Monitoring Vegetation Change and Its Potential Drivers in Mongolia from 2000 to 2018

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ABSTRACT: Mongolia is a typically arid and semi-arid country with vegetation prominently affected by global warming and human activities. Therefore, investigating the past and future vegetation change and its impact mechanism is important for assessing the stability of the ecosystem and the ecological policy formulation. Vegetation changes, sustainability characteristics, and the mechanism of natural and anthropogenic effects in Mongolia during the peak growing season of 2000–2018 were examined using moderate resolution imaging spectroradiometer (MODIS) normalized difference vegetation index (NDVI) data with spatial resolution of 1km. Theil–Sen trend analysis, Mann–Kendall method, the coefficient of variation method, partial correlation, and residual analysis method were used to analyze the spatiotemporal variability characteristics and sustained stability of the NDVI. The interannual variation of NDVI is stable in most area of Mongolia. The NDVI significant positive and negative area account for 77.9% and 22.1% ($p < 0.05$). Specifically, 13% of Mongolia is significantly greening ($p < 0.01$) from 2000 to 2018. Considering the climate drivers of the NDVI in peak growing season, the partial correlation showed that NDVI was negatively correlated with temperature (controlling precipitation) in 86.7% of Mongolia while positively correlated with precipitation (controlling temperature) in 94.9% of Mongolia. The NVDI residual analysis in this paper showed the positive and negative trend of residual are 65.82% and 31.18% from 2000 to 2018 in Mongolia. The results of this study will assist in understanding the influence of natural elements and human activities on vegetation changes and their driving mechanisms, while providing a scientific basis for the rational and effective protection of the ecological environment in Mongolia.

1 INTRODUCTION

The worldwide significant warming over the past few decades produced a significant impact on vegetation (Nemani et al., 2003; Wu et al., 2021). Vegetation plays an irreplaceable role in terrestrial carbon cycles, energy exchange and water balance at various time and spatial scale (Brookshire & Weaver, 2015), and its change could also affect the climate by the feedback of surface moisture and thermal regulation (Zeng et al., 2017). Vegetation change has been found to be influenced by natural and anthropogenic factors (You et al., 2021). The spatial differences in climate and vegetation relationships are complicated and need to explore the spatially relationship at regional scale.

With the continuous development and availability of remote sensing products and statistical methods, the research content and methods of vegetation dynamics and its impact factors have become diverse. The normalized density vegetation index (NDVI) well indicate the growth status and spatial distribution density of vegetation. Many studies have investigated vegetation dynamics and its impact factors based on NDVI and statistical methods, considering temperature and precipitation as main climate factors to assess their impact on vegetation. However, the dominant factors affecting NDVI dynamics are different at regional scale (Meng et al., 2020).

We analysed the vegetation change and calculated the correlation between vegetation and climatic factors in Mongolia from 2000 to 2018. On this basis, we used residual analysis to explore the impact of human activities on vegetation. The purpose of this paper is (1) to understand the changing pattern of vegetation on Mongolia from 2000 to 2018; (2) to understand the main driving mechanism of vegetation change from the perspective of both climatic and human factors.

2 MATERIALS AND METHODS

2.1 STUDY AREA

Mongolia is situated in the north-central Asian mainland (41.5°–52.1° N, 87.70° –119.9°E), with an average elevation of about 1580 m above sea level (Fig. 1). Mongolia has a continental, semi-arid climate with low precipitation (nationwide annual precipitation is 227.3 mm) and high temperature fluctuations. Temperatures in Mongolia are projected to continue rising in future under the impact of global climate change. With a population of three million, Mongolia is a largely agricultural nation, known for vast grassland and grazing livestock. The main types of vegetation are forest, steppe, and Gobi Desert from north to south. The steppe is the main land cover type of Mongolia, accounting for 66% of the total area of the country. The Gobi Desert area is mainly distributed in the southwest of Mongolia with sparse and rare vegetation.

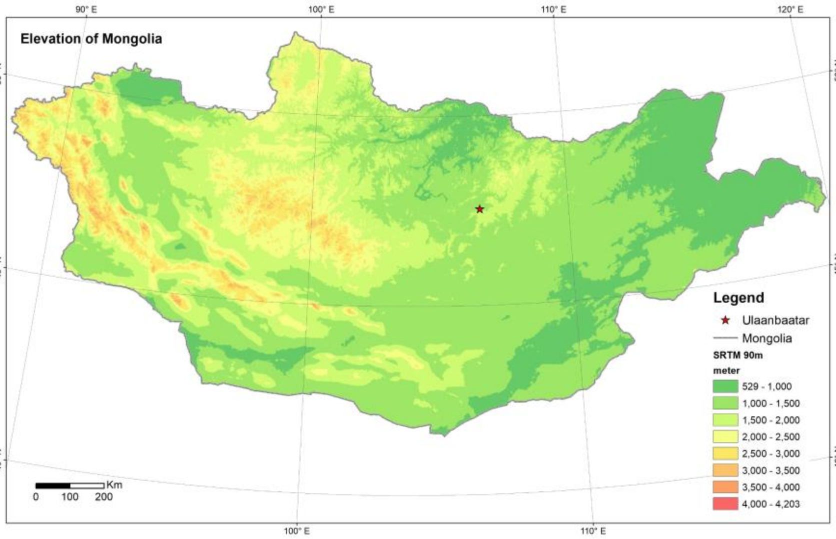

Fig. 1 Elevation distribution of Mongolia.

2.2 DATA

NDVI The NDVI products were from Terra Moderate Resolution Imaging Spectroradiometer (MODIS) Vegetation Indices Monthly (MOD13A3) Version 6.1 data between 2000 and 2018 (https://lpdaac.usgs.gov/products/mod13a3v061/). The MODIS NDVI products are computed from surface reflectance corrected for molecular scattering, ozone absorption, and aerosols and provides continuity for time series historical applications. We generated NDVI in peak growing season by averaging the MOD13A3 NDVI in June, July and August annually from 2000 to 2018.

Climate factors The climatic data used in this study include temperature, precipitation, maximum temperature and minimum temperature. All of the climate data were generated from CHELSA (Climatologies at high resolution for the earth's land surface areas) version 2 from https://chelsa-climate.org/. CHELSA is a global climate data set with very high resolution (30 arc sec, ~1km) based on a mechanistical statistical downscaling of global reanalysis data or global circulation model output (Karger et al., 2021). The monthly temperature, precipitation, maximum temperature and minimum temperature were downloaded and averaged in June, July and August during 2000 to 2018. Then, the pre-processed temperature and precipitation were used to perform partial correlation analysis with NDVI.

2.3 METHODS

2.3.1 Coefficient of Variation

The coefficient of variation (CV) is a statistical index that describes the ratio of a variable relative to its mean, and is regarded as a useful indicator of interannual variability in an ecosystem. Specifically, a lower CV value indicates a lower fluctuation and greater stability of the vegetation, while a higher CV value indicates less stable vegetation. The calculation is as follows:

$$CV = \frac{1}{\overline{x}}\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i-\overline{x})^2}$$

Where x_i is the value in year i. $\overline{x}$ is the average value from 2000 to 2018.

The stability of the interannual variation of the NDVI, temperature and precipitation in Mongolia were expressed using CV to indicate the fluctuation of NDVI per-pixel from 2000 to 2018.

2.3.2 Theil–Sen trend analysis and the Mann–Kendall test

The combination of the Theil–Sen trend analysis and the Mann–Kendall test does not require the data to follow a certain distribution when analysing trends over a time series.

Theil–Sen trend analysis is a very reliable non-parametric statistical calculation method that is computationally efficient, insensitive to measurement errors and outlier data, and is often used in the trend analysis of long time series. This is calculated as follows:

$$\beta = Median(\frac{x_j - x_i}{j-i})$$

where x_j and x_i are the values of a certain pixel in years j and i. $Median$ is the median of the requested series. The value of β represents the trend over the period, with negative, zero and positive meaning decreasing, stable and increasing trend.

The Mann–Kendall method is a non-parametric statistical test with an advantage not requiring normally distributed measurements or a linear trend and remains unaffected by missing values or outliers. It is widely used for the trend significance testing of long-series data (Bao et al., 2021).

2.3.3 partial correlation

The partial correlation coefficient reflects a more intrinsic correlation of the two variables by eliminating the influence of random variables on the correlation of these two variables. Partial correlation analysis can make the results precise and credible. The partial correlation method can be widely employed in investigating the relationship between vegetation and climate factors (You et al., 2021).

2.3.4 Residual analysis

The residual analysis method was used to analyse the impact of human activities on vegetation change. Based on 20 years of the GNDVI, temperature, and moist coefficient data, we establish the multiple linear regression model of vegetation and climatic factors through the least square method at pixel scale:

$$\hat{NDVI} = a \times Temperature + b \times \Pr ecipitation + \varepsilon$$

where $\hat{NDVI}$ is the calculated value of the NDVI, $Temperature$ is temperature, $\Pr ecipitation$ is precipitation, ε is the random error, a and b are regression coefficients. The calculated NDVI value was obtained through temperature and precipitation of each year. Then, the NDVI residual was obtained by calculating the difference between the calculated NDVI value and the original value. Finally, the NDVI residual trend was calculated using trend analysis method mentioned in section 2.3.2. Positive residuals represent the promotion effect of human activities on the vegetation.

3 RESULTS AND DISCUSSION

3.1 coefficient of variation of NDVI during 2000 to 2018

The coefficient of variation (CV) represents the relative fluctuation degree over a period for exploring the stability of vegetation. The high CV value means the high volatility of the vegetation, meaning the disturbance of vegetation is high. We calculated the CV of NDVI from 2000 to 2018 and divided the values into 5 levels (Ma et al., 2021) (Fig. 2). The value of CV between 0 and 0.05, 0.05 and 0.1, 0.10 and 0.15, 0.15 and 0.2, hiher than 0.2 represents low volatility, relatively low volatility, medium volatility, relatively high volatility, and high volatility, respectively. The NDVI fluctuated slightly in most areas of Mongolia, considering 97.9% of the pixels with a CV value is smaller than 0.1. The area of low volatility accounted for 45.8% and was mainly distributed in sourth part of Mongolia, especially in Gobi area. The area with relatively low volatility accounted for 52.1% and was mainly located in the north region of Mongolia. The area proportions of medium volatility and relatively high volatility in Mongolia were only 1.8% and 0.2%, and were mainly located in mountainous areas in Mongolia.

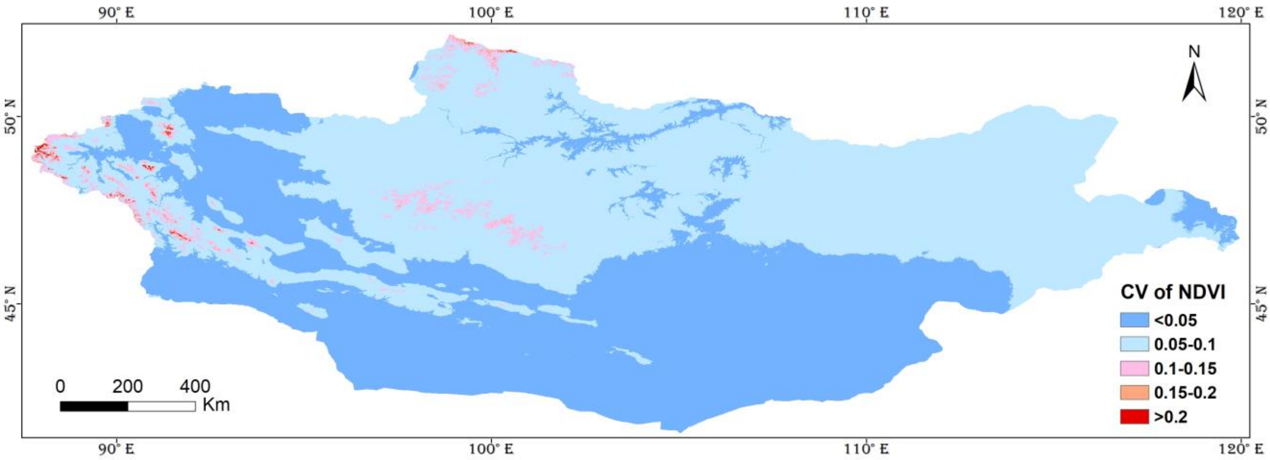

Fig. 2 The coefficient of variation (CV) of NDVI during 2000 to 2018 in Mongolia.

3.2 trend analysis of NDVI

Trend analysis of NDVI were performed pixel by pixel at a significance level of 0.05 (Fig. 3). statistically, significant positive and negative area account for 77.9% and 22.1%, respectively. Specifically, 13% of Mongolia is significantly greening ((p <0.01)) from 2000 to 2018. Spatially, pixels that show positive NDVI trends were located in the north and middle part of Mongolia, especially in forest. Pixels with significant negative NDVI trends were distributed in most part of Mongolia. Our result is similar with Meng et al (2020).

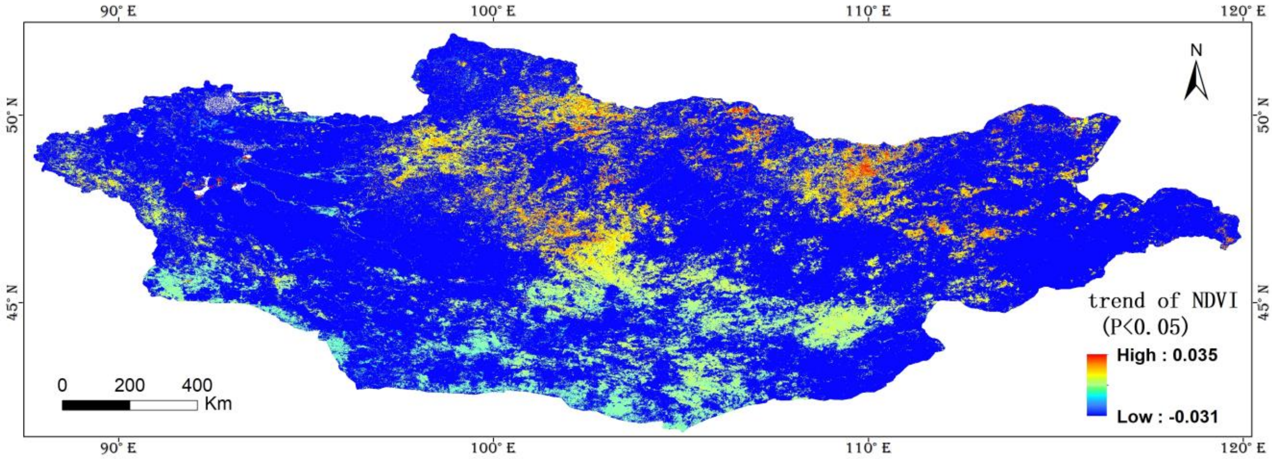

Fig. 3 The trend of NDVI during 2000 to 2018 in Mongolia.

3.3 partial correlation of NDVI with temperature and precipitation

Partial correlation analyses were conducted to reveal the roles of the comparable climate variables (temperature vs. precipitation) on the inter-annual variation of NDVI. NDVI was negatively correlated with temperature (controlling precipitation) in 86.7% of Mongolia (Fig. 4). NDVI was positively correlated with precipitation (controlling temperature) in 94.9% of Mongolia (Fig. 5). These results show the spatial pattern of vegetation response to the climate change spatially differs in the study area.

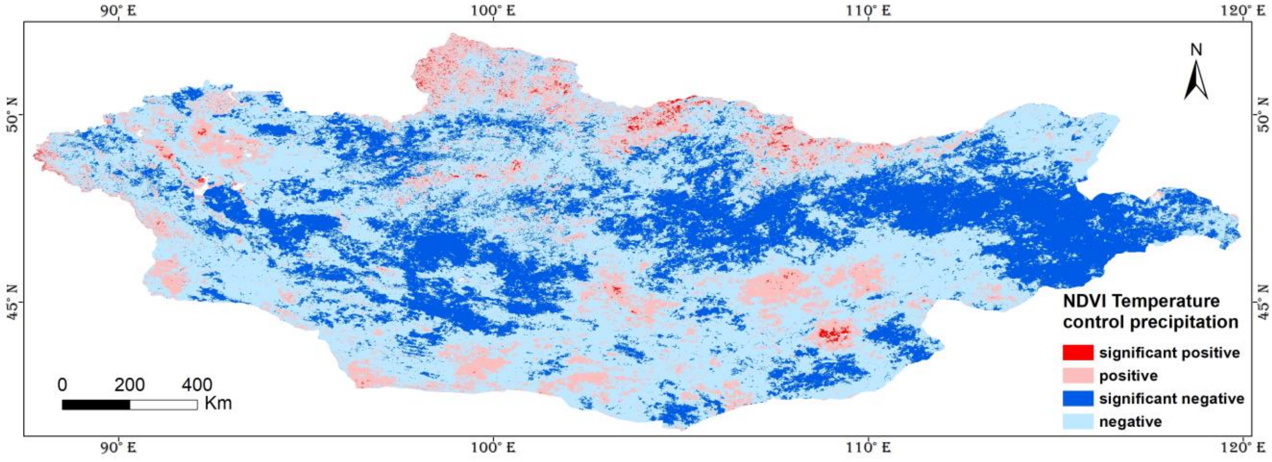

Fig. 4 Partial correlation analysis between NDVI and temperature (controlling precipitation) from 2000 to 2018 in Mongolia.

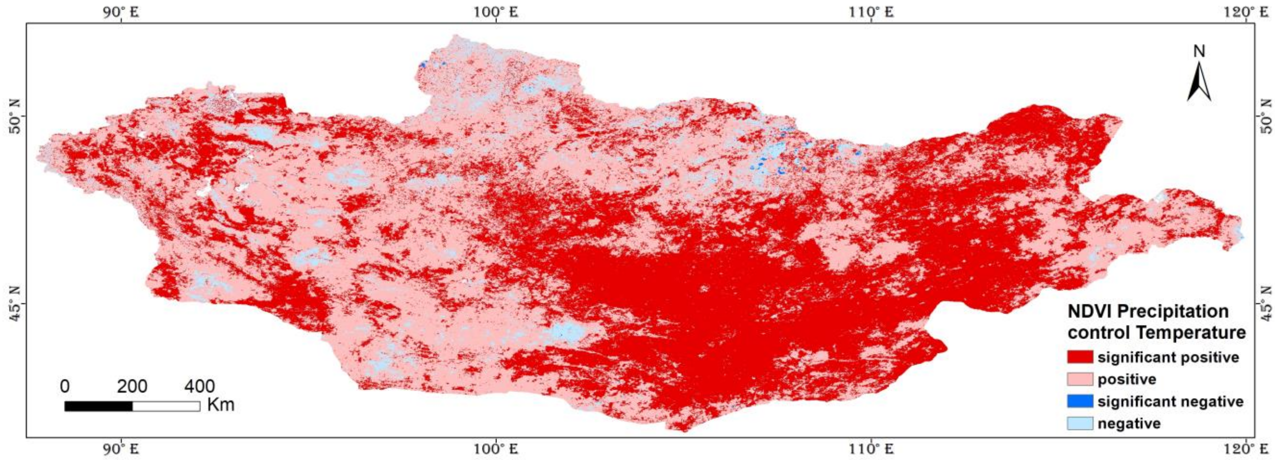

Fig. 5 Partial correlation analysis between NDVI and precipitation (controlling temperature) from 2000 to 2018 in Mongolia.

3.4 residual analysis of NDVI

The NVDI residual analysis in this paper showed the positive and negative trend of residual are 65.82% and 31.18% from 2000 to 2018 in Mongolia (Fig. 6). Spatially, the relatively high trend locates in forest region of Mongolia. The overall residual trend of the plateau was mainly positive, especially in the north of Mongolia, indicating that vegetation dynamic is driven by other factors besides temperature and precipitation. However, the NDVI residual trend remained negative around Ulaanbaatar and northeast region, where urban expansion might affect vegetation change. Therefore, appropriate policy should be made to prevent the further degradation of vegetation in these areas.

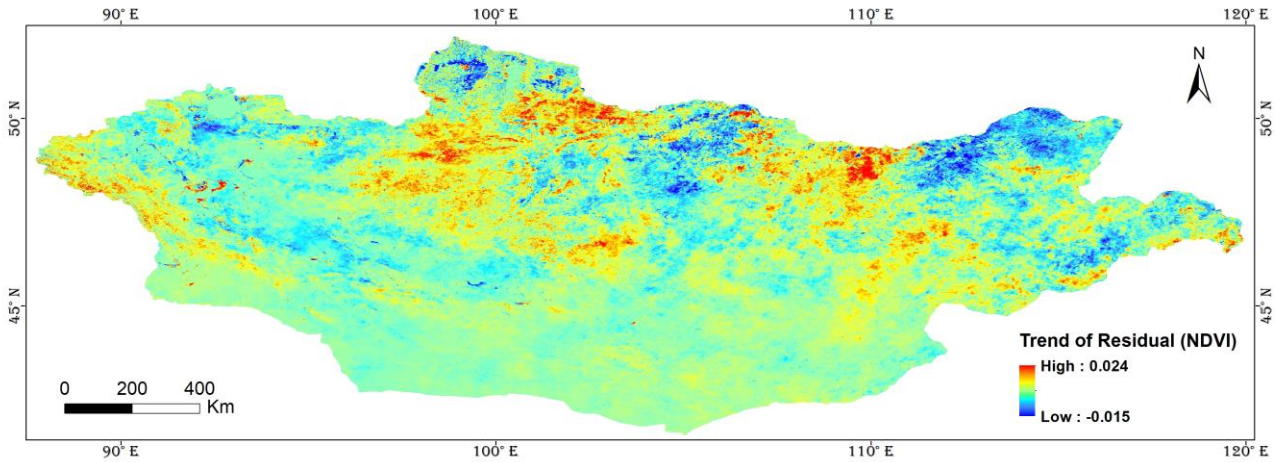

Fig. 6 Trend of NDVI residual from 2000 to 2018 in Mongolia.

4 CONCLUSIONS

We analysed the vegetation change and calculated the correlation between vegetation and climatic factors in Mongolia from 2000 to 2018. Theil–Sen trend analysis, Mann–Kendall method, the coefficient of variation method, partial correlation, and residual analysis method were used to analyse the spatiotemporal variability characteristics and sustained stability of the NDVI. The interannual variation of NDVI is stable in most area of Mongolia. The NDVI significant positive and negative area account for 77.9% and 22.1% ($p < 0.05$). Specifically, 13% of Mongolia is significantly greening (($p < 0.01$)) from 2000 to 2018. Considering the climate drivers of the NDVI in peak growing season, the partial correlation showed that NDVI was negatively correlated with temperature (controlling precipitation) in 86.7% of Mongolia while positively correlated with precipitation (controlling temperature) in 94.9% of Mongolia. The NVDI residual analysis in this paper showed the positive and negative trend of residual are 65.82% and 31.18% from 2000 to 2018 in Mongolia. In future, more factors should be considered to explore the dynamics of vegetation, e.g., soil moisture, soil texture, wind speed, solar radiance, livestock.

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