Chin. Geogra. Sci. 2016 Vol. 26 No. 2 pp. 216–228
doi: 10.1007/s11769-016-0801-6

Springer Science Press
www.springerlink.com/content/1002-0063

Did Ecological Engineering Projects Have a Significant Effect on Large-scale Vegetation Restoration in Beijing-Tianjin Sand Source Region, China? A Remote Sensing Approach

LI Xiaosong[1], WANG Hongyan[1], ZHOU Shufang[2], SUN Bin[3], GAO Zhihai[3]

(1. *Key Laboratory of Digital Earth Science*, *Institute of Remote Sensing and Digital Earth*, *Chinese Academy of Sciences*, *Beijing* 100094, *China*; 2. *Twenty First Century Aerospace Technology Co. Ltd.*, *Beijing* 100096, *China*; 3. *Institute of Forest Resources Information Technique*, *Chinese Academy of Forestry*, *Beijing* 100091, *China*)

Abstract: Aiming for the restoration of degraded ecosystems, many ecological engineering projects have been implemented around the world. This study investigates the ecological engineering project effectiveness on vegetation restoration in the Beijing-Tianjin Sand Source Region (BTSSR) from 2000 to 2010 based on the rain use efficiency (RUE) trend in relation to the land cover. More than half of the BTSSR experienced a vegetation productivity increase from 2000 to 2010, with the increasing intensity being sensitive to the indicators chosen. A clear tendency towards smaller increasing areas was shown when using the net primary productivity (NPP, 51.30%) instead of the accumulated normalized difference vegetation index (59.30%). The short-term variation in the precipitation and intra-seasonal precipitation distribution had a great impact on the remote sensing-based vegetation productivity. However, the residual trends method (RESTREND) effectively eliminated this correlation, while incorporating the variance and skewness of the precipitation distribution increased the models′ ability to explain the vegetation productivity variation. The RUE combined with land cover dynamics was valid for the effectiveness assessment of the ecological engineering projects on vegetation restoration. Particularly, the result based on growing season accumulated normalized difference vegetation index (ΣNDVI) residuals was the most effective, showing that 47.39% of the BTSSR experienced vegetation restoration from 2000 to 2010. The effectiveness of the ecological engineering projects differed for each subarea and was proportional to the strength of ecological engineering. The water erosion region dominated by woodland showed the best restoration, followed by the wind-water erosion crisscross regions, while the wind erosion regions dominated by grassland showed the worst effect. Seriously degraded regions still cover more area in the BTSSR than restored regions. Therefore, more future effort should be put in restoring degraded land.

Keywords: vegetation restoration; ecological engineering; rain use efficiency (RUE); residual trends method (RESTREND); Beijing-Tianjin Sand Source Region (BTSSR)

Citation: Li Xiaosong, Wang Hongyan, Zhou Shufang, Sun Bin, Gao Zhihai, 2016. Did ecological engineering projects have a significant effect on large-scale vegetation restoration in Beijing-Tianjian sand source region, China? A remote sensing approach. *Chinese Geographical Science*, 26(2): 216–228. doi: 10.1007/s11769-016-0801-6

1 Introduction

Land degradation in the Beijing-Tianjin Sand Source Region (BTSSR) (Wu *et al.*, 2012) caused several environmental problems in two large cities (Beijing and Tianjin) in northern China. Aiming for the restoration of degraded ecosystems, some ecological engineering projects have been performed in recent years, such as the Beijing and Tianjin Sandstorm Source Controlling Program (Wu *et al.*, 2013), the Grain for Green Project

Received date: 2015-03-24; accepted date: 2015-05-21
Foundation item: Under the auspices of National Natural Science Foundation of China (No. 41571421), National Science and Technology Major Project of China (No. 21-Y30B05-9001-13/15)
Corresponding author: GAO Zhihai. E-mail: zhgao@caf.ac.cn

(Stokes *et al.*, 2010), and the Three-North Shelterbelt Project (Ma, 2004). Considering the strong disagreement regarding the effectiveness of ecological engineering projects (Cao, 2008; Liu *et al.*, 2008; Yang and Ci, 2008; Wang *et al.*, 2010) and the major investment in manpower, material, and financial resources (Wang *et al.*, 2007), there is an urgent need for the assessment of the effectiveness of ecological engineering projects in the BTSSR with objective, consistent, and spatially explicit measures.

Vegetation restoration has always been a primary goal in ecological engineering projects in the BTSSR, with measures such as enclosure of grassland, cropland change to grassland or forest, afforestation and reforestation, and grazing prohibition. Therefore, the assessment of the effectiveness of ecological engineering projects on vegetation restoration should be given a high priority. Trend analysis of coarse resolution vegetation indicators based on remote sensing, such as the normalized difference vegetation index (NDVI) and the net primary productivity (NPP), have been widely used to monitor vegetation restoration or degradation (Zhang *et al.*, 2012; Huang *et al.*, 2013; Wu *et al.*, 2013). However, this approach faces two major challenges regarding the effectiveness assessment of ecological engineering projects on vegetation restoration. First, the vegetation dynamics involves human and climatic factors, with high correlations between precipitation and vegetation indicators (Tucker *et al.*, 1991; Du Plessis, 1999; Herrmann *et al.*, 2005; Wu *et al.*, 2013). Since the aim is to detect vegetation changes caused by ecological engineering projects, the confounding effect of the precipitation must be eliminated. Second, the increase or decrease in the vegetation productivity does not necessarily represent vegetation restoration or degradation. For example, when changing cropland to grassland, as in the Grain for Green Project, the vegetation productivity decreased, while representing vegetation restoration.

In this paper, we attempted to solve these challenges and investigate the effectiveness of ecological engineering projects on vegetation restoration in the BTSSR during 2000–2010 (coincident with the first phase of the Beijing and Tianjin Sandstorm Source Controlling Program) using remote sensing. We assessed the vegetation productivity change in the BTSSR during 2000–2010, determined how much of this productivity change resulted from precipitation changes, and explored the differences in the results when using different vegetation productivity indicators. In addition, we assessed if a combination of the rain use efficiency (RUE) trend and land cover dynamics could evaluate better the effectiveeness of ecological engineering projects on vegetation restoration or degradation and if the ecological engineering projects were effective on vegetation restoration, was there any difference between different subareas of the BTSSR? These questions are very important for ecosystem restoration through ecological engineering.

2 Materials and Methods

2.1 Study area

The Beijing-Tianjin Sand Source Region in China (38°50′–46°40′N, 109°30′–120°30′E) (Fig. 1) includes 75 counties in Beijing, Tianjin, Hebei, Shanxi, and Inner Mongolia. It has a total area of 458 000 km^2, of which approximately 101 200 km^2 is desertified, mainly in the Otindag and Horqin Sandy Lands, where land degradation has been attributed to overgrazing, excessive reclamation, deforestation, and climate change (Wu *et al.*, 2006).

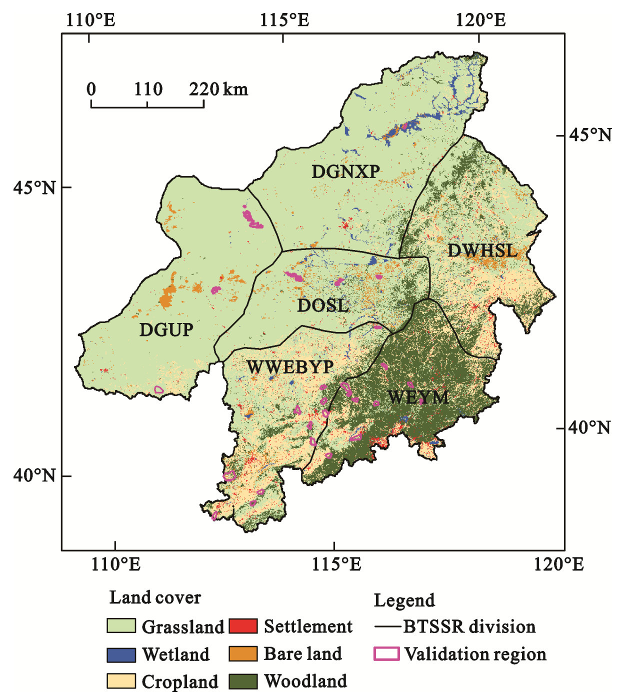


Fig. 1 Location of study area, Beijing-Tianjin Sand Source Region (BTSSR), China. DGUP: degraded grassland on the Ulanqab Plateau; DGNXP: degraded grassland on the North Xilingol Plateau; DOSL: desertified areas in the Otindag Sandy Land; DWHSL: desertified areas in the western Horqin Sandy Land; WWEBYP: wind and water eroded areas in the Bashang and Yanbei plateaus; WEYM: water eroded area in the Yanshan Mountains. Land cover obtained from the ChinaCover 2010

Study area includes arid, semi-arid, dry sub-humid and semi-humid climates, with an annual precipitation ranging from 200 mm in the northwest to 600 mm in the southeast. The topography includes plateaus, mountains, and plains. The Beijing-Tianjin region includes the flood plain in the south of the Yanshan Mountains and a large part of the Inner Mongolian Plateau in the north of the mountains. The northwest corresponds to an arid steppe, mainly typical and desert steppe, mostly of pedocal soils. The southeast includes plateaus and mountains, with mainly temperate deciduous forests and temperate deciduous shrubs, and leached soil. Distinctive vegetation and soil types have developed in these regions under the influence of specific climatic conditions and topography.

The BTSSR was divided in six rehabilitation areas according to the climate zone, land cover type, and degradation characteristics (Wu *et al.*, 2006) (Table 1). Detailed information on the rehabilitation divisions is given in Table 1. Since the ecological engineering projects were scheduled for different rehabilitation divisions, this study uses these divisions to evaluate and compare the effectiveness of ecological engineering on vegetation restoration.

2.2 Data and processing

2.2.1 NDVI

The MOD13Q1 vegetation index product (250 m), from the Earth Observation System (EOS) (Huete *et al.*, 2002), was used to determine the vegetation productiveity changes in 2000–2011. This product was a 16-day composite, in which daily data were selected based on quality factors such as the cloud cover and viewing geometry. To remove any residual cloud effect or other outliers, the harmonic analysis of the normalized difference vegetation index (NDVI) time-series (HANTS) algorithm (Julien and Sobrino, 2010) was adopted to smoothen and reconstruct the NDVI time-series (de Jong *et al.*, 2011). The HANTS-reconstructed data for 2000–2011 were then used in this research.

2.2.2 Meteorological data

A high temporal and spatial resolution meteorological dataset from the Institute of Tibetan Plateau Research, Chinese Academy of Sciences (ITPCAS), validated by 740 China Meteorological Administration stations (Chen *et al.*, 2011), were used to match the NDVI characteristics as closely as possible. The use of Tropical Rainfall Measuring Mission (TRMM) 3B42 precipitation products compensated for the lack of meteorological stations. Additionally, the datasets considered the impact of elevation on the spatial variation of climatic factors, producing a higher accuracy. The spatial resolution of the meteorological data was $0.1° \times 0.1°$, with a temporal resolution of 3 hours. Mainly precipitation, temperature, and solar radiation data were used for the NPP and RUE calculation. The original meteorological data for 2000–2011 were summed to a 16-day value and resampled to 250 m to match the Moderate Resolution Imaging Spectroradiometer (MODIS) NDVI datasets.

2.2.3 Land cover maps

Land cover maps for 2000 and 2010 were obtained from the ChinaCover dataset, mainly developed by the Institute of Remote Sensing and Digital Earth, Chinese Academy of Sciences (http://www.chinacover.org.cn/). This product used an automatic object-oriented classification based on 30 m Landsat and Chinese Huanjing (HJ) 1A/1B satellite data. The classification system consisted of 6 classes in level I and 38 classes in level II, derived from 19 criteria regarding the composition, structure, pattern, phenology, *etc*. (Zhang *et al.*, 2014). Level I classes included woodland, grassland, wetland, cropland, settlement, and bare land. The ChinaCover datasets were well validated, with an accuracy above 85% for 2000 and 2010 (Zhang *et al.*, 2014).

Table 1 Rehabilitation divisions in Beijing-Tianjin Sand Source Region (BTSSR)

Name	Area (km^2)	Climate zone	Dominant land cover	Erosion type
Degraded grassland on Ulanqab Plateau (DGUP)	91 775	Arid	Desert steppe	Wind
Degraded grassland on north Xilingol Plateau (DGNXP)	101 884	Semi-arid	Steppe	Wind
Desertified areas in Otindag Sandy Land (DOSL)	54 543	Semi-arid	Steppe	Wind
Desertified areas in western Horqin Sandy Land (DWHSL)	75 157	Dry sub-humid	Meadow steppe	Wind and water
Wind and water eroded areas in Bashang and Yanbei plateaus (WWEBYP)	70 628	Dry sub-humid	Steppe	Wind and water
Water eroded area in Yanshan Mountains (WEYM)	63 674	Semi-humid	Woodland	Water

2.2.4 Actual observed NPP

In order to validate the simulated NPP, the biomass was obtained at 32 grassland sites in the BTSSR. The observations were made in late August, 2011, when the above-ground biomass reached the maximum. Considering the spatial resolution of simulated NPP (250 m), all sites were flat homogeneous grasslands and the areas were not less than 500 m × 500 m. Each site had three 30 m × 30 m plots, and each plot had three 1 m × 1 m samples, the location of plots and samples were designed evenly distributed in order to ensure the representativeness. For all the samples, the above-ground biomasses were obtained. The ratio of below-ground biomass and above-ground biomass and the carbon content were 2.8 and 47.0% in semi-arid grassland, respectively as recommended by IPCC (2006), based on which, the below-ground biomass was acquired, and then the total dry weight of biomass was converted to weight of carbon. Finally, the average weight of carbon of 9 samples was used as the actual NPP for each site.

2.3 Methods

2.3.1 Measurement of vegetation productivity

The vegetation productivity, i.e., growth in vegetation biomass, can be measured using remote sensing (Tucker *et al.*, 2001; Ludwig *et al.*, 2007; Zhao *et al.*, 2009; Zhang *et al.*, 2011). There are several methods to obtain the NPP from satellite data, mostly depending on the relation between the vegetation indices and the light absorbed by the vegetation photosynthetic part. In this study, the NPP was computed by using the Carnegie-Ames-Stanford approach (CASA) (Potter *et al.*, 1993) with the maximum light use efficiency for each vegetation type referencing to Zhu *et al*. (2005). Base on which, the simulated NPP has been prove to be highly consistent with actual observed NPP in northern China, with an R^2 ranging from 0.4545 to 0.8582 (Zhu *et al.*, 2005; Zhu *et al.*, 2006; Long *et al.*, 2010; Mao *et al.*, 2014). Since the input data sources were not completely consistent with earlier studies, the simulated NPP in this study were validated through comparing with actual observed NPP of 32 sites. The NPP in the growing season (April–September) (hereafter refer to as NPP) was aggregated from the 16-day NPP datasets for 2000–2010 (n = 11).

Except for the CASA-modeled NPP, the growing season-accumulated NDVI (ΣNDVI) was adopted as a surrogate because of the strong linear correlation between the ΣNDVI and NPP for arid and semi-arid vegetation (Prince, 1991; Wessels *et al.*, 2007). The CASA model used the NDVI but also other variables, such as precipitation, temperature, and solar radiation. However, its more mechanistic approach does not necessarily improve the accuracy (Fensholt *et al.*, 2006) and can actually reduce it because of errors in the additional input variables. Therefore, both the NPP and ΣNDVI were used and compared in this study.

2.3.2 Calculation of rain use efficiency

The per-pixel Pearson correlation coefficient (r) was used to analyze the correlation between the ΣNDVI, NPP and precipitation for the 11 year datasets. The RUE was calculated using both the NPP and the ΣNDVI. The RUE was only used for regions where the vegetation productivity was positively related with the precipitation. The residual trends (RESTREND) method proposed by Wessels *et al.* (2007) was used for calculating the RUE. A linear regression of the ΣNDVI (or NPP) with the annual precipitation was performed, after which the residuals (difference between the modeled ΣNDVI (or NPP) and the remote sensing-based ΣNDVI (or NPP)) were calculated for each pixel.

2.3.3 Trend estimation

The Sen′s slope (β), a robust non-parametric estimation of the trend magnitude (Sen, 1968; Topaloglu, 2006), especially effective for small and noisy series, was used for the temporal trend analyses of the precipitation, ΣNDVI, NPP, ΣNDVI residuals ($RUE_{\Sigma NDVI}$), and NPP residuals (RUE_{NPP}) datasets. A positive β represented an increasing trend, while a negative β indicated a decreasing trend. The Mann-Kendall test was used to detect the significance of the trend (Kendall, 1938). When the Mann-Kendall statistic ′z′ was equal to or larger than 1.64, the trend was considered significant at a 90% confidence level.

2.3.4 Evaluation of ecological engineering effectiveness

The effectiveness of the ecological engineering projects was determined by analyzing the land cover conversions and vegetation productivity trends between 2000 and 2010. The effect of the short-term precipitation variation on the productivity was normalized using the RUE for the pixels where the NPP and ΣNDVI were positively correlated with the precipitation. The analysis consisted of four steps. Because of their weak relation with ecological engineering projects, the water bodies, cropland, and settlement regions in 2010 were excluded from the effectiveness evaluation. Then, based on the land cover characteristics, the cropland areas converted to grassland were defined as positive in effectiveness, while for the other regions, if the NPP or ΣNDVI were positively correlated with the precipitation, the RUE time-series determined if the pixel vegetation productivity had increased with time, suggesting an effective vegetation restoration, or vice versa for zero and negative trends. For regions with a negative correlation between the NPP and the precipitation, only the NPP or ΣNDVI temporal trends were examined to evaluate the effectiveness. Caution was needed in the interpretation of the vegetation productivity or RUE trends, since the temporal distribution of the precipitation or other climatic factors could also affect the vegetation productivity.

2.3.5 Validation

To validate the performance of the proposed approach for the effectiveness evaluation of ecological engineering projects on vegetation restoration, 28 regions (of 7–293 km^2), characterized by significant vegetation degradation or restoration from 2000 to 2010, were used (Fig. 1). Among them, 11 were clearly degraded areas identified by the land cover conversion analysis based on the ChinaCover, while the other 17 regions were managed small watersheds, which received thorough ecological engineering measures in 2002 and 2003 under the Planning for Sustainable Utilization of Water Resources in Beijing in the early 21th century and have been acknowledged and reported as significantly restored areas (http://www.gov.cn/ztzl/slgz/content_543529.htm). Each region was considered positive or negative regarding effectiveness, with the proportion of the pixels with the same effectiveness used as a validation region to evaluate the performance of the proposed effectiveness evaluation method.

3 Results and Analyses

3.1 Validation of NPP estimation

Compared with field data, the R^2 between observed NPP and simulated NPP was 0.8032 (P < 0.0001), showing a significant linear relationship between them (Fig. 2). Therefore, the simulated NPP based on CASA could be well used to reflect the temporal and spatial difference of NPP in the BTSSR, which was the foundation of our analysis later. Despite the highly correlation, it could be found that the simulated NPP tended to underestimate the NPP of grassland with relative high biomasses to some extent. Considering the scale difference and multiple uncertainties in field investigation, some difference like this was inevitable. In general, the simulated NPP was considered as reliable and can be used to support research.

3.2 Relationship between NPP, ΣNDVI, and precipitation

The per-pixel Pearson correlation coefficient (r) of the ΣNDVI and NPP for the BTSSR from 2000 to 2010 is shown in Fig. 3. An overall high positive linear relation existed between the ΣNDVI and the NPP (higher than 0.8 in brown), which differed spatially in strength. In general, an increase in the humidity index (from arid to sub-humid conditions) resulted in a decreasing trend in the ΣNDVI and NPP correlation. In particular, most low r values (< 0.4) and all negative r values were located in sub-humid regions (WEYM). The ΣNDVI and NPP relationship was also clearly related with the land cover type, with most low r values located in woodland and bare land, while high r values (> 0.8) spread over other vegetation types.

According to the correlation between the vegetation productivity (ΣNDVI in Fig. 4A and NPP in Fig. 4B) and the precipitation, the relationships between the ΣNDVI and NPP and the precipitation differed in

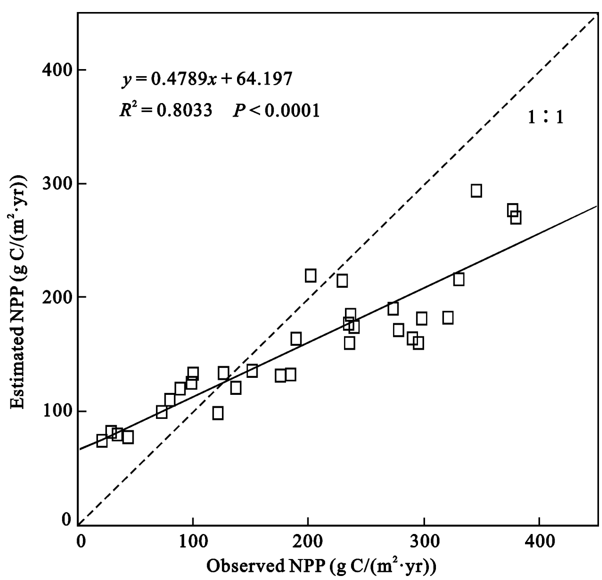


Fig. 2 Comparison between simulated and observed NPP for Inner Mongolia grassland in 2011

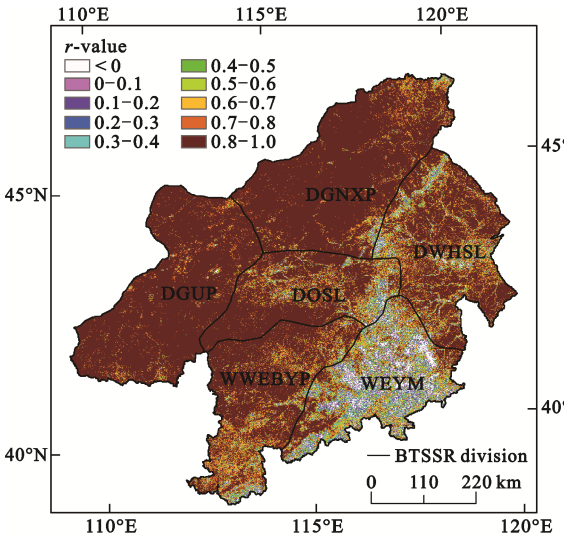
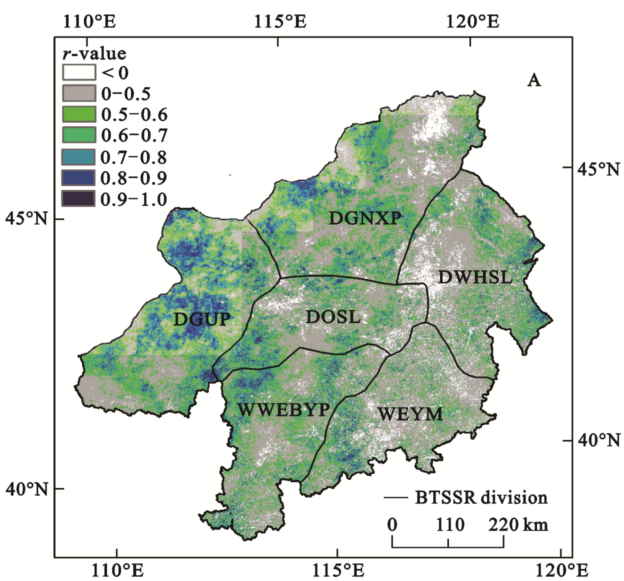


Fig. 3 Accumulated normalized difference vegetation index (ΣNDVI)/net primary productivity (NPP) correlation per-pixel based on annual observations (2000–2010). BTSSR is study area, Beijing-Tianjin Sand Source Region, China

strength, but had similar spatial patterns. The relationship between precipitation and ΣNDVI was generally stronger and significant (α = 0.1) in 44% of the area, while the precipitation-NPP relationships were significant (α = 0.1) in 38% of the study area. On average, the vegetation productivity was significantly and positively related with the precipitation, except in the sub-humid region (WEYM) with woodland cover, where insignificant positive and negative relationships were dominant. The strongest vegetation productivity and precipitation relationships were found in the northwestern BTSSR, covering most of the DGUP, the central and western DOSL, and the northern WWEBYP. Summarizing, the vegetation productivity in the BTSSR was strongly influenced by precipitation, whose effect must be eliminated for an objective assessment of the effectiveness of ecological engineering projects on vegetation restoration.

3.3 Spatial and temporal variability of precipitation, vegetation productivity and RUE

The vegetation productivity trends based on the ΣNDVI (Fig. 5A) and NPP (Fig. 5B) in the BTSSR for 2000–2010 exhibit three northeast to southwest stripes. The northern and southern stripes are mainly characterized by increasing trends, while the middle stripe is dominated by decreasing trends. The statistical analysis revealed that 59.30% of the BTSSR increased in ΣNDVI during 2000–2010, with 12.59% corresponding to a significant increase at a 90% confidence level, while 40.7% decreased, with 4.95% being significant. For the NPP, 51.30% increased (with 7.03% being significant), while 48.7% decreased (with 6.91% being significant) (Table 2). Overall, increasing vegetation productivity was dominant in the BTSSR from 2000 to 2010, with a clear tendency for smaller areas showing increasing trends when using the NPP. The ΣNDVI and NPP trends showed very similar spatial patterns for arid, semi-arid,



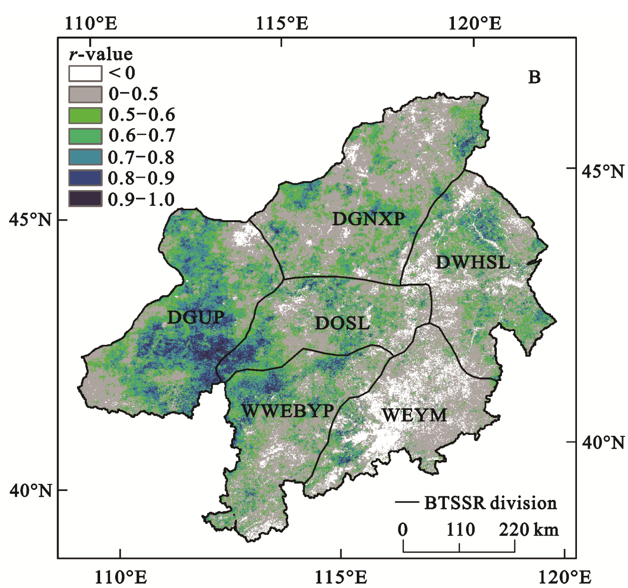


Fig. 4 Correlation between precipitation and accumulated normalized difference vegetation index (ΣNDVI) (A) and net primary productivity (NPP) (B) in study area during 2000–2010. BTSSR is study area, Beijing-Tianjin Sand Source Region, China

and dry sub-humid regions, while clearly differing for sub-humid areas (WEYM), where large areas of significantly increasing ΣNDVI trends were characterized by decreasing NPP trends. The difference was consistent with the negative relationship between the ΣNDVI and NPP (Fig. 3), showing that, in the BTSSR, the interaction between the precipitation and the NPP was more complex for woodlands.

The temporal trends in the ΣNDVI ($RUE_{ΣNDVI}$) and NPP residuals (RUE_{NPP}) are shown in Figs. 5C and 5D, respectively. Comparing with the ΣNDVI and NPP trends, the regions with significantly increasing trends widely decreased, especially between the DGUP and DGNXP, suggesting that, in spite of their significantly increasing trends in vegetation productivity, it was lower than the predicted by the precipitation. Consequently, the regions with decreasing trends expanded to some extent, especially in the DGUP and DOSL, where some originally increasing trends changed to decreasing trends, meaning that precipitation fluctuations explained some of the decrease. The statistical analysis showed that 50.33% of the BTSSR increased in terms of $RUE_{ΣNDVI}$ trends from 2000 to 2010, with 10.86% increasing significantly at a 90% confidence level, while 49.67% decreased, with 9.47% being significant. Regarding the RUE_{NPP} trends, 43.66% increased (with

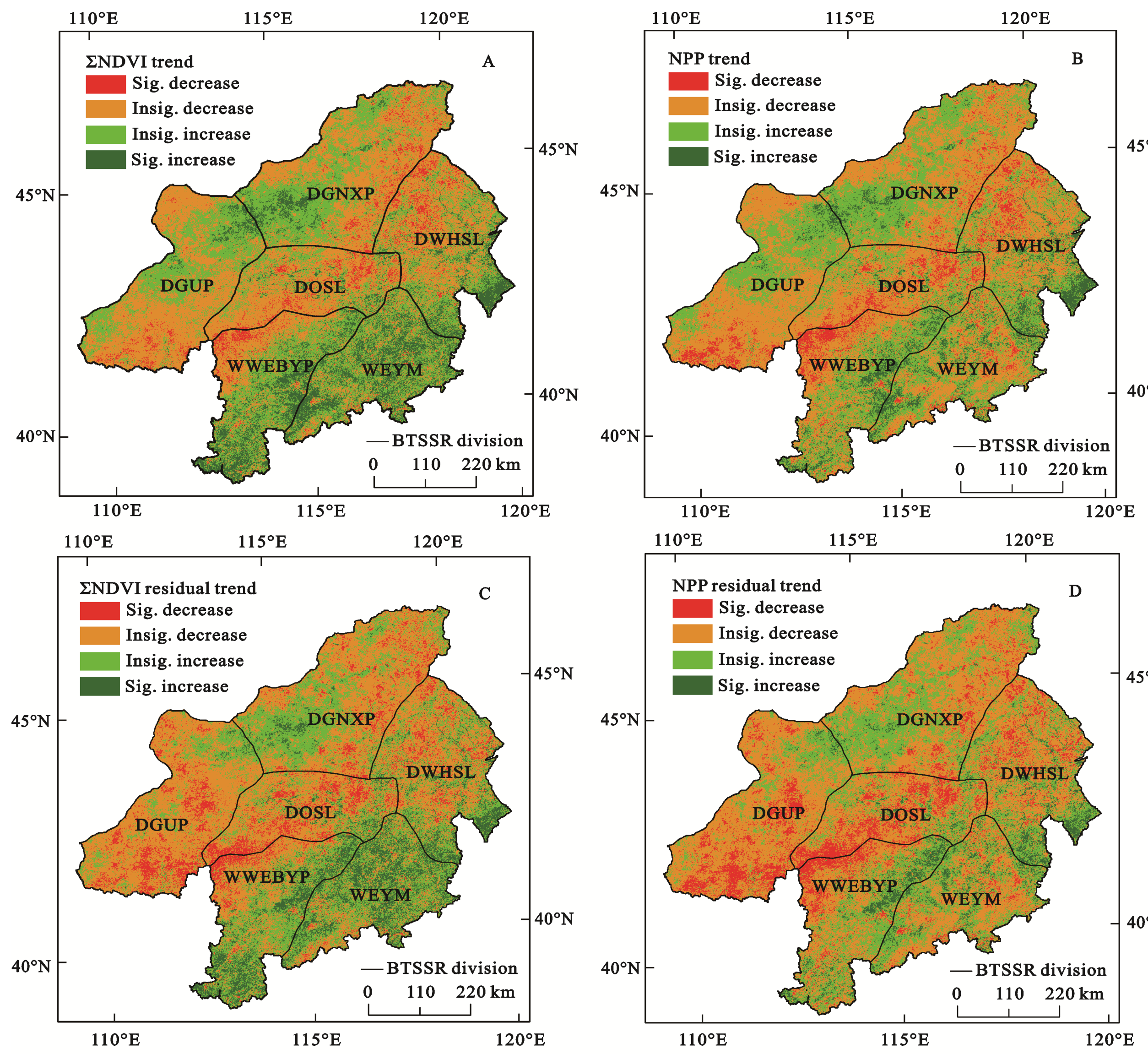


Fig. 5 Linear trends of vegetation productivity from 2000 to 2010 based on accumulated difference vegetation index (ΣNDVI) (A), net primary productivity (NPP) (B), ΣNDVI residuals ($RUE_{ΣNDVI}$) (C), and NPP residuals (RUE_{NPP}) (D). Sig. is significant and Insig. is not significant. BTSSR is study area, Beijing-Tianjin Sand Source Region, China

5.46% being significant) and 56.34% decreased (with 12.03% being significant) (Table 2).

3.4 Evaluation and validation of ecological engineering effectiveness

Based on the proposed methodology and regardless of the difference between the $RUE_{\Sigma NDVI}$ and RUE_{NPP}, the ecological engineering projects proved to be effective on vegetation restoration in the south and central-north of the BTSSR, while being ineffective in the remaining study region (Fig. 6). Based on the $RUE_{\Sigma NDVI}$, 47.39% of the BTSSR experienced vegetation restoration (with 9.59% being significant) from 2000 to 2010. When the RUE_{NPP} was used, this proportion decreased to 41.7% (with 4.42% being significant). Regardless of the vegetation productivity indicator chosen, nearly half of the BTSSR benefited from ecological engineering in terms of vegetation restoration.

The effectiveness of the ecological engineering was validated for 28 regions and the performance using different indicators was compared (Table 3). Results based on $RUE_{\Sigma NDVI}$ and RUE_{NPP} were both consistent with the validation regions, with contrary effectiveness trends seldom existing. The statistical results showed that 96.4% ($RUE_{\Sigma NDVI}$) and 94.7% (RUE_{NPP}) of the vegetation restoration regions had a positive effectiveness, while 93.4% ($RUE_{\Sigma NDVI}$) and 92.9% (RUE_{NPP}) of the vegetation degradation regions had a negative effectiveness. Not all validation regions were identified by our approach, regardless of using the $RUE_{\Sigma NDVI}$ or the RUE_{NPP}, which was expected since the validation regions only assured that most of the area was improving or degrading, but not all pixels.

Since all validation regions were clearly degraded or recovered regions, it was necessary to compare the difference in significant effectiveness. For vegetation restoration regions, 52.7% of the total pixels were assessed as significantly positive using the $RUE_{\Sigma NDVI}$, while only 33.5% were significantly positive when the RUE_{NPP} was used. This large difference (19.2%) was consistent with

Table 2 Statistical results of vegetation productivity and rain use efficiency (RUE) trend from 2000 to 2010

Indicators	Pixels analyzed	Significantly decrease (%)	Insignificantly decrease (%)	Insignificantly increase (%)	Significantly increase (%)
ΣNDVI	7322378	4.95	35.75	46.71	12.59
NPP	7322378	6.91	41.79	44.27	7.03
$RUE_{\Sigma NDVI}$	7322378	9.47	40.20	39.47	10.86
RUE_{NPP}	7322378	12.03	44.31	38.20	5.46

Note: ΣNDVI is accumulated difference vegetation index; NPP is net primary productivity; $RUE_{\Sigma NDVI}$ is ΣNDVI residuals; RUE_{NPP} is NPP residuals

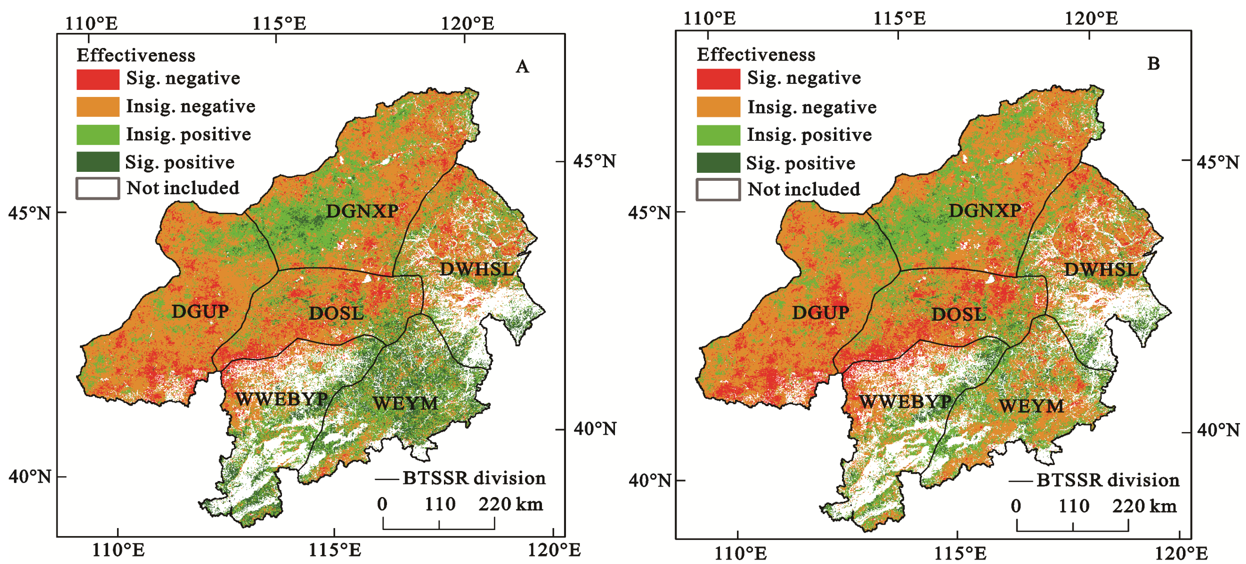


Fig. 6 Effectiveness of ecological engineering projects on vegetation restoration based on accumulated difference vegetation index residuals ($RUE_{\Sigma NDVI}$) (A) and net primary productivity residuals (RUE_{NPP}) (B). Sig. is significant and Insig. is not significant. BTSSR is study area, Beijing-Tianjin Sand Source Region, China

Table 3 Pixel number and percentage of different types of effectiveness summarized in vegetation restoration or degradation validation region based on accumulated difference vegetation index residuals ($RUE_{\Sigma NDVI}$) and net primary productivity residuals (RUE_{NPP})

Effectiveness	Vegetation restoration		Vegetation degradation	
	$RUE_{\Sigma NDVI}$	RUE_{NPP}	$RUE_{\Sigma NDVI}$	RUE_{NPP}
Significantly negative	20 (0.09%)	47 (0.21%)	4644 (73.98%)	4697 (74.83%)
Insignificantly negative	791 (3.48%)	1157 (5.09%)	1219 (19.42%)	1135 (18.08%)
Insignificantly positive	9948 (43.76%)	13 916 (61.22%)	380 (6.05%)	426 (6.79%)
Significantly positive	11 972 (52.67%)	7611 (33.48%)	34 (0.54%)	19 (0.30%)

Note: meanings of all abbreviations see Table 2

the spatial distribution of the significantly positive effectiveness from Fig. 6, which showed that the $RUE_{\Sigma NDVI}$ was preferable for the assessment of positive effectiveness. For vegetation degradation regions, the pixel number of significantly negative effectiveness did not change when choosing the $RUE_{\Sigma NDVI}$ or RUE_{NPP}. Therefore, the $RUE_{\Sigma NDVI}$ was advantageous for the effectiveness assessment of ecological engineering on vegetation restoration.

3.5 Interpretation of effectiveness

Concerning land cover dynamics, 1.5% of the BTSSR experienced land cover conversion between 2000 and 2010. The conversion from grassland to woodland was dominant (26.6%), followed by grassland to settlements (11.4%), cropland to settlements (11.1%), cropland to grassland (8.1%), bare land to grassland (7.7%), wetland to grassland (6.4%), and cropland to woodland (5.2%). Among these changes, the transitions from grassland to woodland, cropland to grassland, bare land to grassland, and cropland to woodland could be considered as results of ecological engineering projects, while cropland/grassland change to settlements resulted from urbanization. The overlapping between the effectiveness assessment and the land cover in 2010 showed that most significantly negative effectiveness areas corresponded to grassland, based on the $RUE_{\Sigma NDVI}$ or RUE_{NPP} (88.78% and 86.77%, respectively). Oppositely, significantly positive effectiveness areas mainly corresponded to woodland (55.36% and 44.85%, respectively) and grassland (40.03% and 48.29%, respectively) based on the $RUE_{\Sigma NDVI}$ or RUE_{NPP}. Therefore, more efforts should be put on grassland restoration in the future.

Based on the distribution for the six rehabilitation subareas, the effectiveness of the ecological engineering differed spatially (Table 4). In order to evaluate the difference of vegetation restoration effectiveness in each sub-area, the ratio between the areas characterized by significantly positive and negative based on $RUE_{\Sigma NDVI}$ was chosen as the valuation criteria. Based on which, the most effective region was the WEYM, followed by the WWEBYP, the DWHSL, the DGNXP, the DOSL, and the DGUP. According to the characteristics of the different subareas, we concluded that water erosion regions dominated by woodland (WEYM) had the best restoration effects, followed by wind-water erosion crisscross regions (WWEBYP, DWHSL), while wind erosion regions dominated by grassland (DGNXP, DGUP, and DOSL) showed the worst restoration. The reasons for this difference in effectiveness could be obtained by comparing the areas under ecological engineering projects with the total areas. According to the

Table 4 Statistics of effectiveness for different sub-areas (pixel numbers) based on accumulated difference vegetation index residuals ($RUE_{\Sigma NDVI}$) and net primary productivity residuals (RUE_{NPP})

Sub-area	Significantly negative		Significantly positive	
	$RUE_{\Sigma NDVI}$	RUE_{NPP}	$RUE_{\Sigma NDVI}$	RUE_{NPP}
WWEBYP	56 911	90 742	146 510	75 040
DGNXP	98 301	88 369	68 019	33 648
DWHSL	84 917	100 371	78 436	61 334
DOSL	130 510	183 030	38 151	27 221
DGUP	130 966	195 230	20 245	16 205
WEYM	9183	33 630	262 681	73 600

Note: meanings of all abbreviations see Table 1

Beijing and Tianjin Sandstorm Source Controlling Program, the proportion of water erosion, wind-water erosion and wind erosion regions was approximately 88%, 68% and 21%, respectively. Therefore, the effectiveness was proportional to the efforts of ecological engineering. The negative effectiveness determined in this study might include the side effects of irrational engineering, but it is more probably because the absence of ecological engineering somewhere.

4 Discussion

The vegetation productivity trends were very sensitive to the choice of vegetation productivity indicator. A clear tendency towards smaller increasing areas was shown when using the NPP (51.30%) instead of the ΣNDVI (59.30%). This finding was consistent with the earlier study of Wu *et al.* (2013). In their study, the proportion of the areas with increasing trend was smaller when the NPP was used (58.34%) instead of the annual integrated NDVI (64.33%). The reasons for this difference mainly resulted from the incorporation of the precipitation in the NPP calculation, since several studies have shown that severe droughts in 2007 and 2009 seriously reduced the vegetation growth in the northern China (Piao *et al.*, 2010; Zhao and Running, 2010).

Consistent with earlier studies (Tucker *et al.*, 1991; Herrmann *et al.*, 2005; Wu *et al.*, 2013), 44% (ΣNDVI) and 38% (NPP) of the pixels analyzed were significantly correlated ($\alpha = 0.1$) with the precipitation in the BTSSR. Therefore, the effect of precipitation variation on the vegetation must be eliminated with the RESTREND method, which has vegetation productivity proportional to the precipitation as a prerequisite (Fensholt *et al.*, 2013). However, this requirement is usually not satisfied for sub-humid areas covered by woodland. The influence of the intra-seasonal precipitation distribution on the vegetation productivity was investigated by incorporating two additional parameters of the precipitation distribution (variance and skewness) in the multivariate regression models. Compared with the model only using the precipitation, the addition of these two parameters increased the ability of the model to explain the vegetation productivity variation (Fig. 7). The explained variance changes varied spatially but were not significantly related with the climate type or land cover, with the areas of most obvious increase (> 40%) coinciding with the areas characterized by insignificant relationships between the vegetation productivity and precipitation. Therefore, the establishment of an improved model for the vegetation productivity and precipitation and other climactic factors was very important when using the RESTREND method. Considering the data accessibility and widespread utilization of the RESTREND, the proposed approach should be effective for other arid and

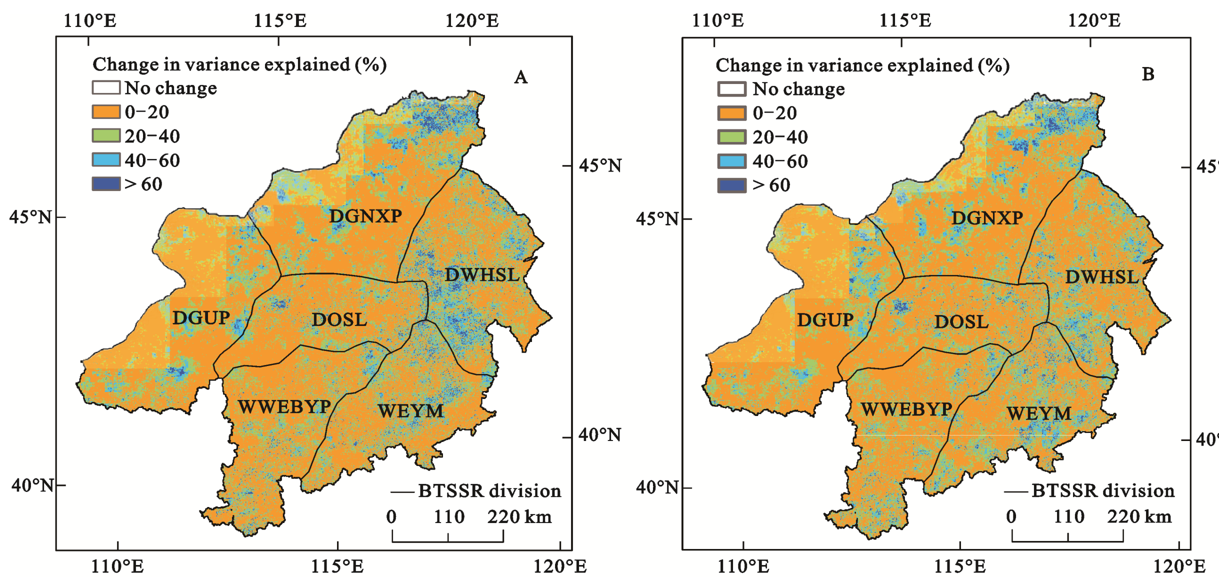


Fig. 7 Comparison of percentage of variance change explained by other variables in addition to precipitation: accumulated normalized difference vegetation index (ΣNDVI) (A) and net primary productivity (NPP) (B). BTSSR is study area, Beijing-Tianjin Sand Source Region, China

semi-arid regions, where the vegetation productivity is strongly affected by the precipitation.

The degradation areas in the BTSSR were regarded as a negative effectiveness of the ecological engineering projects. Most negative effectiveness regions were located in grassland-dominated wind erosion areas. In those regions, the proportion between the areas under ecological engineering projects and the total area was only approximately 21%, meaning that the degradation probably resulted from the lack of ecological engineering measures. Since we did not know the actual spatial distribution of the engineering projects, the negative effectiveness identified in this study included degraded areas caused by the absence of ecological engineering projects. The negative effectiveness regions identified represent hotspots for the analysis of the detailed reasons for degradation and require additional attention in future ecosystem restoration.

5 Conclusions

The effectiveness of ecological engineering projects on vegetation restoration in the BTSSR was assessed using long-term vegetation productivity trends, in which the short-term effects of the precipitation variation on the productivity were normalized using the RUE. The main conclusions were:

(1) More than half of the BTSSR experienced a vegetation productivity increase from 2000 to 2010. The increasing intensity was sensitive to the choice of indicators, with a clear tendency to smaller increasing areas when the NPP (51.30%) was used instead of the ΣNDVI (59.30%).

(2) The short-term variation in the precipitation had a great impact on the remote sensing-based vegetation productivity, with 44% of the ΣNDVI and 38% of the NPP significantly and linearly correlated with the annual precipitation. The RESTREND method effectively eliminated this correlation, widely reducing the increasing and locally expanding the decreasing trends that resulted originally from the precipitation variation. The intra-seasonal precipitation distribution also affected significantly the vegetation productivity. Through incorporating two additional precipitation parameters (variance and skewness), the vegetation productivity variations could be explained better.

(3) The RUE combined with land cover dynamics was valid for the effectiveness assessment of ecological engineering projects on vegetation restoration. Compared with RUE_{NPP}, $RUE_{\Sigma NDVI}$ was more appropriate for vegetation restoration assessment. Based on which, we found that 47.39% of the BTSSR have experienced vegetation restoration from 2000 to 2010. The effectiveness of the ecological engineering projects differed among subareas, with water erosion regions dominated by woodland having the best restoration effects, followed by wind-water erosion crisscross regions, while wind erosion regions dominated by grassland were the worst. The effectiveness was proportional to the strength of the ecological engineering.

(4) Clearly 41.7% of the BTSSR experienced vegetation restoration (with 9.59% being significant). However, serious degradation still outnumbers the restoration. Therefore, more effort should be put in restoring the degraded areas in the future.

References

Cao S, 2008. Why large-scale afforestation efforts in China have failed to solve the desertification problem. *Environmental Science & Technology*, 42(6): 1826–1831.

Chen Y, Yang K, He J *et al*., 2011. Improving land surface temperature modeling for dry land of China. *Journal of Geophysical Research*: *Atmospheres*, 116: D20104. doi: 10.1029/2011JD015921

de Jong R, de Bruin S, de Wit A *et al*., 2011. Analysis of monotonic greening and browning trends from global NDVI time-series. *Remote Sensing of Environment*, 115(2): 692–702. doi: 10.1016/j.rse.2010.10.011

Du Plessis W, 1999. Linear regression relationships between NDVI, vegetation and rainfall in Etosha National Park, Namibia. *Journal of Arid Environments*, 42(4): 235–260. doi: 10.1006/jare.1999.0505

Fensholt R, Sandholt I, Rasmussen M S *et al*., 2006. Evaluation of satellite based primary production modelling in the semi-arid Sahel. *Remote Sensing of Environment*, 105(3): 173–188. doi: 10.1016/j.rse.2006.06.011

Fensholt R, Rasmussen K, Kaspersen P *et al*., 2013. Assessing land degradation/recovery in the African Sahel from long-term Earth observation based primary productivity and precipitation relationships. *Remote Sensing*, 5(2): 664–686. doi: 10.3390/rs5020664

Herrmann S M, Anyamba A, Tucker C J, 2005. Recent trends in vegetation dynamics in the African Sahel and their relationship to climate. *Global Environmental Change*, 15(4): 394–404. doi: 10.1016/j.gloenvcha.2005.08.004

Huang L, Xiao T, Zhao Z *et al*., 2013. Effects of grassland restoration programs on ecosystems in arid and semiarid China.

Journal of Environment Manage, 117: 268–275. doi: 10.1016/j.jenvman.2012.12.04

Huete A, Didan K, Miura T *et al*., 2002. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sensing of Environment*, 83(1): 195–213. doi: 10.1016/S0034-4257(02)00096-2

Intergovernmental Panel on Climate Change (IPCC), 2006. *IPCC Guidelines for National Greenhouse Gas Inventories*. Hayama, Japan: Institute for Global Environmental Strategies.

Julien Y, Sobrino J A, 2010. Comparison of cloud-reconstruction methods for time series of composite NDVI data. *Remote Sensing of Environment*, 114(3): 618–625. doi: 10.1016/j.rse.2009.11.001

Kendall M G, 1938. A new measure of rank correlation. *Biometrika*, 30(1/2): 81–93.

Liu J, Li S, Ouyang Z *et al*., 2008. Ecological and socioeconomic effects of China′s policies for ecosystem services. *Proceedings of the National Academy of Sciences*, 105(28): 9477–9482. doi: 10.1073/pnas.0706436105

Long Huiling, Li Xiaobing, Wang Hong *et al*., 2010. Net primary productivity (NPP) of grassland ecosystem and its relationship with climate in Inner Mongolia. *Acta Ecologica Sinica*, 30(5): 1367–1378. (in Chinese)

Ludwig J A, Bastin G N, Chewings V H *et al*., 2007. Leakiness: a new index for monitoring the health of arid and semiarid landscapes using remotely sensed vegetation cover and elevation data. *Ecological Indicators*, 7(2): 442–454. doi: 10.1016/j.ecolind.2006.05.001

Ma Q, 2004. Appraisal of tree planting options to control desertification: experiences from Three-North Shelterbelt Programme. *International Forestry Review*, 6(3–4): 327–334. doi: 10.1505/ifor.6.3.327.59972

Mao Dehua, Wang Zongming, Wu Changshan *et al*., 2014. Examining forest net primary productivity dynamics and driving forces in northeastern china during 1982–2010. *Chinese Geographical Science*, 24(6): 631–646. doi: 10.1007/s11769-014-0662-9

Piao S L, Ciais P, Huang Y *et al*., 2010. The impacts of climate change on water resources and agriculture in China. *Nature*, 467: 43–51. doi: 10.1038/nature09364

Potter C S, Randerson J T, Field C B *et al*., 1993. Terrestrial ecosystem production: a process model based on global satellite and surface data. *Global Biogeochemical Cycles*, 7(4): 811–841. doi: 10.1029/93GB02725

Prince S D, 1991. Satellite remote-sensing of primary production: comparison of results for Sahelian grasslands from 1981 to 1988. *International Journal of Remote Sensing*, 12(6): 1301–1311. doi: 10.1080/01431169108929728

Sen P K, 1968. Estimates of the regression coefficient based on Kendall′s tau. *Journal of the American Statistical Association*, 63(324): 1379–1389. doi: 10.1080/01621459.1968.10480934

Stokes A, Sotir R, Chen W *et al*., 2010. Soil bio- and eco-engineering in China: past experience and future priorities preface. *Ecological Engineering*, 36(3): 247–257. doi: 10.1016/j.ecoleng.2009.07.008

Topaloglu F, 2006. Regional trend detection of Turkish river flows. *Nordic Hydrology*, 37: 165–182.

Tucker C J, Dregne H E, Newcomb W W, 1991. Expansion and contraction of the Sahara Desert from 1980 to 1990. *Science*, 253(5017): 299–301. doi: 10.1126/science.253.5017.299

Tucker C J, Slayback D A, Pinzon J E *et al*., 2001. Higher northern latitude normalized difference vegetation index and growing season trends from 1982 to 1999. *International Journal of Biometeorology*, 45(4): 184–190. doi: 10.1007/s00484-001-0109-8

Wang G, Innes J L, Lei J *et al*., 2007. China′s forestry reforms. *Science*, 318(5856): 1556. doi: 10.1126/science.1147247

Wang X M, Zhang C X, Hasi E *et al*., 2010. Has the Three Norths Forest Shelterbelt Program solved the desertification and dust storm problems in arid and semiarid China? *Journal of Arid Environments*, 74(1): 13–22. doi: 10.1016/j.jaridenv.2009.08.001

Wessels K, Prince S D, Malherbe J *et al*., 2007. Can human-induced land degradation be distinguished from the effects of rainfall variability? A case study in South Africa. *Journal of Arid Environments*, 68(2): 271–297. doi: 10.1016/j.jaridenv.2006.05.015

Wu Bo, Li Xiaosong, Liu Wen *et al*., 2006. Desertification control regionalization and rehabilitation counter measures of source area of sand and dust endangering Beijing-Tianjin. *Scientia Silave Sinicae*, 42(10): 65–70. (in Chinese)

Wu J, Zhao L, Zheng Y *et al*., 2012. Regional differences in the relationship between climatic factors, vegetation, land surface conditions, and dust weather in China′s Beijing-Tianjin Sand Source Region. *Natural Hazards*, 62(1): 31–44. doi: 10.1007/s11069-011-0039-7

Wu Z, Wu J, Liu J *et al*., 2013. Increasing terrestrial vegetation activity of ecological restoration program in the Beijing–Tianjin Sand Source Region of China. *Ecological Engineering*, 52: 37–50. doi: 10.1016/j.ecoleng.2012.12.040

Yang X, Ci L, 2008. Comment on ′Why large-scale afforestation efforts in China have failed to solve the desertification problem′. *Environmental Science & Technology*, 42(20): 7722–7723.

Zhang G, Dong J, Xiao X *et al*., 2012. Effectiveness of ecological restoration projects in Horqin Sandy Land, China based on SPOT-VGT NDVI data. *Ecological Engineering*, 38(1): 20–29. doi: 10.1016/j.ecoleng.2011.09.005

Zhang L, Li X, Yuan Q *et al*., 2014. Object-based approach to national land cover mapping using HJ satellite imagery. *Journal of Applied Remote Sensing*, 8(1): 083686. doi: 10.1117/1.JRS.8.083686

Zhang Lei, Wu Bingfang, Li Xiaosong *et al*., 2014. Classification system of China land cover for carbon budget. *Acta Ecologica Sinica*, 34(24): 1–8. (in Chinese)

Zhang T T, Zeng S L, Gao Y *et al*., 2011. Using hyperspectral vegetation indices as a proxy to monitor soil salinity. *Ecological Indicators*, 11(6): 1552–1562. doi: 10.1016/j.ecolind.2011.03.025

Zhao B, Yan Y, Guo H *et al*., 2009. Monitoring rapid vegetation succession in estuarine wetland using time series MODIS-based indicators: an application in the Yangtze River Delta area. *Ecological Indicators*, 9(2): 346–356. doi: 10.1016/j.ecolind.2008.05.009

Zhao M S, Running S W, 2010. Drought-induced reduction in global terrestrial net primary production from 2000 through 2009. *Science*, 329: 940–943. doi: 10.1126/science.1192666

Zhu Wenquan, Pan Yaozhong, Long Zhonghua *et al*., 2005. Estimating net primary productivity of terrestrial vegetation based on GIS and RS: a case study in Inner Mongolia, China. *Journal of Remote Sensing*, 9(3): 300–307. (in Chinese)

Zhu W Q, Pan Y Z, Liu X *et al*., 2006. Spatio-temporal distribution of net primary productivity along the northeast China transect and its response to climatic change. *Journal of Forestry Research*, 17(2): 93–98. doi: 10.1007/s11676-006-0022-4