

# Examining the efficacy of revegetation practices in ecosystem restoration programs: insights from a hotspot of sandstorm in northern China

Ziqiang DU<sup>1,2,3</sup>, Rong RONG<sup>1,2,3</sup>, Zhitao WU (✉)<sup>1,2,3</sup>, Hong ZHANG<sup>1,4</sup>

<sup>1</sup> Institute of Loess Plateau, Shanxi University, Taiyuan 030006, China

<sup>2</sup> Shanxi Key Laboratory for Ecological restoration of Loess Plateau, Taiyuan 030006, China

<sup>3</sup> Field Scientific Observation and Research Station of the Ministry of Education of Shanxi Subalpine Grassland Ecosystem, Taiyuan 030006, China

<sup>4</sup> College of Environmental & Resource Sciences, Shanxi University, Taiyuan 030006, China

© Higher Education Press 2021

**Abstract** Retrospectively evaluating the efficacy of revegetation practices is helpful in planning and implementing future ecosystem restoration programs (ERP). Having a good understanding of how human activities can affect vegetation cover, both before and after ERP, is particularly important in sandstorm hotspot areas. The Beijing–Tianjin Sandstorm Source Region (BTSSR) is one such area. We conducted an investigation into vegetation dynamics within the BTSSR. This was done using remote sensing data in conjunction with climate data sets and land use data spanning the 1982–2014 period. The relationships between climatic factors (such as precipitation and temperature), and vegetative change were modeled using a neural network method. By a process of residual analysis, the proportions of human-induced vegetative change both before and after the ERP were established. Our results show that: 1) before the ERP (1982–2000), 40.96% of the study area exhibited significantly progressive vegetation changes ( $p < 0.05$ ). This proportion decreased to encompass only 20.23% of the study area in the period following the ERP (2001–2014). 2) 89.55% of the study area showed signs of human-induced vegetation degradation before the ERP. Between 2001 and 2014 however, following ERP, this figure fell to only 27.78%. 3) ERP implementation led to visible improvements in vegetative conditions within the BTSSR, especially in areas where ecological restoration measures were directly and anthropogenically applied. These results highlight the benefits that positive human action (i.e., revegetation initiatives implemented under the framework of an ERP) have brought to the BTSSR.

**Keywords** vegetation dynamics, human activities, ERP, neural network model, Beijing–Tianjin sandstorm source region

## 1 Introduction

In the spring of 2000, Beijing, Tianjin and some parts of northern China suffered from multiple sandstorm events (Tu et al., 2016; Wu et al., 2019). To reduce the severity of such events in future, and to improve the general condition of the ecosystem, China implemented a sandstorm control program in the Beijing–Tianjin sandstorm source region (BTSSR). This sandstorm control program was named the Beijing–Tianjin Sand Source Control Project and range from 2001 to 2022 (Gao, 2012; Shan et al., 2015). In the past five decades, the BTSSR has experienced remarkable climatic changes, including warming temperatures and fluctuations in regional precipitation (Sun et al., 2014). Furthermore, anthropogenic factors such as grazing prohibition, “Grain for Green” program and enclosure are implemented. Vegetation is an important natural resource and is entirely irreplaceable within terrestrial ecosystems. Long-term vegetation change always reflects the impacts of both natural and anthropogenic processes on the ecosystem (Fensholt and Proud, 2012; Pei et al., 2018). Consequently, it is necessary to examine the efficacy of revegetation practices for sandstorm control program in BTSSR.

With the development of satellite remote sensing technologies, the parameters most commonly utilized in remotely-sensed studies of vegetation growth are Normalized Difference Vegetation Index (NDVI) (Liu et al., 2018; Mu et al., 2018; Anikó et al., 2020). Over the past 30 years, scholars have used NDVI change measured at large

temporal and spatial scales to study changes in vegetation cover at the continental and even global level (Liu and Chang, 2015; Qu et al., 2018; Chen et al., 2019; Zhao et al., 2020). To examine the efficacy of revegetation practices, it is must separate the impacts of climate change and human activities on vegetation change. The primary methods used have included the comparative method, the experimental method, and residual analyses (Jiang et al., 2017; Liu et al., 2010). Of these methods, the residual analysis approach has been most widely used (Herrmann et al., 2005; Cao et al., 2006; Zhuo et al., 2007; Cai and Yu, 2009). Vegetative parameters are simulated using relationships quantified between climate and vegetation processes, with simulated values representing the ideal growth conditions of vegetation under projected climatic changes (e.g., changes in temperature and rainfall, including drought events), excluding any human activity. The influences of human activities on regional vegetation are subsequently inferred by comparing simulated values to the actual, real-world values. Using the residual method in this way, Sun et al. (2010) analyzed the impact of human activities on vegetation change in Inner Mongolia. Yu et al. (2021) also used this approach to quantify the effect of human activities on patterns of vegetation change in various ecologically engineered areas.

However, quantifying each driving factor's contribution to the vegetation change is challenging. Statistical correlations or regression analyses have traditionally been used, but these approaches suffer from two potential limitations (Peng et al., 2012; Cai et al., 2014; He et al., 2015): First, where linear regression models are established with vegetative factors providing the dependent variables and climate factors providing the independent variables (Herrmann et al., 2005; Qu et al., 2018), dependencies between vegetation variables and climatic factors are characterized as simple linear regression relationships. This perspective ignores the response of physiologic vegetative processes to climate change (Ma et al., 2013; Zhao et al., 2018). Secondly, statistical analyses assume that the climatic factors which come to bear on vegetation growth are independent of each other – an over-simplification of reality. These limitations have, however, been recognized and are in the process of being overcome through the application of nonlinear models such as Neural Network models and Support Vector Machine models (Tang et al., 2019). For example, Tang et al. (2019) has explored the driving forces behind vegetation cover changes in the source regions of the Yangtze River between 1982 and 2015 using a Back Propagation Neural Network model (Tang et al., 2019). When compared with Support Vector Machine model performance, the Neural Network model approach exhibits stronger capabilities in forecasting NDVI (Huang et al., 2017).

Examining the efficacy of revegetation practices in the BTSSR are varied and complex due to the conflicting

effects of both intensified human interference and climate change (Wu et al., 2019). The ways in which vegetation coverage changes before and after ERP intervention does, however, require further study. There are a number of questions that remain to be answered: in particular, uncertainty exists over whether post-ERP climatic changes will prove detrimental to the efforts of ecological projects in the BTSSR. The objectives of this study, which was based on long-term remote sensing data, climatic data, land use data, and statistical yearbook data, were to (i) investigate vegetation variation both before and after the implementation of ERP in the BTSSR; (ii) separate the impacts of climate change and human activities on observed vegetation change, and; (iii) examine the efficacy of ERP revegetation practices.

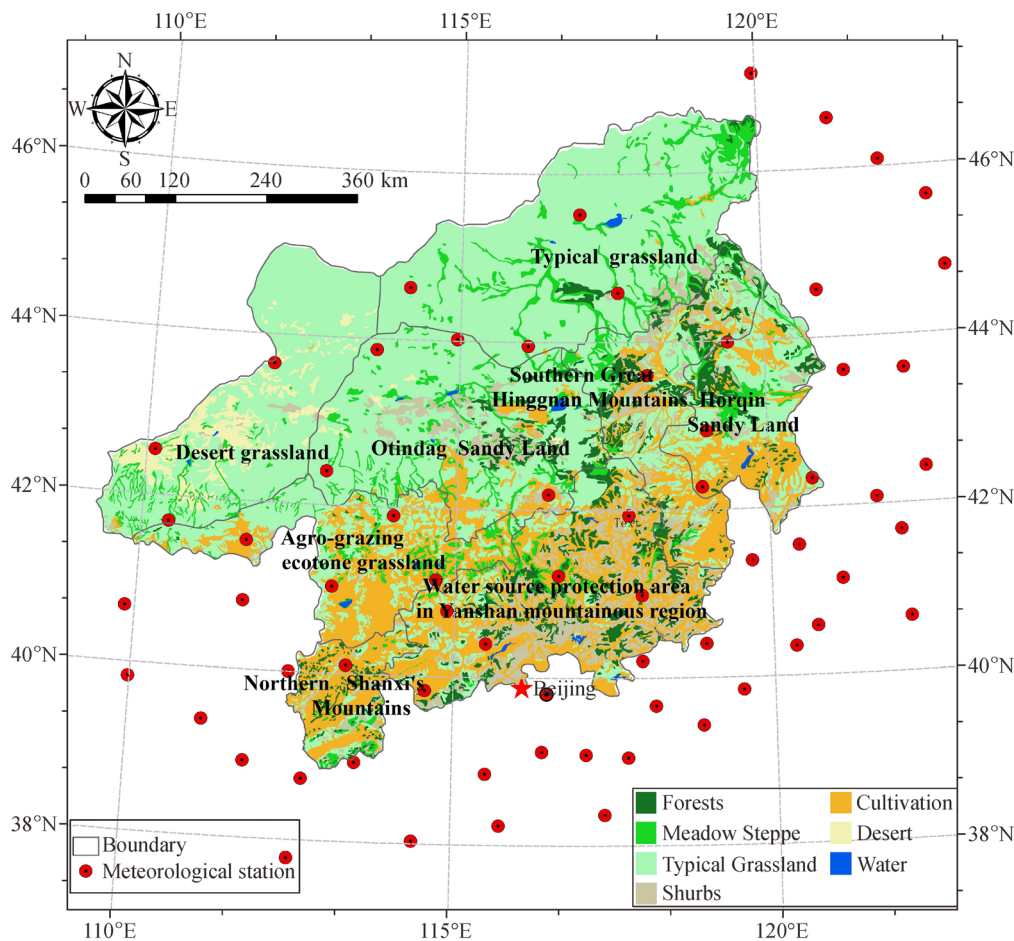
---

## 2 Study area and data set

### 2.1 Study area

The BTSSR is located in northern China (Fig. 1). In this area, due to ongoing ecological issues, desertified land accounts for 101200 km<sup>2</sup> of the area's overall 458000 km<sup>2</sup> footprint. The BTSSR incorporates elements of 75 counties (banners, cities, or districts), including Inner Mongolia's Darhan Muminggan Joint Banner and Ar Horqin Banners, Shanxi's Dai County and the northern parts of Inner Mongolia's East Ujimqin Banner. It also spans territory in five regions including Beijing, Tianjin, Hebei, Shanxi, and Inner Mongolia (38°50'–46°40' N, 109°30'–119°20' E). The slope of altitude in the BTSSR varies, and the highest elevations are in the region of 3000 m. The terrain in the study area is characterized by a west–east downward trend. Due to the complex topography of the area, climate displays strong regional differences, with a pronounced tendency toward arid and semi-arid conditions. The average annual temperature is 7°C, with a range of 3.5°C to 8.5°C. The annual precipitation, which declines from west to east, ranges from 254 mm to 468 mm.

The distribution of vegetation types is shown in Fig. 1. These types were grouped as follows: typical grasslands, meadow steppe, forests, shrubs, cultivation, and deserts (Editorial Board of Vegetation Map of China Academy of Sciences, 2001). Grasslands constitute the dominant, most widely-distributed vegetation type in the study area's northern part (Inner Mongolia). In this region, the most prominent ecological problems are land degradation and desertification caused by grazing. Therefore, grassland management (achieved via methods such as livestock enclosure and former pasture rehabilitation) was a key focus of the ERP. Considering the prevalent conditions within the BTSSR (as above), we divided the study area into eight sub-regions. These included three land types: grasslands, sandy lands, and mountains. There



**Fig. 1** Study area.

were two types of grasslands: desert grassland and typical grassland; two sandy lands: Horqin and Otindag sandy land; and three mountains: south of Greater Hinggan Mountains, northern Shanxi's Mountains and the water source protection area in Yanshan Mountainous region. And the BTSSR's remaining subregion is the typical agro-grazing "ecotone," or transitional zone, which occupies numerous provincial border areas (Liu et al., 2013; Li et al., 2015). To combat the process of desertification and improve the area's general ecological condition, large-scale restorative measures were implemented in the BTSSR. Some "before and after" photographs, taken over the course of the ERP, have been made available in supplementary material (S1).

## 2.2 Data set

The Global Inventory Modeling and Mapping Studies (GIMMS) NDVI3g data set (with a spatial resolution of 8 km) was used to monitor vegetation change from 1982 to 2014. This data was obtained from the National Oceanic and Atmospheric Administration (NOAA) (available at NOAA website). It provides long-term NDVI data and more accurately represents the response of vegetation to climatic variability than some old data sets (Miao et al.,

2015; Cao et al., 2018). The available NDVI was calculated by the maximum value composite (MVC) method and excluded the pixels with an average value of less than 0.05 (Piao et al., 2014). Monthly climate data (including records of temperature and precipitation), collected at 67 screened meteorological stations was supplied by the Chinese National Meteorological Center. We calculated the Standardized Precipitation Evapotranspiration Index (SPEI) with a 12-month time scale so as to represent the drought conditions at annual scale (Vicente-Serrano et al., 2010). The SPEI considers the effect of reference evapotranspiration on drought severity, identifying climate change processes (Tong et al., 2018). Additional information on how to compute the SPEI is provided in supplementary material (S2).

Land use data of the BTSSR in 2000 and 2015 were obtained from the Resource and Environment Data Cloud Platform of the Chinese Academy of Sciences (RESDC) with 1 km resolution (available at Resource and Environment Data Cloud Platform website) (Li et al., 2018; Wei et al., 2018). To further verify the accuracy of this land cover data in study area, we conducted large-scale field surveys in 2011, 2012, and 2018. Further details on these surveys can also be found in supplementary material (S3). All data were interpolated to 8 km resolution, ensuring

compatibility with the NDVI data sets. The impacts of grassland management on vegetation dynamics were assessed following the methods of Chi et al. (2018), using the Grazing Pressure Index (GPI). GPI is calculated as follows:

$$GPI_t = S_t / NPP_t, \quad (1)$$

where  $GPI_t$  is the grazing pressure index for  $t$  years and  $S_t$  is the total number of sheep at the end of the year. In the case of larger livestock breeds (e.g., cattle, horses, and camels), one individual is equal to five sheep. Livestock data covering the period from 2001 to 2014 were extracted from the Inner Mongolia statistical yearbook.  $NPP_t$  is net primary productivity for year  $t$ . Because the land type is grassland, the NPP was estimated as follows (Piao et al., 2004):

$$NPP_t = 179.71 \times NDVI_{t_{\max}}^{1.6228}, \quad (2)$$

where,  $NDVI_{t_{\max}}$  is the maximum value of NDVI in year  $t$ .

### 2.3 Methods

In this study, the linear regression method was applied to detect trends in vegetation coverage (Tong et al., 2018). Due to the nonlinear associations between climate change and vegetation dynamics, a neural network approach was used to model the relationship between climate (temperature, precipitation, and SPEI) and NDVI from 1982 to 1990 (Chen et al., 2014). The back propagation (BP) neural network model is a multi-layer feedforward network trained according to an error back-propagation algorithm. It is the most widely used model in neural network design (Islam et al., 2018). All inputs (temperature, precipitation, and SPEI) were standardized to within a specific range and the network was trained using MATLAB software. The main principles of the BP neural network are provided in supplementary material (S4).

To separate the impacts of climate change and human activity on vegetation, the residual analysis method was applied (Herrmann et al., 2005; Wu et al., 2014). First, we assumed that vegetation patterns were little affected by human activities prior to 1990. Secondly, the predicted NDVI from 1991 to 2014 was determined using the BP neural network model. Then, the residual, as defined by the difference between observed and predicted NDVI, was computed for each year as follows:

$$NDVI_{r,t} = NDVI_{o,t} - NDVI_{p,t}, \quad (3)$$

where  $NDVI_{r,t}$ ,  $NDVI_{o,t}$ , and  $NDVI_{p,t}$  are residual NDVI, observed NDVI and predicted NDVI for year  $t$ , respectively. The  $NDVI_{r,t}$  represents the part of the observed NDVI value that is not explained by climate change. A positive  $NDVI_{r,t}$  indicates human-induced improvement, whereas a negative  $NDVI_{r,t}$  indicates human-induced degradation. Finally, human-induced vegetation changes

were evaluated according to observed trends in the  $NDVI_{r,t}$  for the years 1991–2000 and 2001–2014. Figure 2 is the flowchart of residual analysis.

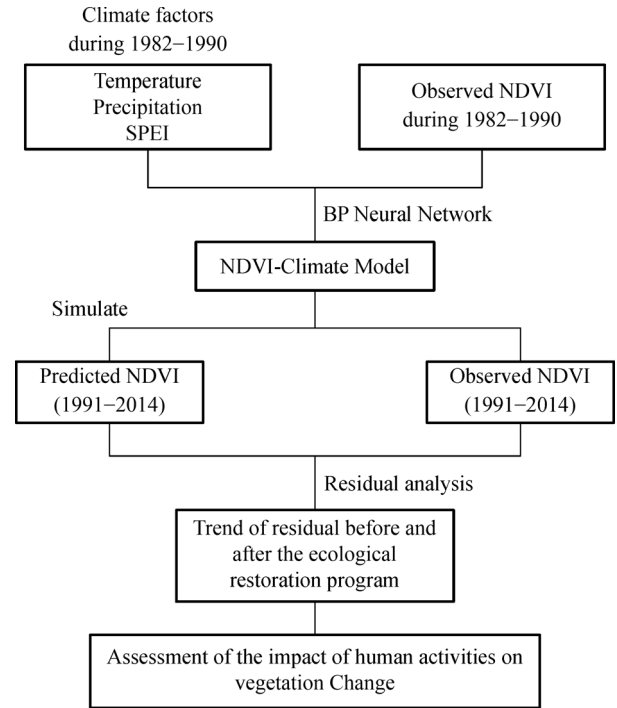


Fig. 2 Flowchart of residual analysis.

## 3 Results

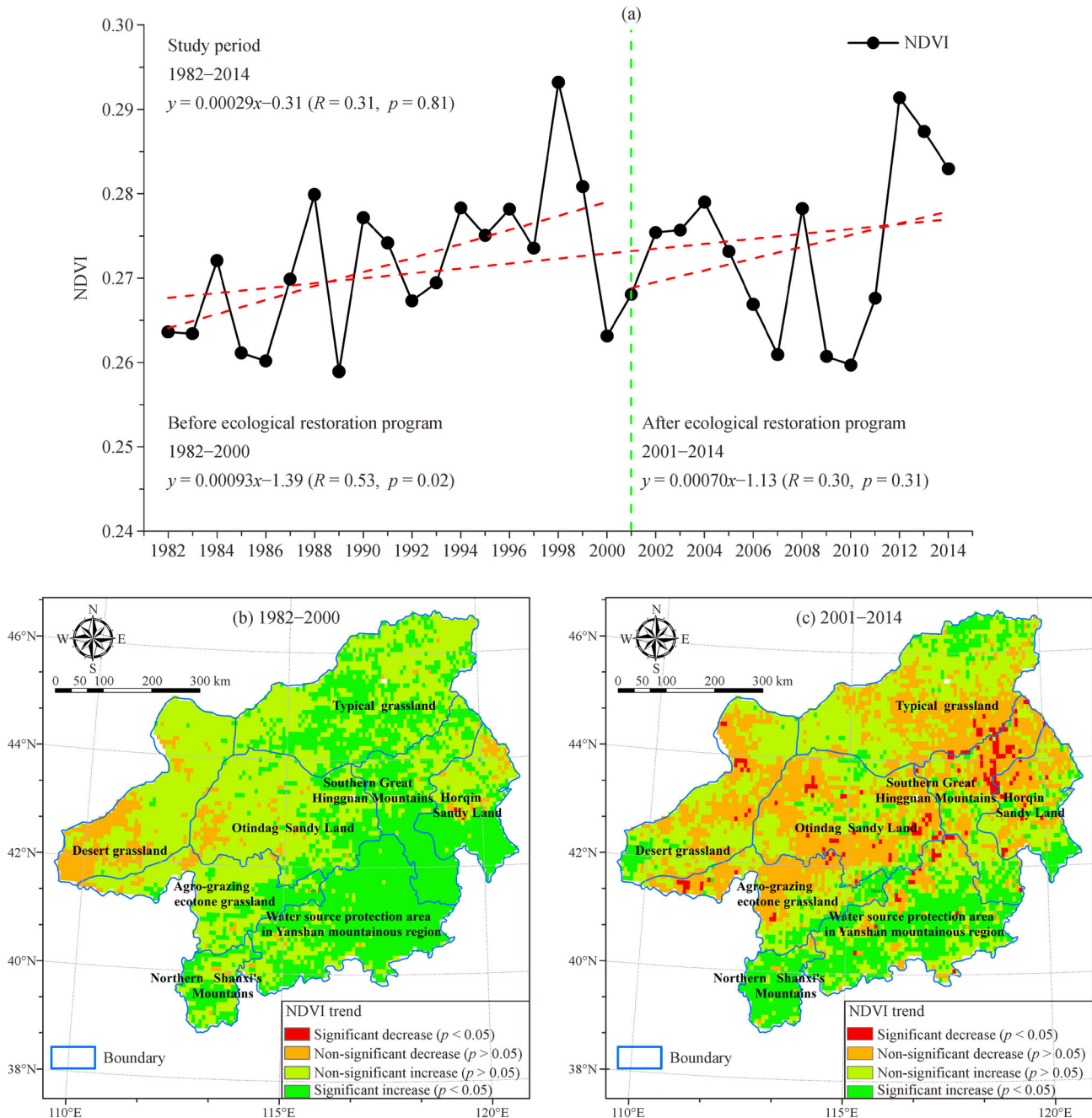
### 3.1 Vegetation coverage dynamics in the study area before and after the ERP

Using long-term NDVI measurements, we analyzed changes in vegetation cover between 1982 and 2014, specifically in the two sub-periods defined as follows: 1982–2000 and 2001–2014. Over the course of the study period (1982–2014), vegetation coverage was non-significantly increased (Fig. 3(a)), with a trend of  $2.9 \times 10^{-4} \text{ year}^{-1}$  ( $p = 0.81$ ). Higher vegetation coverage values were observed in 1998 and 2012, lower values appearing in 2000, 2007, and 2009. Before the ERP (1982–2000), vegetation coverage displayed a significantly upward trend ( $9.3 \times 10^{-4} \text{ year}^{-1}$ ,  $p < 0.05$ ). After the ERP (2001–2014), vegetation coverage showed more of a tendency toward fluctuation, albeit with a slightly positive trend of  $7.0 \times 10^{-4} \text{ year}^{-1}$ . Contrary to expectations, the overall state of vegetation coverage in the BTSSR did not increase significantly post-ERP. Furthermore, NDVI increased with a stronger positive trend prior to the ERP (1982–2000) than after it (2001–2014).

We analyzed intra-area trends in vegetation coverage at an individual pixel scale over the course of each defined

study period (Figs. 3(b) and 3(c)). Spatial heterogeneity was found to be high both prior to the ERP (1982–2000) and after it (2001–2014). As shown at Fig. 3(b), before the ERP, vegetation coverage was observed to increase in various parts of the study area. And 40.96% of the study area experienced a significantly increase in vegetation cover. A tendency toward decline was only observed in the north of Horqin and in the southwest of the desert

grassland area. Following the ERP, increases in vegetation cover were observed primarily in the southern parts of the study area (Fig. 3(c)). Decreases in vegetation cover occurred throughout most of the agro-grazing ecotone regions, for example in southern Otindag, northern Greater Hingnan, and in the southeastern typical grassland area. Statistically speaking, we found that only 20.23% of the area continued to recover afterwards (2001–2014).



**Fig. 3** (a) The variations of NDVI in the study area during the 1982–2014 period; (b) the spatial trends of NDVI before the ecological restoration program during the 1982–2000 period and; (c) after the ecological restoration program during the 2001–2014 period.

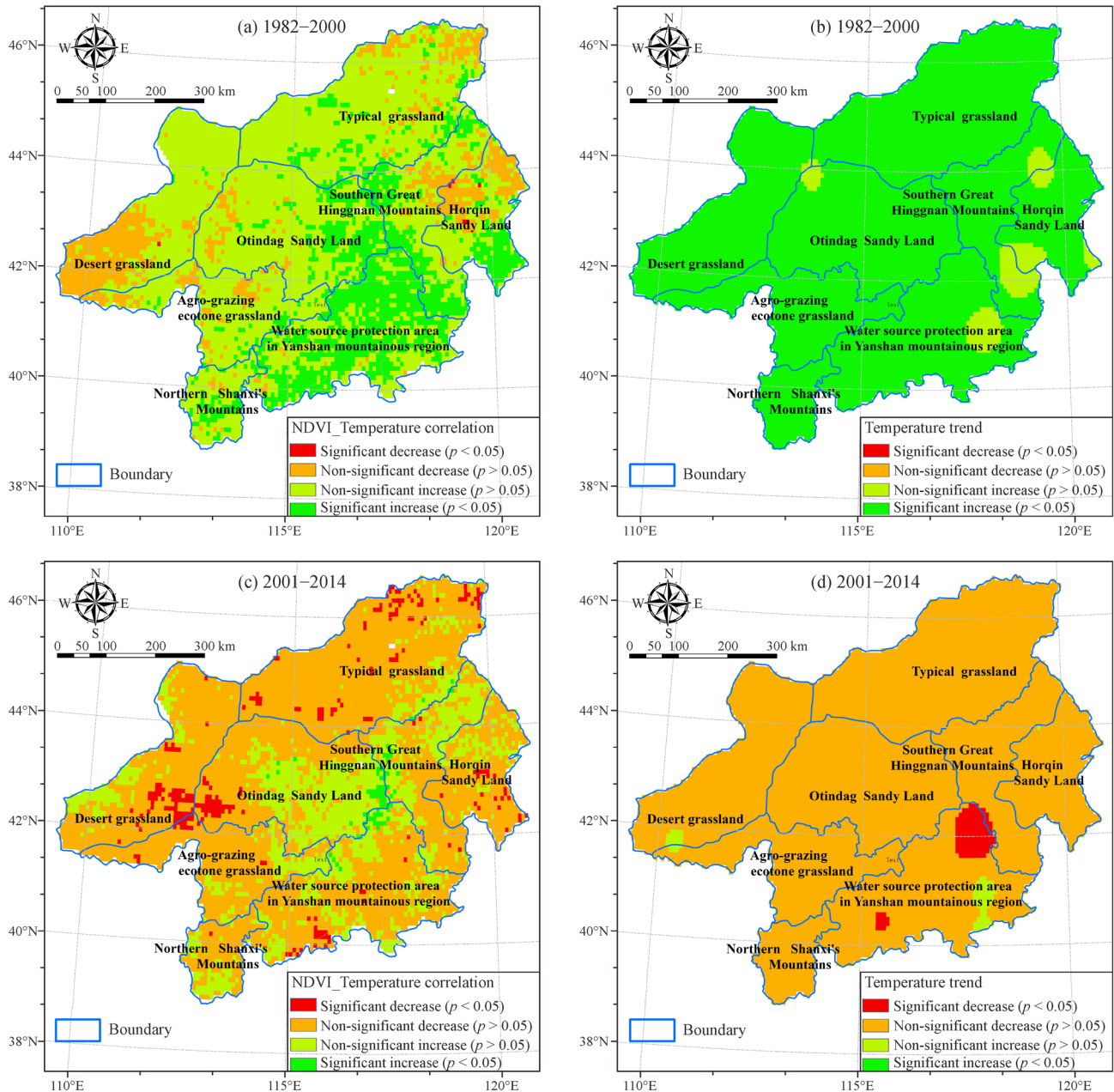
### 3.2 Impacts of climate change on vegetation coverage dynamics before and after the ERP

Temperature, precipitation and extreme climate events are the most important natural factors affecting vegetation coverage change. Correlations between NDVI and climatic factors were investigated so as to better understand how climate impacted NDVI for different periods.

#### 3.2.1 Impacts of temperature change on vegetation coverage dynamics before and after the ERP

In this section, we discussed the impact of temperature

change on vegetation dynamics before and after the ERP. Before the ERP, the correlation coefficients between temperature and NDVI in most parts of the BTSSR (85.99%) from 1982 to 2000 were dominantly positive coefficients (Fig. 4(a), Table 1). Moreover, temperature was significantly increased in most parts of BTSSR during 1982–2000 (Fig. 4(b)). After the ERP, 74.47% of the study area had a negative correlation coefficient between NDVI and temperature, among which 3.78% of the pixels had a significant negative correlation at the 5% level (Fig. 4(c)). And a non-significantly decrease trend in regional temperature was found in most study area from 2001 to 2014 (Fig. 4(d)). However, before or after the ERP,



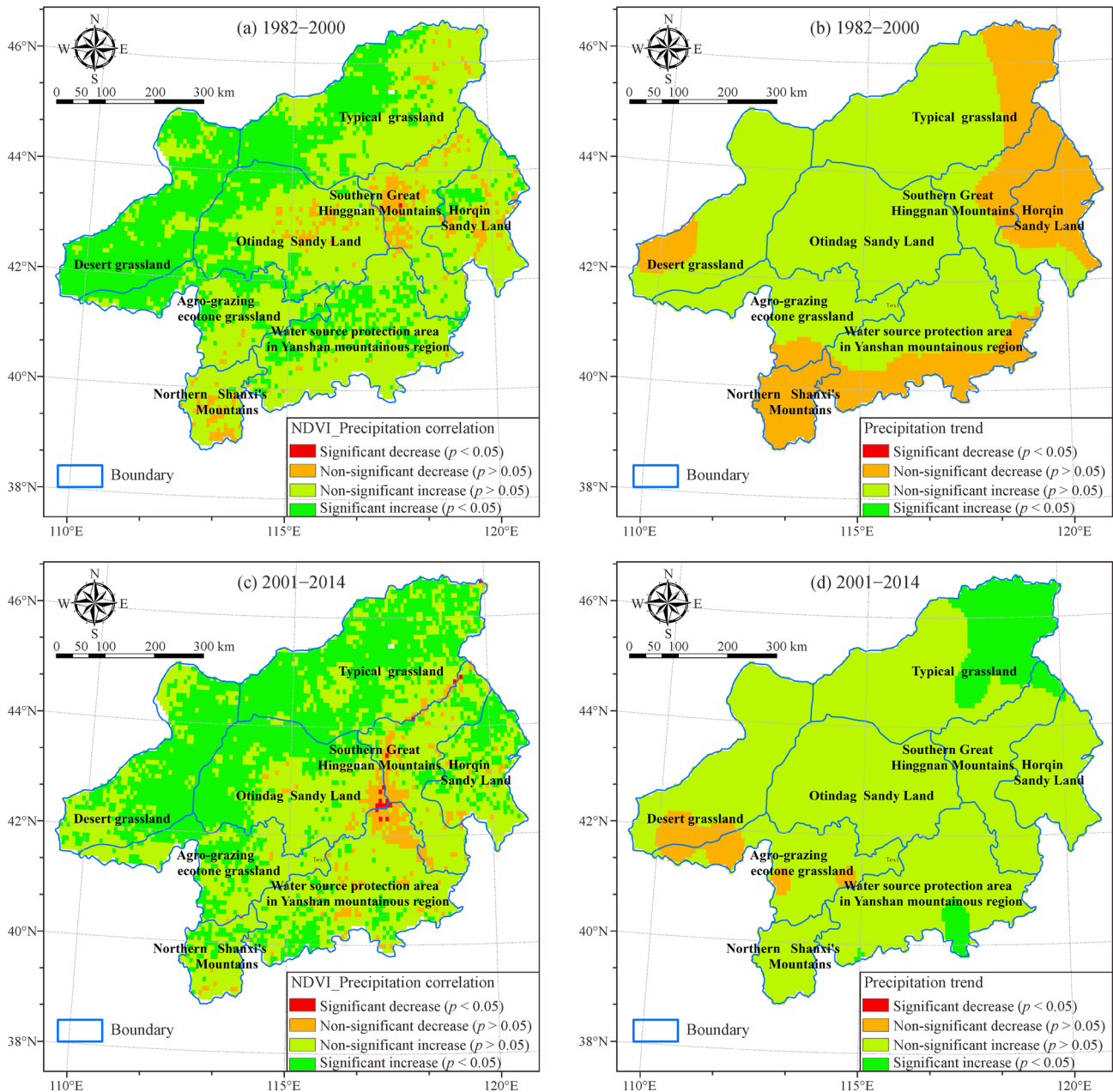
**Fig. 4** Spatial pattern of the correlation coefficients between NDVI and temperature and the trend of temperature for different periods: (a) and (b) 1982–2000; (c) and (d) 2001–2014.

there was no same spatial trend between temperature and NDVI.

### 3.2.2 Impacts of precipitation change on vegetation coverage dynamics before and after the ERP

Before the ERP, 94.74% of the total area had a significantly positive correlation between NDVI and precipitation, mainly in the desert grassland, typical grassland, Otindag, Greater Hingnan Mountains, and Horqin (Fig. 5(a), Table 1). The BTSSR has experienced fluctuations in

regional precipitation during 1982–2000. The non-significantly increased precipitation was found in most parts of study area and the non-significantly decreased precipitation was found in eastern and southern BTSSR (Fig. 5(b)). After the ERP, from 2001 to 2014, a positive correlation between NDVI and precipitation was also found in most areas of the study area (94.83%). In terms of study area, 43.12% had significantly positive correlations between NDVI and precipitation, mainly in the desert grassland, typical grassland, Otindag, Greater Hingnan Mountains, and Horqin (Fig. 5(c)). Furthermore, the



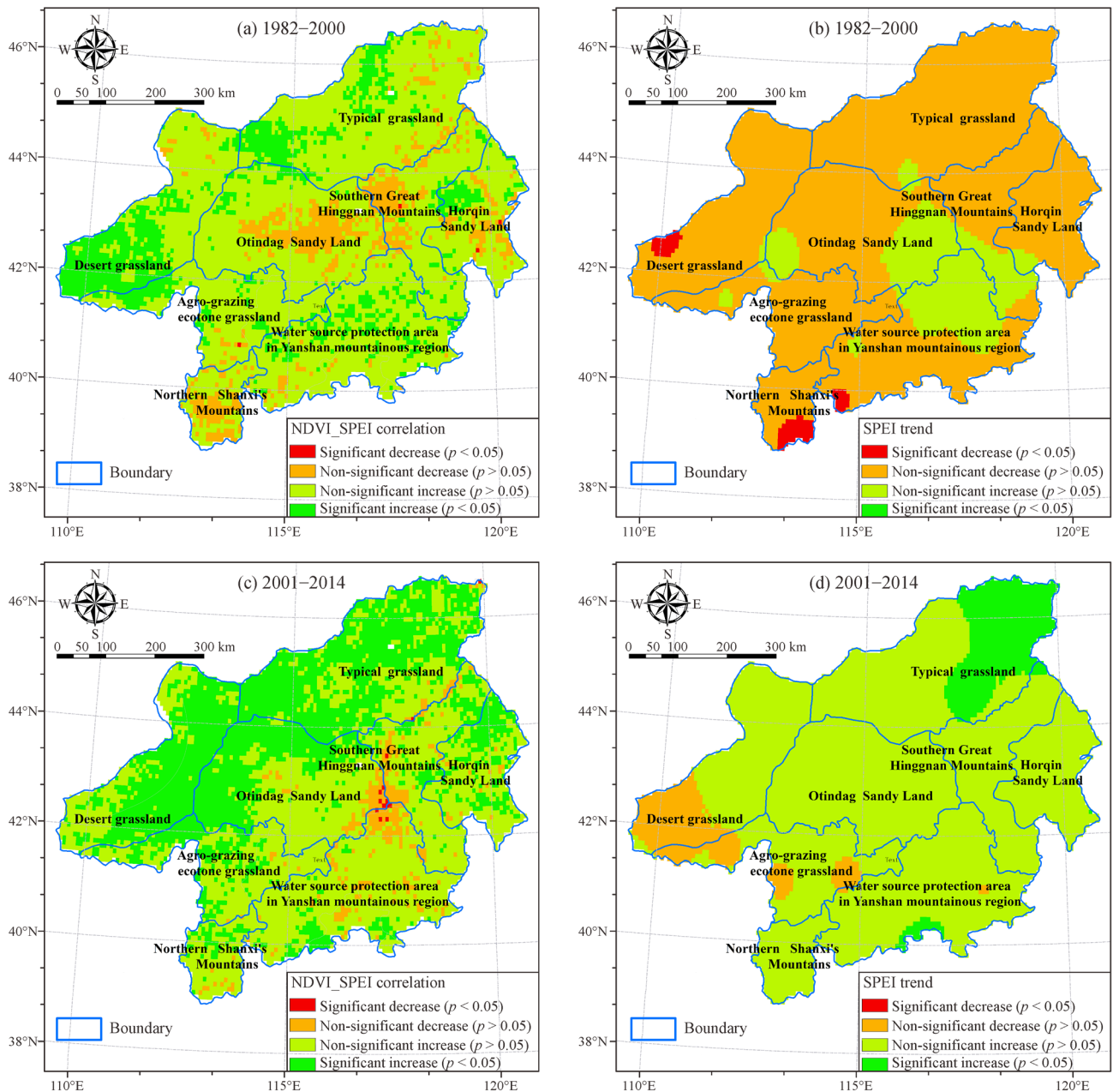
**Fig. 5** Spatial pattern of the correlation coefficients between NDVI and precipitation and the trend of precipitation for different periods: (a) and (b) 1982–2000; (c) and (d) 2001–2014.

fluctuations of precipitation were found in most parts of study area. The significantly increased trend of precipitation was mainly distributed in northeast of typical grassland (Fig. 5(d)). Therefore, it suggested that vegetation coverage in the BTSSR is more sensitive to changes in precipitation than to changes in temperature.

### 3.2.3 Impacts of SPEI change on vegetation coverage dynamics before and after the ERP

In this section, we discussed the impacts of drought on vegetation dynamics before and after the ERP. Before the

ERP, SPEI was positively correlated with NDVI and only 16.90% of the regions showed significant positive correlation, mainly in the southwest desert grassland (Fig. 6(a), Table 1). SPEI was observed to decrease in various parts of the study area. And a tendency toward increase was only observed in the east of Otindag and in north of the Yanshan (Fig. 6(b)). Following the ERP, there was a positive correlation between SPEI and NDVI in 94.81% of the study area, within which 41.69% passed the significance test (Fig. 6(c)). SPEI was observed to increase in various parts of the study area. And a significantly increase trend was observed in the north of Typical



**Fig. 6** Spatial pattern of the correlation coefficients between NDVI and SPEI and the trend of SPEI for different periods: (a) and (b) 1982–2000; (c) and (d) 2001–2014.

**Table 1** Correlations between NDVI and climate factors (temperature, precipitation and SPEI) in different periods

Correlation	Period	Significant negative/%	Non-significant negative/%	Non-significant positive/%	Significant positive/%
NDVI_T	1982–2000	0.10	13.91	64.30	21.69
	2001–2014	3.78	70.69	24.52	1.01
NDVI_P	1982–2000	0.01	5.25	59.66	35.08
	2001–2014	0.24	4.93	51.71	43.12
NDVI_SPEI	1982–2000	0.05	11.35	71.70	16.90
	2001–2014	0.20	4.99	53.12	41.69

Note: SPEI is Standardized Precipitation Evapotranspiration Index.

grassland. The decreased trend was only found in the west of Desert grassland (Fig. 6(d)). Therefore, the impact of SPEI on the regional vegetation increased with the implementation of ERP. Moreover, the three most serious drought events from 1982 to 2014 in the BTSSR were found by drought intensity, which were happened in 2005, 2007, and 2009. And the spatial patterns of severe droughts in those 3 years always led to vegetation degradation. More information can be found in supplementary material (S5). After the ERP (2001–2014), drought may contribute to the decreased vegetation coverage.

### 3.3 The impacts of human activities on vegetation coverage dynamics before and after the ERP

In this study, changes observed in vegetation coverage between 1982 and 1990 were thought to be climate induced. The neural network model (NDVI-climate model) from 1982 to 1990 was established using temperature, precipitation, and SPEI (cumulatively) as the input layer and NDVI as the output layer (S6). We found that the BP neural network model simulated NDVI well. We then analyzed the impact of human activities on vegetation change during the periods from 1991 to 2000 and 2001 to 2014 (Fig. 7). Pronounced deteriorations or improvements in vegetation cover induced by anthropogenic activity are represented by significant ( $p < 0.05$ ) decreases or increases in the NDVI residual. Before the ERP (1991–2000), human activities resulted in 89.55% of the study area experiencing vegetation degradation, confirming that certain anthropogenic stressors such as excessive grazing or mineral mining had a negative effect on vegetation cover.

However, 72.22% of the BTSSR experienced apparent vegetation recovery by human activities in the years following the ERP, with 9.22% of the study area experiencing “strong improvement” (defined as improvements that were statistically significant at the 5% level). These statistically significant improvements occurred mainly in the southern, middle and eastern parts of the BTSSR, corresponding to those areas in which “key” ERP measures were taken (measures such as afforestation, reforestation, prohibition of grazing, landscape engineering measures and the implementation of various supporting

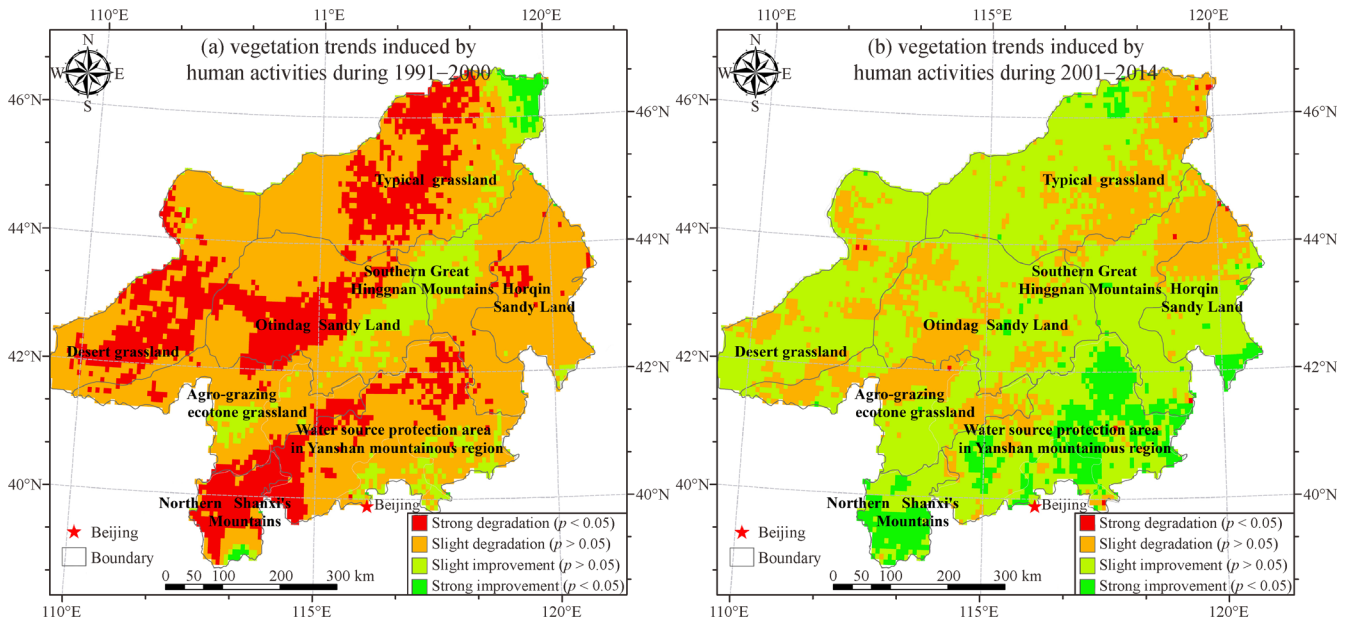
policies). We propose that the observed human-induced degradation seen in the eastern parts of the typical grassland area may be associated with mining. Similarly, the deterioration observed in the desert grassland area, as well as in small parts of the agro-grazing ecotone and in Otindag, may result from the recurrence of grazing and the reclamation of land for agricultural purposes. In summary however, we maintain that human activities have, for the most part, a positive impact on vegetation cover in the BTSSR since implementation of the ERP.

Compared with levels seen pre-ERP (1991–2000), the impact of human activities on vegetation degradation decreased from 2001 onwards (Fig. 7, Table 2). During 1991–2000, 26.58% of the area showed strong degradation as a result of human activities. Between 2001 and 2014 however, only 0.19% of the area underwent strong anthropogenically driven degradation. As a result of positive ecological engineering, human activity has become a driving force for environmental recovery. Therefore, although the NDVI trends were more positive in the 1990s than in the 2000s, the impact of visible vegetation recovery by human activities has increased, indicating that most of the measures taken during the ERP were environmentally beneficial.

### 3.4 Impacts of ERPs on vegetation coverage dynamics

#### 3.4.1 Grain for Green, afforestation and reforestation

The ERP was first implemented in 2001 and ended in 2012. Due to the limited quantity of available land use data, this study used data from the year 2000 as a proxy for conditions in the BTSSR prior to the ERP and land use data from 2015 to represent those post-ERP. According to results derived from field sampling tests, manual land use classifications derived from Landsat-TM data typically achieve an accuracy of more than 90%. As a direct result of the ERP, forest cover had increased (Fig. 8(a)). These changes indicate that the implementation of the “Grain for Green” program, positive afforestation measures and attempts to re-forest previously felled land were effective. Regions that experienced an increase in forested area are mainly distributed in the middle parts of Otindag, the western Desert grassland, the central agro-grazing ecotone,



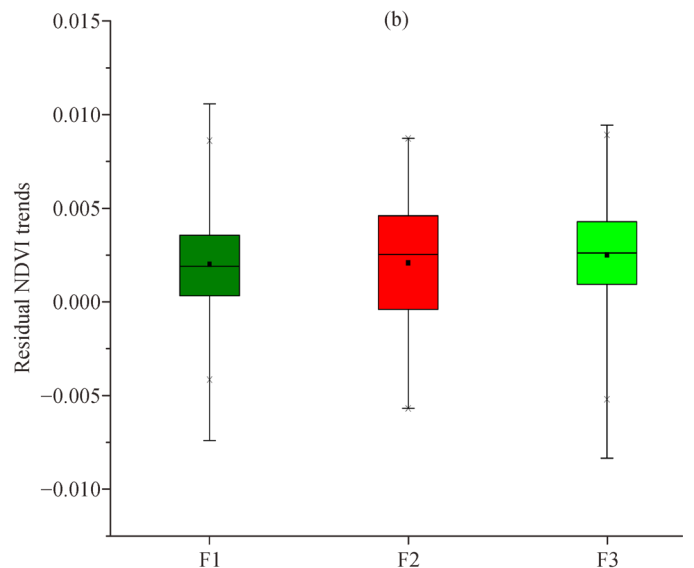
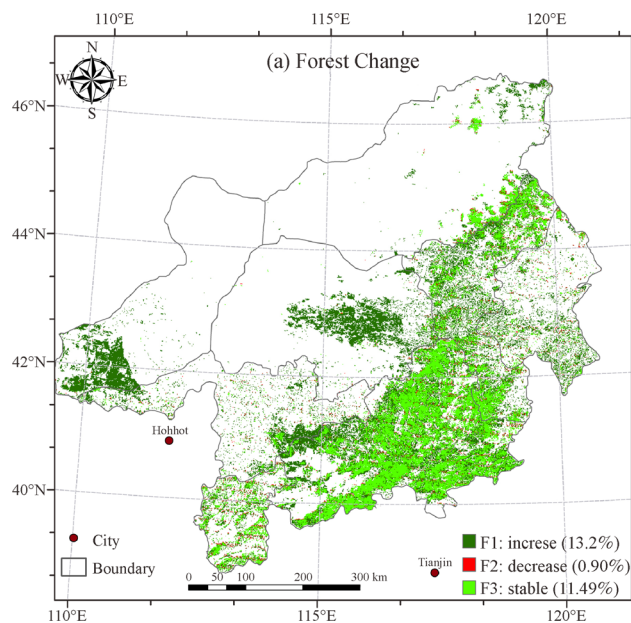
**Fig. 7** Quantitative assessment of regional vegetation change induced by human activities in different periods: (a) 1991–2000 and (b) 2001–2014. Strong deteriorations or improvements are defined as significant decreases or increases in the trend of NDVI residuals at the 0.05 significant level.

**Table 2** Percentages of human-induced improvement and degradation of vegetation before and after ERP in the BTSSR

Period	1991–2000	2001–2014
Significant Degradation/%	26.58	0.19
Slight Degradation/%	62.97	27.59
Slight improvement/%	9.36	63.00
Significant improvement/%	1.09	9.22

Note: BTSSR is Beijing-Tianjin Sandstorm Source Region.

and Yanshan, accounted for 13.2% of the entire study area (Fig. 8(a)). We have divided areas that experienced changes in forest cover into three groups: “F1” describes where other land use types have transitioned to forestry; “F2” describes where forests have made way for other land uses; and “F3” defines “persistent forest”, where previously forested land has remained so. In classes F1 and F3, the mean of the residual NDVI trend is positive (Fig. 8 (b)). The distribution of F1 regions and that of areas classed as having undergone human-induced vegetation



**Fig. 8** (a) Spatial pattern of forest change from 2000 to 2015 and (b) trends of residual NDVI in different forest change types.

improvements share similarities in their spatial footprints. Increases in forest cover can be seen in the Otindag and southwestern desert grassland. These are also areas that experienced human-induced vegetation improvements as a result of the ERP. Furthermore, due to natural forest protection legislation and human-induced improvements, persistent forest areas occurred in the Greater Higngan Mountains, Yanshan, and also in northern Shanxi.

#### 3.4.2 Grassland managements

Grassland, which is most prevalent in the northern parts of the study area, was still the dominant vegetation type in the BTSSR after ERP completion (Fig. 9(a)). To foster ecosystem recovery in these areas, grassland management measures such as grassland enclosure and the application of grazing prohibition or rotation regimes were applied. The grazing pressure index (GPI) can provide an indication of how grazing is affecting vegetation cover. We studied the GPI of the largest Xilin Gol Grassland between 2001 and 2014. The index showed a downward trend, as can be seen in Fig. 9(b), indicating a degree of recovery in the Xilin Gol Grassland during this period. Moreover, it also proves that the ERP had a positive effect on vegetation recovery in the Xilin Gol Grassland area.

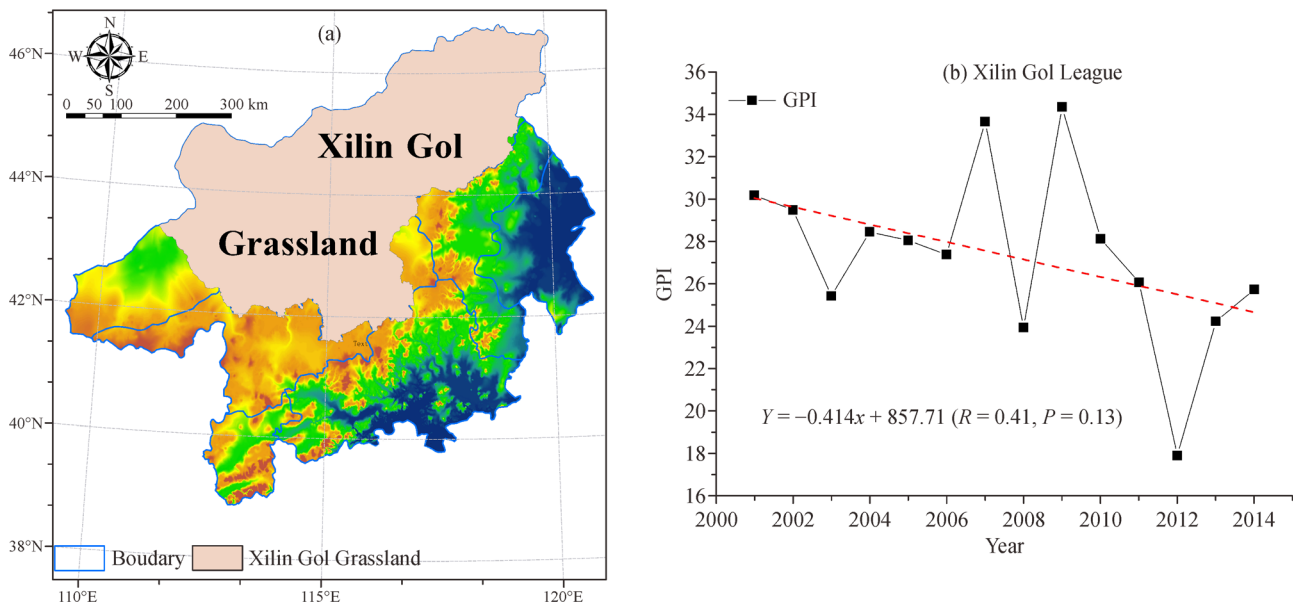
## 4 Discussion

Studying vegetation coverage both before and after the ERP reveals obvious changes between the two periods. We have found that by 2014, vegetation coverage within the BTSSR had cumulatively improved since 1982; these findings are consistent with the results of other studies (Wu et al., 2013; Yu et al., 2021). Prior to the ERP (between

1982 and 2000), the vast majority of the study area showed an increase in NDVI. Some studies have found that vegetation coverage was increasing throughout the study area, both as a whole and on a sub-region level, before the ERP was implemented (Liu et al., 2013). Interestingly, and contrary to expectations, this upward trend did not continue at the same pace after the ERP. Previous studies have also found that over 50% of the BTSSR experienced an increase in vegetation coverage between 2000 and 2010 (Yang et al., 2015). Consequently, the vegetation in most parts of the study area can be said to have shown an overall upward trend both before and after the ERP, but due to the combined effects of both climatic change and human activities, the vegetation restoration situation was grim.

Some studies have indicated that precipitation and temperature have a considerable effect on the rapidity and extent of vegetation change (Lamchin et al., 2016; Luo et al., 2018; Yu et al., 2021). This study demonstrated that extreme climatic events (especially drought) also have a profound effect on processes of vegetative change. Precipitation, rather than temperature, is the dominant factor controlling vegetation “greenness” in the study area, and the response of vegetation to SPEI is high (Pei et al., 2013). Prior to the ERP, the BTSSR experienced an increase in average annual precipitation (Sun et al., 2014). Therefore, we suggest that the increasing trend visible in NDVI before ERP enactment may be a result of precipitation increases during that time. Short-term variations and intra-seasonal distributions of precipitation can also be seen to have had a significant impact on vegetation productivity throughout the BTSSR between 2000 and 2010 (Li et al., 2016).

Before the ERP (1991–2000), under the development of economy and society, vegetation degradation appears primarily to have been caused by the human activities



**Fig. 9** (a) The location of Xilingol Grassland in study area and (b) the trend of GPI from 2001 to 2014 in the Xilin Gol League.

that were undertaken without any consideration for ecological management or protectionism. Examples of such activities include deforestation, land reclamation for agriculture, grazing and so on. However, after the ERP (2001–2014), most of the BTSSR experienced a degree of vegetation restoration as a direct result of human activities. Some ERP measures were implemented, including the protection of natural vegetation, afforestation, “Gain for Green,” grassland management practices (including grazing control,) and comprehensive management of small watersheds (Liu et al., 2013; Wu et al., 2019). Following the implementation of the ERP, vegetation coverage increased between 2000 and 2010. This repeatable measurement was conducted using remotely sensed and ground-based data sets (Wu et al., 2013). Positive human activities undertaken as part of the ERP significantly improved vegetation conditions within the BTSSR. Verification of these observations was achieved by means of in-field surveys. Li et al. (2016) using a residual analysis technique, found that 47% of the study area showed signs of vegetative recovery between 2000 and 2010. These results are in agreement with our own.

Our findings indicate that the ERP had a positive impact on vegetation dynamics in the BTSSR. A spatial correlation is apparent between areas where environmental management measures were implemented and areas in which forest coverage has increased over the course of our study period. The most obvious recovery datable between 2000 and 2010 appears to have occurred in the water source protection area region, which is dominated by forest (Li et al., 2016; Yu et al., 2021). Because hydrological conditions were more favorable, vegetation in this area fared better than elsewhere. Secondly, some studies found that where the grazing pressure index (GPI) was lowered, grasslands began to recover. Conversely, where GPI increased, grasslands degraded. In short, a negative relationship was shown to exist between grassland restoration and GPI (Zhuo et al., 2007). The grazing pressure index (GPI) of the Xilin Gol Grassland showed a downward trend over the past 15 years, indicating that long-term grassland managements are likely to have positive impacts on the vegetation in this area. Chi et al. (2018) found a similarly negative correlation between vegetation coverage and GPI in 94.6% of the Xilin Gol Grassland. Finally, an assessment of overall land use change demonstrates that the ERP led to increase in forest cover. Wang et al. (2013) developed an “Ecological Benefit Evaluation Index (EBEI)” system. This incorporated observations of vegetation changes in both forested and grassland areas, land improvement indices, dust storm records, air quality data, and both soil and water conservation management measures. They used this EBEI to show that the ecological benefits enjoyed by the BTSSR as a result of the ERP have been remarkable. Vegetation cover began to increase after key ecological

interventions had been made, indicating that the implementation of the ERP improved vegetative conditions in the BTSSR during the 2001–2014 period (Jiang et al., 2017; Jiang et al., 2018; Yu et al., 2021).

GIMMIS NDVI data is widely used in the longer-term analysis of vegetation dynamics. Due to the differences in sensors, spectral response functions and the correction methods applied during the acquisition phase leading-up to NDVI production, the research results may be affected. We have found that if corrections are not applied in order to account for any possible data processing errors, substantial “noise” may be introduced into the final NDVI data set. In addition to NDVI-based studies, we argue that two other important impact factors need to be quantified when investigating vegetative change. Based on verified results, we present our new method, as applied in the evaluation of regional ecological impacts following a regional scale ERP. We must be careful to protect the environment, striving for balance between forest and farmland, and paying close attention to climatic factors, a better understanding of which will benefit future environmental management programs.

---

## 5 Conclusions

Using long-term, remotely sensed data sets in conjunction with a BP Neural Network Model, this study showed that although the rate of increase in vegetation cover slowed following the implementation of ecological restoration measures in the BTSSR, instances of vegetation recovery attributable to human intervention increased considerably as a direct result of the ERP. Temperature, precipitation, and extreme climatic events affected vegetation changes at a regional scale. In particular, we observed that precipitation had a greater impact than temperature on vegetation dynamics in the study area. Observed changes in forest area and grazing pressure index demonstrated that vegetation coverage improved following the implementation of key ecological restoration measures. The vegetation recovery and restoration situation within the BTSSR is still precarious. However, despite the effects of climate change, human activities can still play a positive role in rebuilding the area’s ecosystem, working in accordance with local conditions, as opposed to against them.

**Acknowledgements** The authors are grateful to the editor and anonymous reviewers of this paper. This research received financial supports from the National Natural Science Foundation of China (Grant Nos. 41977412, U1810101, and 41871193) and the Scientific and Technological Innovation Programs of Higher Education Institutions in Shanxi (No. 2020L0014) and Higher Education Institution Project of Shanxi Province: Ecological Remediation of Soil Pollution Disciplines Group (No. 20181401).

**Electronic supplementary material** is available in the online version of this article at <http://doi.org/10.1007/s11707-021-0936-3> and is accessible for authorized users.

## References

- Cai B F, Yu D (2009). Advance and evaluation in the long time series vegetation trends research based on remote sensing. *Nat Remote Sens Bull*, 13: 1170–1176 (in Chinese)
- Cai H, Yang X, Wang K, Xiao L (2014). Is forest restoration in the southwest china karst promoted mainly by climate change or human-induced factors? *Remote Sens*, 6(10): 9895–9910
- Cao X, Gu Z H, Chen J, Liu J, Shi P J (2006). Analysis of human-induced steppe degradation based on remote sensing in Xilingole, Inner Mongolia, China. *J Plant Ecol*, 30(2): 268–277
- Cao Z, Li Y R, Liu Y S, Chen Y F, Wang Y S (2018). When and where did the Loess Plateau turn “green”? Analysis of the tendency and breakpoints of the normalized difference vegetation index. *Land Degrad Dev*, 29(1): 162–175
- Chen J, Quan W T, Cui T W, Song Q J, Lin C S (2014). Remote sensing of absorption and scattering coefficient using neural network model: Development, validation, and application. *Remote Sens Environ*, 149: 213–226
- Chen C, Park T, Wang X, Piao S, Xu B, Chaturvedi R K, Fuchs R, Brovkin V, Ciais P, Fensholt R, Tømmervik H, Bala G, Zhu Z, Nemani R R, Myneni R B (2019). China and India lead in greening of the world through land-use management. *Nat Sustain*, 2(2): 122–129
- Chi D K, Wang H, Li X B, Liu H H, Li X H (2018). Assessing the effects of grazing on variations of vegetation NPP in the Xilin Gol Grassland, China, Using a grazing pressure index. *Ecol Indic*, 88: 372–383
- Editorial Board of Vegetation Map of China Academy of Sciences (2001). *Vegetation Atlas of China (1:1000000)*. Beijing: Science Press
- Fensholt R, Proud S R (2012). Evaluation of earth observation based global long term vegetation trends—Comparing GIMMS and MODIS global NDVI time series. *Remote Sens Environ*, 119: 131–147
- Gao S Y (2012). *Benefits of Beijing–Tianjin Sand Source Control Engineering (2nd ed)*. Beijing: Science Press
- He B, Chen A F, Wang H L, Wang Q F (2015). Dynamic response of satellite-derived vegetation growth to climate change in the Three North Shelter Forest Region in China. *Remote Sens*, 7(8): 9998–10016
- Herrmann S M, Anyamba A, Tucker C J (2005). Recent trends in vegetation dynamics in the African Sahel and their relationship to climate. *Glob Environ Change*, 15(4): 394–404
- Huang S Z, Ming B, Huang Q, Leng G Y, Hou B B (2017). A case study on combination NDVI forecasting model based on the entropy weight method. *Water Resour Manage*, 31(11): 3667–3681
- Islam K, Rahman M F, Jashimuddin M (2018). Modeling land use change using cellular automata and artificial neural network: the case of Chunati Wildlife Sanctuary, Bangladesh. *Ecol Indic*, 88: 439–453
- Jiang C, Nath R, Labzovskii L, Wang D W (2018). Integrating ecosystem services into effectiveness assessment of ERP in northern China’s arid areas: Insights from the Beijing–Tianjin Sandstorm Source Region. *Land Use Policy*, 75: 201–214
- Jiang M, Tian S, Zheng Z, Zhan Q, He Y (2017). Human activity influences on vegetation cover changes in Beijing, China, from 2000 to 2015. *Remote Sens*, 9(3): 271
- Lamchin M, Lee J Y, Lee W K, Lee E J, Kim M, Lim C H, Choi H A, Kim S R (2016). Assessment of land cover change and desertification using remote sensing technology in a local region of Mongolia. *Adv Space Res*, 57(1): 64–77
- Li J, Wang Z, Lai C, Wu X, Zeng Z, Chen X, Lian Y (2018). Response of net primary production to land use and land cover change in mainland China since the late 1980s. *Sci Total Environ*, 639: 237–247
- Li X S, Wang H Y, Wang J Y, Gao Z H (2015). Land degradation dynamic in the first decade of twenty-first century in the Beijing–Tianjin dust and sandstorm source region. *Environ Earth Sci*, 74(5): 4317–4325
- Li X S, Wang H Y, Zhou S F, Sun B, Gao Z H (2016). Did ecological engineering projects have a significant effect on large-scale vegetation restoration in Beijing–Tianjin Sand Source Region, China? A remote sensing approach. *Chin Geogr Sci*, 26(2): 216–228
- Liu Z Q, Zhu Q K, Qin W, Li P, Wang J, Kuang G M (2010). Comparison of vegetation community between natural recovery and artificial restoration in semiarid loess area. *Ecol Environ*, 4: 857–863
- Liu D, Chang Q L (2015). Ecological security research progress in China. *Acta Ecol Sin*, 35(5): 111–121
- Liu J H, Wu J J, Wu Z T, Liu M (2013). Response of NDVI dynamics to precipitation in the Beijing–Tianjin sandstorm source region. *Int J Remote Sens*, 34(15): 5331–5350
- Liu R, Xiao L L, Liu Z, Dai J C (2018). Quantifying the relative impacts of climate and human activities on vegetation changes at the regional scale. *Ecol Indic*, 93: 91–99
- Luo L H, Ma W, Zhuang Y, Zhang Y L, Yi S, Xu J, Long Y, Ma D, Zhang Z (2018). The impacts of climate change and human activities on alpine vegetation and permafrost in the Qinghai–Tibet Engineering Corridor. *Ecol Indic*, 93: 24–35
- Ma H, Lv Y, Li H X (2013). Complexity of ecological restoration in China. *Ecol Eng*, 52: 75–78
- Miao L, Liu Q, Fraser R, He B, Cui X F (2015). Shifts in vegetation growth in response to multiple factors on the Mongolian Plateau from 1982 to 2011. *Phys Chem Earth Parts ABC*, 87–88: 50–59
- Mu X, Song W, Gao Z, McVicar T R, Donohue R J, Yan G (2018). Fractional vegetation cover estimation by using multi-angle vegetation index. *Remote Sens Environ*, 216: 44–56
- Pei F S, Wu C J, Liu X P, Li X, Yang K Q, Zhou Y, Wang K, Xu L, Xia G R (2018). Monitoring the vegetation activity in China using vegetation health indices. *Agric Meteorol*, 248: 215–227
- Pei L, Huang S W, Chen L P (2013). Vegetation spatio-temporal changes and the relationship with climate factors in the Beijing–Tianjin Sand Source Region. *J Desert Res*, 5: 1593–1597
- Peng J, Dong W J, Yuan W P, Yong Z (2012). Response of grassland and forest to temperature and precipitation changes in Northeast China. *Adv Atmosph Sci*, 29(5): 1063–1077
- Piao S, Fang J, He J, Xiao Y (2004). Spatial distribution of grassland biomass in China. *Chin J Plan Ecol*, 28(4): 491–498
- Piao S, Nan H, Huntingford C, Ciais P, Friedlingstein P, Sitch S, Peng S, Ahlström A, Canadell J G, Cong N, Levis S, Levy P E, Liu L, Lomas M R, Mao J, Myneni R B, Peylin P, Poulter B, Shi X, Yin G, Viovy N, Wang T, Wang X, Zaehle S, Zeng N, Zeng Z, Chen A (2014). Evidence for a weakening relationship between interannual temperature variability and northern vegetation activity. *Nat Commun*, 5(1):

5018–5024

- Qu S, Wang L C, Lin A W, Zhu H J, Yuan M X (2018). What drives the vegetation restoration in Yangtze River basin, China: climate change or anthropogenic factors? *Ecol Indic*, 90: 438–450
- Shan N, Shi Z, Yang X, Gao J, Cai D (2015). Spatiotemporal trends of reference evapotranspiration and its driving factors in the Beijing–Tianjin Sand Source Control Project Region, China. *Agr Forest Meteorol*, 200: 322–333
- Sun B, Gao Z H, Wang H Y, Wu J J, Li C L (2014). Dry/Wet variation of Beijing–Tianjin dust and sandstorm source region during 1981–2010. *J Arid Land Resour Environ*, 28: 164–170
- Sun Y L, Guo P, Yan X D, Zhao T B (2010). Dynamics of vegetation cover and its relationship with climate change and human activities in Inner Mongolia. *J Natu Resour*, 3: 407–414
- Tang J, Cao H Q, Chen J (2019). Effects of ecological conservation projects and climate variations on vegetation changes in the source region of the Yangtze River. *Acta Geogr Sin*, 74: 76–86
- Tong X, Brandt M, Yue Y, Horion S, Wang K, Keersmaecker W D, Tian F, Schurgers G, Xiao X, Luo Y, Chen C, Myneni R, Shi Z, Chen H, Fensholt R. (2018). Increased vegetation growth and carbon stock in China karst via ecological engineering. *Nat Sustain*, 1(1): 44–50
- Tu Z F, Xian M L, Tao S (2016). The status and trend analysis of desertification and sandification. *Forest Resour Manag*, 1: 1–5
- Vicente-Serrano S M, Begueria S, Lopez-Moreno J I (2010). A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. *J Clim*, 23(7): 1696–1718
- Wang L Q, Qiao N, Kang R B (2013). Review of the research on ecological effects and evaluation of Sandstorm Source Control Project in and around Beijing and Tianjin. *Forest Econom*, (6): 14–18 (in Chinese)
- Wei B C, Xie Y W, Jia X, Wang X Y, He H J, Xue X Y (2018). Land use/land cover change and its impacts on diurnal temperature range over the agricultural pastoral ecotone of northern China. *Land Degrad Dev*, 29: 3009–3020
- Wu Z, Wu J, He B, Liu J, Wang Q, Zhang H, Liu Y (2014). Drought offset ecological restoration program-induced increase in vegetation activity in the Beijing–Tianjin Sand Source Region, China. *Environ Sci Technol*, 48(20): 12108–12117
- Wu Z T, Wu J J, Liu J H, He B, Lei T J, Wang Q F (2013). Increasing terrestrial vegetation activity of ERP in the Beijing–Tianjin Sand Source Region of China. *Ecol Eng*, 52: 37–50
- Wu Z, Yu L, Zhang X, Du Z, Zhang H (2019). Satellite-based large-scale vegetation dynamics in ecological restoration programmes of northern China. *Int J Remote Sens*, 40(5-6): 2296–2312
- Yang X C, Xu B, Jin Y X, Qin Z H, Ma H L, Li J Y, Zhao F, Chen S, Zhu X H (2015). Remote sensing monitoring of grassland vegetation growth in the Beijing–Tianjin sandstorm source project area from 2000 to 2010. *Ecol Indic*, 51: 244–251
- Yu L, Wu Z T, Du Z Q, Zhang H, Liu Y (2021). Insights on the roles of climate and human activities to vegetation degradation and restoration in Beijing–Tianjin sandstorm source region. *Ecol Eng*, 159: 106105
- Zhao L, Dai A G, Dong B (2018). Changes in global vegetation activity and its driving factors during 1982–2013. *Agric Meteorol*, 249: 198–209
- Zhao Y Y, Chi W F, Kuang W H, Bao Y F, Ding G D (2020). Ecological and environmental consequences of ecological projects in the Beijing–Tianjin sand source region. *Ecol Indic*, 112: 106111
- Zhuo L, Cao X, Chen J, Chen Z X, Shi P J (2007). Assessment of grassland ecological restoration project in Xilin Gol Grassland. *Acta Geogr Sin*, 62(5): 471–480