Assessing the effects of drought and “Grain for Green” Program on vegetation dynamics in China’s Loess Plateau from 2000 to 2014

Anzhou Zhaoa,b,*, Anbing Zhanga,b,*, Jianhong Liuc,d, Lili Fenga, Yuling Zhaoa,b

a School of Mining and Geomatics, Hebei University of Engineering, Handan 056038, Hebei, China
b Hebei Collaborative Innovation Center of the Comprehensive Development and Utilization of Coal Resource, Hebei University of Engineering, Handan 056038, Hebei, China
c Shaanxi Key Laboratory of Earth Surface System and Environmental Carrying Capacity, Northwest University, Xi’an 710127, China
d Hebei Collaborative Innovation Center of the Comprehensive Development and Utilization of Coal Resource, Hebei University of Engineering, Handan 056038, Hebei, China

A R T I C L E   I N F O

Keywords:
Vegetation dynamics
Drought
The Grain for Green Project
China’s Loess Plateau

A B S T R A C T

China’s Loess Plateau (CLP) has experienced severe water loss and soil erosion over the past few decades. To prevent water loss and soil erosion and improve ecological environment, the Grain for Green Project (GGP) was launched in 1999. Meanwhile, the frequency and severity of drought in CLP has shown an increasing trend in the recent years. However, few studies have addressed the coupled effects of drought and the GGP on vegetation dynamics in this area. Based on the Standardized Precipitation Evapotranspiration Index (SPEI) and Normalized Difference Vegetation Index (NDVI), this study assesses the changes of drought and vegetation dynamics and the role of droughts and GGP on trends in vegetation dynamics. Results show that: (1) At the regional scale, annual and seasonal NDVI show a significant increase from 2000 to 2014; however, drought change trends were insignificant. (2) At the pixel scale, annual, spring, summer, and autumn NDVI increased in the CLP from 2000 to 2014, with 51.92%, 50.04%, 74%, and 62.69% of the study area showing a significant increase, respectively, with $p < 0.05$. Summer drought had the strongest effect on vegetation dynamics. (3) Drought was one of the primary reasons for the decreasing trend of NDVI in the northern CLP. The severe and extreme drought (SPEI $< -1.5$) in summer of 2001 and 2005 reduced the NDVI by 22.44% and 9.98%, respectively. (4) The residual analysis results indicate that 21.54% of the CLP was affected by drought. 43.64% and 34.82% of the CLP experienced human induced improvement and degradation, respectively. (5) The GGP had an important influence on vegetation dynamics, strong correlations between the cumulative afforestation area and annual NDVI in Yan’an and Yulin from 2000 to 2013 were found, with $r = 0.96$ and 0.65. The spatial pattern of the cumulative afforestation area ratio matched quite well with the NDVI change trend.

1. Introduction

Soil erosion, desertification, sand storms, land degradation and other ecological problems have increased in China over the past few decades (Xu et al., 2006; Wu et al., 2014). In order to mitigate these problems, the Chinese government implemented a series of nationwide ecological recovery programs known as the ‘Grain for Green Program (GGP)’, ‘Three-North Shelterbelt Project’, ‘Natural Forest Conservation Program,’ the ‘Sand Control Project,’ and the ‘Forest Industrial Base Development Program’ since the late 1990s (Lü et al., 2012; Wu et al., 2013). Thus, the ecological environment of China has been greatly improved after implementation of these ecological recovery programs (Wu et al., 2014). Vegetation, a vital part of the terrestrial ecosystem, is highly sensitive to climate change and human influences. Vegetation change represents change to the ecological environment (Hanafi and Jauffret, 2008). The Normalized Difference Vegetation Index (NDVI) is a good indicator for monitoring vegetation growth and cover, and has been widely used to analyze vegetation changes (Tian et al., 2015; Xu et al., 2016; W.J. Hua et al., 2017; T. Hua et al., 2017). In recent years, numerous studies have shown that vegetation cover has increased due to the implementation of ecological recovery programs (Xiao, 2014; Tian et al., 2015; Zhao et al., 2017).

In addition to ecological recovery programs, climate change (such as precipitation, temperature, and drought) is also a driver of vegetation dynamics (Cao et al., 2018; Zhao et al., 2017; Zhao et al., 2018). Numerous studies used various drought indices to assess the response of vegetation to drought. Q. Zhang et al. (2017) evaluated the response of vegetation to multiple droughts of various duration across China, and
results show that NDVI and SPEI positively correlate in most regions of China. Vicente-Serrano et al. (2013) analyzed the relationship between NDVI and SPEI across global land biomes, and found that 72% of vegetated land area showed a significant correlation. Gong et al. (2017) analyzed the relationship between NDVI and Palmer drought severity index (PDSI) across the North China, and results showed a positive correlation between the PDSI and the NDVI. Gouveia et al. (2017) analyzed the impact of drought on NDVI in the Mediterranean basin and found NDVI in the Mediterranean basin was significantly influenced by drought. During past five decades, the frequency and duration of droughts in fragile ecological areas such as CLP have increased significantly due to global warming. For example, Wu et al. (2018) used the nonparametric standardized runoff index (NSRI) to assess the change trend (−0.569~−0.241) of drought in CLP, and indicated an upward trend in drought severity from 1961 to 2013. Wang et al. (2015) used the drought threshold method to assess the change trend of drought in CLP, and found an increase trend in the frequency (85.1%~96.4%) of moderate drought occurrence on the CLP from 1961 to 2012. However, the effects of drought and ecological restoration programs on vegetation activity are unclear in these fragile ecological areas, especially in the dry-land ecosystems. Although Wu et al. (2014) assessed impacts of drought and ecological restoration programs on vegetation activity in the Beijing-Tianjin Sand Source Region, China, this study used the Standardization precipitation index (SPI) to assess the drought. SPI calculation was based on only precipitation data and neglected the influence of evaporation. However, evapotranspiration will be increased and have important effect on drought in the context of regional global warming (Adams et al., 2009).

The CLP is dominated by a semi-humid and semi-arid climate and has the most severe soil and water erosion in the world (Xie et al., 2016). To control soil and water erosion, the largest ecological construction Project—GGP was implemented in 1999. Numerous Chinese researchers indicated that the vegetation level in this area increased and soil and water erosion has been effectively controlled after the implementation of the GGP (Zhang et al., 2015; Li et al., 2015; Li et al., 2017). Other studies indicated that GGP could lead to increased ecosystem deterioration and wind erosion in semiarid and arid regions (Gao, 2008; Cao et al., 2011). In addition, numerous studies also have analyzed the vegetation change and its response to climate change or drought in CLP using NDVI, such as the Land Long Term Data Record (LTD-NDVI), Moderate Resolution Imaging Spectroradiometer (MODIS)-NDVI, Global Inventory Modeling and Mapping Studies (GIMMS)-NDVI, and Systeme Probatoire d‘Observation de la Terre VEGETATION (SPOT- VGA) NDVI. Results indicate that vegetation dynamics were responsive to drought or other climate change (Ning et al., 2015; W.G. Jiang et al., 2015; Sun et al., 2015; Zhang et al., 2016; Zhao et al., 2017; Zhao et al., 2018). However, few studies have quantitatively analyzed the effects of drought on vegetation dynamics when assessing the benefits of the GGP in the CLP.

Therefore, the specific objectives of this study are as follows: (1) assess the spatiotemporal changes in vegetation dynamics and drought from 2000 to 2014 using a trend analysis method; (2) assess the effect of drought on vegetation dynamics from 2000 to 2014 at annual and seasonal scales; (3) evaluate the relative contribution of drought and human activities to vegetation dynamics from 2000 to 2014; (4) and investigate the effects of the GGP on vegetation dynamics.

2. Materials and methods

2.1. Study region

The CLP (104°54′–114°33′E, 33°43′–41°16′N) is located along the middle reaches of the Yellow River, North China. The CLP covers 6.49 × 105 km² and includes most of the Shaanxi and Shanxi provinces, as well as Gansu, Ningxia, Qinghai, Henan, and Inner Mongolia. The CLP has undulating terrain and slopes from northwest to southeast (Fig. 1). This region is dominated by a temperate continental monsoon climate, and the annual average precipitation ranges from 200 to 750 mm, with approximately 60% of precipitation occurring from June to September (Zhang et al., 2013). The average annual temperature ranges from 4.3°C in the northwest to 14.3°C in the southeast (Guo et al., 2010). There has been a significant increase in vegetation dynamics since 1999, and the severity and frequency of droughts have exhibited an overall increasing trend (Zhang et al., 2016).

2.2. Data source and processing

The MODIS-NDVI dataset obtained from NASA’s Earth Observing System was used to assess variations in vegetation cover. This dataset spans from 2000 to 2014 with a 250 m × 250 m spatial resolution and 16-day temporal resolution. The monthly NDVI was calculated by using the maximum value composite (MVC) technique, which minimizes the effects of atmospheric interference, scan angle, cloud contamination, and solar zenith angle (Holben, 1986). The average annual NDVI was defined as the average monthly composite NDVI from January to December. Spring was defined as the average monthly composite NDVI from March to May. Summer was defined as the average monthly composite NDVI from September to November. Meteorological data (monthly maximum air temperature, monthly minimum air temperature, monthly precipitation, wind speed, relative humidity, and sunshine duration) from 53 meteorological stations distributed throughout the CLP from 2000 to 2014 were downloaded from the China Meteorological Data Sharing Service System (http://data.cma.cn/). Afforestation area data were collected from China forestry statistics yearbook from 2001 to 2014. Land use data in 2000, 2005 and 2010 from Resource and Environment Data Cloud Platform (http://www.resdc.cn/).

2.3. Research methods

2.3.1. Calculation of the SPEI

SPEI was developed by Vicente-Serrano and used to evaluate change trend of drought and the impact on the vegetation dynamics. SPEI incorporates both the multi-scalar character of the standardized precipitation index (SPI) and the evaporation component of the PDSI, and is better for drought assessment in the context of global warming, especially in semi-arid and arid regions (Vicente-Serrano et al., 2010). In this study, calculation of the evapotranspiration potential in SPEI is based on the Penman-Monteith equation with the Hargreaves-Samani modification (Hargreaves and Samani, 1985) as described in FAO-56 (Allen et al., 1998). SPEI-1, SPEI-3, and SPEI-12 were used to represent monthly, seasonal, and annual drought conditions, respectively. The SPEI is calculated as follows:

\begin{equation}
\text{PET} = \frac{0.408\Delta (R_n - G) + \gamma \frac{100}{\gamma} \left( \epsilon_s - \epsilon_v \right)}{\Delta + \gamma (1 + 0.34u_2)}
\end{equation}

where \(T\), \(G\), and \(u_2\) are the temperature at the height of 2 m (°C), the soil heat flux density (MJ m\(^{-2}\) day\(^{-1}\)) and the wind speed at the height of 2 m (m s\(^{-1}\)), respectively; \(\epsilon_s\) and \(\epsilon_v\) are the saturated water vapor pressure and the actual water vapor pressure (kPa); \(R_n\) is the net radiation (MJ m\(^{-2}\) day\(^{-1}\)). \(\lambda_a\) and \(\gamma\) are the slope of the saturation vapor pressure curve (kPa°C\(^{-1}\)) and the psychrometric constant (kPa°C\(^{-1}\)). The calculation method of \(\Delta\), \(\gamma\), \(R_n\), and \(u_2\) can be referred to the Shan et al. (2015).

(2) The difference (\(D\)) between PET and precipitation (\(P\)) is calculated as follows:

\begin{equation}
D = \text{PET} - P
\end{equation}
where $k$, $i$, and $j$ are the timescale, the beginning and end of the analyzed months, respectively.

The probability distribution function at different timescales by a three-parameter log-logistic distributed function can be showed as:

$$F(x) = \left[ 1 + \left( \frac{a}{x - y} \right)^{\frac{1}{\gamma}} \right]^{-1}$$

where $a$ represents the scale, $\beta$ represents the shape and $\gamma$ represents the origin.

The SPEI can be calculated as follows:

$$\text{SPEI} = \frac{W - C_0 + C_1 W + C_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3}, \quad p \leq 0.5$$

$$W = \sqrt{ - 2 \ln(p)} , \quad p \leq 0.5$$

$$W = \sqrt{-2 \ln(1 - p)}, \quad p > 0.5$$

$$p = 1 - F(x)$$

where $p$ is the standardizing probability density function; $C_0$, $C_1$, $C_2$, $d_1$, $d_2$, and $d_3$ are constants, and the value is the 2.515517, 0.802853, 0.010328, 1.432788, 0.189269 and 0.001308, respectively.

The categorization of drought/wet based on the SPEI is given in Table 1 (Vicente-Serrano et al., 2010). Further interpolation of the surface data was performed using the Kriging interpolation method to achieve a final resolution of 250 m to match NDVI datasets (Oliver and Webster, 1990).

### 2.3.2. Trend analysis

Ordinary least-squares (OLS)-based linear regression analysis was used to detect the NDVI or SPEI change trends. The slope of the linear regression was used as an indicator to detect the NDVI or SPEI changes for each pixel using OLS for the period 1982–2013, which can comprehensively reflect the spatiotemporal change in NDVI or SPEI (Liu et al., 2014). The slope was calculated as follows:

$$\text{Slope} = \frac{n \sum_{i=1}^{n} x_i y_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{n \sum_{i=1}^{n} x_i^2 - \left( \sum_{i=1}^{n} x_i \right)^2}$$

where $\text{Slope}$ is the trend of annual, spring, summer and autumn NDVI or SPEI, $n$ is the time series, $x_i$ is the annual, spring, summer, or autumn NDVI, and $y_i$ is the NDVI or SPEI in the $i$th year or season. When $\text{Slope} > 0$, the time-series of NDVI or SPEI is increasing; when $\text{Slope} < 0$, the time-series of NDVI or SPEI is decreasing.

### 2.3.3. Correlation analysis

Pearson correlation analysis was employed to examine the correlation between NDVI and SPEI (Xu, 2002):

$$R = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2 \sum_{i=1}^{n} (y_i - \bar{y})^2}}$$

where $R$ is correlation coefficient, $n$ is the time series, $x_i$ is the annual, spring, summer, or autumn NDVI, $y_i$ is the annual, spring, summer, autumn SPEI, or accumulative afforestation area, $\bar{x}$ is the average NDVI and $\bar{y}$ is the average SPEI or accumulative afforestation area.

### 2.3.4. Residuals analysis

The residual trends method was used to distinguish the effects of drought and human-induced NDVI in this study (Herrmann et al., 2005). The relationship between annual NDVI and annual SPEI for each pixel was calculated using linear regression. This relationship was used to obtain the predicted NDVI. The difference between the observed annual NDVI and the predicted annual NDVI was evaluated for each pixel. This difference is the residuals, which is the annual NDVI change not due to drought. If the residuals show an insignificant trend from...
2000 to 2014, NDVI change is due to drought. If the residuals show a significant trend from 2000 to 2014, NDVI change is caused by human activity. Positive residuals show a region experiencing human-induced improvement, while negative residuals show human-induced degradation.

3. Results

3.1. Regional trends in NDVI and SPEI

Fig. 2 shows annual, spring, summer, and autumn trends in vegetation activity and SPEI in the CLP from 2000 to 2014. NDVI shows complex variations from 2000 to 2014, with a significant increasing trend \((p < 0.01)\) of 0.0042/yr, 0.0031/yr, 0.0075/yr, and 0.0043/yr for the annual, spring, summer, and autumn periods, respectively (Fig. 2). Similar to the NDVI change trends, the SPEI during the annual, spring, summer, and autumn periods showed increasing trends of 0.015/yr, 0.083/yr, 0.026/yr, and 0.021/yr, respectively. However, the overall increase in SPEI was not significant. The decreases in annual, spring, summer, and autumn SPEI and NDVI occurred in 2001, 2005, and 2011 (Fig. 2). Therefore, the NDVI in the CLP shows a degree of correlation with drought in the annual, spring, summer, and autumn periods.

3.2. Spatial patterns of NDVI and SPEI trends

The spatial trend of annual NDVI showed obvious heterogeneity in CLP, where some regions showed significant increased NDVI trend while few regions showed significant decreased NDVI trend. A significant increase occurred in the northern Shaanxi, southern Ningxia, and western Shanxi (Fig. 3a). Specially, annual mean NDVI increased in 88.24% of the CLP from 2000 to 2014, and 51.92% of the entire study area recorded a significant increase in NDVI, with \(p < 0.05\). Spatial pattern of change trends in SPEI matched quite well with NDVI, and showed an increasing trend in the middle of the CLP (Fig. 3b). To further evaluate the impact of annual drought on NDVI, the correlation between annual NDVI values and SPEI were calculated for the CLP (Fig. 3c). Annual mean NDVI positively correlates with SPEI in the northwestern CLP and negatively correlates with SPEI in the southern CLP, indicating that the vegetation in the northwestern CLP was more affected by drought. The mean correlation is 0.26, and the value of 0.53 for correlations passes the 0.05 significant level.

In order to explore the change in NDVI and SPEI at the seasonal scale, the change trends and correlations of NDVI and SPEI in spring, summer, and autumn were evaluated for 2000 to 2014 in the CLP. In spring, NDVI trends increased in most areas, especially in the western Shanxi and northern Shaanxi (Fig. 3d). Spring NDVI increased in 95.85% of the entire study area, and 50.04% of the study area showed a significant increase \((p < 0.05)\). SPEI trends increased in most of the CLP, and only decreased in the northern CLP (Fig. 3e). The correlation of spring NDVI and SPEI was calculated for each grid. Spring NDVI was positively correlated with SPEI in most of study area (85.83%), especially in the middle of the CLP. Only small areas (in south and north of the CLP) NDVI was negatively correlated with SPEI (Fig. 3f). The change trend of spring NDVI was affected by spring droughts, and the mean correlation between spring NDVI and SPEI is 0.17. The majority of the CLP experienced an increasing trend in the summer NDVI from 2000 to 2014 (Fig. 3d). The summer NDVI increased in 90.36% of the study area, and 74.0% of the study area showed a significant increased \((p < 0.05)\). Similar to the trend in the summer NDVI, the SPEI trend increased in most parts of the CLP, except for the southeastern CLP (Fig. 3e). The spatial distribution of the change trend of summer NDVI and SPEI correlate well. Moreover, the correlation of summer NDVI and SPEI was calculated for each grid. Summer NDVI positively correlates...
with SPEI in most areas (77.46%), particularly in the northern CLP (Fig. 3i). It is implying that the effects of summer drought on decreased NDVI in those areas, and the mean correlation between summer NDVI and SPEI is 0.32. In autumn, the NDVI change trend was similar to spring. Autumn NDVI increased in 89.78% of the CLP, and significantly increase in 62.69% of the CLP (p < 0.05). A significant increasing trend in the autumn NDVI was observed in the middle CLP (Fig. 3j). However, autumn SPEI trends increased in the eastern CLP, and decreased in the western CLP. Meanwhile, the correlation of autumn NDVI and SPEI was calculated for each pixel. Autumn NDVI positively correlates with SPEI in the eastern part of the CLP (74.19%) (Fig. 3i), and the mean correlation between autumn NDVI and SPEI is 0.14. The summer drought, rather than spring and autumn droughts had strongest effect on the NDVI.

3.3. Drought impact on NDVI in the CLP

In order to further evaluate the effects of drought on NDVI trends, we selected the year 2001 and 2005 based on analysis of the SPEI in the CLP. In these two years, the SPEI values were −1.13 and −1.48, respectively. The total area of moderate, severe, and extreme drought was > 50% (57.59% and 77.87%). Next, we analyzed the effect of drought on NDVI in 2001 and 2005. Figs. 4 and 5 show the spatial distribution of SPEI and percentage of NDVI anomaly (PNA) in 2001 and 2005. In 2001, the spatial distribution of the annual and seasonal SPEI did not match well with PNA. The annual PNA in northern Shaanxi was reduced > 20% (Fig. 4e), while this area only experienced a slight to moderate drought (Fig. 4a). In spring, the southeastern CLP experienced extreme drought (Fig. 4b), while PNA in this area was reduced < 10% (Fig. 4f). Because the GGP was implemented in 1999, the decreased PNA in 2001 was related to anthropogenic factors. However, the spatial distribution of PNA in 2005 matched quite well with that of SPEI. A moderate to slight drought occurred in the southeastern CLP, where PNA decreased by < 10%. An extreme drought occurred in the northwestern CLP, where PNA decreased > 20% (Fig. 5a and e). This spatial pattern is particularly evident in the summer (Fig. 5c and g). The summer drought, rather than spring and autumn drought had the strongest effect on NDVI.
3.4. Residual analysis

Fig. 6 shows the spatial pattern of annual residual NDVI from 2000 to 2014 in the CLP. Regions with increased residual NDVI were primarily in northern Shaanxi, southern Ningxia, and western Shanxi, indicating that these regions were affected by the GGP, grassland restoration and conservation, and other ecological construction projects. The GGP and other human activities had a positive effect on vegetation change in those regions. Inner Mongolia and Southern Ningxia showed no change in residual NDVI. Southern Shaanxi, northern Shanxi, southern Ningxia, Qinghai, and Henan show decreased annual residual NDVI. These regions experienced overgrazing, urban expansion, and other unreasonable human activities. 21.54% of the CLP was affected by drought from 2000 to 2014. 43.64% of the CLP experienced human induced improvement, and 34.82% of the CLP experienced human induced degradation.

3.5. The effect of different drought classification on NDVI

Table 2 shows the effect of moderate, severe, and extreme drought on NDVI at the annual and seasonal scales. The mean percentage of NDVI anomaly (MPNA) was different due to the different drought classifications. In 2001, the percentage of areas that experienced moderate, severe, and extreme drought were 33.04%, 23.15%, and 1.36%, with reduction in NDVI of 12.93%, 15.74%, and 21.89%, respectively. In 2005, areas of moderate, severe, and extreme drought accounted for 12.94%, 35.43%, and 29.57% of the entire study area, with a reduction in NDVI of 2.01%, 4.16%, and 9.19%, respectively. The reduction in NDVI increases as drought intensity increases.

At the seasonal scale, percentage of area that experienced moderate, severe, and extreme drought in summer 2001 is 28.95%, 30.49%, and 1.44% of the entire study area, which resulted in a decreased NDVI of 0.85%, 20.36% and 23.54%, respectively. In summer of 2005,
and Table 3). Since the implementation of the GGP, there was an obvious decrease of cropland area and increase in forest and grassland areas in Yulin and Yan’an. Forested areas increased from 11,183.15 km² in 2000 to 12,343.25 km² in 2010, while cropland in Yulin and Yan’an decreased from 28,423.21 km² in 2000 to 27,250.46 km² in 2010 (Table 3). Hence, the GGP contributes to increase NDVI in the CLP.

4. Discussion

4.1. Impacts of drought on vegetation activity

The CLP has been considered to be the most fragile ecological environment in China, and has experienced a long-term warming-drying climatic trend in the past few decades (Yao et al., 2013; Sun et al., 2015). Numerous studies have reported that the severity and frequency of droughts has increased trend in the CLP (Yao et al., 2013; R.G. Jiang et al., 2015; Zhang et al., 2016; B.Q. Zhang et al., 2017). In this study, we used the MODIS-NDVI and SPEI (an effective drought index that could contain information on evapotranspiration in drought monitoring) to assess the change trend of vegetation and drought in the CLP. Results indicate that vegetation dynamics in most areas of the CLP showed an increase trend from 2000 to 2014 (88.24% of the CLP and 51.92% at the 95% confidential level). However, the spatial distribution of the annual and seasonal NDVI trends exhibited a complex pattern in response to drought and the GGP. Decreasing NDVI trends were primarily located in the southeastern and northwestern CLP (Fig. 3). Numerous studies also showed that overgrazing, urban expansion, industrialization, and other improper anthropogenic activities lead to the negative NDVI trends in these areas (Liu et al., 2016; Cao et al., 2018). However, our results indicate that drought in these areas was also a primary driving factor for NDVI reduction (Fig. 6).

The spatiotemporal variability in annual and seasonal vegetation dynamics coincided with drought in the CLP (Fig. 3). The decrease trend of the drought in 2001, 2005, and 2011 coincided with the decrease trend of vegetation dynamics. Results indicate that intense droughts happened in 2001 and 2005, and summer drought was the main driving force for the decrease trend of NDVI. Our results agree with many previous studies, which have shown that vegetation was significantly affected by drought in arid and semi-arid regions. For example, Vicente-Serrano et al. (2013) found that 72% of the vegetated land area of the world was affected by drought; Q. Zhang et al. (2017) indicated that NDVI was significantly affected by drought in most regions of China; T. Hua et al. (2017) showed that growing season NDVI correlates with drought in northern China.

4.2. Impacts of GGP on vegetation activity

Drought, precipitation, temperature, and other climate factors are the main drivers of vegetation change in the CLP. However, there is no doubt that the GGP also has an important influence on the vegetation activities (Zhang et al., 2000; Wu et al., 2013). From 1999 to 2006, afforested areas in the CLP increased from $3 \times 10^4$ km² to $5.9 \times 10^4$ km², and NDVI in the CLP showed an overall increasing.

Table 2

<table>
<thead>
<tr>
<th>Drought</th>
<th>Annual</th>
<th>Spring</th>
<th>Summer</th>
<th>Autumn</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>MPNA(%)</td>
<td>PDA(%)</td>
<td>MPNA(%)</td>
<td>PDA(%)</td>
</tr>
<tr>
<td>2001</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Moderate</td>
<td>−12.93</td>
<td>33.04</td>
<td>−5.96</td>
<td>6.83</td>
</tr>
<tr>
<td>Severe</td>
<td>−15.74</td>
<td>23.15</td>
<td>−9.59</td>
<td>74.78</td>
</tr>
<tr>
<td>Extreme</td>
<td>−21.89</td>
<td>1.36</td>
<td>−16.14</td>
<td>18.27</td>
</tr>
<tr>
<td>SPEI &lt; −1.5</td>
<td>−16.08</td>
<td>24.51</td>
<td>−14.14</td>
<td>93.05</td>
</tr>
<tr>
<td>2005</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Moderate</td>
<td>−2.01</td>
<td>12.94</td>
<td>−3.04</td>
<td>25.05</td>
</tr>
<tr>
<td>Severe</td>
<td>−4.16</td>
<td>35.43</td>
<td>−7.51</td>
<td>28.47</td>
</tr>
<tr>
<td>extreme</td>
<td>−9.19</td>
<td>29.57</td>
<td>−13.40</td>
<td>20.59</td>
</tr>
<tr>
<td>SPEI &lt; −1.5</td>
<td>−6.45</td>
<td>65.00</td>
<td>−9.98</td>
<td>49.06</td>
</tr>
</tbody>
</table>
Fig. 7. Correlations between the annual mean NDVI and cumulative afforestation during 2000–2013.

Fig. 8. Spatial patterns of the cumulative afforestation area ratio from 2000 to 2013 in the Yan’an and Yulin.

Fig. 9. Land use changes in three years (2000, 2005 and 2010) during 2000 to 2010 in the Yan’an and Yulin.
especially in Yan’an and Yulin in the northern Shaanxi Province (Sun et al., 2015). Moreover, sediment transfer from the CLP to the Yellow River declined from 1.6 to 0.14 billion tons over the past few decades (Sun et al., 2015). In our study, we first calculated the relationship between NDVI and the cumulative afforestation areas in the pilot regions for ecological restoration (Yulin and Yan’an) from 2000 to 2013, then the spatial pattern CAAR and NDVI change trend were analyzed in Yulin and Yan’an, and we analyzed the impacts of land use change on vegetation activity. Vegetation cover in Yulin and Yan’an exhibited an overall increasing since 2000. A strong correlation between vegetation cover and the cumulative afforestation areas was detected from 2000 to 2013 (Fig. 7). The CAAR and the trend of NDVI from 2000 to 2013 matched quite well (Fig. 8). Our results are also consistent with Cao et al. (2018), who found areas with significant increases in NDVI were loess hilly and gully regions after implementing the GGP. Meanwhile, we also found that cropland area decrease and forest and grassland area increase were important land use changes in Yulin and Yan’an from 2000 to 2010 (Fig. 9 and Table 3). These changes were located in the loess hilly and gully regions of the CLP and represented one of the GGP pilot regions. In summary, the afforestation, conversion of cropland to forest and other ecological restoration programs could be largely responsible for the improvements in vegetation and control of soil and water losses.

It should be noted that the ecological restoration program must also consider drought and other climate change that affects tree and shrub planting in semiarid and arid regions. The afforested areas in Shaanxi, Shaanxi, and Ningxia increased from 8.6 × 10^4 km² in 1998 to 120.46 × 10^3 km² in 2003 (Zhao et al., 2017). However, increased afforestation areas would increase transpiration and result in water shortages and deterioration of soil ecosystems at a local scale. From 1982 to 2005, the overall survival rate of trees in afforestation projects was only 24% (Wang et al., 2007). The drought may be the key driving force for the decline in annual and seasonal NDVI in 2005, 2011, and 2013 (Fig. 2). Our results indicate that severe and extreme drought reduced the NDVI by 22.44% and 9.98% in the summer of 2001 and 2005, respectively (Table 2). Therefore, the effect of drought and other climate changes on the GGP and ecological restoration program must be considered.

5. Conclusions

In this study, we analyzed the effect of drought and GGP on vegetation activity in the CLP from 2000 to 2014. Results indicate that the annual and seasonal NDVI show a significant increase after the implementation of the GGP, and drought, especially severe and extreme drought was also one of the primary reasons for the decrease of NDVI in the northern CLP. Residual analysis results indicate that the GGP has a positive effect on vegetation change in northern Shaanxi, southern Ningxia, and western Shanxi. Overgrowing, urban expansion, and other unreasonable human activities had a negative effect on the vegetation change in southern Shaanxi, northern Shanxi, and southern Ningxia. There is a strong correlation between the cumulative afforestation area and NDVI in Yan’an and Yulin. The CAAR spatial pattern was matched quite well with NDVI trends, and the decrease in cropland and increase forest and grassland areas indicated that the GGP has an important influence on vegetation. However, the response of vegetation to drought was highly variable due to different vegetation types, and the role of drought in evaluating the effectiveness of other ecological recovery program regions (such as the Three Norths Shelter Forest System Project, Natural Forest Conservation Program and the Wildlife Conservation and Nature Reserves Development Program) is also uncertain. In addition, the temperature, precipitation change and other human activities (Such as irrigations, check-dam construction, and terracing) also the key driving forces for the annual and seasonal variation in NDVI in CLP. Moreover, using linear methods to analyze correlations between SPEI and NDVI were limited, and the vegetation dynamics is quite complex and responses to drought and “Grain for Green” Program may be nonlinear. Consequently, nonlinear method such as principal component analysis (PCA) should be used to study the relationships between NDVI and SPEI. These are all valuable topics for further in-depth studies. Our findings provide implications for evaluating and predicting vegetation response to drought and ecological restoration programs in other regions.

Acknowledgements

The work was partially supported by the Humanities and Social Sciences Project of Ministry of Education of China(NO. 18YJCZH257), Natural Science Foundation of Hebei Province, China (NO. D2017402159), National Key Research and Development Program of China (NO. 2017YFC0404302), and Program of Education Department of Hebei Province, China (NO. BJ2018043, QN2018054).

References


学霸图书馆 (www.xuebalib.com) 是一个 “整合众多图书馆数据库资源，提供一站式检索和下载服务” 的24小时在线不限IP图书馆。

图书馆致力于便利、促进学习与科研，提供最强文献下载服务。

图书馆导航：

图书馆首页 文献云下载 图书馆入口 外文数据库大全 疑难文献辅助工具