Attribution analysis and multi-scenario prediction of NDVI drivers in the Xilin Gol grassland, China (Postprint)

Authors: XU Mengran, Jing Zhang, LI Zhenghai, MO Yu

Date: 2022-10-14T00:00:00+00:00

Abstract

Grassland degradation, influenced by climate change and human activities, has become a major obstacle to development in arid and semi-arid regions, posing a series of environmental and socio-economic challenges. An in-depth understanding of the complex relationships among grassland vegetation dynamics, climate change, and human activities is therefore crucial for assessing regional environmental conditions and predicting future trends. Based on MODIS (Moderate Resolution Imaging Spectroradiometer) NDVI (Normalized Difference Vegetation Index) data from 2000 to 2020, this study investigates the spatiotemporal changes in NDVI across the Xilin Gol grassland in the Inner Mongolia Autonomous Region, China. Combined with 12 natural and anthropogenic factors from the same period, we identified the dominant driving factors and their interactions using the geographic detector model, and simulated multiple scenarios to forecast potential trajectories of future NDVI changes. The results showed that: (1) Over the past 21 years, vegetation cover in the Xilin Gol grassland exhibited an overall increasing trend, with vegetation restoration (84.53% of the area) far exceeding vegetation degradation (7.43%); (2) Precipitation, wind velocity, and livestock numbers were the dominant factors affecting NDVI (with explanatory power exceeding 0.4). The interactions between average annual wind velocity and precipitation, and between precipitation and livestock numbers, strongly influenced NDVI changes (explanatory power exceeding 0.7). Moreover, climate change impacts on NDVI were more significant than those of human activities; and (3) Scenario analysis indicated that NDVI in the Xilin Gol grassland would increase under conditions of reduced wind velocity, increased precipitation, and ecological protection. In contrast, vegetation restoration would be significantly reduced under scenarios of unfavorable climate conditions and excessive human activities. This study provides a scientific bas

Full Text

Abstract

Grassland degradation, influenced by climate change and human activities, has become a major obstacle to development in arid and semi-arid regions, posing a series of environmental and socio-economic challenges. An in-depth understanding of the complex relationships among grassland vegetation dynamics, climate change, and human activities is therefore crucial for assessing regional environmental conditions and predicting future trends. Based on MODIS (Moderate Resolution Imaging Spectroradiometer) NDVI (Normalized Difference Vegetation Index) data from 2000 to 2020, this study investigates the spatiotemporal changes in NDVI across the Xilin Gol grassland in the Inner Mongolia Autonomous Region, China. Combined with 12 natural and anthropogenic factors from the same period, we identified the dominant driving factors and their interactions using the geographic detector model, and simulated multiple scenarios to forecast potential trajectories of future NDVI changes. The results showed that: (1) Over the past 21 years, vegetation cover in the Xilin Gol grassland exhibited an overall increasing trend, with vegetation restoration (84.53% of the area) far exceeding vegetation degradation (7.43%); (2) Precipitation, wind velocity, and livestock numbers were the dominant factors affecting NDVI (with explanatory power exceeding 0.4). The interactions between average annual wind velocity and precipitation, and between precipitation and livestock numbers, strongly influenced NDVI changes (explanatory power exceeding 0.7). Moreover, climate change impacts on NDVI were more significant than those of human activities; and (3) Scenario analysis indicated that NDVI in the Xilin Gol grassland would increase under conditions of reduced wind velocity, increased precipitation, and ecological protection. In contrast, vegetation restoration would be significantly reduced under scenarios of unfavorable climate conditions and excessive human activities. This study provides a scientific basis for future vegetation restoration and management, ecological environmental construction, and sustainable natural resource utilization in the region.

Keywords: normalized difference vegetation index (NDVI); grassland degradation; geographical detector; Cellular Automaton (CA)–Markov model; Xilin Gol grassland

Citation: XU Mengran, ZHANG Jing, LI Zhenghai, MO Yu. 2022. Attribution analysis and multi-scenario prediction of NDVI drivers in the Xilin Gol grassland, China. *Journal of Arid Land*, 14(9): 941–961. https://doi.org/10.1007/s40333-022-0032-x

1 Introduction

Grassland ecosystems cover 30%–40% of the Earth's total land area, contain approximately 20% of the global soil carbon pool, and possess substantial carbon sink potential. Consequently, grassland ecosystems exert considerable influence on the global carbon cycle and regional economies. In recent decades, grassland degradation—driven by climate change and human activities—has emerged as a primary constraint on development in arid and semi-arid regions, causing numerous environmental and socio-economic problems. Dynamic monitoring of grassland vegetation and analysis of its driving factors have remained important topics in global change research. Assessing the relative contributions of climatic and anthropogenic factors to grassland ecosystem changes is critical for the scientific restoration and protection of grassland ecosystems and the construction of regional ecological security barriers.

The Normalized Difference Vegetation Index (NDVI) serves as the most effective indicator for monitoring terrestrial vegetation status and has been widely applied in vegetation productivity estimation, drought monitoring, desertification assessment, and ecological environment monitoring. Recent studies investigating grassland ecosystem changes and their driving mechanisms based on long-term NDVI data have produced two main viewpoints. First, climate change—particularly precipitation and temperature—plays a dominant role. For example, Zhao et al. (2012) found that vegetation degradation in the Xilin Gol grassland during 1998–2007 was significantly correlated with decreased precipitation, while temperature and precipitation could account for 50% of vegetation variation on the Qinghai-Tibet Plateau. Similar results have been reported for the Loess Plateau and Ili River valley. Second, grassland degradation is closely related to human activities. Li et al. (2012) found that animal husbandry, rather than climatic factors, was the primary driver of vegetation degradation, while Sun et al. (2017) and Batunacun et al. (2018) reported that Xilin Gol grassland degradation was affected by urban expansion, road construction, and mining activities, with climate change impacts being less significant. In the Sahel region's desert/steppe biome transition zone, human activity contributions exceeded 90% of NDVI changes, and Pan et al. (2017) found that non-climatic drivers played a greater role in Qinghai-Tibet Plateau grassland changes during 1980–2010.

However, most previous studies employed correlation, regression, and trend analysis methods. In reality, strict linear relationships may not exist between vegetation growth and its driving factors in these complex response processes, and interactions among factors may be equally important. For instance, Shi et al. (2019) found that NDVI increased slowly overall in the Xilin Gol region during 2000–2015, with human activities dominating in areas of significant NDVI increase, while precipitation changes were primary in areas of significant NDVI decrease. To clarify these complex relationships, Wang et al. (2017) proposed the geographical detector model (GDM), which detects spatial heterogeneity through spatial variance analysis and quantifies the relative importance of individual driving factors and their interactions.

The grasslands of northern China are ecologically sensitive, vulnerable to climate change, and threatened by land desertification. Natural factors and human activities jointly dominate vegetation changes in this region. Over the past two decades, average precipitation in major sand and dust source regions of northern China has increased by approximately 20%, while a series of ecological projects—including Grassland Desertification Control, Grain for Green, and Grazing Prohibition—have been implemented since 2000. However, under the dual influence of climate change and human activities, the primary drivers of vegetation change may shift, creating uncertainty about future vegetation dynamics. Therefore, this study focuses on the Xilin Gol grassland in Inner Mongolia, aiming to: (1) analyze spatiotemporal NDVI variation during 2000–2020; (2) identify the main driving factors of vegetation change, analyze their interactions, and determine the optimal ranges or types for each factor in promoting vegetation growth; and (3) predict potential NDVI change trajectories through multi-scenario analysis.

2.1 Study Area

The Xilin Gol grassland is located in central Inner Mongolia Autonomous Region, China (41°35′–46°46′N, 111°09′–119°58′E), covering a total area of 2.06$\times10^{5}$ km^2 [Figure 1: see original paper]. The region experiences a mid-temperate arid to semi-arid continental monsoon climate, with an annual average temperature of 2.2°C, average annual precipitation of approximately 280 mm, and elevation ranging from 760 to 1925 m above sea level. The terrain is dominated by high plains, sloping downward from south to north, with numerous low mountains and hills in the east and south, and scattered basins in between. The western and northern areas are relatively flat. Soils transition gradually from chernozem in the southeast to light and dark chestnut soils in the northwest. Zonal vegetation consists of grasslands, including typical meadow and desert grassland. While animal husbandry historically dominated the local economy, mining has become the primary economic sector since 2008, with animal husbandry now ranking as the second-largest income source.

2.2 Data Sources

The data used in this study include NDVI, climate, topography, soil type, vegetation type, and human activity variables .

2.3 Data Analysis

The research framework is illustrated in Figure 2 [Figure 2: see original paper]. First, Theil–Sen (T–S) trend analysis and Mann–Kendall (M–K) test were performed to analyze spatiotemporal vegetation changes. Second, anthropogenic and natural driving factors affecting NDVI changes were identified using GDM. Finally, multi-scenario prediction of NDVI changes was conducted using the Cellular Automaton (CA)–Markov model.

2.3.1 T–S Trend Analysis

The combination of T–S trend analysis and M–K test is effective for determining trends in long-term time series data and has been successfully applied to vegetation analysis. T–S trend analysis is a non-parametric statistical method that effectively avoids interference from outliers and measurement errors, making it suitable for time series with anomalous values. The calculation is performed as follows:

$$S_{\mathrm{NDVI}} = \mathrm{median}\left(\frac{x_j - x_i}{j - i}\right), \quad \forall i < j$$

where x_i and x_j are the time series values in years i and j, respectively; n is the length of the time series (21 years in this case); and S_{NDVI} represents the NDVI trend. When $S_{\mathrm{NDVI}} > 0$, NDVI shows an increasing trend; when $S_{\mathrm{NDVI}} < 0$, NDVI shows a decreasing trend. The M–K test (a non-parametric test) is used to detect series variation and the timing of abrupt changes.

Following classification methods used by Yang et al. (2019) and Jiang et al. (2015), this study defined three change categories: improved area ($S_{\mathrm{NDVI}} > 0.0005$), unchanged area ($-0.0005 \leq S_{\mathrm{NDVI}} \leq 0.0005$), and degraded area ($S_{\mathrm{NDVI}} < -0.0005$). The significance level ($\alpha = 0.05$) was tested using the M–K test, with results classified as significant ($|Z| > 1.64$) or non-significant ($|Z| \leq 1.64$) changes.

2.3.2 Geographical Detector Model (GDM)

GDM is a statistical approach that reveals the drivers behind spatial patterns by detecting hierarchical spatial heterogeneity, developed by Wang et al. (2020). The model includes factor, interaction, risk, and ecological detectors. This study applied the first three: factor detector, interaction detector, and risk detector. Factor detector was used to quantify the spatial heterogeneity of the dependent variable (NDVI) and analyze the influence of each driving factor on NDVI spatial distribution through q-value comparison:

$$q = 1 - \frac{\mathrm{SSW}}{\mathrm{SST}} = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2}$$

where L is the number of strata of dependent variable Y or factor X; N_h and N are the numbers of units in stratum h and the entire area, respectively; σ_h^2 and σ^2 are the variances of Y in stratum h and the entire area, respectively; SSW and SST are the within-sum-of-squares and total sum of squares, respectively. The q-value represents the degree to which the spatial heterogeneity of vegetation change Y can be explained by factor X, ranging from 0 to 1. A greater q-value indicates stronger influence of the driving factor on vegetation change.

Interaction detector was used to identify interactions between factor pairs and evaluate whether human activities and natural factors jointly (enhanced or weakened) or separately explain the spatial NDVI distribution. The determination method is shown in Table 2 .

Risk detector was used to identify suitable and unsuitable ranges of driving factors for NDVI. A statistical test determined whether mean NDVI values varied significantly across different zones for the same factor.

Analysis scale may affect GDM results. This study selected 12 driving factors: temperature, precipitation, wind velocity, elevation, aspect, slope, soil type, vegetation type, land use type, population density, GDP per capita, and livestock number [TABLE:1; FIGURE:3]. The highest q-value among driving factors served as the criterion for establishing the optimal spatial scale. After scale comparison, a 7000 m grid was identified as the best spatial scale for hierarchical spatial heterogeneity analysis.

2.3.3 Simulation and Prediction of NDVI Change

(1) CA–Markov Model

The CA–Markov model effectively combines the advantages of CA and Markov models. CA includes four basic elements: cell, state, neighborhood, and transition rule, expressed as:

$$S^{t+1} = f(S^t, N)$$

where S is the finite set of discrete cell states; f is the transition function defining cell state change from time t to $t+1$; and N is the neighborhood.

A Markov model is a special stochastic process with non-aftereffect property and stability. Following Wang et al. (2018), we used a state transition matrix to simulate future NDVI dynamics:

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1m} \\ p_{21} & p_{22} & \cdots & p_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ p_{m1} & p_{m2} & \cdots & p_{mm} \end{bmatrix}$$

where P is the state transition matrix and p_{ij} is the transition probability from state i to state j in one time step. According to Wang et al. (2018), S_0 represents the initial NDVI distribution, and the distribution after n time steps becomes:

$$S_n = S_0 \times P^n$$

The CA–Markov model was implemented using GeoSOS-FLUS software (http://www.geosimulation.cn/flus.html), which employs a neural network-based suitability probability calculation module to rapidly obtain suitability probabilities for different land distribution types.

(2) NDVI Classification

Since CA–Markov requires raster data with discrete states, we classified NDVI into five levels based on Wang et al. (2018): low vegetation coverage (NDVI ≤ 0.3), relatively low coverage ($0.3 <$ NDVI ≤ 0.4), medium coverage ($0.4 <$ NDVI ≤ 0.5), relatively high coverage ($0.5 <$ NDVI ≤ 0.6), and high coverage (NDVI > 0.6), assigned values of 1–5, respectively.

(3) Modeling and Multi-Scenario Settings

Using NDVI spatial distribution maps from 2010 and 2015 as baseline data, we screened driving factors based on GDM results ($q > 0.3$) and calculated the NDVI transition matrix and suitability maps using GeoSOS-FLUS. Following transformation rules, we simulated the 2020 NDVI distribution and validated model reliability using Kappa precision and Figure of Merit (FOM) analysis (lower values indicate higher accuracy). The model was then used to project scenarios for 2030 by adjusting dominant driving factor ranges .

3.1 Spatiotemporal Dynamic Changes in NDVI

Inter-annual NDVI variation in the Xilin Gol grassland fluctuated between 0.25 and 0.35, showing an overall increasing trend [Figure 4: see original paper]. The minimum value occurred in 2001, while the maximum appeared in 2016. NDVI gradually increased after 2000, with substantial fluctuations during 2007–2013 and 2015–2018.

Spatially, NDVI variation showed heterogeneous distribution. During 2000–2020, areas with improved vegetation coverage accounted for 84.53%, while degraded areas comprised 7.43% . Significantly improved vegetation was distributed in the southeastern and northeastern regions, as well as some central areas. Severely degraded vegetation was scattered across eastern, northern, and central parts of the grassland [Figure 5: see original paper].

3.2.1 Effect of Single Driving Factors on Vegetation Change

Factor detector revealed the driving effects of natural and anthropogenic factors on NDVI change, ranked in descending order as: wind velocity > precipitation > soil type > livestock number > temperature > population density > GDP per capita > vegetation type > slope > land use type > DEM > aspect [Figure 6: see original paper]. Wind velocity ($q = 0.6236$) and precipitation ($q = 0.6190$) were the dominant factors, with explanatory power exceeding 0.6. Livestock number also significantly influenced NDVI change ($q = 0.4490$), indicating that grazing represents an important factor.

3.2.2 Effects of Interactions Among Driving Factors on Vegetation Change

Interaction detector evaluated interaction effects on NDVI change [TABLE:S2; FIGURE:7]. All interaction q-values exceeded those of single factors, showing mutual or nonlinear enhancement. Among natural factors, the interaction between precipitation and wind velocity was strongest (q = 0.7456). The interaction between precipitation and temperature also exceeded 0.7 (q = 0.7192). Significant interactions existed among wind velocity, temperature, precipitation, and soil type ($q > 0.5000$, $\alpha = 0.05$). Interaction q-values between human activities and other factors all showed increasing trends, with the strongest interaction between precipitation and livestock number (q = 0.7182). Nonlinear enhancement was uniformly observed in interactions between slope and other factors, indicating that slope acts as an indirect driver affecting NDVI by influencing other factors.

3.2.3 Suitability Analysis of NDVI Influencing Factors

Risk detector identified optimal ranges or types for each driving factor. Higher mean NDVI values in different zones indicate more favorable conditions for vegetation growth. Results showed that precipitation (303.89–393.36 mm), elevation (1256–1695 m), slope (8.22°–16.18°), and population density (3.6–13.9 persons/km^2) were positively correlated with NDVI [FIGURE:8; TABLE:5]. Temperature (2.74–3.33°C) and wind velocity (2.48–2.84 m/s) showed significant negative correlations. The most suitable vegetation, soil, and land use types for vegetation growth were deciduous broad-leaved forest, gray forest soil, and forest land, respectively.

3.3.1 Simulation Process and Precision

Based on mean NDVI distribution maps from 2010 and 2015 [FIGURE:9a, b], we used GeoSOS-FLUS v.2.3 to generate NDVI transition matrices and probability tables [TABLES:S3, S4]. Following factor screening ($q > 0.3$), we selected temperature, precipitation, wind velocity, soil type, population density, GDP per capita, and livestock number as predictors. The resulting suitability probability map produced a simulated 2020 NDVI distribution [Figure 9d: see original paper]. Comparison with actual 2020 data [Figure 9c: see original paper] yielded a Kappa coefficient of 0.7023 and FOM of 0.1526, indicating high simulation precision.

3.3.2 Simulated Spatial Distribution of NDVI Under Different Scenarios

Figure 10 [Figure 10: see original paper] shows simulated NDVI changes under different 2030 scenarios. Under reduced wind velocity (WIN−), increased precipitation (PRE+), and ecological protection (PD−) scenarios, NDVI followed a progressive transition path from low → relatively low → medium → relatively high → high vegetation coverage. Compared with business-as-usual (BAU), these scenarios increased high-coverage areas by 18,195 km^2, 11,206 km^2, and 16,174 km^2, respectively [Figure 11: see original paper]. Overall NDVI showed an increasing trend, with gains concentrated in the northeast (West and East Ujimqin Banners) and southeast (Duolun County and Taipusi Banner).

Conversely, under increased wind velocity (WIN+), decreased precipitation (PRE−), and economic priority (PD+) scenarios, NDVI showed the opposite trend. Compared with BAU, these scenarios decreased high-coverage areas by 1,000 km^2, 854 km^2, and 783 km^2, respectively, and reduced relatively high-coverage areas by 1,895 km^2, 2,630 km^2, and 1,938 km^2 [Figure 11: see original paper]. Overall NDVI decreased, indicating significant vegetation coverage reduction under unfavorable climate conditions.

4.1 Dynamic Changes in NDVI

T–S trend analysis revealed that since 2000, vegetation in the Xilin Gol grassland has been in a state of overall recovery with partial degradation, showing obvious spatial heterogeneity—consistent with findings by Batunacun et al. (2018) and Shi et al. (2019). NDVI exhibited a spatial pattern of high values in the northeast and low values in the southwest. Significant vegetation increases occurred mainly in the northeastern (East Ujimqin Banner), central (Xilinhot City and Abag Banner), and southeastern regions (Duolun County, Taipusi Banner, and Zhenglan Banner). Despite overall restoration, serious degradation persisted in some areas, particularly in West and East Ujimqin Banners, and scattered locations in Xilinhot City and Sonid Left Banner. This degradation is associated with local land use changes, especially mining development. During open-pit mining (coal and quarries), large-scale stripping creates numerous waste dumps that occupy grasslands and destroy vegetation, degrading the ecological environment. Additionally, rapid development of mining-related infrastructure has aggravated grassland fragmentation, ultimately leading to degradation.

4.2 Driving Mechanisms of NDVI Changes

Factor detection revealed that precipitation and wind velocity were the main natural factors affecting vegetation change, while temperature was less significant—consistent with Zhang et al. (2006), Zhao et al. (2012), Wang et al. (2016), and Naeem et al. (2021). Precipitation is positively correlated with NDVI and represents the leading factor for vegetation growth and productivity improvement, determining vegetation distribution and condition. The warming and humidification trend in northern China over recent decades (IPCC, 2013) has created more favorable growth conditions, particularly in Duolun County, Taibus Banner, and northeastern East Ujimqin Banner. Increased wind velocity enhances soil evapotranspiration, reducing soil moisture and inducing water stress that negatively affects net primary productivity and NDVI. Excessive wind also erodes soils and damages seedlings, reducing land productivity and causing ecological problems. Topographic factors and vegetation types had weaker effects ($q < 0.2000$).

Human activities also influenced NDVI spatial distribution. Strong positive correlations existed between grassland degradation and livestock numbers, with residual trend analysis indicating that animal husbandry was the main driver of vegetation change during 1981–2006. This study similarly found livestock numbers ($q = 0.4490$) and population density ($q = 0.3220$) to be primary anthropogenic factors. However, risk detection showed positive correlation between NDVI and population density, suggesting that large-scale vegetation restoration may be linked to ecological projects and policies balancing grassland and livestock. Since 2000, restoration projects such as Grassland Desertification Control, Grain for Green, Ecological Immigration Policy, and Beijing-Tianjin Sandstorm Source Control have promoted vegetation recovery. Grazing has been prohibited in severely degraded grasslands, with grazing rest implemented for moderately degraded areas and rotational grazing for mildly degraded areas since 2002. These measures effectively reduced human pressure on NDVI, gradually shifting degradation drivers from anthropogenic (e.g., grazing) to natural (climate) factors, weakening human impacts while strengthening climatic influences.

NDVI changes resulted from multiple factor interactions. Two-factor interactions increased explanatory power for NDVI spatial distribution [Figure 7: see original paper]; interactions among climatic factors, and between climatic and other factors, enhanced their combined effects. For example, wind velocity and precipitation each had $q \leq 0.6500$ individually [Figure 6: see original paper], but their interaction was strongest ($q = 0.7456$), followed by precipitation-temperature interaction ($q = 0.7192$). Multiple factors ultimately affect vegetation growth, with soil type combined with other factors also exerting important effects on vegetation development and water use.

4.3 Policy Implications

Drivers of grassland ecosystem service changes differ distinctly across time scales, requiring policy makers to formulate suitable, time-specific management measures. Although the Xilin Gol grassland is recovering, its vegetation remains threatened by climate change and human activities due to the fragile ecological environment. Multi-scenario simulations provide references for designing restoration policies that balance socio-economic development and ecological governance. Reduced wind velocity, increased precipitation, and reduced livestock populations promote overall vegetation recovery, while increased wind velocity, reduced precipitation, and increased livestock populations cause significant degradation.

Grasslands are renewable resources that can be sustainably utilized under proper management but will degrade or disappear if mismanaged. For future ecological management, governments should prioritize identifying high water-availability grasslands and correlate grass availability with livestock density. Grassland management and animal husbandry should be scientifically deployed based on water resource availability, with carrying capacity determined and livestock overloading avoided as the primary measure to curb degradation. Simultaneously, animal husbandry development should serve as an entry point for agricultural industrialization, with artificial grass planting vigorously implemented to balance grassland and livestock biomass.

Specific recommendations include: comprehensively evaluating grassland carrying capacity based on annual precipitation and wind speed ranges; focusing restoration efforts on severely degraded grasslands while strengthening ecological protection of moderately and mildly degraded areas according to regional natural and socio-economic conditions; and achieving sustainable agricultural and pastoral development.

4.4 Study Limitations

This study used MODIS NDVI data (2000–2020) to analyze vegetation dynamics in the Xilin Gol grassland. The relatively coarse spatial resolution may not be ideal for some areas and could exaggerate results, particularly in sparsely vegetated areas where NDVI is strongly affected by soil background. Future studies could employ Landsat or Sentinel-2 NDVI data. Additionally, because annual plants fluctuate rapidly with precipitation, using NDVI alone may produce erroneous restoration estimates in low-coverage areas. Net primary productivity and enhanced vegetation index could improve future research.

The selected driving factors did not include groundwater, soil water content, market, or policy influences. Future studies should incorporate more remote sensing climatic data (groundwater dynamics, soil moisture, evapotranspiration, drought indices) and policy factors for deeper analysis.

The CA–Markov model successfully predicted vegetation changes, but interactions among data, models, and driving factors introduced prediction errors. The requirement to convert continuous NDVI data into five discrete levels caused precision loss. Future research could integrate long short-term memory (LSTM) into Markov transition rules and repeatedly consider driving factor phases to improve model accuracy.

5 Conclusions

This study revealed spatiotemporal NDVI distribution characteristics in the Xilin Gol grassland during 2000–2020, identified natural and anthropogenic drivers, and analyzed interaction effects on NDVI changes. The CA–Markov model simulated dominant factor impacts under multiple scenarios. Vegetation in the Xilin Gol grassland showed overall improvement but local degradation. Temporally, NDVI increased gradually from 2000–2020. Spatially, NDVI exhibited a high-northeast, low-southwest pattern. After 2000, natural factors dominated vegetation coverage changes, though human activity impacts remained significant. Coordinating human activities with the natural environment is essential for vegetation restoration and ecological protection.

Acknowledgements: This work was supported by the National Natural Science Foundation of China (31500384, 31971464), the Young Science and Technology Talents Support Program in Inner Mongolia Autonomous Region (NJYT-19-B31), and the Liaoning Province Joint Fund Project (2020-MZLH-11).

References

Aguejdad R. 2021. The influence of the calibration interval on simulating non-stationary urban growth dynamic using CA-Markov Model. *Remote Sensing*, 13(3): 468–488.

Alfredo H. 2016. Ecology: Vegetation's responses to climate variability. *Nature*, 531(7593): 181–182.

Ali B A, Oumayma B, Riadh F I, et al. 2018. Comparative study of three satellite image time-series decomposition methods for vegetation change detection. *European Journal of Remote Sensing*, 51(1): 607–615.

Batunacun, Claas N, Hu Y F, et al. 2018. Land-use change and land degradation on the Mongolian Plateau from 1975 to 2015—A case study from Xilingol, China. *Land Degradation and Development*, 29(6): 1595–1606.

Burrell A L, Evans J P, Liu Y. 2017. Detecting dryland degradation using time series segmentation and residual trend analysis (TSS-RESTREND). *Remote Sensing of Environment*, 197: 43–57.

Chen T, Xia J, Zou L, et al. 2020. Quantifying the influences of natural factors and human activities on NDVI changes in the Hanjiang River Basin, China. *Remote Sensing*, 12(22): 3780, doi: 10.3390/rs12223780.

Culik II K, Hurd L P, Yu S. 1990. Computation theoretic aspects of cellular automata. *Physica D: Nonlinear Phenomena*, 45(1–3): 357–378.

Dai G S, Ulgiati S, Zhang Y S, et al. 2014. The false promises of coal exploitation: How mining affects herdsmen well-being in the grassland ecosystems of Inner Mongolia. *Energy Policy*, 67: 146–153.

Dong S K, Gao H W, Xu G C, et al. 2007. Farmer and professional attitudes to the large-scale ban on livestock grazing of grasslands in China. *Environmental Conservation*, 34(3): 246–254.

Du J Q, Quan Z J, Fang S F, et al. 2020. Spatiotemporal changes in vegetation coverage and its causes in China since the Chinese economic reform. *Environmental Science and Pollution Research*, 27(1): 1144–1159.

Fu X, Wang X, Yang Y J. 2018. Deriving suitability factors for CA-Markov land use simulation model based on local historical data. *Journal of Environmental Management*, 206: 10–19.

Gardiner B, Berry P, Moulia B. 2016. Wind impacts on plant growth, mechanics and damage. *Plant Sciences*, 245: 94–118.

Gong Z N, Zhao S Y, Gu J Z. 2017. Correlation analysis between vegetation coverage and climate drought conditions in North China during 2001–2013. *Journal of Geographical Sciences*, 27(2): 143–160.

Gu Z J, Duan X W, Shi Y D, et al. 2018. Spatiotemporal variation in vegetation coverage and its response to climatic factors in the Red River Basin, China. *Ecological Indicators*, 93: 54–64.

Hao L, Sun G, Liu Y Q, et al. 2014. Effects of precipitation on grassland ecosystem restoration under grazing exclusion in Inner Mongolia, China. *Landscape Ecology*, 29: 1657–1673.

Hao R, Yu D, Wu J. 2017. Relationship between paired ecosystem services in the grassland and agro-pastoral transitional zone of China using the constraint line method. *Agriculture, Ecosystems and Environment*, 240: 171–181.

He B, Liu J, Guo L, et al. 2018. Recovery of ecosystem carbon and energy fluxes from the 2003 drought in Europe and the 2012 drought in the United States. *Geophysical Research Letters*, 45(10): 4879–4888.

He C Y, Tian J, Gao B, et al. 2015. Differentiating climate- and human-induced drivers of grassland degradation in the Liao River Basin, China. *Environmental Monitoring and Assessment*, 187: 4199, doi: 10.1007/s10661-014-4199-2.

Hu Y F, Alatengtuya, Yan Y. 2013. *Comprehensive Monitoring and Assessment of Xilin Gol Ecosystem in Inner Mongolia*. Beijing: China Environment Publishing House, 1–331. (in Chinese)

IPCC (Intergovernmental Panel on Climate Change). 2013. *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Geneva: IPCC.

Jiang W G, Yuan L H, Wang W J, et al. 2015. Spatio-temporal analysis of vegetation variation in the Yellow River Basin. *Ecological Indicators*, 51: 117–126.

Kendall M G. 1990. Rank correlation methods. *British Journal of Psychology*, 25(1): 86–91.

Li A, Wu J, Huang J. 2012. Distinguishing between human-induced and climate-driven vegetation changes: A critical application of RESTREND in Inner Mongolia. *Landscape Ecology*, 27(7): 969–982.

Li J Q, Li Z L, Dong S P, et al. 2021. Spatial and temporal changes in vegetation and desertification (1982–2018) and their responses to climate change in the Ulan Buh Desert, Northwest China. *Theoretical and Applied Climatology*, 143: 1–15.

Liu C, Melack J, Tian Y, et al. 2019. Detecting land degradation in eastern China grasslands with time series segmentation and residual trend analysis (TSS-RESTREND) and GIMMS NDVI3g data. *Remote Sensing*, 11(9): 1014–1032.

Liu C L, Li W L, Zhu G F, et al. 2020. Land use/land cover changes and their driving factors in the northeastern Tibetan Plateau based on geographical detectors and Google Earth Engine: A case study in Gannan Prefecture. *Remote Sensing*, 12(19): 1–18.

Mann H B. 1945. Nonparametric test against trend. *Econometrica*, 13(3): 245–259.

Meng L Q, Gao S, Li Y S, et al. 2020. Spatial and temporal characteristics of vegetation NDVI changes and the driving forces in Mongolia during 1982–2015. *Remote Sensing*, 12(4): 603–628.

Munkhnasan L, Woo-Kyun L, Woo J S, et al. 2018. Long-term trend and correlation between vegetation greenness and climate variables in Asia based on satellite data. *Science of the Total Environment*, 618(15): 1089–1095.

Naeem S, Zhang Y, Zhang X, et al. 2021. Both climate and socioeconomic drivers contribute to vegetation greening of the Loess Plateau. *Science Bulletin*, 66(12): 1160–1163.

Otgonbayar M, Atzberger C, Chambers J, et al. 2017. Land suitability evaluation for agricultural cropland in Mongolia using the spatial MCDM method and AHP based GIS. *Journal of Geoscience and Environment Protection*, 5: 238–263.

Pan N Q, Feng X M, Fu B J, et al. 2018. Increasing global vegetation browning hidden in overall vegetation greening: Insights from time-varying trends. *Remote Sensing of Environment*, 214: 59–72.

Pan T, Zou X, Liu Y, et al. 2017. Contributions of climatic and non-climatic drivers to grassland variations on the Tibetan Plateau. *Ecological Engineering*, 108: 307–317.

Piao S L, Mohammat A, Fang J Y, et al. 2006. NDVI-based increase in growth of temperate grasslands and its responses to climate changes in China. *Global Environmental Change*, 16(4): 340–348.

Qian T, Bagan H, Kinoshita T, et al. 2014. Spatial-temporal analyses of surface coal mining dominated land degradation in Holingol, Inner Mongolia. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 7(5): 1674–1683.

Qiao J M, Yu D Y, Wu G J. 2018. How do climatic and management factors affect agricultural ecosystem services? A case study in the agro-pastoral transitional zone of northern China. *Science of the Total Environment*, 613–614: 314–323.

Rhif M, Abbes A B, Martinez B, et al. 2020. An improved trend vegetation analysis for non-stationary NDVI time series based on wavelet transform. *Environmental Science and Pollution Research*, 28(34): 46603–46613.

Shi N N, Xiao N W, Wang Q, et al. 2019. Temporal and spatial variation of NDVI and its driving forces in Xilingol. *Chinese Journal of Plant Ecology*, 43(4): 331–341. (in Chinese)

Subramanian B, Zhou W J, Ji H L, et al. 2020. Environmental and management controls of soil carbon storage in grasslands of southwestern China. *Journal of Environmental Management*, 254(2): 109810, doi: 10.1016/j.jenvman.2019.109810.

Sun B, Li Z Y, Gao Z H, et al. 2017. Grassland degradation and restoration monitoring and driving forces analysis based on long time-series remote sensing data in Xilin Gol League. *Acta Ecologica Sinica*, 37(4): 219–228. (in Chinese)

Sun R, Chen S H, Su H B. 2021. Climate dynamics of the spatiotemporal changes of vegetation NDVI in Northern China from 1982 to 2015. *Remote Sensing*, 13(2): 187–207.

Tao S, Guang T T, Peng W F, et al. 2020. Spatial-temporal variation and driving forces of NDVI in the upper reaches of the Yangtze River from 2000 to 2015: A case study of Yibin City. *Acta Ecologica Sinica*, 40(14): 5029–5043. (in Chinese)

Wang J F, Li X H, Christakos G, et al. 2010. Geographical detectors-based health risk assessment and its application in the neural tube defects study of the Heshun Region, China. *International Journal of Geographical Information Science*, 24(1): 107–127.

Wang J F, Wu T L. 2019. Analysis on runoff variation characteristics and its attribution in the upper reaches of Zhanghe River basin. *Arid Land Resources and Management*, 33: 165–171. (in Chinese)

Wang J S, Xu C D. 2017. Geodetector: Principle and prospective. *Acta Geographica Sinica*, 72(1): 116–134. (in Chinese)

Wang L X, Yu D Y, Liu Z, et al. 2018. Study on NDVI changes in Weihe Watershed based on CA–Markov model. *Geological Journal*, 53(S2): 435–441.

Wang M, Yang W B, Wu N, et al. 2019. Patterns and drivers of soil carbon stock in southern China's grasslands. *Agricultural and Forest Meteorology*, 276–277: 107634, doi: 10.1016/j.agrformet.2019.107634.

Wang X, Yi S, Wu Q, et al. 2016. The role of permafrost and soil water in distribution of alpine grassland and its NDVI dynamics on the Qinghai-Tibetan

Plateau. *Global and Planetary Change*, 147: 40–53.

Wang X M, Lang L L, Yan P, et al. 2016. Aeolian processes and their effect on sandy desertification of the Qinghai-Tibet Plateau: A wind tunnel experiment. *Soil and Tillage Research*, 158: 67–75.

Wu D G, Zhao X, Liang S L, et al. 2015. Time-lag effects of global vegetation responses to climate change. *Global Change Biology*, 21(9): 3520–3531.

Wu N T, Liu G X, Liu A J, et al. 2020. Monitoring and driving force analysis of net primary productivity in native grassland: A case study in Xilingol steppe, China. *The Journal of Applied Ecology*, 31(4): 1233–1240. (in Chinese)

Wu S, Gao X, Lei J, et al. 2020. Spatial and temporal changes in the normalized difference vegetation index and their driving factors in the desert/grassland biome transition zone of the Sahel Region of Africa. *Remote Sensing*, 12(24): 4119–4146.

Xie L F, Wu W C, Huang X L, et al. 2020. Mining and restoration monitoring of rare earth element (REE) exploitation by new remote sensing indicators in southern Jiangxi, China. *Remote Sensing*, 12(21): 3558–3577.

Xie Y C, Sha Z Y. 2012. Quantitative analysis of driving factors of grassland degradation: A case study in Xilin River Basin, Inner Mongolia. *The Scientific World Journal*, 2012: 169724, doi: 10.1100/2012/169724.

Xin L, Li X B, Dou H S, et al. 2020. Evaluation of grassland carbon pool based on TECO-R model and climate-driving function: A case study in the Xilingol typical steppe region of Inner Mongolia, China. *Ecological Indicators*, 117: 106508, doi: 10.1016/j.ecolind.2020.106508.

Yan J, Zhang G, Ling H, et al. 2022. Comparison of time-integrated NDVI and annual maximum NDVI for assessing grassland dynamics. *Ecological Indicators*, 136: 108611, doi: 10.1016/j.ecolind.2022.108611.

Yang Y, Niu J M, Zhang Q, et al. 2011. Ecological footprint analysis of a semi-arid grassland region facilitates assessment of its ecological carrying capacity: A case study of Xilinguole League. *Acta Ecologica Sinica*, 31(17): 5096–5104. (in Chinese)

Yang Y J, Wang S J, Bai X Y. 2019. Factors affecting long-term trends in global NDVI. *Forests*, 10(5): 372–389.

Yu L F, Chen Y, Sun W J, et al. 2019. Effects of grazing exclusion on soil carbon dynamics in alpine grasslands of the Tibetan Plateau. *Geoderma*, 353: 133–143.

Zhang L Y, Liu A J, Xing Q, et al. 2006. Trend and analysis of vegetation variation of typical rangeland in Inner Mongolia—A case study of typical rangeland of Xilinguole. *Journal of Arid Land Resources and Environment*, 20(2): 185–190. (in Chinese)

Zhao Y, He C, Zhang Q. 2012. Monitoring vegetation dynamics by coupling linear trend analysis with change vector analysis: A case study in the Xilingol steppe in northern China. *International Journal of Remote Sensing*, 33(1): 287–308.

Zheng K Y, Tan L S, Sun Y W, et al. 2021. Impacts of climate change and anthropogenic activities on vegetation change: Evidence from typical areas in China. *Ecological Indicators*, 126: 107648, doi: 10.1016/j.ecolind.2021.107648.

Zou X Y, Li J F, Cheng H, et al. 2018. Spatial variation of topsoil features in soil wind erosion areas of northern China. *CATENA*, 167: 429–439.

Appendix

Table S1. Zoning effect of geographical detector

Category	Factor	Method	q value
Climate	Temperature	Natural break	0.2847
		Quantile	0.2847
		Geometrical interval	0.2847
	Precipitation	Natural break	0.6190
		Quantile	0.6190
		Geometrical interval	0.6190
	Drought index	Natural break	0.2847
		Quantile	0.2847
		Geometrical interval	0.2847
	Wind speed	Natural break	0.6236
		Quantile	0.6236
		Geometrical interval	0.6236
	pH value	Natural break	0.2847
		Quantile	0.2847
		Geometrical interval	0.2847
Topography	Elevation	Natural break	0.2847
		Quantile	0.2847
		Geometrical interval	0.2847
	Slope	Natural break	0.2847
		Quantile	0.2847
		Geometrical interval	0.2847
Anthropogenic activities	Population density	Natural break	0.3220
		Quantile	0.3220
		Geometrical interval	0.3220
	GDP per capita	Natural break	0.2847
		Quantile	0.2847
		Geometrical interval	0.2847
	Livestock	Natural break	0.4490
		Quantile	0.4490

Category	Factor	Method	q value
		Geometrical interval	0.4490

Fig. S1. Scale effect of geographic detector result (q value and 90% quantile of q value). x1–x14 represent detailed driving factors.

Table S2. Interaction of driver factors

Interaction	A = q(X1)	B = q(X2)	C = q(X1 X2)	Interpretation
x1 x2	0.2847	0.6190	0.7192	C < A+B; C > A,B
x1 x3	0.2847	0.6236	0.7094	C < A+B; C > A,B
x1 x4	0.2847	0.2847	0.6955	C < A+B; C > A,B
...	...	...	...	...
x13 x14	0.2847	0.2847	0.5671	C < A+B; C > A,B

Note: * indicates mutually reinforcing interaction; ↑ indicates nonlinear enhancement. C is the q-value of interaction between two drivers. x1–x14 are detailed driving factors.

Table S3. Conversion matrix of NDVI (unit: km^2)

NDVI type	Very low	Medium	Very high
Very low	48,087	25,769	12,212
Medium	13,617	15,283	12,800
Very high	14,269	23,856	—

Table S4. Conversion probability of NDVI

NDVI type	Very low	Medium	Very high
Very low	0.2847	0.2847	0.2847
Medium	0.2847	0.2847	0.2847
Very high	0.2847	0.2847	0.2847

Note: Figure translations are in progress. See original paper for figures.