Article

Analysis of the Driving Forces in Vegetation Variation in the Grain for Green Program Region, China

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Abstract: The Chinese government introduced six ecological restoration programs to improve its natural environment. Although these programs have proven successful in improving local environmental conditions, some studies have questioned their effectiveness when regions suffer from extreme weather conditions. Using the Grain for Green Program (GGP) region as a study area, we estimated vegetation activities in the GGP region from 2000 to 2010 to clarify the trends in vegetation growth and their driving forces. The results showed that: (1) vegetation activities improved in the GGP region during 2000–2010, with 58.94% of the area showing an increased trend in the NDVI (normalized difference vegetation index); (2) 26.33% of the increased vegetation was caused by human interference, and 11.61% by climate variation, human activity was the dominant cause, and resulted in 54.68% of the degradation compared to 4.74% from climate change; and, (3) the contribution of different land use types to the NDVI interannual variations showed that high contribution regions were focused in the arid and semiarid areas, where the vegetation growth is associated with variations in precipitation and temperature. However, conversions between farmland and grassland or forest had a significant effect on the change in the NDVI trend. Therefore, although climate conditions can affect vegetation growth, human activities are more important in vegetation changes, and appropriate human activities would contribute to its continual improvement. Hence, we recommend establishing an assessment and scientific management mechanism for eco-risks in the design and management of ecosystem restoration programs.

Keywords: grain for green program; NDVI; climate fluctuation; human activity

1. Introduction

For many years, especially before the end of the 20th century, the sustained development of China’s economy has been accompanied by severe ecological problems, such as land desertification, soil erosion, vegetation degradation, and biodiversity loss [1,2]. To solve these problems, the Chinese government introduced six ecological restoration programs, among which are the “Three-North Shelterbelt Project”, the “Natural Forest Protect Project”, and the “Grain for Green Program” (GGP) [3–5]. Several studies have reported that these programs have improved the local environment significantly [6–8], and among them, the GGP has become one of the largest-scale ecosystem projects in the world [9]. From 1999 to 2008, the Chinese government invested approximately 28.8 billion USD in the GGP, and helped 0.12 billion farmers restore sloping croplands to economic woodland, artificial forest, and grassland [10]. Therefore, vegetation restoration in the GGP region is an area of interest for
research on the effectiveness of ecological restoration programs. Generally, researchers believe that ecological restoration programs reduce land degradation, increase vegetation coverage, and improve soil carbon storage [11–13]. However, the findings of several recent studies have challenged these conclusions [14,15]. Wang et al. pointed out a low survival rate of the planted trees and shrubs were found in the GGP region because of the climate change [16]. Cao stated further that afforestation could cause increasing ecosystem deterioration and wind erosion in semiarid and arid areas [17]. The principal reasons for these conflicting results are the effects of climate change and human activity in restoring vegetation.

On the one hand, climate change affects vegetation growth directly—links between climatic variables and vegetation have been demonstrated conclusively [18–21]. For example, increased temperature and precipitation have extended the growing season of the vegetation in the Loess Plateau. However, if the rainfall fails to offset the increased evapotranspiration caused by the warming climate, the length of the growing season will be shortened [22]. On the other hand, human activity also affects vegetation growth [23–25]. The negative effects of activities such as urbanization and overgrazing, among many, have caused different levels of soil degradation and erosion, and become the primary factors that degrade vegetation cover [26,27]. Equally important, positive human activities such as enclosure of grazing, returning farmland to forest and grassland, reforestation, and afforestation can contribute to increased soil conservation and water preservation ability, which lead to sustained vegetation growth [28,29]. Even so, we believe that past research has made insufficient efforts to study the relation between climate change and human activity, both of which influence vegetation growth positively/negatively. Research that relies solely on climate change or human activity data will fail to illuminate the relation between vegetation growth and its driving forces fully [30,31]. Neglecting human activity, while exaggerating the effect of climate change may underestimate the benefits of ecological restoration programs. Similarly, neglecting climatic conditions in assessment of ecological restoration programs may fail to improve the local environment.

Whether a decreasing trend in vegetation in restoration program regions is caused by climate change or human activity remains unclear. It is also is unclear whether extreme weather has a significant influence on the results of ecological restoration programs or whether it should be considered when assessing their benefits. To address both of these issues, this study chose the GGP region as the study area and adopted the normalized difference vegetation index (NDVI), remote data, and climatic data in the GGP region to identify the spatio-temporal patterns in vegetation from 2000–2010. Based on the land use data and the results of the residual analysis, we separated the effects of climate and human activity on the NDVI. The study’s final objective was to identify the influence of human activity on vegetation growth by calculating the contribution rate of different land use types, and investigating the importance of considering climate change as a feature in assessing the efficacy of ecological restoration programs.

2. Data and Methods

2.1. Study Area

The Chinese government introduced the GGP in 1999. The program’s objective was to halt erosion, protect biodiversity, and improve the ecological environment by encouraging farmers to convert abandoned farmland and degenerated grassland to trees and grasses [32]. The government has invested over 430 billion Yuan in the program, and it has been implemented in 1897 counties in 25 provinces in China, which together cover 74% of China’s total land area (Figure 1) [33,34]. By late 2012, the GGP had converted 9.7 million hectares of farmland into forest and grassland [35]. The final goal of the GGP is to convert all of the region’s steep slope lands into forest to control the most severe farmland desertification and increase China’s grassland and forestland coverage by 4.5%, thereby improving its natural environment significantly [36].
2.2. Dataset

This study adopted the annual average temperature and annual precipitation data (2000 to 2010) from the China Meteorological Data Sharing Service System (http://cdc.cma.gov.cn/). Using data from 676 stations in China, we estimated the spatio-temporal patterns of the climatic factors in the study area. To produce the spatial maps, we used the Kriging interpolation method, and the resolution of the maps was 1 km.

The study used the annual average NDVI data (2000 to 2010) from the International Scientific and Technical Data Mirror Site, Computer Network Information Center, Chinese Academy of Sciences (http://www.gscloud.cn), which have a resolution of 1 km. To minimize disturbance in the NDVI trends, such as those attributable to bare soil and sparsely vegetated areas, we excluded all of the grid cells with an average annual NDVI value less than 0.05 [37,38].

Land use maps for the GGP region in 2000 and 2010 were obtained from the Center for Earth Observation and Digital Earth, China (http://www.ceode.cas.cn/sjyhfw/). Based on the Landsat satellite remote data and the vegetation type map, a series of 30-m resolution land use maps was created with an accuracy rate greater than 94%.

Figure 1. Location of the Grain for Green Program (GGP) in China.

Legend
- National boundary
- DEM of the GGP region (m)
- High: 6989
- Low: -277
2.3. Methods

To measure the vegetation dynamics, the following formula of ordinary least-squares regression was applied to examine the linear trends in the NDVI data:

\[
Slope = \frac{\sum_{i=1}^{n} x_i y_i - \frac{1}{n} (\sum_{i=1}^{n} x_i)(\sum_{i=1}^{n} y_i)}{\sum_{i=1}^{n} x_i^2 - \frac{1}{n} (\sum_{i=1}^{n} x_i)^2}
\]  

(1)

where \(x_i\) is the years' order from 1 to \(n\), \(n\) is the number of years, and \(y_i\) signifies the NDVI variables when time is \(x_i\). Regions with a positive slope value indicate an increasing trend, while those with a negative slope value indicate a decreasing trend [39,40].

Three forms of the NDVI were computed for each year and each pixel to distinguish the effect of climate and human activity on vegetation [40,41]. First was the predicted NDVI, in which we estimated the linear regression for each pixel between the annual precipitation, annual average temperature, and the annual NDVI using the following formula:

\[
NDVI_P = aP + bT + c
\]

(2)

where \(NDVI_P\) indicates the predicted NDVI without human disturbance, \(P\) and \(T\) are annual precipitation, and annual average temperature, respectively, \(a\) and \(b\) are regression coefficients, and \(c\) is a regression constant. The effect of climate change on vegetation can be defined by the slopes of the NDVI\(_P\) (\(S_p\)) according to Equation (1). A positive value indicates that climate change improves vegetation growth, while a negative value indicates that climate change degrades vegetation growth.

The second was the actual NDVI (\(NDVI_A\)), which was derived from the annual average NDVI data. The effects of both climate change and human activity on vegetation can be defined by the slopes of the NDVI\(_A\) (\(S_A\)). A positive value of \(S_A\) indicates that vegetation growth during this period is improved. In contrast, a negative value indicates that vegetation growth during this period is degraded.

The third NDVI was the NDVI residuals (\(NDVI_R\)), which were the disparity between the actual NDVI (\(NDVI_A\)) and the predicted NDVI (\(NDVI_P\)):

\[
NDVI_R = NDVI_A - NDVI_P
\]

(3)

The slope of the NDVI\(_R\) (\(S_R\)) signifies changes in the vegetation for reasons other than climate change. A positive value indicates human-induced improvement, while a negative value indicates human-induced degradation in an area [42,43].

Accordingly, six scenarios can be defined by the slopes of the NDVI\(_A\) (\(S_A\)), the NDVI\(_P\) (\(S_p\)), and the NDVI\(_R\) (\(S_R\)) (Table 1). Based on the changing trends in the three NDVIs, the scenarios can distinguish between climate and human factors in changing vegetation growth in the study area [44,45]. However, when \(S_A > 0\), \(S_p < 0\), \(S_R < 0\), or \(S_A < 0\), \(S_p > 0\), and \(S_R > 0\), an error scenario may occur, indicating that vegetation growth increased, but climate and human factors promoted degradation, or the vegetation growth decreased, but climate and human factors promoted vegetation growth. Because of the different scales of the dataset, this error may occur only in a few areas (less than 1%). According to previous research, this does not affect the accuracy of the final results [46,47].

To estimate the contribution of different land use types to the NDVI interannual variations, an index was adopted that scores individual geographic locations according to the consistency, over time, with which the local NDVI flux resembles the sign and magnitude of GGP region NDVI [48].

\[
f_j = \frac{\sum \frac{x_i |X_i|}{X_i}}{\sum |X_i|}
\]

(4)
where $x_{jt}$ is the anomaly for land use type $j$ at time $t$, $t$ is the order of the year, and $X_{t}$ is the GGP anomaly, so that $X_{t} = \sum_{j} X_{jt}$. The equation shows that $f_j$ is the average relative anomaly $x_{jt}/X_{t}$ for region $j$, weighted by the GGP anomaly $|X_{t}|$. A positive result indicates a greater contribution that affects the NDVI change trend in the GGP region. In this research, the index adopted does not reflect the variation of NDVI in different areas; rather, it achieves a comparison of these areas’ relative contribution in governing the NDVI in the GGP region.

Table 1. Scenarios that distinguishing climate and human factors in changing vegetation growth.

<table>
<thead>
<tr>
<th>Vegetation growth increased (SA &gt; 0)</th>
<th>SP</th>
<th>SR</th>
<th>Roles of Climate and Human Factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scenario 1</td>
<td>&lt;0</td>
<td>&gt;0</td>
<td>Vegetation restoration attributable largely to human factors</td>
</tr>
<tr>
<td>Scenario 2</td>
<td>&gt;0</td>
<td>&lt;0</td>
<td>Vegetation restoration attributable largely to climate factors</td>
</tr>
<tr>
<td>Scenario 3</td>
<td>&gt;0</td>
<td>&gt;0</td>
<td>Vegetation restoration attributable largely to both climate and human factors</td>
</tr>
<tr>
<td>Vegetation growth decreased (SA &lt; 0)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scenario 1</td>
<td>&gt;0</td>
<td>&lt;0</td>
<td>Vegetation degradation attributable largely to human factors</td>
</tr>
<tr>
<td>Scenario 2</td>
<td>&lt;0</td>
<td>&gt;0</td>
<td>Vegetation degradation attributable largely to climate factors</td>
</tr>
<tr>
<td>Scenario 3</td>
<td>&lt;0</td>
<td>&lt;0</td>
<td>Vegetation degradation attributable largely to both climate and human factors</td>
</tr>
</tbody>
</table>

$S_A$ is the slope value of the actual NDVI, $S_P$ is the slope value of the potential NDVI, and $S_R$ is the slope value of the residual NDVI.

3. Results

3.1. Spatio-Temporal Vegetation Patterns

The spatial distribution of NDVI showed varied characteristics in the GGP region from 2000 to 2010 (Figure 2). Over half (58.94%) of the region showed an increasing trend in the NDVI during the time the study covered. Regions showed an extremely significant increasing trend in NDVI at the 0.95 confidence intervals, which account for 11.22% of total vegetation, as compared to those areas with extremely significant NDVI decreasing trend at 0.95 confidence intervals, which account for 3.91% (Table 2). The NDVI increased areas were chiefly found in the Loess Plateau, specifically in the Lüliang Mountains area, Northern Shaanxi, and southern Gansu. Meanwhile, the decreasing trend of the NDVI was located mainly in the Tian Shan Mountains, northwest of the Hunshadake Sandy Land area and the middle of the Sichuan Basin.

Table 2. Spatial changes in normalized difference vegetation index (NDVI) in the GGP region from 2000 to 2010.

<table>
<thead>
<tr>
<th>Variables</th>
<th>NDVI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Increasing (%)</td>
<td>58.94</td>
</tr>
<tr>
<td>Increasing significantly (%)</td>
<td>16.3</td>
</tr>
<tr>
<td>Increasing extremely significantly (%)</td>
<td>11.22</td>
</tr>
<tr>
<td>Decreasing</td>
<td>41.06</td>
</tr>
<tr>
<td>Decreasing significantly (%)</td>
<td>6.58</td>
</tr>
<tr>
<td>Decreasing extremely significantly (%)</td>
<td>3.91</td>
</tr>
</tbody>
</table>

Note: significantly indicates areas that changed significantly at the 0.90 confidence intervals. Extremely significantly indicates areas that changed significantly at the 0.95 confidence levels.
3.2. Effects of Climate Change and Human Activity on Vegetation

Vegetation restoration caused by climate change or human activity was analyzed, and is shown in Figure 3a. The results demonstrated that the combined effects contributed the most to restoration (62.06%), followed by human activity (26.33%), and climate change (11.61%). Vegetation restoration attributable to human activity was found primarily in the Loess Plateau and the North China Plain, which indicates that ecological projects such as the GGP have achieved notable results in these regions. Vegetation restoration attributable to climate change was scattered in arid and semiarid areas of China, in which vegetation growth is relatively sensitive to temperature and precipitation changes.

The driving factors of vegetation degradation also were analyzed, and are shown in Figure 3b. Degradation attributable to human activity was distributed widely in the GGP region and accounted for 54.68% of the degraded area. Climate change and the joint effects caused 4.47% and 40.58% of the degradation, respectively. When human activity and the joint effects were considered together, over 95% of the vegetation degradation was caused by human activity. These findings show that vegetation degradation has reached an alarming scale, with much of it being related to human activity, especially in regions with fragile ecological environments, including the arid and semiarid areas and the mountainous areas of southwest China.
3.3. Vegetation Variation Affected by Human Activity

3.3.1. Land Use Change

To investigate the effect of human activity on vegetation variation, the change in land use and the contribution of various land use types to the NDVI interannual variations were analyzed. In accordance with the land use change transfer matrix in Table 3, forest and urban land increased by 0.77% and 21.67%, respectively, in the last 11 years. The principal increase in forest was attributable to farmland conversion that corresponds to the introduction of the GGP. Meanwhile, urban land increased significantly, largely because of conversion from farmland, indicating that the process of urbanization in the GGP region has been impressive; thus, its accompanying ecological problems should be given close attention in the future. Because of the land use change, which is associated closely with vegetation restoration and urbanization, there had been a significant decrease in farmland. Although forest, grassland, and wetland had been converted to new farmland, the net change in farmland was still negative. Grassland in the GGP region showed a negative growth trend, and significant mutual transformation between grassland and forest had occurred, the effect of which on the NDVI change trend needs to be studied further.

Table 3. The conversion of land use change in percent during 2000–2010 in the GGP region (Unit: %).

<table>
<thead>
<tr>
<th>Land Use Type</th>
<th>Forest</th>
<th>Grassland</th>
<th>Wetland</th>
<th>Farmland</th>
<th>Urban Land</th>
<th>Bare Land</th>
<th>Net Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>98.97</td>
<td>0.25</td>
<td>0.01</td>
<td>0.51</td>
<td>0.13</td>
<td>0.12</td>
<td>0.77</td>
</tr>
<tr>
<td>Grassland</td>
<td>0.87</td>
<td>97.93</td>
<td>0.07</td>
<td>0.73</td>
<td>0.19</td>
<td>0.21</td>
<td>−0.78</td>
</tr>
<tr>
<td>Wet land</td>
<td>0.27</td>
<td>1.14</td>
<td>93.09</td>
<td>3.65</td>
<td>0.32</td>
<td>1.53</td>
<td>−1.70</td>
</tr>
<tr>
<td>Farmland</td>
<td>1.45</td>
<td>0.93</td>
<td>0.10</td>
<td>95.93</td>
<td>1.30</td>
<td>0.29</td>
<td>−1.72</td>
</tr>
<tr>
<td>Urban land</td>
<td>0.08</td>
<td>0.08</td>
<td>0.01</td>
<td>0.48</td>
<td>99.26</td>
<td>0.08</td>
<td>21.67</td>
</tr>
<tr>
<td>Bare land</td>
<td>0.17</td>
<td>0.32</td>
<td>0.09</td>
<td>0.27</td>
<td>0.11</td>
<td>99.04</td>
<td>−0.15</td>
</tr>
</tbody>
</table>
3.3.2. Contribution of Different Land Use and Land Use Change Types to the NDVI Interannual Variations

To investigate more closely the way in which land use and land use change influence the variations in interannual NDVI, we partitioned NDVI in the GGP region among land use types in accordance with the contribution of individual regions (grid cells or land use types) in the whole area. The contribution rate of each land use type overall was the sum of both the positive and negative contributions of each grid cell (Tables 4 and 5). The results are shown in Figure 4: high contribution regions chiefly were in the arid and semiarid areas in China, especially in the Loess Plateau and Inner Mongolia regions. The contribution rate on the NDVI interannual variations of unchanged land use types were, in order, grassland (37%), farmland (31%), forest (20%), and wetland (1%) (Table 4). For land use types that changed from 2000 to 2010, the changes between farmland and grassland or farmland and forest made greater contributions. Specifically, four of the top five high contribution land use changes occurred between farmland and grassland or forest: grassland to farmland (6.27‰), farmland to grassland (4.49‰), forest to farmland (3.68‰), and farmland to forest (2.81‰) (Table 5). This indicates that the conversion between farmland and grassland or forest had a greater effect on NDVI interannual variations than did the transition between land use types with vegetation-coverage and those without vegetation. Thus, the introduction of the GGP affected the vegetation change trends significantly.

Figure 4. Spatial pattern of the local NDVI contribution to the NDVI interannual variations in the GGP region.
Table 4. Statistics of the contribution rate of unchanged land use types to the NDVI interannual variations in the GGP region.

<table>
<thead>
<tr>
<th>Land Use Types</th>
<th>Contribution Rate to the NDVI Interannual Variations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grassland</td>
<td>37%</td>
</tr>
<tr>
<td>Farmland</td>
<td>31%</td>
</tr>
<tr>
<td>Forest</td>
<td>20%</td>
</tr>
<tr>
<td>Wet land</td>
<td>1%</td>
</tr>
</tbody>
</table>

Table 5. Statistics of the contribution rate of changed land use types to the NDVI interannual variations in the GGP region.

<table>
<thead>
<tr>
<th>Land Use Changes</th>
<th>Contribution Rate to the NDVI Interannual Variations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grassland to farmland</td>
<td>6.27%</td>
</tr>
<tr>
<td>Grassland to forest</td>
<td>5.86%</td>
</tr>
<tr>
<td>Farmland to grassland</td>
<td>4.49%</td>
</tr>
<tr>
<td>Forest to farmland</td>
<td>3.68%</td>
</tr>
<tr>
<td>Farmland to forest</td>
<td>2.81%</td>
</tr>
<tr>
<td>Bare land to farmland</td>
<td>1.66%</td>
</tr>
<tr>
<td>Forest to grassland</td>
<td>1.48%</td>
</tr>
<tr>
<td>Farmland to urban land</td>
<td>1.23%</td>
</tr>
<tr>
<td>Grassland to urban land</td>
<td>1.07%</td>
</tr>
<tr>
<td>Bare land to grassland</td>
<td>1.05%</td>
</tr>
</tbody>
</table>

4. Discussion

4.1. Methodology

Climate change and human activity are the two primary driving forces in vegetation variation. Previous studies have tried to distinguish their relative roles in affecting vegetation variation using various methods. However, most studies have focused on statistical methods, such as correlation analysis and principal component analysis [49,50]. Without considering the spatio-temporal differences in vegetation growth fully, these methods fail to reflect the spatial distribution and varying trends in the driving forces in vegetation growth [51,52]. Several recent studies have offered a new method to solve this problem by comparing actual and predicted vegetation growth [43,46]. Wu et al. designed this methodology to investigate the role of droughts and human activity in vegetation growth in the Beijing-Tianjin Sand Source Region [15]. Gang et al. assessed the contribution of climate and human activity in grassland change trends on the global scale [40]. Therefore, this study adopted the same methodology to investigate the driving force of vegetation variation in the GGP region.

The results indicated that the vegetation conditions had improved in the GGP region in the last decade because of restoration activities, as the NDVI in this area generally showed an increasing trend from 2000 to 2010. The research also showed demonstrated that 58.94% of the program area showed an increased trend in the NDVI and 11.22% showed a significant increasing trend at 0.95 confidence intervals. This result is consistent with those of related studies, which have shown clearly improved vegetation quality in the afforestation area [53,54]. Chang et al. concluded that because of the GGP, vegetation and soil carbon storage had increased in the Loess Plateau area [55]. Piao et al. reported that the primary reason for the improvements in China’s vegetation was human activity, such as afforestation and agricultural management [56]. Therefore, implementing ecological restoration programs, including the GGP, was both necessary and effective.

Although the residual of the NDVI (difference between actual and predicted NDVI) identified the driving forces of vegetation growth successfully, this method still has its limitations. The predicted NDVI is estimated with the assumption of an ideal environment in which only temperature and precipitation affect vegetation growth [41,57]. Thus, the relative roles of climate and human activity
in vegetation variation are based on the hypothesis that vegetation growth is affected only by those factors [58, 59]. However, other factors also affect vegetation growth trends, such as animal species, forest fires, pests, and diseases. Future studies should investigate these influential processes.

4.2. Driving Forces

Climate change, including temperature and precipitation changes, may be a principal factor in vegetation growth [60]. According to this research, 11.61% of the restoration was induced by climate change and was concentrated in China’s arid and semiarid areas. Previous studies have found that the vegetation in water-limited areas is sensitive to climate variation, especially precipitation changes [61, 62]. The most recent studies have also shown that there was a rising trend in both temperature and precipitation in northwest China, and the precipitation there had increased significantly since the 1980s [63, 64]. A pure increase in temperature will accelerate evapotranspiration and decrease soil moisture, which leads to drought and limits vegetation growth [65]. However, the significant increase in precipitation, which offsets the loss of water and improves soil moisture, helps vegetation survive a drought. Meanwhile, clouds accompany precipitation, and also reduce the evapotranspiration of vegetation, thereby increasing water use efficiency further [66]. Therefore, the improved vegetation growth in water-limited areas is indeed affected by climate change.

Although climate factors can affect vegetation growth in water-limited areas, human activity plays a more significant role in changing vegetation trends. Our results showed that 26.33% of the restoration in which the NDVI increased and 54.68% of the degradation in the area in which the NDVI decreased was related to human activity. Moreover, taking both human activity and the joint effects into consideration, human behavior led to over 95% of the vegetation degradation. When compared to climatic factors, human activity affects vegetation growth more directly and efficiently [29]. The continuous growth in population, overgrazing, excessive wood cutting, landscape fragmentation caused by urban expansion, and conversion of grassland into cropland have all exerted pressure on the natural environment and contributed significantly to vegetative degradation [67–69]. Thus, the destructive influence of human activity on vegetation is the main cause of its degradation.

At the same time, positive human activities, such as ecological restoration programs, can promote local vegetation restoration and bring several benefits to the local environment, such as increasing the vegetation cover, reducing soil erosion, and increasing soil organic carbon [3, 35, 70]. Our research confirmed that, in accordance with the land use change transfer matrix, the primary increase in forest and grassland derived from farmland, which was consistent with the introduction of the GGP. The statistics on the contributions of changed land use types to the NDVI interannual variations showed that conversion between farmland and grassland or farmland and forest accounted for the higher contributions. Thus, land use changes caused by human activity can have beneficial effects on vegetation change trends. Xiao reported that the GGP increased the enhanced vegetation index (EVI), and the leaf area index of forest in the Loess Plateau. Similarly [71], Wang et al. stated that, because of the success of the GGP and other environmental protection measures, soil erosion in China decreased appreciably from 2000 to 2010 [61]. In fact, carbon fixation in the GGP region also should increase, because larger forests facilitate soil carbon fixation [12]. Therefore, the introduction of ecological programs, including prohibiting grazing, converting croplands to grasslands and forests, and natural forest regulations, should, with patience and persistence, yield even greater ecological benefits.

5. Conclusions

This study assessed the effects of climate change and human activity on vegetation growth in the GGP region from 2000–2010. The results showed that vegetation activity increased in the GGP region. The vegetation in the arid and semiarid areas is sensitive to climate variation, especially precipitation change. Thus, climate change has become a key factor that affects vegetation growth in such areas. However, human activity exerted a greater influence on vegetation change trends. The results of this research showed that human activity played a more direct and efficient role in changing vegetation
growth. The destructive influence of negative human activity was the primary reason for vegetation degradation in the area in which the NDVI decreased. Meanwhile, the land use change contribution rate analysis showed that the conversions between farmland and grassland or forest had a significant effect on the NDVI change trend. Therefore, positive human activities, such as the introduction of ecological programs, can contribute to continued improvement in vegetation.

The methodology of comparing actual and predicted vegetation growth based on NDVI variations in this study proved to be relatively accurate and can be applied in other ecological restoration program regions to distinguish the driving forces of vegetation growth. Further, as the roles of climate change and human activity are highly divergent in China, future studies should consider the climate factors that might affect the effectiveness of new ecological projects. Therefore, we recommend an eco-risk assessment and scientific management mechanism in the design and implementation of ecosystem restoration projects.

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References


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