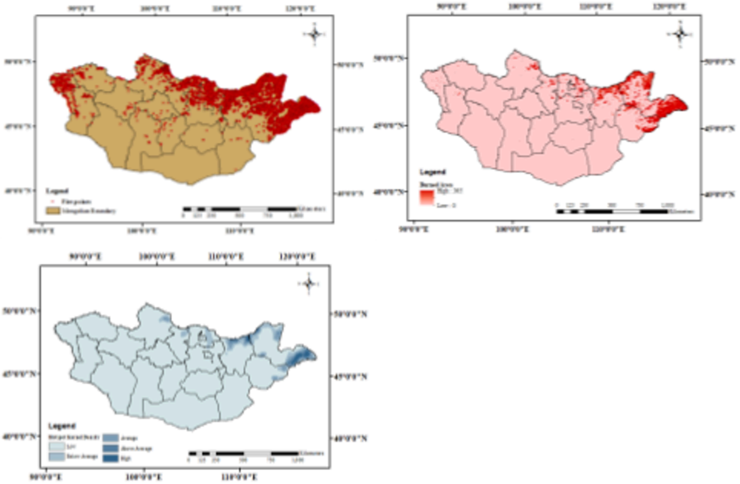

Fig.3. (a) Fire point distribution of Mongolia, (b) Burned area map of Mongolia, (c) Kernel density distribution map of Mongolia.

4.2 Spatial trend of wildfire in Mongolia

Spatiotemporal cube analysis of wildfire patterns from January 2005 to December 2024 revealed seven key trends (Fig. 4). The most common trend, oscillating cold spots (53.5% of fires), are mainly found in Darkhan-Uul, Selenge, Khentii, and parts of Dornod and Sukhbaatar provinces near the Russian border. The oscillating hotspots (18.9%) occur predominantly in Dornod, Sukhbaatar, and Khuvsgul provinces.

Intensifying cold spots (10.3%) are concentrated in Bayan-Ulgii and parts of Khentii and Sukhbaatar, while sporadic cold spots (5.7%) show no clear pattern and are scattered near the Dornod-Sukhbaatar border. The intensifying hotspot trend (4.9%) is observed in eastern Dornod, indicating increasing fire activity over time.

Lastly, persistent hotspots (4.1%) exhibit consistent high fire clustering, and diminishing hotspots (2.6%) show decreasing fire intensity; both are located in Dornod near the China border.

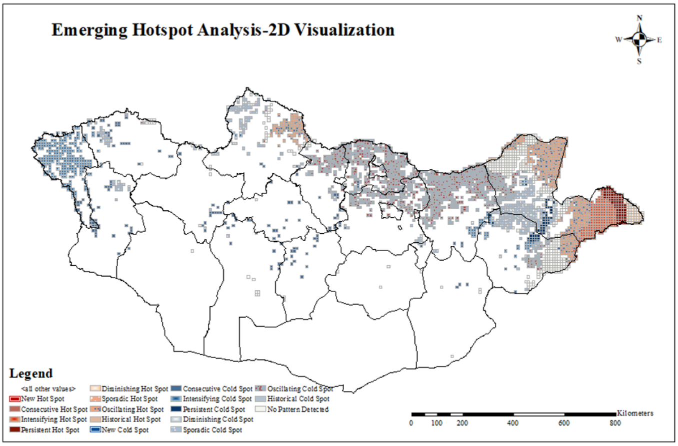

Fig. 4. Emerging hotspot spatial trend analysis and its 2D visualization.

4.3 Temporal trend of wildfire in Mongolia

Figure 5b presents the temporal trends of burned areas across Mongolia. The year 2012 recorded the largest burned area at 22,469 km^2, followed by 2023 (19,330 km^2) and 2015 (18,915 km^2). The lowest wildfire activity occurred in 2018 (327 km^2), 2020 (644 km^2), and 2021 (1,098 km^2), reflecting significant interannual variability likely driven by climatic and vegetation factors. Overall, a decreasing trend in burned area was observed over the 20-year period. Seasonal analysis shows that most wildfires occur during spring and autumn, with spring accounting for 62% of the burned area, coinciding with dry grasslands and strong winds. Summer fires represent 21%, autumn 16%, and winter only 1% (Fig. 5c). Monthly peaks occur from March to May and a secondary peak from August to October, with some exceptions in certain years (Fig. 5a).

Fig.5. (a) Monthly, (b) yearly, (c) seasonally wildfire pattern in Mongolia from January 2005 to December 2024.

The temporal analysis revealed notable interannual variability in wildfire occurrence and burned area across Mongolia. This variability is closely linked to climate fluctuations such as periods of drought, higher temperatures, and strong winds, particularly during spring and early summer months. Dry conditions during these periods increase vegetation flammability, providing ample fuel for wildfires, while prevailing winds facilitate their rapid spread. Years with extreme fire activity, such as 2012, 2015, and 2023, coincided with these unfavorable climatic conditions, showing the important role climate variability plays in shaping wildfire patterns in Mongolia.

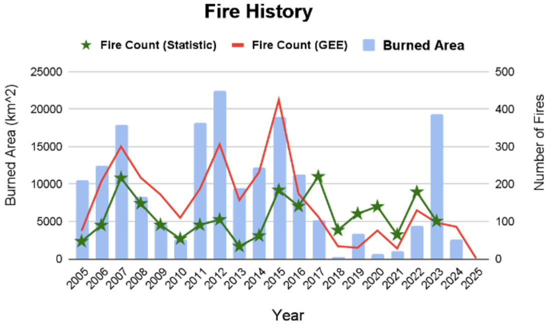

Fig. 6. Satellite data and fire incidents report data.

Figure 6 compares wildfire incidents from satellite-derived MODIS data and official Mongolian Statistical Information Service (MSIS) records. While both datasets show similar fluctuating trends from 2005 to 2023, satellite estimates generally exceed MSIS records before 2016. After 2016, MSIS reported more incidents, except for 2017 when satellite data recorded more wildfires. The highest number of satellite-detected wildfires was in 2015 (425 incidents), while MSIS reported a peak in 2017 (220 incidents).

4.4. Temporal Trend of Wildfire in Eastern Mongolia

Figure 7 compares wildfire incidents and burned areas in Khentii, Dornod, and Sukhbaatar provinces using MODIS satellite data and MSIS records. Dornod experienced the most frequent and extensive fires, with peak years like 2008 and 2023 reaching up to 15,000 km^2 burned. Sukhbaatar had major fires in 2014 and 2016, while Khentii saw smaller fires, mostly before 2010. Fire activity was minimal across all provinces in 2019, 2020, and 2024. Although temporal patterns are similar between datasets, MSIS often reports fewer incidents. Gaps in MSIS data, such as the absence of records for Sukhbaatar (2005–2015) and for Dornod and Khentii in 2010, limit its reliability for long-term analysis.

Additionally, similar monthly and seasonal analysis was made in the eastern part of Mongolia. And as a result, between January 2005 and December 2024, 186,182 km^2 of land burned across Mongolia, with 91.6% (170,639.14 km^2) occurring in the eastern provinces alone. Wildfires in eastern Mongolia exhibit a strong seasonal pattern, with the vast majority occurring during the spring months, especially in April and May. These two months consistently saw the largest burned areas, including major fire years such as 2012, 2015, and 2023. In contrast, fire activity during summer was minimal, and winter fires were virtually absent due to cold temperatures and snow cover.

Seasonal patterns remained relatively stable throughout the period, though some variation was observed. In the early years (2005–2009), fires were more evenly spread between spring and autumn. However, from 2010 onward, fire activity became increasingly concentrated in the spring, particularly in April. Summer fires were occasionally observed in certain years, such as 2016, 2017, and 2018, but remained comparatively rare.

Fig.7. Comparison of fire incidents and its corresponding burned areas of Khentii, Dornod, and Sukhbaatar provinces from January 2005 to December 2024.

In recent years, particularly from 2020 to 2024, an earlier onset of the fire season became evident. Fires increasingly began in March and peaked in April, with April

2023 marking an extreme case; over 60% of that year's fires occurred in a single month. While the long-term trend suggests a gradual decline in total burned area, the occurrence of high-severity fire years demonstrates that wildfire risk remains significant and persistent across eastern Mongolia.

4.5 Maximum Entropy Analysis of Wildfire

For this study, averaged monthly fire point data from the past 20 years were used as presence-only input for MaxEnt modeling. Separate models were developed for each month to assess spatial wildfire risk and the role of monthly environmental factors. April, July, and October were selected for detailed analysis: April representing peak fire activity, October the secondary peak, and July the lowest fire occurrence. Models for all other months (except fire-free January and December) were also created. In Fig. 8 wildfire risk model is mapped across the last 20 years of period in each month.

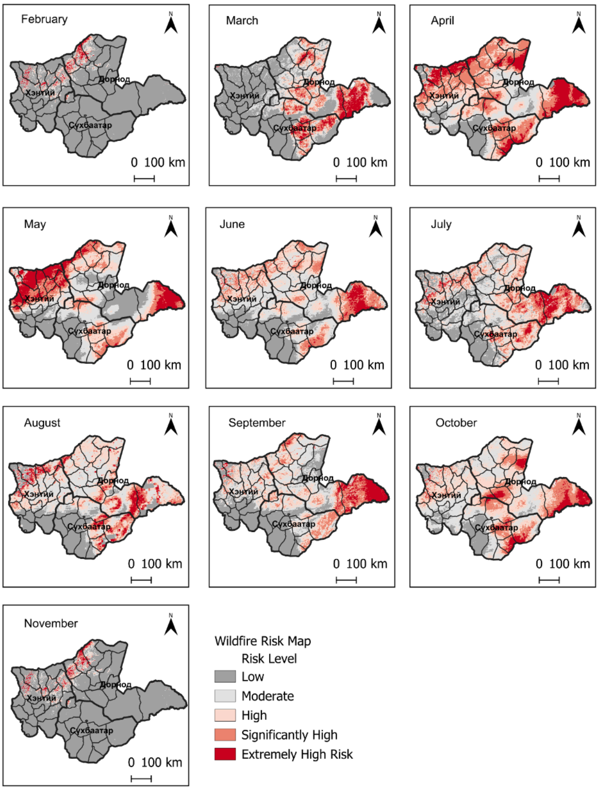

Fig.8. The wildfire risk model covers February to November, using observed data from January 2005 to December 2024.

The spatiotemporal wildfire trends observed in Eastern Mongolia are driven largely by key climate factors including temperature, precipitation, and wind speed that influence both fire ignition and propagation. Furthermore, the region's fuel composition, with extensive grasslands and scattered forest patches, contributes to the variability in fire behavior and risk, as reflected in the MaxEnt model results.

The emerging hot spot analysis and MaxEnt fire risk modelling show strong spatial correspondence. Areas identified as persistent, oscillating, and intensifying hotspots and even oscillating cold spots are mainly in eastern provinces like Dornod, Khentii and Sukhbaatar provinces that coincide closely with regions predicted by MaxEnt as having high fire risk. This alignment validates the MaxEnt model's effectiveness in confirming that these high-risk zones experience frequent and severe fire activity over time.

5 Conclusion

This study examined wildfire patterns in Eastern Mongolia from January 2005 to December 2024, focusing on the timing, location, and key drivers of fire activity. The results show that the eastern steppe regions near the Russian border were hit the hardest, with the largest burned areas and frequent fire hotspots over the years.

Most wildfires occurred in spring, especially from March to May, which made up about 62% of the total burned area. While the number of fires has generally gone down, some years like 2012, 2015, and 2023 still saw intense and widespread fires.

Using the MaxEnt model, the research identified land surface temperature and wind speed as the key environmental factors behind fire risk in the region. These findings provide essential guidance for targeted wildfire risk management and contribute to the development of more effective fire prevention strategies in Eastern Mongolia.

However, this study has some limitations. The MODIS burned area data's 500 m resolution may miss small fires and affect accuracy in mixed landscapes. The MaxEnt model includes only environmental factors and does not account for human activities like land use or accidental fires, which are important in Mongolia. Also, the study uses observed data up to 2024 but does not consider future climate change impacts, limiting its predictive scope. Satellite data uncertainties and incomplete official records may also affect results.

Future research should integrate higher-resolution satellite data, include human and land-use factors, and use climate projections to better predict wildfire risks. Improving ground monitoring in Mongolia would also help validate satellite data and enhance model reliability. These steps will support more effective wildfire management tailored to regional conditions.

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