



Dynamic characteristics and driving factors of vegetation greenness under changing environments in Xinjiang, China

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Abstract

Global environment changes rapidly alter regional hydrothermal conditions, which undoubtedly affects the spatiotemporal dynamics of vegetation, especially in arid and semi-arid areas. However, identifying and quantifying the dynamic evolution and driving factors of vegetation greenness under the changing environment are still a challenge. In this study, gradual trend analysis was applied to calculate the overall spatiotemporal trend of the normalized difference vegetation index (NDVI) time series of Xinjiang province in China, the abrupt change analysis was used to detect the timing of breakpoint and trend shift, and two machine learning methods (boosted regression tree and random forest) were used to quantify the key factors of vegetation change and their relative contribution rate. The results have shown that vegetation has experienced overall recovery over the past 20 years in Xinjiang, and greenness increased at a rate of $17.83 \times 10^{-4} \text{ year}^{-1}$. Cropland, grassland, and sparse vegetation were the main biome types where vegetation restoration is happening. Nearly 10% of the pixels (about 166000 km²) were detected to have breakpoints from 2004 to 2016 of the monthly NDVI, and most of the breakpoints were concentrated in the ecotone of various biomes. CO₂ concentration was the most prevalent environmental factor to increase vegetation greenness, because continuous emission of CO₂ greatly enhanced the fertilization effect, further promoted vegetation growth. Besides, cropland expansion and desertification control were the vital anthropogenic factors to vegetation turning “green” in Xinjiang, and most areas under anthropogenic were mainly in oasis areas. These findings provide new insights and measures for the regional response strategies and terrestrial ecosystem protection.

Keywords Vegetation greenness · Abrupt change · Gradual change · Environmental factors · Land-use management · Xinjiang

Highlights

The Sen's and BFAST analysis were jointly used to explore the vegetation dynamics of various biomes in Xinjiang, China.

The growth rate of vegetation in Xinjiang accelerated significantly after 2010. In space, most of the breakpoint pixels concentrate in the ecotone of various biomes.

CO₂ fertilization effect was the primary driving factors of vegetation greening. Land-use management directly leads to the vegetation turn “green” around the oasis.

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Introduction

Vegetation plays an important role in regulating the carbon cycle and offsetting greenhouse gas emissions as an intermediate link between the hydrosphere, atmosphere, and lithosphere (Piao et al. 2019b). Accurate and efficient comprehensive investigation and evaluation of the spatiotemporal variations of vegetation in the regional and scales are essential for understanding the sustainability of terrestrial ecosystems, especially in areas extremely sensitive to environmental changes (Sun et al. 2015). However, alteration of land-atmosphere energy exchanges fluxes caused by global climate change is further affecting the growth of vegetation. Therefore, a comprehensive understanding of the vegetation evolution characteristics and its contributing factors in the context of climate change is of great significance for ecosystem protection, water resources management, and climate change adaptation strategies.

Under the background of global environment change, mechanisms and driving factors of vegetation dynamics have become of growing research interest. NDVI (normalized difference vegetation index) is one of the most prevalent indicators for quantitative assessing vegetation growth status, widely used in vegetation coverage monitoring and vegetation-climate correlation researches (Fensholt et al. 2012a, Kong et al. 2018). Recent observations has revealed widespread vegetation greening, especially in the middle and high latitude regions of the northern hemisphere (Zhu et al. 2016), among which the vegetation greenness in China (Du et al. 2019a), Europe, and North America (de Jong et al. 2011, Liu et al. 2015) has increased in varying degrees. In arid and semi-arid areas, the vegetation also showed a noticeable increasing trend (Fensholt et al. 2012b), such as savannah areas in Africa (Brandt et al. 2015) and Australia (Donohue et al. 2009). However, temperature and precipitation, the two primary important meteorological factors regulating the vegetation dynamic on the earth's surface, are not adequate to explain the phenomenon of turning “green” in the arid regions at global or local scale. This highlights the demands for thorough analysis of vegetation changes in the hydrothermal deficient areas.

Inter-annual and seasonal variations are descriptive indicators to evaluate the vegetation resilience to external disturbance and are of great significance for assessing the impact of climate change on vegetation (Ma et al. 2019a). At present, there are typically two approaches to quantify the spatiotemporal dynamics of vegetation greenness: gradual change analysis and abrupt change analysis. The gradual change can be estimated by the linear or Sen's trend, because the slope reflects the direction and rate of vegetation change over time. For the long-term trend of vegetation characteristics and its response to climate, gradual change analysis has a more intuitive description. However, in the growth process of vegetation, it is likely to experience various kinds of short-term

stresses, such as heatwaves, drought events, etc. (Marengo and Espinoza, 2016, Ummenhofer and Meehl, 2017). Information of abrupt changes induced by extreme weather events can be omitted by gradual change analysis of satellite time series (Pan et al. 2018). Moreover, the ecosystem is prone to undergone abrupt and drastic change when the interference of human activities, such as afforestation and coal mining, exceeds the threshold (Tong et al. 2018). Vegetation greenness trend can be easily interrupted by natural or artificial disturbance and then stagnated or reversed completely (de Jong et al. 2013). Therefore, gradual change analysis still has some shortcomings in analyzing vegetation indicator change characteristics in the long-term dataset. Based on this, it is crucial to effectively and accurately identify the abrupt change events in satellite time series (Verbesselt et al. 2010a). Segmentation algorithms detect breakpoints and estimate trends that can generalize vegetation dynamic characteristics, and among which are Detecting Breakpoints and Estimating Segments in Trend (DBEST) (Jamali et al. 2015), the Vegetation Change Tracker (VCT) (Huang et al. 2010), and Breaks For Additive Season and Trend (BFAST) (Verbesselt et al. 2010b). All these algorithms use linear or piecewise linear models to quantitatively measure vegetation's annual and seasonal changes. In particular, the BFAST algorithm can automatically analyze at per pixel level in time series dataset without the need of parameters turning; and for which reason, it has been widely applied in the classification of land use (Xu et al. 2020), accurate monitoring of forest interference (Wu et al. 2020), monitoring of breakpoint time, and detecting marks of flood and fire in recent years (Watts and Laffan, 2014). However, there is still a lack of understanding of vegetation greenness's abrupt change characteristics in the time series.

Besides, the dynamics of vegetation greenness is influenced by precipitation, solar radiation, and CO₂ (Piao et al. 2019a). Among them, the fertilization effect of CO₂ can stimulate the plant's photosynthetic capacity, expediting plants to produce more carbohydrates (Liu et al. 2016), promote leaf and stem growth (Donohue et al. 2013), and further enhance the carbon sequestration capacity and the canopy greenness of vegetation. Some studies have shown that CO₂ concentration is the dominant factor controlling global vegetation change (Ballantyne et al. 2012, Zhu et al. 2016). However, there has been limited amount of quantitative analysis on the contribution of CO₂ concentration to vegetation greenness, especially in arid areas with relatively low vegetation greenness. Moreover, human activities through land-use management will significantly change the vegetation greenness and coverage (Chen et al. 2019). For example, the rapid urbanization process can reduce the city's greenness and biomass at the initial stage, but the construction of parks and green belts will indirectly compensate for the loss of urban vegetation greenness after the city matures (Zhong et al. 2019). Recent studies

have shown that human-induced processes such as afforestation and intensive agriculture practices have also made a great contribution to the trend of vegetation turning “green” (Chen et al. 2019). The implementation of large-scale afforestation and other ecological engineering in China can directly increase the carbon storage of terrestrial ecosystems (Yue et al. 2021), while intensive agriculture can enable people to plant more crops on the same area of land. In particular, the expansion of cropland can serve as an indicator of the magnitude of anthropogenic disturbance in that agricultural activities can contribute to the increasing photosynthetic capacity reflected by spectral information from satellite images (Huang et al. 2018). Modern Resolution Imaging Spectroradiometer (MODIS) satellite observation dataset improves our ability to monitor spatial change of vegetation, which makes accurate evaluation at finer resolution possible. Therefore, a comprehensive analysis of the driving factors affecting the vegetation greenness and the quantification of their contribution is needed, which can provide suggestions for improving sustainability of ecosystems and the implementation of environmental management policies under the background of global climate change.

Xinjiang, located in the northwest of China and the center of Eurasia, plays an irreplaceable role in maintaining ecological security in China (Du et al. 2020). In recent years, the changing environments make the vegetation dynamics in Xinjiang increasingly unstable and unpredictable. Increasing temperature and moisture have changed the terrestrial ecosystem’s energy and water balance (Yao et al. 2020), and the evolving climate anomaly has changed the spatiotemporal pattern of vegetation in Xinjiang (Guli-Jiapaer et al. 2015). Some studies had explored the spatial-temporal variation of vegetation and climate parameters in Xinjiang and their relationship. For example, Guli et al. studied leaf area index of Xinjiang and revealed that the vegetation in this area had displayed obvious geographical differentiation and has been gradually recovering over the last decade and also found vegetation varies in biological communities and seasons (Guli-Jiapaer et al. 2015). Peng et al. found that precipitation is the main climatic factor affecting the seasonal variation of net primary productivity in Xinjiang (Peng et al. 2008). Du et al. claimed that hydrothermal conditions should be the primary control of vegetation growth in Xinjiang. NDVI was more sensitive to the thermal factors such as temperature and potential evapotranspiration in spring and autumn. At the same time, precipitation and humidity index was stronger in summer (Du et al. 2015). However, previous studies rarely discussed the impact of CO₂ fertilization effects and land-use management on vegetation dynamics in Xinjiang. There is lack of discussion on the controlling factors and relative contributions of environmental factors and human activities to vegetation greenness under the rapid climate change.

Based on this, this study intends to explore the spatiotemporal dynamics and driving factors of vegetation greenness change in Xinjiang by considering more comprehensive climate factors and different biome types, which not only provides a novel approach for the study of the vegetation-climate relationship in arid areas but also establishes an important basis for scientific assessment and response to climate change. This study’s main objectives are (1) to investigate the spatiotemporal evolution characteristics of vegetation greenness during 2000–2019 and (2) to explore the main driving factors that affect vegetation greenness and quantify their contribution.

Materials and methods

Overview of study area

The study area is located in the Xinjiang Uygur Autonomous Region of China, the center of Eurasia. Its unique geographical location has formed a regional unit of the diverse landscape consisting of mountain, oasis, and desert ecosystems. The two of the largest deserts in China (Taklimakan Desert and Gurbantunggut Desert) are inside Xinjiang. The main mountains are Altai Mountain in the north, Tianshan Mountain in the middle, and Kunlun Mountain in the south (Fig. 1a). The vegetation showed spatial heterogeneity in Xinjiang (Fig. 1b); the distribution of vegetation is characterized by higher density of vegetation in the West and Northwest and lower in the East and Southeast. Most of the areas with good vegetation growth are concentrated in Tianshan, Altai, Kunlun Mountains, and the oasis around Junggar Basin and Tarim Basin. Dominant vegetation types include herbs and small shrubs, which belong to a typical temperate desert with few species and low greenness. The climate characteristics belong to temperate continental arid and semi-arid climate, with annual sunshine of 2500–3500 h, an annual average temperature of 5–7 °C. The annual precipitation in most areas is less than 200 mm, more precipitation in the West than in the East, and more in the mountains than in plains and basins (Guli-Jiapaer et al. 2015). On the whole, the area is characterized by abundant photothermal resources, deficient precipitation, and strong evaporation. As a typical arid and semi-arid area, its ecosystem has low vegetation coverage, extremely sensitive to climate change and human activities.

Data introduction

Vegetation greenness datasets

NDVI has a linear or near-linear relationship with green leaf density, vegetation productivity, photosynthetic effective

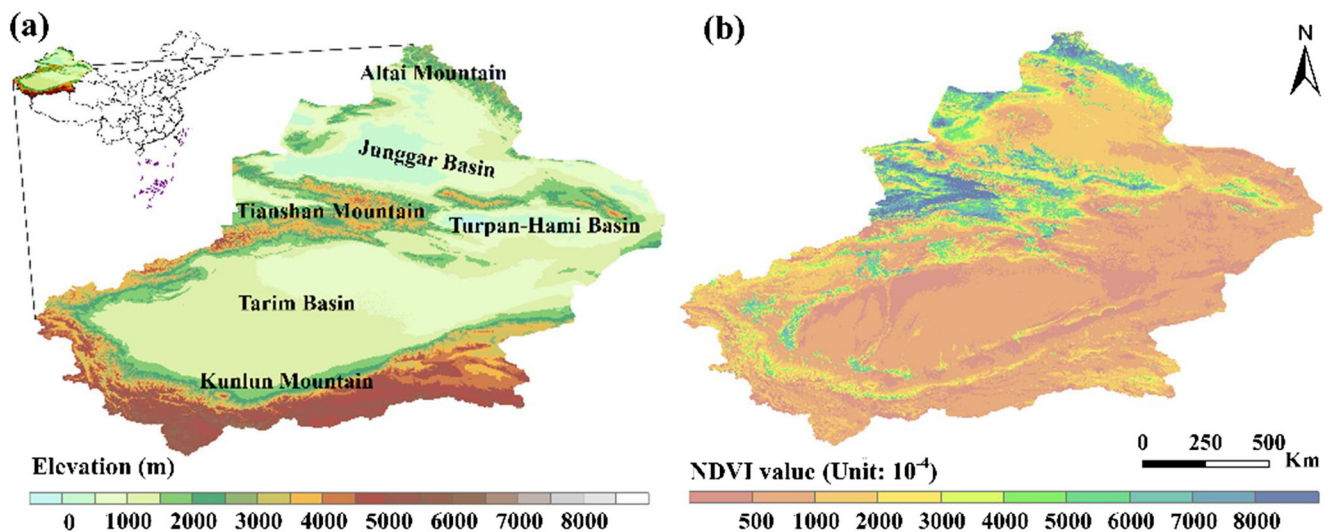


Fig. 1 The location of the study area. **a** Spatial distribution of elevation. The 30-m resolution digital elevation data was obtained from the Shuttle Radar Topography Mission dataset; **b** spatial distribution of vegetation

greenness. Value is the intercept of the MODIS NDVI during 2000–2019, representing the average value of vegetation greenness over the past 20 years.

radiation, and cumulative biomass, reflecting vegetation greenness and growth. The MODIS NDVI dataset for 2000–2019 was obtained from the MOD13A1 product from the NASA data distribution center, which is widely used in the study of global and regional vegetation change due to its moderate resolution (500 m) and low uncertainty (Novillo et al. 2019). Its original value range is –2000–10000, multiplied by the scale factor of 0.0001, and its value range is –0.2~1 after the calibration. Generally, the larger the NDVI value, the better the vegetation greenness and growth condition. In this study, to reduce the influence of cloud, atmosphere, solar elevation angle, and other uncertain factors, the maximum value composite (MVC) was used to generate annual NDVI maximum values (Holben 1986). The formula is as follows:

$$NDVI_{max} = \text{Max}(NDVI_t) \tag{1}$$

In this formula, $NDVI_{max}$ refers to the NDVI annual maximum corresponding each pixel during 2000–2019. Besides, to avoid the interference of non-vegetation information on the underlying surface to the vegetation NDVI, referring to the previous study of vegetation NDVI threshold (Zhang et al. 2017), the area with NDVI value greater than 0 is selected as the study area.

Climate datasets

Climate datasets such as temperature, precipitation, and radiation were collected from China Meteorological Forcing Dataset (CMFD) (He et al. 2020). The climate dataset from 1979 to 2018 has a time resolution of 3 h and a spatial resolution of 0.1 degrees. Previous studies have demonstrated that the climate dataset of CMFD coincides with the observed data. In this paper, we used gridded meteorological forcing variables (0.1 degree,

2000–2019) of precipitation rate (Prec), air temperature (Temp), and shortwave radiation (Radi) for further analysis.

CO₂ concentration scenarios

The CO₂ dataset is derived from the earth’s carbon dioxide concentration data observed at Mauna Kea Observatories in Hawaii, USA, which is the most frequently quoted CO₂ background dataset in the world. Its concentration change can be regarded as the trend of CO₂ emissions on the earth. By December 2019, the CO₂ concentration has reached 413.2 ppm, breaking the record (Supplementary Figure 1).

Land cover datasets

Global land cover product MCD12Q1, with a spatial resolution of 500 m, contains 6 types of land cover classification systems. In this study, the global vegetation classification scheme of IGBP (the International Geosphere-Biosphere Programme) was used for further analysis. The land-use types were reintegrated into 6 types of biomes: forest (FR), shrub (SS), grassland (GL), cropland (CL), urban areas (UB), and sparse vegetation (SV) (Fig. 2a).

In addition, MOD13A1 and MCD12Q1 datasets were initially processed and downloaded on Google Earth Engine (GEE) platform.

Methods

Detect the trend of time series

In this paper, the Manner-Kendall (M-K) nonparametric test method was used to calculate the trend of NDVI, climate

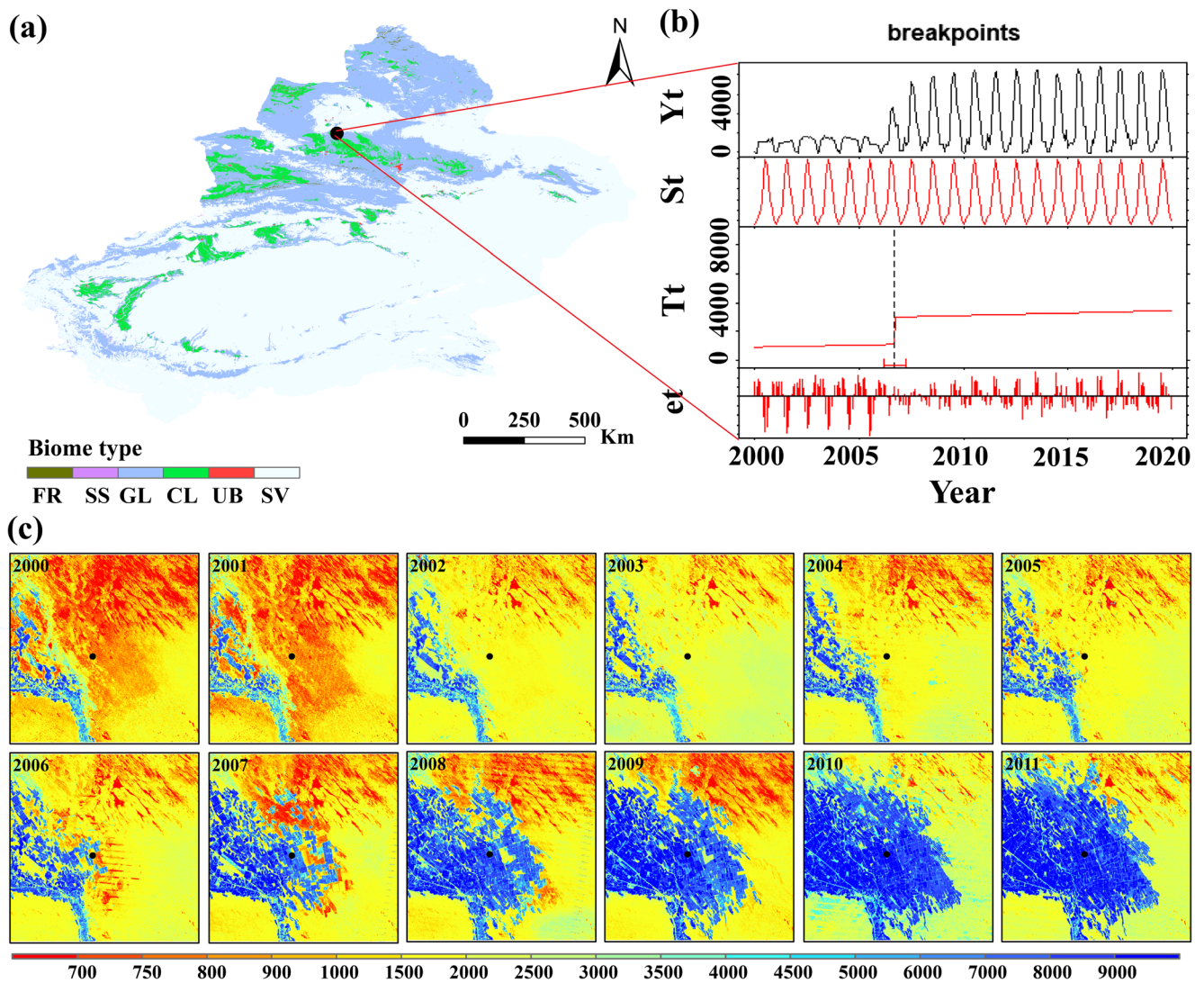


Fig. 2 A case study verifies the effectiveness of the BFAST algorithm for monitoring the breakpoint on the time series. **(a)** Classification of biome types in Xinjiang. FR, SS, GL, CL, UB, and SV represent forests, shrub, grassland, cropland, urban areas, and sparse vegetation. The black spots in the map represent the pixels selected to verify the effectiveness of the BFAST algorithm. **(b)** BFAST algorithm to decompose the three variables in the time series, and Y_t represents the trend of vegetation

during 2000–2019. S_t represents the seasonal component by the representative. Tt represents the breakpoint (abrupt change) caused by the BFAST algorithm; **(c)** the BFAST algorithm detected the Landsat NDVI on the breakpoint pixel, which is gradually encroached cropland with high greenness from the bare land with very low greenness. The GEE platform processes the Landsat NDVI value, and the cloud interference is removed to generate the annual maximum NDVI value.

variables, and land-use probability over time (Kendall and Gibbons, 1990). Suppose there are n years of time series (x_1, \dots, x_n), for all $k, j \leq n$, and $k \neq j$ and the distribution of x_j and x_k is different, calculate the test statistic S ; the formula is as follows:

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^n \text{Sgn}(x_j - x_k) \tag{2}$$

$$\text{Sgn}(x_j - x_k) = \begin{cases} +1 & (x_j - x_k) > 0 \\ 0 & (x_j - x_k) = 0 \\ -1 & (x_j - x_k) < 0 \end{cases} \tag{3}$$

S is a normal distribution with a mean value of 0, variance (S) = $n(n-1)(2n+5)/18$. When $n > 10$, the standard normal

statistical variables are calculated by the following formula:

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}} & S > 0 \\ \frac{S-1}{\sqrt{\text{Var}(S)}} & S < 0 \end{cases} \tag{4}$$

In this formula, when $Z > 0$, the trend is increased; otherwise, it decreases.

The Sen’s slope estimation is the method of selecting the sampling points (simple linear regression) to fit the line to the plane iteratively through the median value of the slope of all points of the pair points. This method can well reflect the change range of the series trend, and the formula of Sen’s

slope is as follows:

$$\text{Slope} = \text{median}(\theta_i) \tag{5}$$

$$\theta_i = \frac{x_j - x_k}{j - k} \tag{6}$$

In this formula, i is the constant and the value is $(1, 2, \dots, n)$; n is the length of time series; x_j and x_k are the sequences of j and k , respectively, and $j > k$.

Detection of breakpoint and shift in time series dataset

The BFAST algorithm decomposes the original time series into three parts: long-term trend, seasonal phenology, and residual components by iterative time series decomposition method (Fig. 2b). This algorithm can be directly applied to the original satellite time series, without additional calibration, and does not need to set threshold and pre-define the prior phenological track (Verbesselt et al. 2012). Meanwhile, BFAST also integrates the phenological harmonic model, which can effectively handle less sample data, and has higher accuracy when monitoring vegetation abrupt changes at the pixel level (Verbesselt et al. 2010a). As shown in Fig. 2b, the BFAST algorithm is sensitive to monitoring the abrupt change of MODIS NDVI in the time series due to cropland’s reclamation. And Landsat NDVI, as a validation dataset, also found that the vegetation greenness in 2006 suddenly increased (Fig. 2c).

$$Y_t = S_t + T_t + e_t (t = 1, \dots, n) \tag{7}$$

In this formula, Y_t is the observation data at t time. S_t , T_t , and e_t represent the seasonal phenology, the long-term trend, and the residual of the whole time series, respectively. T is the observation time, and n represents the length of the time series.

Suppose there is p breakpoint $(\tau_1^\#, \dots, \tau_p^\#)$, which defines the $\tau_1^\# = 0, \tau_{p+1}^\# = n$. The fitted seasonal harmonic model S_t is expressed as follows:

$$S_t = \sum_{k=1}^k a_{j,k} \sin\left(\frac{2\pi kt}{f} + \delta_{j,k}\right) \tag{8}$$

$$\left(\tau_{j-1}^\# < t < \tau_{j-1}^\#, j = 1, \dots, p\right) \tag{9}$$

In this formula, j is the breakpoint location, the value is $1 \sim p$, p is the number of breakpoints, and k is the number of harmonic items. $a_{j,k}$, $\delta_{j,k}$, and f respectively represent amplitude, phase, and frequency of a segment.

Suppose there are p breakpoints $(\tau_1^\#, \dots, \tau_p^\#)$, the time series is divided into $p+1$ intervals. T_t is a piecewise linear combination of all time intervals, which is directly related to the slope of each interval, and then T_t can be expressed as follows:

$$T_t = \alpha_i + \beta_i t \left(\tau_{j-1}^\# < t < \tau_j^\#\right) \tag{10}$$

In this formula, $i = 1, \dots, p, \tau_1^\# = 0, \tau_{p+1}^\# = n, \alpha_i$, and $\beta_i t$ represent the constants and trends of the piecewise linear trend model, respectively.

In the BFAST decomposition algorithm application process, it is necessary to determine the specific time, the number of breakpoints, and other parameters. Due to the interference of natural disasters, human activities, or sensor errors, it is possible to miscalculate the breakpoint of satellite time series. How to precisely detect and distinguish these abrupt points from seasonal phenology and trends is a challenge. Verbesselt et al. solved this problem using the ordinary least squares residual-based moving sum. They used the Bayesian information criteria to determine the optimal number of breakpoints (Verbesselt et al. 2010b).

In this paper, to detect the NDVI major breakpoint of the time series, we applied the BFAST method by “bfast01” function in R to detect the most important breakpoints at a per-pixel level during 2000–2019 and further determine the position and time of the breakpoint. In addition, the breakpoint types of vegetation were divided into 6 categories according to the previous studies (de Jong et al. 2013) (Supplementary Figure 2).

Identification of influence factors and their relative contribution to NDVI dynamics

In this study, to analyze the impact of different factors on vegetation, we preprocessed the dataset as follows:

First, considering the spatial resolution mismatch between climate datasets and NDVI, we resampled NDVI to 0.1 degrees. It is noteworthy that the CO₂ concentration in the atmosphere is uniform for per pixel, and the increase is consistent. Thus, we generate the grid dataset of CO₂ concentration based on Hawaii observatory at the 0.1° resolution as a replacement for Xinjiang’s CO₂ dataset.

Second, to analyze the impact of human activities on vegetation dynamics, we calculated the transfer matrix between land use in 2001 and 2018. Considering that MODIS land classification has a resolution of 500 m, while other environmental driving factors as 0.1 degree resolution (about 11 km). Therefore, we build a grid of 0.1° and count the probability of 500 m MODIS pixels falling on the grid of 0.1° for each land-use types (2001–2018). We then, selected all datasets in our study area (Xinjiang) and study period (annual, 2001–2018) for further analysis.

Boosted regression tree (BRT) is self-learning and nonlinear regression algorithm based on classification and regression tree algorithm, which combines regression characteristics and boosting model (Elith et al. 2008). The advantage of BRT is that it has great flexibility in dealing with different data formats, can improve the model’s stability and predictability, and improve the accuracy of the model. Moreover, BRT analysis

can reveal the contributing factors and the relative contribution of each independent variables (Ma et al. 2017). In this study, BRT was used to analyze and evaluate the relative contribution of driving factors to NDVI dynamics at per-pixel level in Xinjiang. In addition, the random forest (RF) method was used to verify the reliability of the BRT method. When deploying machine learning algorithms (BRT and RF), we first take MODIS NDVI of annual time series as dependent variables and take temperature, precipitation, radiation, CO₂ concentration, cropland probability, and spare vegetation probability of annual time series as independent variables. Then, we applied “gbm” and “randomForest” package of R software to calculate the order of influence factors (annual climate factors, land-use changes, and CO₂) and their relative contribution to NDVI dynamics.

Results

Temporal and spatial characteristics of vegetation greenness

The annual maximum value of NDVI for 2000–2019 was taken as the representative of vegetation greenness for each year, and the annual trend of NDVI was plotted (Fig. 3). NDVI value fluctuated between 0.17 and 0.21 in Xinjiang, the minimum year appeared in 2001, and the maximum year appeared in 2017. From 2000 to 2009, the overall is slightly more positive than neutral, while the growth rate of NDVI during 2010–2019 was obviously higher than that before 2010.

Vegetation greenness showed a predominantly increasing trend across the entire Xinjiang. The pixels with trend > 0 accounted for 90.63%, and the pixels with trend > 20 and trend > 40 accounted for 22.43% and 10.69% of the areas,

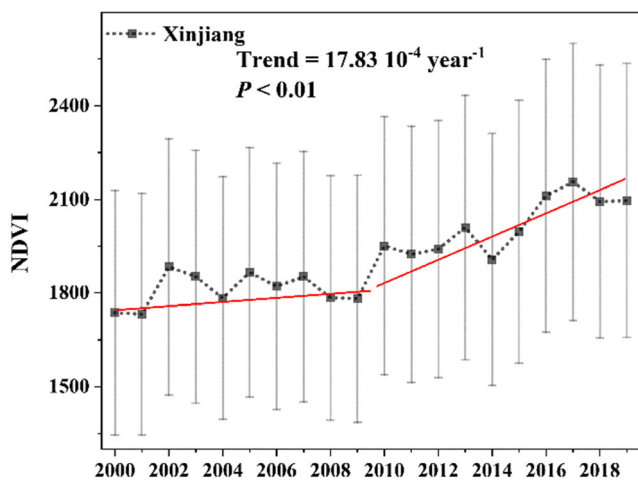


Fig. 3 Interannual variability of vegetation greenness in Xinjiang during 2000–2019. The black point represents the annual maximum vegetation greenness of the MODIS NDVI dataset, and the standard deviation of vegetation greenness per year (± 5) is given

respectively (Fig. 4). More than 50% of the pixels showed a significant increase, while only 1.19% of the areas showed a significant decrease. During 2000–2019, the area with a significant increase in Xinjiang vegetation was mainly the northern base of the Tianshan Mountains and the edge of Tarim Basin. The areas with a decrease in vegetation were randomly scattered in Xinjiang. In particular, it could be noticed that the pixel of increased vegetation is mainly found in the oasis, which was obviously consistent with the pixel of cropland. Moreover, pixels with minor change magnitude were mainly distributed in the areas with a sparse population and harsh condition. For each biome, the biome with a maximum growth rate is cropland at $91.28 \times 10^{-4} \text{ year}^{-1}$, the biome with a minimum growth rate is forest at $4.24 \times 10^{-4} \text{ year}^{-1}$, and the averaged growth rates of shrub, grassland, and sparse vegetation were 40.59, 31.12, and $8.63 \times 10^{-4} \text{ year}^{-1}$, respectively (Fig. 5).

Shift and timing in trends of NDVI time series

It can be clearly seen from Fig. 6 that the pixels with breakpoint account for 9.11% in vegetation time series over the Xinjiang areas, and most of the pixels has not been detected with abrupt change in the past 20 years. Increase to increase, monotonic increase, and decrease to increase were the relatively dominant breakpoint types, accounting for 2.92%, 2.20%, and 1.61% of all pixels in Xinjiang, respectively. From the perspective of space, most of the abrupt change pixels were concentrated in the ecotone of the oasis, grassland, and desert, such as the Tarim Basin and the alluvial plain in Northern Xinjiang.

The BFAST algorithm detected the significant breakpoints in 2003–2016 based on MODIS NDVI dataset, most of which are concentrated in 2010 and 2016 (Fig. 7a). The cumulative number of pixels with detectable breakpoints in each year showed a gradually increasing trend, and for each biome, it also displayed a gradual increase trend (Fig. 7b). The proportion of SV pixels with breakpoint was much higher than that of other types; the most important breakpoint type in SV was “increase to decrease” (Table 1). Besides, GL and CL also have relatively more breakpoint pixels.

1–6 represents different types of the breakpoint, refer to Fig. 6a

In a broad view, the growth rate of vegetation is likely to accelerate after the breakpoint. Before the breakpoint, the vegetation in Xinjiang increased at an overall rate of $1.36 \times 10^{-4} \text{ month}^{-1}$, while after the breakpoint, the growth rate increased to $1.87 \times 10^{-4} \text{ month}^{-1}$ (Fig. 8). Moreover, the spatial pattern of change direction is different before and after the breakpoint. Before the breakpoint, the edge of Tarim Basin and most northern Xinjiang areas showed an obvious positive trend. After the breakpoint, the vegetation greenness in southern Tarim Basin and eastern Xinjiang showed a negative trend. Most of the biomes in Xinjiang showed a consistent direction

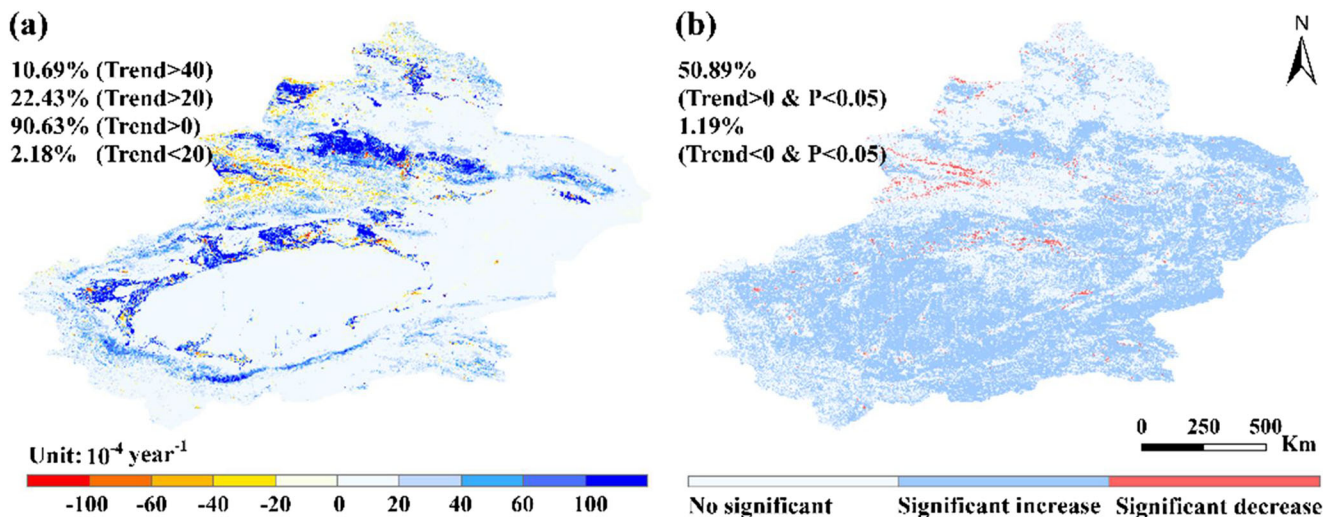


Fig. 4 Spatial distribution of vegetation greenness trend during 2000–2019. a Change direction and magnitude; b pixels with significant increase and decrease

of change (Fig. 9). In particular, SV decreased from $0.47 \cdot 10^{-4}$ month⁻¹ before breakpoint to $0.07 \cdot 10^{-4}$ month⁻¹ after the breakpoint.

Impact of influence factors on NDVI dynamics

The climate had shown a complex and divergent trend on the Xinjiang (Fig. 10). The precipitation increased significantly mainly in the southwest and north of Xinjiang while decreased in the Tianshan Mountains and the East (Fig. 10a). The temperature was relatively high in the northeast of Xinjiang;

however, it decreased significantly in the middle of Xinjiang (Fig. 10b). The significant increase of solar radiation is mainly in Xinjiang’s central region, and the spatial differentiation is not obvious (Fig. 10c). On the whole, the climate was an important factor affecting vegetation dynamics, but the main climate factors (such as temperature, precipitation, and radiation) were difficult to explain the vegetation greening trend on the Xinjiang.

We further analyzed the impact of human activities on vegetation dynamics (Fig. 11). Using the land-use transfer matrix, we found that the change of land use from GL and

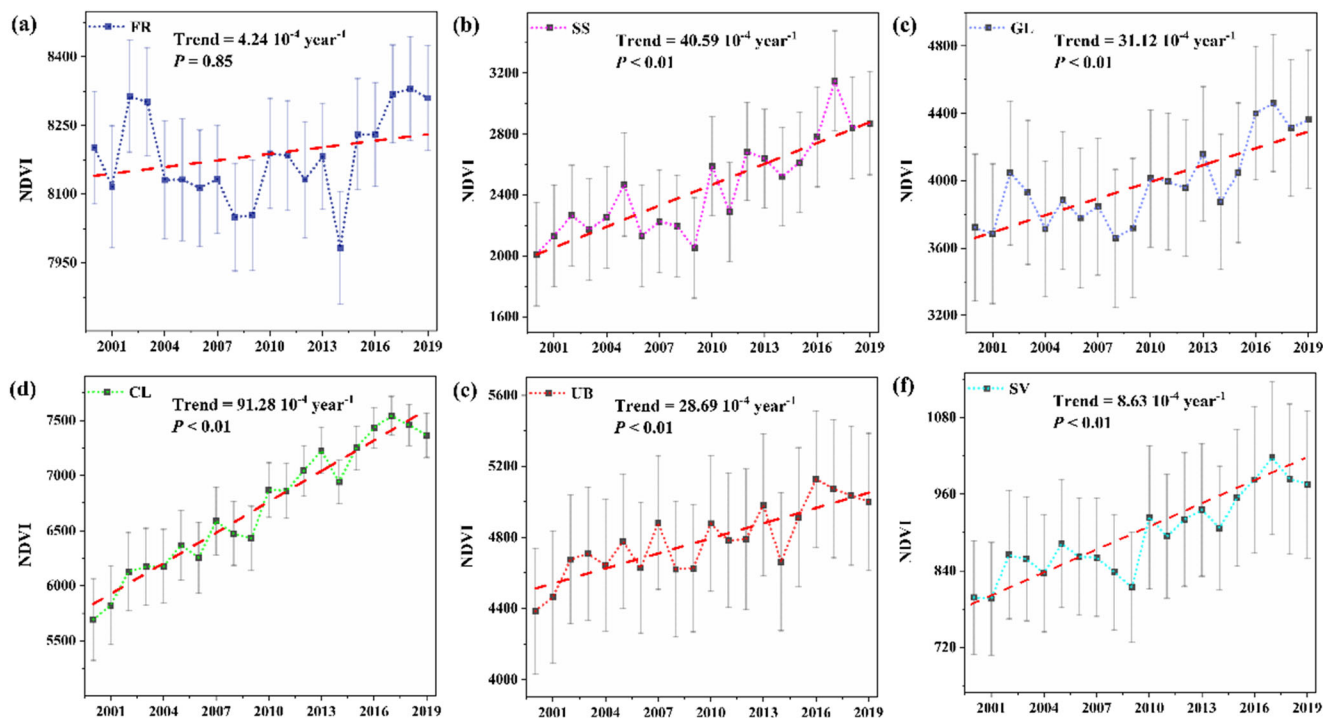


Fig. 5 Interannual variation trends of vegetation greenness in each biome type. The standard error shown was divided by 5. FR, SS, GL, CL, UB, and SV represent forests, shrub, grassland, cropland, urban areas, and sparse vegetation

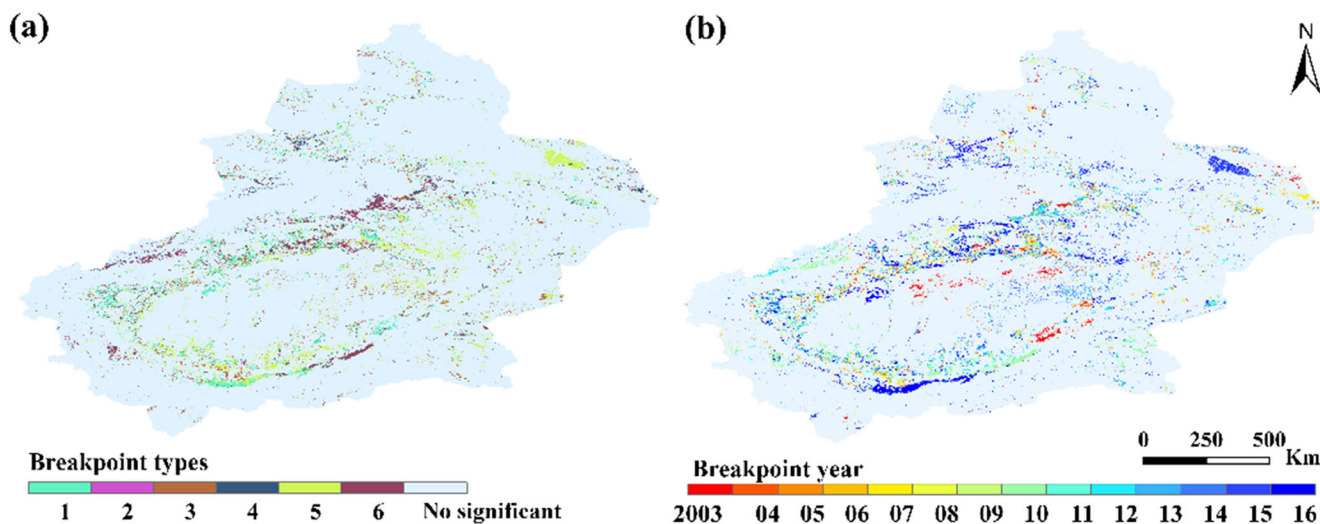


Fig. 6 Spatial distribution of breakpoints in monthly time series during 2000–2019, **(a)** the vegetation breakpoint type; **(b)** the vegetation breakpoint year. 1–6 represent 6 types of breakpoints, and type 1 is a monotonic increase, type 2 is monotonic decrease, type 3 is increased

with a negative break, type 4 decreases with a positive break, type 5 is increased to decrease, and type 6 is decrease to increase (Supplementary Figure 1). Only pixels with significant breakpoints were shown

SV to CL was relatively dominant (Fig. 11a); that is, the pixels classified as cropland in each oasis in 2018 increased significantly compared with in 2001, which was closely related to the increase of cultivated land due to the implementation of land development policy in oasis area of Xinjiang. We also found that the most significant land-use change in Xinjiang is “SV to GL,” from spare vegetation and desert in 2001 to grassland in 2018. This change was mainly concentrated in the southern edge of the Gurbantunggut Desert in Northern Xinjiang and around the oases in southern Xinjiang (Fig. 11a), which means that the vegetation coverage in this area gradually changes from the original sparse vegetation to grassland or cropland. As shown in Fig. 11b, the proportion of cropland in Xinjiang has increased year by year, and sparse vegetation has gradually decreased. Therefore, we realized that the main human activities affecting Xinjiang’s vegetation dynamics are the cropland expansion and desertification control. Then, we found that the cropland in Xinjiang increased rapidly in space from 2001 to 2018, especially in the main oases of northern and southern Xinjiang (Fig. 11c). The degree of desertification

in most Xinjiang areas has decreased, especially in the southern edge of the Gurbantunggut Desert and around the Taklimakan Desert (Fig. 11d). On the whole, human activities have a profound impact on vegetation dynamics in Xinjiang. The increase of cultivated land transforms previous grassland or wasteland with low greenness to cropland with high greenness. Meanwhile, desertification replaces makes the original low greenness barren by newly planted grassland and cropland. In conclusion, the cropland expansion and desertification control by human activities have greatly promoted the raise of vegetation greenness on the Xinjiang.

Besides, to further analyze the environmental and human factors that impact Xinjiang’s vegetation dynamics, we used two machine learning methods to explore the key drivers. We found that the results of boosted regression tree and random forest methods were similar (Fig. 12). CO₂ concentration was the most important controlling factor affecting vegetation greenness at the spatial scale, accounting for 73% of the total pixel in Xinjiang (Fig. 12 a and c). The most important environmental factors’ relative contribution rate was heterogeneous in spatial terms (Fig. 12 b and d). In areas with sparse vegetation (such as Tarim Basin and Turpan-Hami Basin), the relative contribution rate was more than 50%, while in Tianshan Mountains and oases, the contribution rate of CO₂ concentration was mostly between 30 and 50%. Climate factors (such as temperature, precipitation, and radiation) were also important factors affecting Xinjiang’s vegetation dynamics, especially in the Tianshan Mountains and oases areas. Cropland expansion and desertification control were the most important control factors of the area which are mainly distributed near oases or deeply affected by human activities. Therefore, we can conclude that the rising CO₂ concentration may be the main driving factor for raising vegetation

Table 1 The proportion of breakpoint pixels in different biome types accounts for the proportion of the total pixels

| | Type 1 | Type 2 | Type 3 | Type 4 | Type 5 | Type 6 |
|----|--------|--------|--------|--------|--------|--------|
| FR | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| SS | 0.04 | 0.00 | 0.01 | 0.01 | 0.01 | 0.05 |
| GL | 10.03 | 0.07 | 3.93 | 3.09 | 5.27 | 8.74 |
| CL | 3.62 | 0.00 | 1.34 | 0.17 | 1.02 | 1.11 |
| UB | 0.07 | 0.01 | 0.12 | 0.01 | 0.08 | 0.09 |
| SV | 10.57 | 0.23 | 11.58 | 5.33 | 25.65 | 7.76 |

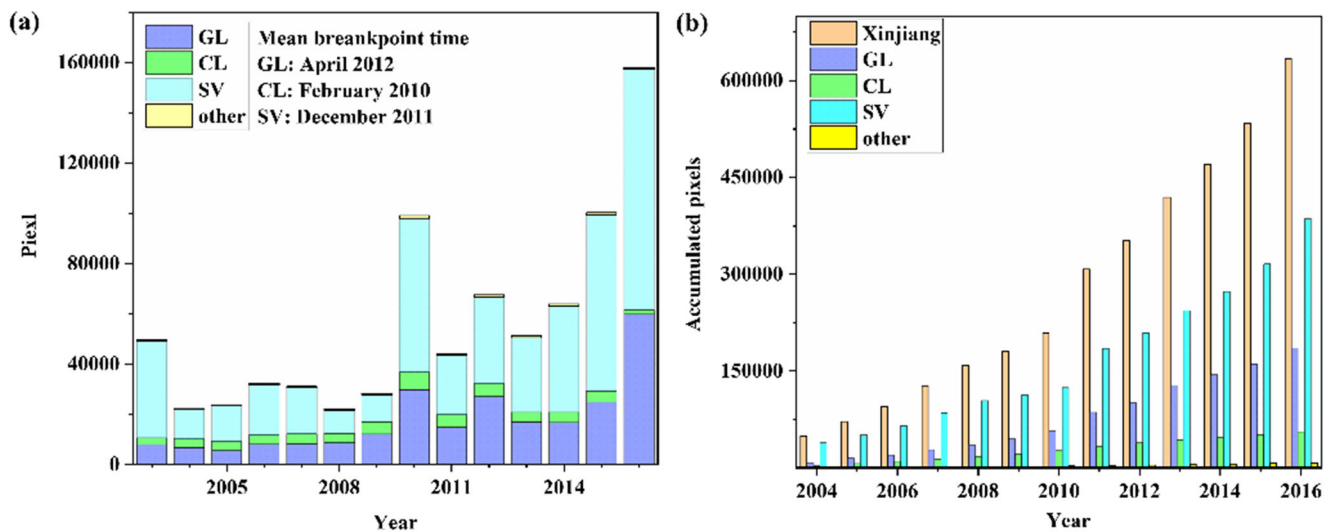


Fig. 7 The year of vegetation breakpoint in each biome. **a** The number of breakpoints per year and **b** the accumulated breakpoints

greenness in most deserts in Xinjiang, while climate change and land-use change are the main influencing factors affecting the oasis greenness.

Discussion

Spatiotemporal patterns of vegetation greenness in Xinjiang over the past 20 years

Using the MODIS sensor, we studied the vegetation dataset during 2000–2019, analyzed, and discussed the rate, spatial pattern, and weigh of control factors of vegetation greening in Xinjiang. Our results showed that Xinjiang’s vegetation greenness increased during 2000–2019, similar to previous studies (Du et al. 2015, Guli-Jiapaer et al. 2015, Peng et al.

2008, Xu et al. 2015, Zhuang et al. 2020). The spatial heterogeneity of vegetation greenness in Xinjiang is relatively strong, with the obvious increase mainly concentrated in the vicinity of oases, the browning trend mainly concentrated in the agro-pastoral ecotone, the desert edge, and the interior of Tianshan Mountains. In the past 20 years, vegetation has turned green widely in Xinjiang, with 91% of the area showing increases, while only 9% showing browning trend. Meanwhile, the raise of vegetation greenness in Xinjiang is mainly due to the increase of cropland, grassland, and sparse vegetation. Among them, the greening trend of the oasis is more obvious than other areas (Guli-Jiapaer et al. 2015). Cropland is the main vegetation type in the oasis zone, which is deeply influenced by human activities (Yang et al. 2019) and has unique interannual characteristics compared with other biome types in natural habitats. The dynamics of cropland

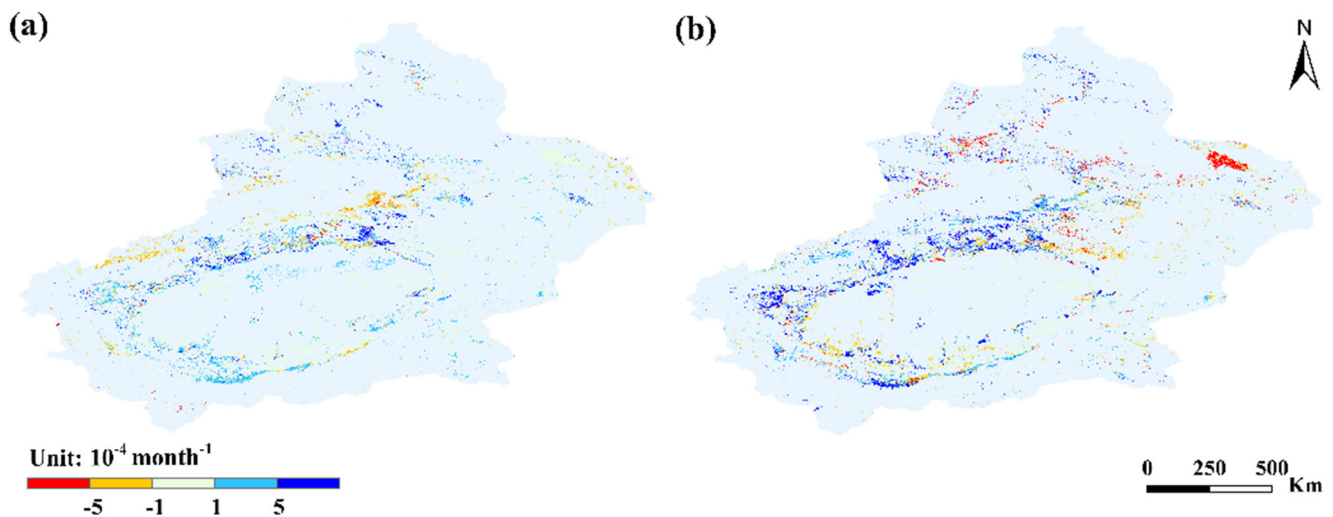


Fig. 8 Spatial distribution of trend before and after vegetation the breakpoint. **a** The trend before breakpoint and **b** trend after breakpoint. Only statistically significant pixels were counted

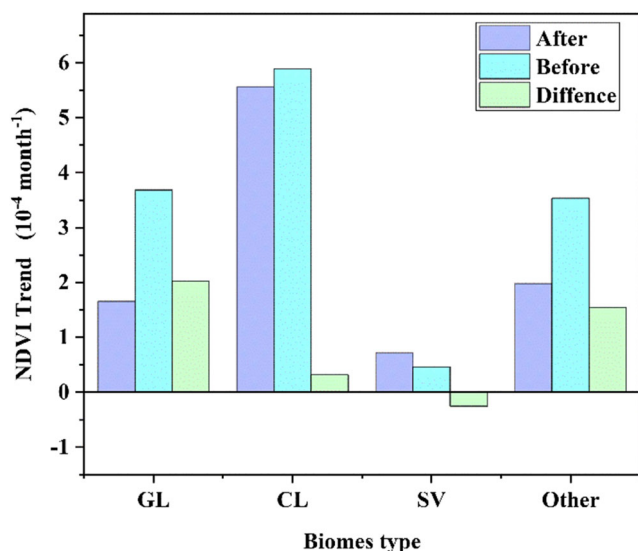


Fig. 9 The changing trend of NDVI dataset in time series before and after breakpoint at the biome level. Before represents the changing trend before the vegetation breakpoint, after represents the changing trend after the vegetation breakpoint, and the difference represents the trend of after minus before

greenness from 2000 to 2019 remained stable and continuously increased (Fig. 5d), which may be related to the progress of cropland management measures (Du et al. 2015).

The vegetation dataset detected by the BFAST algorithm has undergone an abrupt change in time series during 2004–2016. The breakpoint type and breakpoint time are spatially distributed with large dispersion and elusion sign of aggregation, which indicated that causes of the abrupt change of vegetation greenness had great spatial-temporal variations. Most of the breakpoint pixels are concentrated in the ecotone zone of sparse vegetation, grassland, and cropland, fragile and easily disturbed (Amuti and Luo, 2014). There are sophisticated and multiple reasons for vegetation abrupt change in Xinjiang's ecotone, including succession and abrupt change under strong disturbance. For example, the oasis expansion is an important reason for vegetation breakpoint (Bai et al. 2014). Precision irrigation succeeded the sparse vegetation with very low greenness by cropland (Fig. 2c), which to a

large extent leads to the fact that mosaic area of multiple biome types is prone to the abrupt change of vegetation pixel. Many oases in Xinjiang are still threatened by desertification. The desertification process is likely to reverse the vegetation type of natural grassland to sparse vegetation, leading to abrupt points detected in the ecotone zone of vegetation time series (Zhang et al. 2018). In addition, the latest report found that the melting rate of glaciers and snow in the Tianshan Mountains in Xinjiang has been accelerating during the past 20 years (Deng et al. 2019). Most of the glaciers and snow lost in the mountains have infiltrated into the downstream soil and end up refilling groundwater (Du et al. 2019b). Increasing water potential of soil enhances the ability of herbs and small shrubs to thrive in deserts and grasslands. It considerably increases vegetation coverage and biomass (Zhang et al. 2012), which may also be an important reason for the abrupt change of pixels in the agro-pastoral ecotone.

Before 2010, vegetation, on the whole, showed a negligible trend of increase, but after 2010, the growth rate of vegetation was obviously faster than the previous period. It should be mentioned that the trend of grassland and sparse vegetation before and after 2010 is significantly different (Fig. 5c and f). Similar to the gradual analysis, the breakpoint algorithm also detects that 2010 is the year with the most breakpoint pixels, and 2010 is an important time node (Fig. 7a). Climate change and human activities may jointly lead to the change characteristics of vegetation in Xinjiang. On the one hand, climate change can have a profound impact on vegetation in Xinjiang. Land degradation caused by the destruction of grassland and sparse vegetation by human activities before 2010 largely offset the increase of vegetation greenness induced by climate change (Yang et al. 2017), while the overall warming and moisturization of Northwest China after 2010 has a positive impact on vegetation greenness (Li et al. 2011, Zhuang et al. 2020). On the other hand, afforestation, grazing prohibition, and other ecological restoration projects are important driving forces for vegetation recovery (Lu et al. 2018, Niu et al. 2019). The restoration effect of ecological project in the early stage of implementation is limited by plant traits (low survival rate of trees, small leaf area of seedlings, etc.), so

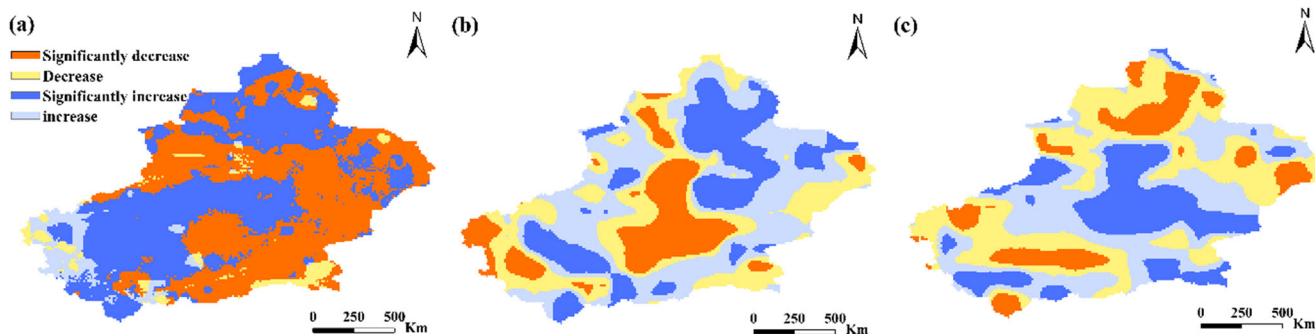


Fig. 10 Spatial variation of climate factors in Xinjiang during 2001–2018. **a** Prec, precipitation rate; **b** Temp, air temperature; **c** Radi, downward shortwave radiation

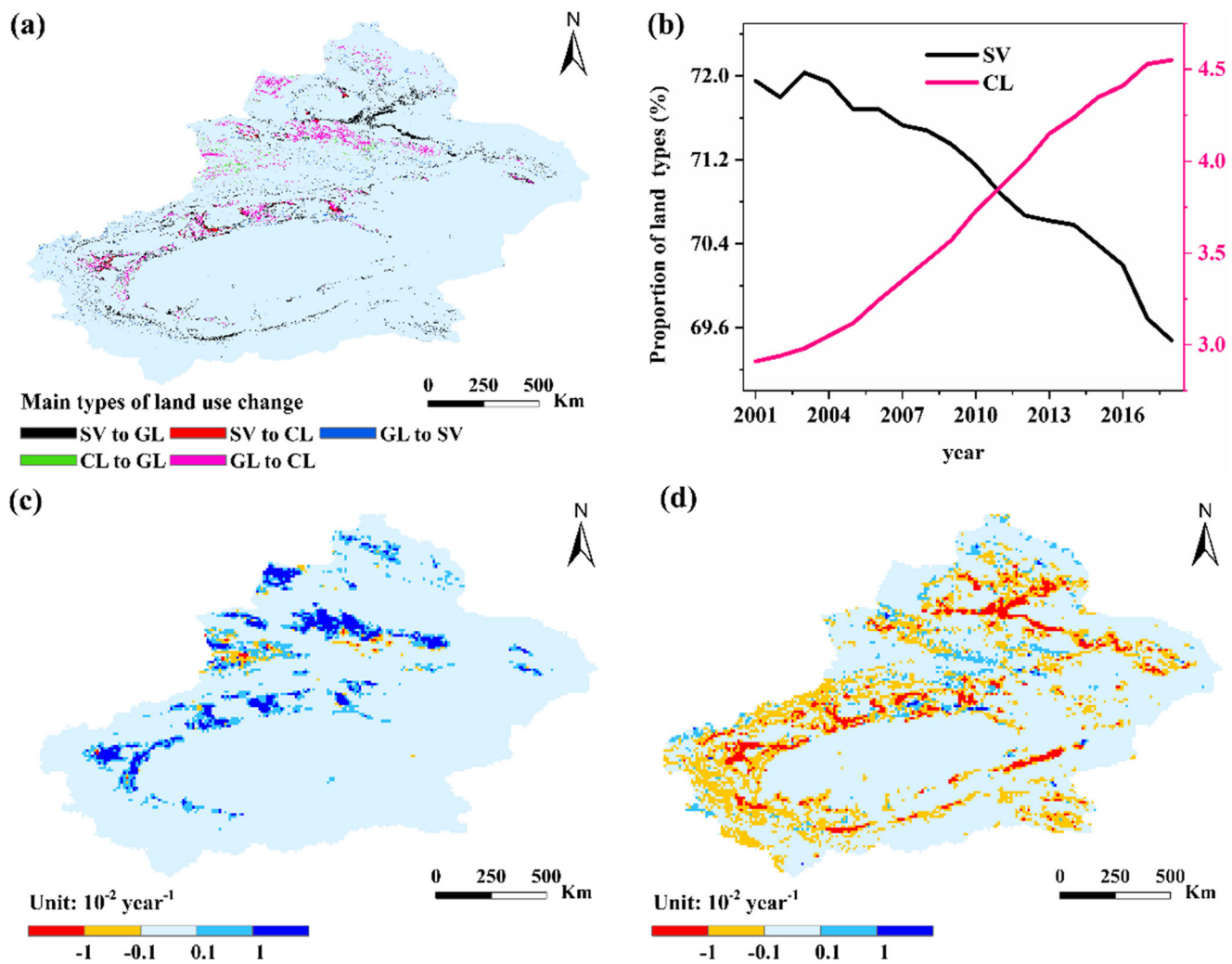


Fig. 11 Land-use change dominated by human activities in Xinjiang. **a** The main types of land change in Xinjiang; **b** probability change of SV and CL during 2001–2018; **c** spatial variation of probability for CL; and **d**

SV during 2001–2018. SV, GL, and CL represent sparsely vegetation, grassland, and cropland, respectively

vegetation’s increasing trend in the natural environment is not evident. However, after 10 years of implementing the ecological project, grassland and sparse vegetation’s photosynthetic capacity has been generally enhanced and greatly restored (Ma et al. 2019a). The greenness also showed an obvious upward trend in the later stage. Hence, the number of vegetation breakpoint pixels that can be detected has reached the maximum. Also, 2016 was a year with a vast number of breakpoint pixels and mainly in sparse vegetation. The main breakpoint type was an increase to decrease, which may be due to the abnormal climate or the human disturbance (Chen et al. 2020). For the sustainable development of the regional environment, we should formulate and strengthen environmental protection policies in regions of low resilience.

To sum up, two approaches of gradual change (trend analysis) and abrupt change (breakpoint analysis) have found that NDVI has been generally increasing in Xinjiang. For more accurate and rigorous monitoring of vegetation greenness’s

spatiotemporal dynamics, a combination of gradual change and abrupt change should be used in the future to explore the temporal and spatial dynamics of vegetation.

Influence factors affecting vegetation greenness in Xinjiang

The excessive emission of greenhouse gases such as CO₂ caused by human activities has been recognized as the most important causes of global climate change (Kweku et al. 2018). At present, the atmospheric CO₂ concentration is still increasing at a rate of 1.8 ppm per year, which is equivalent to a discharge of 3.8 PgC (1 PgC = 10¹⁵ g) in the air per year, and further projections predicted that CO₂ concentration will reach 600 ppm by 2030 (Stocker et al. 2013). The effects of elevated CO₂ can promote photosynthesis of plants in almost all functional types, which can lead to the phenomenon of vegetation becoming green. Previous studies had found that at least 40%

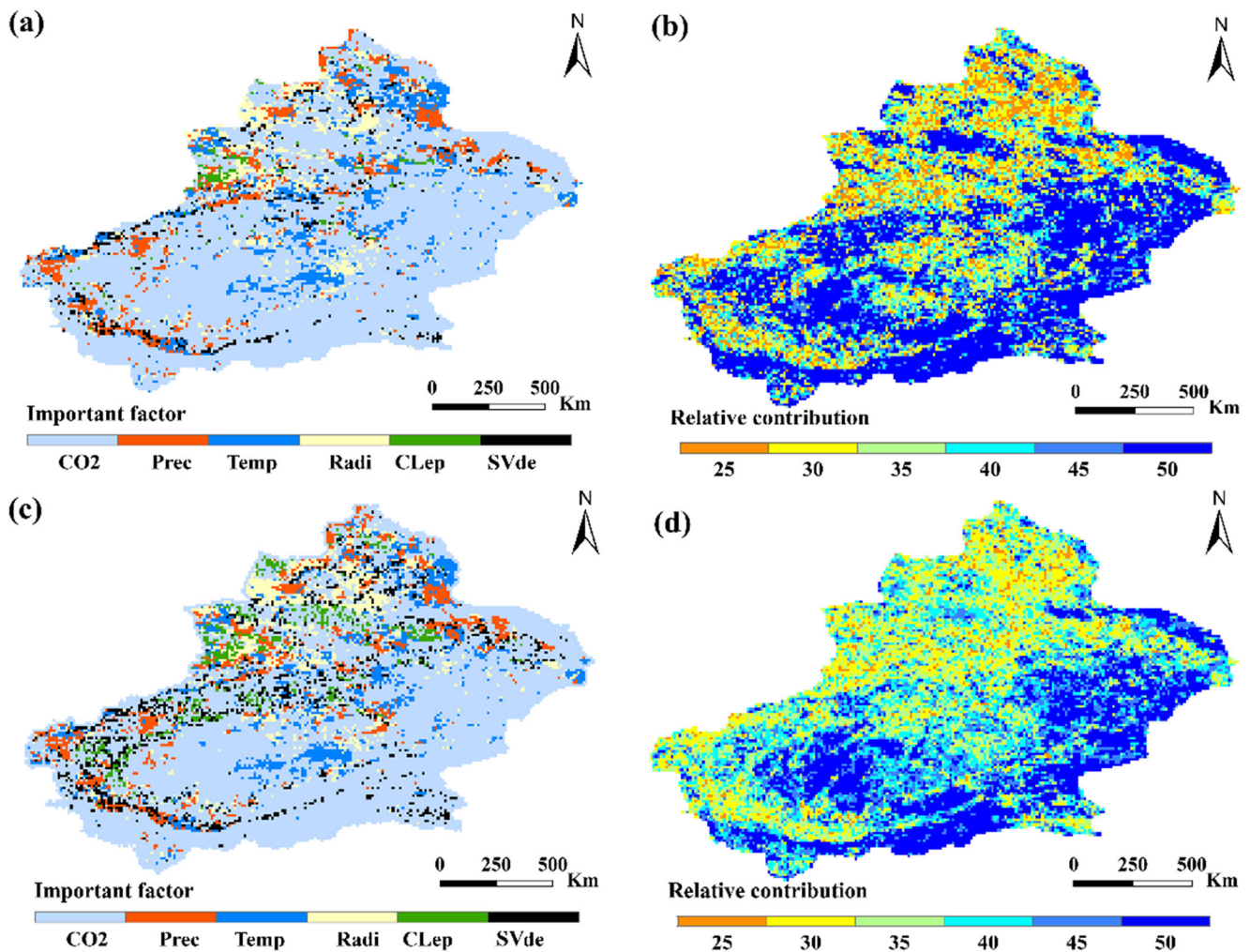


Fig. 12 The most important influence factors controlling vegetation greenness in Xinjiang. The most important environmental factors through (a) boosted regression tree methods and (c) random forest methods, respectively; the relative contribution of the most important environment through (b) boosted regression tree methods and (d)

random forest methods, respectively. CO₂, carbon dioxide concentration; Prec, precipitation rate; Temp, air temperature; Radi, downward shortwave radiation; CLep, cropland expansion; SVde, sparse vegetation decrease

of the global vegetation greening trend can be explained by the fertilization effect of CO₂ (Los 2013). Recently, Zhu et al. applied the factor simulation of the global ecosystem model to reveal that the CO₂ fertilization effect contributed 70% to the turning “green” of global vegetation. In the arid and semi-arid regions of China, the increase of CO₂ concentration was claimed to contribute 5–10% to the increase of vegetation coverage in the arid environment (Bi and Xie, 2015, Donohue et al. 2013). More importantly, our study found that the overall greening of vegetation in Xinjiang is mainly due to the enhancement of the photosynthetic capacity of biological communities caused by the CO₂ fertilization effect. Increasing atmospheric CO₂ concentration promotes the large-scale restoration and turning “green” of vegetation, especially in areas with sparse vegetation, which is similar to Zhu’s results (Zhu et al. 2016).

Furthermore, other climatic factors also play an important role in vegetation turning green (Xiao et al. 2015, Zhou et al. 2020). Most researches about the impact of climatic factors on vegetation change were based on analyzing plant physiology: the pairwise correlation between vegetation greenness and temperature, precipitation, etc. (Cui et al. 2018). However, vegetation greenness’s response to the change of temperature and precipitation varies greatly, so selecting a single climatic factor may cause great deviation to the result (Piao et al. 2019b). Rishmawi et al. found that the change of NDVI and multiple climatic factors such as precipitation, humidity, atmospheric pressure, and solar radiation can better explain the change of vegetation greenness than precipitation or temperature alone (Rishmawi et al. 2016). Jiang et al. indicated that the shift in climate conditions was the predominant reason of the increase of net primary productivity of vegetation,

precipitation, and solar radiation is likely to be the main factors that regulate the vegetation dynamics in Xinjiang (Jiang et al. 2020). Guli et al. believed that the universal constraint affecting vegetation dynamics in mountainous areas was precipitation. In contrast, the vegetation on plain substantially constrained by the average temperature in spring and summer (Guli-Jiapaer et al. 2015). Our research found that climatic factors such as precipitation, radiation, and temperature were the important reasons for affecting the vegetation dynamics of the oasis in Xinjiang.

Moreover, it should be noted that the relative contribution rate of the land-use management is strikingly prominent in oasis with strong human disturbance (Fig. 12), which indicates that the land-use factors affecting vegetation greenness should be considered in the selection of influence factors as to improve the reliability of the results. Croplands are intensively managed by humans, so the vegetation greenness is extremely susceptible to modification by cropland expansion and abandonment (Yu and Lu, 2018). Generally, the croplands had a higher maximum photosynthetic capacity than areas of grassland and forest (Huang et al. 2018), and so the expansion of cropland area will promote the increase of land greenness, especially in arid and semi-arid areas (Ma et al. 2019b). Previous study noted that the grassland or wasteland with very low vegetation cover was directly cultivated by human beings to grow high-yield cotton or wheat in Xinjiang (Ma et al. 2019b). We also found that annual cropland fractional in each oasis showed a rapid increase, which means that cropland expands rapidly over the past 20 years. Therefore, the rapid and continuous increase of cropland greenness in the oasis may be closely related to cropland expansion, and effective land management has greatly improved the vegetation greenness in Xinjiang. Meanwhile, human-led desertification control can also significantly modify the vegetation greenness in ecotone (Lal 2001). Over the past few decades, Xinjiang has been threatened by large-scale desertification (Hu et al. 2004). Previous prevention actions are restricted to reactive actions and control projects in the marginal areas of each Oasis (surrounded by desertification and sandy land), to slow down the progress of desert and stop the pace of desertification (Fan et al. 2002). However, since the beginning of the twenty-first century, Xinjiang has formed and popularized a number of proactive and practical desertification control maneuver (Lyu et al. 2020), such as planting *Tamarix*, grass-grid laying, non-irrigated afforestation, aerial sowing of forage, and engineering desertification control, gradually restoring ecosystems services that have been undermined due to desertification and transforming the desert into grassland or shrub landscape. Moreover, the Chinese government has implemented a series of ecological restoration policies (such as enclosure, nature reserve construction), which greatly reduced the human disturbance in the ecotone and indirectly promoted the vegetation restoration (Lu et al. 2018, Niu et al. 2019). Therefore, we

deemed that the desertification reduction in Xinjiang accelerates the rising rate of vegetation greenness to a great extent; that is, the low greenness desert is replaced by high-greenness new land cover (such as grassland). At present, the desertification control has achieved outstanding results in policy mechanism, technical mode, industrial development, and management system in Xinjiang (Lyu et al. 2020). It is expected that the ecological security of oasis edge can be guaranteed in the future.

Conclusions

In this study, Sen's trend (gradual change) analysis and BFAST breakpoint (abrupt change) analysis were applied to study the spatiotemporal dynamics of vegetation greenness in Xinjiang over the past 20 years and to further distinguish and quantify the impact of influence factors on vegetation dynamics. The results have shown that most Xinjiang areas showed widespread vegetation greening during 2000–2019, and the growth rate of vegetation greenness in 2010–2019 was significantly accelerated. The increasing trend of cropland greenness was the most obvious. About 10% (about 166000 km²) of Xinjiang's pixels have a breakpoint, and most of the breakpoint was concentrated in the ecotone of cropland, grassland, and sparse vegetation. Besides, the combination of gradual change and abrupt change can better monitor the vegetation dynamics of satellite time series. Furthermore, the CO₂ fertilization effect was the most important factor to control vegetation turning "green" over the sparse vegetation area. The influence of climate factors on the long-term variation of vegetation was complex, which has a great influence on the vegetation dynamics of the oasis in Xinjiang. In particular, our research highlights that land-use management such as cropland expansion and desertification control will have positive feedback on vegetation greenness in the agro-pastoral ecotone, which may be an important reason for the rapid increase of cropland and sparse vegetation greenness. Therefore, we recommend that when exploring the driving factors of vegetation in other similar areas in the future, we should pay more attention to the impact of human activities on vegetation change and further promote a sustainable eco-hydrological environment in the arid areas.

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Data availability The datasets and codes used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval The authors declare that the manuscript has not been published previously.

Consent to participate All authors voluntarily participated in this research study.

Consent for publication All authors consent to the publication of the manuscript.

Competing interest The authors declare no competing interests.

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