LETTER

Contributions of ecological programs to vegetation restoration in arid and semiarid China

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Abstract

Over the past four decades, large-scale ecological programs, including the ‘Great Green Wall Program’ (1978–present), ‘Grain for Green Program’ (1999–present), ‘Grassland Ecological Protection Program’ (2000–present), and ‘Beijing-Tianjin Sandstorm Source Control Project’ (2002–present), were launched to restore vegetation, to combat desertification, and to control dust storms in arid and semiarid China. The gross investments of these programs have exceeded 1700 billion RMB (~260 billion USD, accounting for ~1% GDP in the region) by now, however, the effects of these programs on vegetation restoration have not been settled. In this study, the vegetation indices, land-uses, and climatic factors were used to estimate the contribution of the above programs on vegetation restoration. The results showed that consistent vegetation restoration has occurred in about 45.3% of the vegetated areas in arid and semiarid China from 1982 to 2000, and the percentage decreased to 33.6% after 2000 despite more ecological programs have been launched. Changes in climatic factors (precipitation, temperature, solar radiation, and wind speed) and elevated atmospheric CO2 concentration contributed more than 50% and 70% to vegetation restoration in periods of 1982–2000 and 2001–2015, respectively, however, the contribution rate of ecological programs kept stable at about 20%. Climate changes in the past forty years played a dominant role, although the ecological programs showed a noticeable effect on vegetation restoration. Further investment in ecological restoration practices might need to be critically evaluated on the cost-effectiveness.

1. Introduction

Arid and semiarid China covers the northeastern, northern, and northwestern regions (‘Three North’) of the country, which falls in locations to the north of 35°N with annual rainfall generally less than 450 mm (figure 1). Over the last thousands of years, these regions have traditionally been managed as pastoral and agricultural lands [1]. Even until now, there are more than 70% of the lands still in use for grazing and reclamation practices, facing high risks of aeolian desertification [2, 3]. Under intensive pressures of aeolian desertification, deterioration of the local ecosystems may jeopardize the settlements of 200 million people [3, 4].

To reverse or improve local ecosystem quality, the Chinese governments have launched many ecological programs since the late 1970s, including the ‘Great Green Wall Program’ (GGWP, aiming afforestation, 1978–present), ‘Grain for Green Program’ (GGP, returning farmland or grazing land to forest or grassland, 1999–present), ‘Grassland Ecological Protection Program’ (GEPP, grazing prohibition, 2000–present), and ‘Beijing-Tianjin Sandstorm Source Control Project’ (BSSCP, to control dust storms and protect ecological environments, 2002–present).
Figure 1. Spatial extent of the ecological programs. The red dashed line is the boundary of the arid and semiarid China (450 mm isohyet); the GGWP is the ‘Great Green Wall Program’; and BSSCP is the ‘Beijing-Tianjin Sandstorm Source Control Program’; ‘Grassland Ecological Protection Program’ (GEPP) and ‘Grain for Green Program’ (GGP) are conducted nationwide. The land-use data in 2015 was from the Data Center for Resources and Environmental Sciences (http://www.resdc.cn).

[5, 6] (figure 1). These programs focus on controlling desertification and dust storms, improving regional ecological environments, and ensuring food security, through approaches of large-scale afforestation, returning cultivated lands to forests or grasslands, grazing prohibition, and grassland enclosure. Up to now, the gross investments of these programs have roughly exceeded 1700 billion RMB (equals to about 260 billion USD based on comparable prices in 2017, which accounts for ~1% GDP in the region, figure S1 (available online at stacks.iop.org/ERL/15/114046/mmedia), table S1). The Chinese government [7, 8] and some studies [9–13] have reported that these programs have made great achievements in improving the ecological environments, although such statements are still questioned in some other studies [6, 14–17].

Although many efforts have been made to attribute the vegetation restoration in China, there are still disputes on the contribution rate of various ecological programs and the resulting spatiotemporal variations in vegetation restoration. Vegetation degradation and restoration occurred alternatively with the climate change in arid and semiarid China over the past centuries [18–20]. On the national scale, the rising atmospheric CO₂ concentration [CO₂] and nitrogen deposition explained 85% and 41% of the greening in China over the last 30 years, respectively [21]. Annual air temperature contributed 36.8% and afforestation contributed 25.5% to the changes in vegetation productivity in China from 1982 to 2006 [22]. However, some studies showed that growing-season precipitation or land-use changes were the dominant factors [23–25]. On the regional scale, it has been reported that climate change contributed 74%, human activities and other natural factors contributed 23%, and land-use changes only contributed 3% to the NPP changes from 2000 to 2010 in the ‘Three North’ regions [26]. However, some studies pointed out that ecological programs greatly contributed to the greening and effectively reduced the occurrence and intensities of the dust storm in the ‘Three North’ regions [5, 12]. Studies also suggested human activities (ecological programs included) contributed 55% and dominated the vegetation restoration in the Loess Plateau from 2000 to 2015 [27]. It is still unclear about the influences of the various ecological programs in parallel with climate change on vegetation restoration in arid and semiarid China since the start of these ecological programs. Quantitative evaluation of the respective contributions of ecological programs and climate changes would assist in decision-making on ecological restoration practices in the arid and semiarid areas of China.

In this study, by using satellite-derived vegetation indices, climate data, land-use data, and covered areas of these ecological programs from 1982 to 2015, we aimed to (1) investigate the spatiotemporal
patterns of vegetation restoration through analyzing multiple vegetation indices, (2) distinguish the relative roles of climate change and ecological programs on vegetation restoration, and (3) quantify their contribution rates on vegetation restoration. This study may provide crucial guidance for decision-makers in countries facing a dilemma between serious desertification and vast investments in ecological projects.

2. Materials and methods

2.1. Data sources and processing

To investigate vegetation restoration, multiple vegetation indices, including normalized difference vegetation index (NDVI), gross primary productivity (GPP), and leaf area index (LAI), were selected as representative indicators. The 1/12-degree GIMMS-NDVI 3g.v1 dataset (1982–2015) from the Global Inventory Modeling and Mapping Studies (https://ecocast.arc.nasa.gov/data/pub/gimms/) was employed as a long-term vegetation index. To minimize the effects of atmospheric and aerosol scattering, the growing season NDVI (NDVIgs) was aggregated by the maximum value composites (MVC) method [28]. In addition, the Savitzky-Golay method was used to filter NDVI data for all years to construct a high-quality time series [29]. Pixels with maximum NDVIgs from 1982 to 2015 less than 0.1 were considered as non-vegetated areas (bare land) and were removed [30].

The 8-day 5-km GLASS GPP dataset (1982–2015) and GLASS LAI dataset (1982–2015) were obtained from the National Earth System Science Data Center, National Science & Technology Infrastructure of China (www.geodata.cn). The two long-term GLASS datasets were developed from time series of NOAA/AVHRR reflectance data [31]. GLASS GPP was integrated from eight light use efficiency models by the Bayesian multi-algorithm integration method [32]. The 8-day GLASS GPP data in growing season was summed to total values (GPPgs). Validation of the GLASS GPP data is presented in supplementary text S1. GLASS LAI was retrieved by the method of general regression neural networks (GRNNs) [33]. The 8-day GLASS LAI data in growing season was also aggregated by the MVC method (LAIgs). Validation indicated better performance of GLASS LAI dataset compared with the other three widely used LAI datasets [34]. Therefore, the robustness of GLASS vegetation indices enables the analysis of long-term vegetation dynamics. Besides, the three vegetation indices were analyzed in two periods: 1982–2000 and 2001–2015, and the year 2000 was chosen as breakpoint because most ecological programs (GGP, GEPP, BSSCP) were launched around 2000 (table S1).

Also, the reduction in dust storm intensity is partly due to vegetation restoration. Therefore, the dust events data (including floating dust, blowing dust, and dust storm which corresponds to reported visibilities of >10, 1–10, and <1 km, respectively) [35, 36] from 1960 to 2010 were obtained from the China Meteorological Administration (CMA, http://data.cma.cn/). And the dust events were normalized as a simple dust intensity index (DI) [37, 38]:

$$DI = FD + 3 \times BD + 9 \times DS$$  (1)

where FD, BD, and DS are the days of floating dust, blowing dust, and dust storm, respectively.

The climate data in the growing season, including monthly total precipitation (Pgs), mean air temperature (Tgs), mean solar radiation (Rgs), and mean wind speed (Wgs) in 1982–2015 from 2400 meteorological stations (figure S2) were also obtained from the CMA. With the aid of the DEM (Shuttle Radar Topography Mission [SRTM] Worldwide Elevation Data with a 90-m resolution, http://srtm.csi.cgiar.org/), the climatic data were interpolated into 1/12-degree climate surfaces using ANUSPLIN software (v4.4) [39, 40].

The 30-m land-use data (in 1980, 2000, and 2015) were acquired from the Data Center for Resources and Environmental Sciences (http://www.resdc.cn), and were resampled to the same spatial resolution of the NDVI data by nearest-neighbor sampling strategy which was also applied to other resampling needs. There are six primary land-use types of this dataset, which include cultivated lands, forests, grasslands, waters, built-up lands, and unused lands [41] (figure 1). Because this study aims to explore the restoration of natural vegetation, the cultivated lands, waters, and built-up lands in 2015 were excluded (mask) and the land-uses in 1980 and 2000 were also applied to this mask. The cultivated lands that were returned before 2015 through GGP program were still considered in our analysis. In this context, the vegetated area refers to the area with maximum NDVIgs > 0.1 and excluding cultivated lands, waters, and built-up lands. The spatial extent of the four ecological programs was obtained from the National Forestry and Grassland Data Center (www.forestdata.cn/index.html). And the annual statistical data at the city level were obtained from the national forestry yearbooks [7], national/local government statistical yearbooks, and state bulletins [42]. The statistical data included the covered areas (including afforestation and protected grassland areas) and investments of the ecological programs. In addition, the growing season monthly mean atmospheric CO2 concentration ([CO2]gs) (1982–2015) measuring as a mole fraction in dry air at Mauna Loa Observatory, Hawaii was obtained from the Global Greenhouse Gas Reference Network (http://www.esrl.noaa.gov/gmd/ccgg/trends/). More details about the uncertainties in data processing are provided in the supplementary text S1 of the supporting information.
2.2. Methods

2.2.1. Trend analysis and correlation analysis
The ordinary least square linear regression can be used to detect the changing trend of NDVI, GPP, LAI, DI, and climatic factors [30]. After that, the vegetation restoration area was defined as the increases in the three vegetation indices NDVI, GPP, and LAI. The Pearson correlation analysis was employed to reveal the relations between vegetation changes and climatic factors [11, 43]. More details about trend analysis and correlation analysis are described in the supplementary text S2 of the supporting information.

2.2.2. Attributing relative contributions to vegetation restoration
To attribute the relative contributions of climate change and ecological programs on vegetation restoration, only the areas with vegetation restoration were extracted for this analysis. Generally, the vegetation growth is determined by climatic and non-climatic factors, taken NDVI for illustration [27, 44]:

\[
\text{NDVI}_O = \text{NDVI}_P + \text{NDVI}_R
\]  

(2)

where \( \text{NDVI}_O \), \( \text{NDVI}_P \), and \( \text{NDVI}_R \) are observed NDVI, predicted NDVI, and NDVI residuals, respectively. \( \text{NDVI}_P \) is explained as climate contributions, and \( \text{NDVI}_R \) is the residual that is caused by non-climatic factors in which ecological programs are involved. At a pixel scale, the \( \text{NDVI}_P \) is given by the multiple linear regression (MLR) method [44, 45]:

\[
\text{NDVI}_O = \text{NDVI}_P + \text{NDVI}_R = \left( b + \sum_{i=1}^{n} a_i x_i \right) + \text{NDVI}_R
\]  

(3)

where \( b \) is regression constant, \( a_i \) (\( i = 1, 2, \ldots, n \)) is regression coefficient; \( x_i \) is the climatic factors (\( P_{go}, T_{go}, R_{go}, W_{go}, [CO_2]_{go} \)), time series were standardized by Z-score method; \( \text{NDVI}_R \) is the same meaning as in equation (2). The coefficient of determination \( (R^2) \) given by MLR regression conducted at a pixel scale means the variances explained by the model, which indicates the contribution rate was attributed to climatic factors only. And at a regional scale (the whole vegetation restoration area), the relative contributions of the climatic and of the ecological programs could be determined as follows [46, 47]:

\[
\text{NDVI}_O = \left( b + \sum_{i=1}^{n} a_i x_i \right) + c \cdot A + \text{NDVI}_R
\]  

(4)

\[
\text{Con}_{clm} = R^2 \times \frac{\sum |a_i|}{\sum |a_i| + |c|} \times 100\%
\]  

(5)

where \( \text{NDVI}_O \) is regional mean NDVI, \( b \) is regression constant, \( a_i \) (\( i = 1, 2, \ldots, n \)) and \( c \) are regression coefficients, \( x_i \) is regional mean climatic factors (\( P_{go}, T_{go}, R_{go}, W_{go}, [CO_2]_{go} \)), \( A \) is the covered area of the ecological programs, including the areas of afforestation and covered grasslands; \( \text{NDVI}_R \) is the residual that is caused by non-climatic factors other than these ecological programs; \( R^2 \) in equation (5) is the coefficient of determination given by equation (4), \( \text{Con}_{clm} \) is the contribution of the climatic factors, and the contribution of ecological programs can be determined the same way. Besides, a \( t \)-test \( (p < 0.05) \) was used to examine the significance of all statistical analyses.

3. Results

3.1. Observed vegetation restoration
Because the GGWP covered most areas of arid and semiarid China, therefore, here we take the regions covered by GGWP as the main study area. The trends in multiple vegetation indices showed that from 1982 to 2015, about 44.1% of the vegetated areas have experienced continuous vegetation restoration processes and regions with the significant ones included Mu Us Desert, some oasis regions in northwestern China, and around Otindag Desert (figures 2(a)–(d)). In regions covered by GGWP, about 68.8% of the vegetated areas showed increasing NDVI trends, while only 10.9% of the areas showed significantly decreasing trends, which is consistent with the changes in GPP and LAI (tables S2–S4). From 1982 to 2000, the NDVI in 73.2% of the vegetated areas showed an increasing trend, and the percent are 71.6% and 62.5% for GPP and LAI, respectively. And there was no obvious vegetation restoration observed in Loess Plateau and northeastern areas of the GGWP. However, the areas with continuous vegetation restoration decreased to 33.6% in 2001–2015 compared to 45.3% in 1982–2000 (figures 2(h) and (l)). Significant vegetation restoration processes were mainly observed in the Loess Plateau, Hulunbuir Desert, and some oasis areas in northwestern China after 2000 (figure 2(l)). In regions covered by BSSCP, even with BSSCP being launched since 2002, the vegetation restoration area still decreased after its implementation compared to the previous stage, which indicates there were no significant vegetation restoration processes in the region except for some sporadic areas. Besides, vegetation deterioration was also observed in northeastern areas and the areas covered by BSSCP after 2001.

3.2. Changes in DI
Changes in DI showed that DI decreased all over the arid and semiarid China from 1961 to 2010 (figure 3(a), table S5). Due to the relatively long time series of the DI data, the study periods were further divided into three sections: 1961–1978, 1979–2000, and 2001–2010. From 1961 to 1978, which is the period before the GGWP being launched, DI increased (not significant) all over the arid and semiarid China apart from some sporadic areas (figure 3(b)), while during 1979–2000, DI decreased in nearly
all the areas (figure 3(c)); and in 2000–2010, DI continued to decrease (not significant) in 87.2% of the areas except few parts of regions in the west exhibiting an increasing trend (figure 3(d)).

3.3. Relations between vegetation indices, climate change, and ecological programs
The correlation results in vegetation restoration areas showed that from 1982 to 2015, the ecological programs (covered area, \( r = 0.83, p < 0.05 \)), \( P_G \) (\( r = 0.41, p < 0.05 \)), \( T_G \) (\( r = 0.54, p < 0.05 \)), and \( [CO_2]_G \) (\( r = 0.83, p < 0.05 \)) were positively correlated to NDVI\(_G\), whereas \( R_G \) and \( W_G \) (\( r = -0.79, p < 0.05 \)) were negatively correlated to NDVI\(_G\) (figure 4(a)). Among these factors, except for the \( T_G \), the others showed consistent correlations to NDVI\(_G\) in the two periods. And the GPP\(_G\) and LAI\(_G\) share the same correlations as NDVI\(_G\) does (figures 4(b) and (c)). In the vegetation restoration area, the \( P_G \) trend increased from \(-0.2 \text{ mm yr}^{-1}\) in 1982–2000 to \(4.2 \text{ mm yr}^{-1}\) in 2001–2015, the \( T_G \) trend decreased from 0.06 to \(-0.02 \text{ °C yr}^{-1}\), \( R_G \) decreased to \(-0.9 \text{ W m}^{-2} \text{ yr}^{-1}\), and the amplitude of \( W_G \) also decreased (table S6). Simultaneously, the NDVI\(_G\) trend increased from
Figure 4. Correlations between regional mean vegetation indices, covered area, and regional mean climatic factors in vegetation restoration areas covered by GGWP. (a) NDVI<sub>gs</sub>, (b) GPP<sub>gs</sub>, (c) LAI<sub>gs</sub>. A is the afforestation area and grassland area covered by these ecological programs, and P<sub>gs</sub>, T<sub>gs</sub>, R<sub>gs</sub>, W<sub>gs</sub>, and [CO<sub>2</sub>]<sub>gs</sub> are total precipitation, mean air temperature, mean solar radiation, mean wind speed, and mean [CO<sub>2</sub>] in the growing season, respectively. The asterisk (*) denotes the correlations passing 0.05 significance level.

0.0015 to 0.0034 yr<sup>-1</sup> in the region, and the trends in GPP<sub>gs</sub> and LAI<sub>gs</sub> also increased substantially (tables S2–S4). It came to that ecological programs, elevated [CO<sub>2</sub>]<sub>gs</sub>, and increased P<sub>gs</sub> as well as decreased W<sub>gs</sub> have contributed to the vegetation restoration processes. However, a decrease in R<sub>gs</sub> may have weak effects on vegetation restoration, and there is a significant positive correlation between the increase in T<sub>gs</sub> and vegetation restoration from 1982 to 2000 while it seems that there is no correlation in the later period.

### 3.4. Contributions of ecological programs and climate change on vegetation restoration

The correlation analyses showed that all the climatic factors have considerable impacts on NDVI<sub>gs</sub>. We conducted MLR analysis in the vegetation restoration areas at a pixel scale, the coefficient of determination (R<sup>2</sup>) given by the MLR model indicates the vegetation restoration explained by climate change. Consequently, the residuals contain the remaining changes that are attributed to other factors in which ecological programs are involved.

The contributions of selected climatic factors and of the non-climatic factors to vegetation restoration are shown in figure 5. The results showed that from 1982 to 2000, the changes being explained by climatic factors were relatively low with an average of 41.1% in contrast to 58.9% that were explained by non-climatic factors (table 1). However, from 2001 to 2015, contribution rate of climatic factors on vegetation restoration increased to 52.9%, and consequently, the impact of non-climatic factors decreased to 47.1%. It was observed that in significant vegetation restoration areas (p < 0.05), the vegetation restoration process from 1982 to 2015 was mainly attributed to climate changes, especially in 2001–2015 (table 1). Furthermore, despite that more ecological programs were launched around 2000 in arid and semiarid China, the contributions of climate change to vegetation restoration still increased by 11.8%. It is noticed that ecological programs are included in the non-climatic factors, therefore, the independent contributions of these ecological programs might be even lower than what has been estimated in this study.

Along with the ecological programs, significant land-use variations were also observed in arid and semiarid China (table S7). From 1980 to 2000, although some cultivated lands and grasslands were returned to forests, some other forests were cultivated or turned into pastures, which resulted in a decrease in the total size of forests (table S8). In this period, the contributions of climatic factors to vegetation restoration in regions of stable forests,
Figure 5. The contributions of climatic (Clm, upper two rows: (a)–(f)) and non-climatic factors (Non-Clm, lower two rows: (g)–(l)) to vegetation restoration over the periods of 1982–2000 (a)–(c), (g)–(i) and 2001–2015 (d)–(f), (j)–(l)). The regions that passed the significance test (p < 0.05) are marked out by a cross.

Table 1. Climatic and non-climatic factors explained vegetation restoration over the regions of BSSCP and GGWP.

| Index | Region | Explained by climatic factors (%) | Explained by non-climatic factors (%) |
|-------|--------|-----------------------------------|---------------------------------------|
|       |        | 1982–2000                         | 2001–2015                             | 1982–2000                             | 2001–2015                             |
|       | Overall p < 0.05 | Overall p < 0.05 | Overall p < 0.05 | Overall p < 0.05 | Overall p < 0.05 |
| NDVI  | BSSCP  | 43.7 ± 15.8 60.3 ± 15.8 69.3 ± 13.0 | 56.3 ± 15.8 44.3 ± 14.1 39.7 ± 15.8 | GGWP  | 42.0 ± 18.3 61.7 ± 15.3 59.0 ± 14.5 | 72.0 ± 13.3 41.0 ± 19.3 28.0 ± 13.3 |
|       | GGWP   | 42.0 ± 18.3 61.7 ± 15.3 59.0 ± 14.5 | 72.0 ± 13.3 41.0 ± 19.3 28.0 ± 13.3 |       | 42.0 ± 18.3 61.7 ± 15.3 59.0 ± 14.5 | 72.0 ± 13.3 41.0 ± 19.3 28.0 ± 13.3 |
| GPP   | BSSCP  | 43.3 ± 13.7 60.6 ± 14.2 70.4 ± 10.3 | 56.2 ± 16.5 39.4 ± 14.2 44.2 ± 16.8 29.1 ± 10.3 | GGWP  | 42.9 ± 17.3 60.8 ± 13.7 49.2 ± 18.7 66.4 ± 13.2 | 57.1 ± 17.3 39.2 ± 13.7 50.8 ± 18.7 33.6 ± 13.2 |
|       | GGWP   | 42.9 ± 17.3 60.8 ± 13.7 49.2 ± 18.7 66.4 ± 13.2 | 57.1 ± 17.3 39.2 ± 13.7 50.8 ± 18.7 33.6 ± 13.2 |       | 42.9 ± 17.3 60.8 ± 13.7 49.2 ± 18.7 66.4 ± 13.2 | 57.1 ± 17.3 39.2 ± 13.7 50.8 ± 18.7 33.6 ± 13.2 |
| LAI   | BSSCP  | 41.7 ± 14.1 60.3 ± 14.2 70.9 ± 12.8 | 58.3 ± 17.2 39.7 ± 14.1 48.2 ± 19.2 29.1 ± 12.9 | GGWP  | 38.3 ± 18.3 58.0 ± 13.9 50.5 ± 20.7 71.4 ± 14.7 61.7 ± 17.3 42.0 ± 13.9 49.5 ± 20.7 28.6 ± 14.7 |
|       | GGWP   | 38.3 ± 18.3 58.0 ± 13.9 50.5 ± 20.7 71.4 ± 14.7 61.7 ± 17.3 42.0 ± 13.9 49.5 ± 20.7 28.6 ± 14.7 |       | 38.3 ± 18.3 58.0 ± 13.9 50.5 ± 20.7 71.4 ± 14.7 61.7 ± 17.3 42.0 ± 13.9 49.5 ± 20.7 28.6 ± 14.7 |
| Summary| BSSCP  | 41.3 ± 14.1 58.8 ± 14.1 56.0 ± 17.3 70.2 ± 12.0 | 56.9 ± 16.5 41.2 ± 14.1 44.0 ± 17.3 29.8 ± 12.0 | GGWP  | 41.1 ± 17.6 60.2 ± 14.3 52.9 ± 19.8 69.9 ± 13.7 58.9 ± 17.6 39.8 ± 14.3 47.1 ± 19.8 30.1 ± 13.7 |
|       | GGWP   | 41.1 ± 17.6 60.2 ± 14.3 52.9 ± 19.8 69.9 ± 13.7 58.9 ± 17.6 39.8 ± 14.3 47.1 ± 19.8 30.1 ± 13.7 |       | 41.1 ± 17.6 60.2 ± 14.3 52.9 ± 19.8 69.9 ± 13.7 58.9 ± 17.6 39.8 ± 14.3 47.1 ± 19.8 30.1 ± 13.7 |

Note: ‘Overall’ and ‘p < 0.05’ denote the MLR statistical results based on all the pixels and pixels that passing the significance test (p < 0.05) only, respectively.

grasslands, and unused lands were 40.7%, 42.1%, and 38.1%, respectively, whereas the contributions of non-climatic factors have increased due to the launch of ecological programs (table 2). From 2001 to 2015, the contributions of climatic factors to vegetation restoration in stable areas of the three land-use types were found to increase to 50.0%, 55.5%, and 49.7%, respectively. Besides, compared to stable areas of the three land-use types, there were higher contributions of climatic factors to vegetation restoration in their expansion areas, and climatic factors dominated the vegetation restoration in expansion areas from 2001 to 2015.

Over the vegetation restoration areas, the MLR analysis was also conducted at a regional scale by considering the covered areas of ecological programs, results indicate that from 1982 to 2000, 73.7% (p < 0.01) of the vegetation restoration could be explained by those selected factors, of which climatic factors and ecological programs explained 54.4% and 19.3%, respectively (table 3). After more ecological programs being launched around 2000, vegetation restoration...
explained by those selected factors increased to 95.6% (p < 0.01), meanwhile, the contribution rate of climatic factors increased largely to 76.1% against ecological programs kept stable in 19.4%. Taken together, the contribution rate of climate change on vegetation restoration is estimated by more than 50% and about 20% for ecological programs, which indicates climate change is still the key control of vegetation restoration in arid and semiarid China, but the implementation of these ecological programs may accelerate the process.

4. Discussion

4.1. Uncertainties in the methodology

To accurately distinguish the contribution rate of human activities especially ecological programs on vegetation restoration is traditionally difficult. However, currently, statistical methods are still the widely used approaches in attributing the contribution rates, although they were always criticized for lacking a physical basis [22, 23, 47, 48]. In this study, the MLR analysis was used to separate the climatic and non-climatic factors on vegetation restoration at pixel scale and regional scale. At the pixel scale, although four climatic factors and [CO₂] were selected, their representativeness may be insufficient and some of them may have nonlinear correlations to vegetation growth [25, 49]. And at the regional scale, although the covered area of the ecological programs was considered, there are still some limitations, for example, the spatial heterogeneities were neglected. And due to the limitations in statistical methods, the changes in vegetation could not be fully caught by the regression models and selected factors, e.g. explanation of the remaining 30% contribution rate. However, the results of pixel and regional scales both indicated that climate change dominated the vegetation restoration, other factors, especially ecological programs had limited contributions. Even so, the MLR results may still have underestimated the contributions of climate change as previous studies suggested [21, 24]. Further study is needed in applying more effective approaches to quantify the relative contributions of climate change and ecological programs.

4.2. Contributions of climate change and ecological programs

In our study, by analyzing multiple vegetation indices, the results converged to the same conclusion, which is climate change dominated the vegetation restoration and its contribution rate was estimated as higher than 50%, while ecological programs have limited effects.

In arid and semiarid China, due to water limitations, variations in precipitation seem to be the dominant controls on regional ecological environments [20]. In regions covered by GGWP, \( P_{gs} \) decreased at a rate of −0.2 mm yr\(^{-1}\) before 2000 but increased at a rate of 4.2 mm yr\(^{-1}\) after 2000 (table S6), which may benefit the vegetation restoration. It is observed that vegetation restoration areas were highly overlapped with the regions of increasing \( P_{gs} \) (figures 2 and S3). Rise in \( T_{gs} \) may enhance evapotranspiration

and reduce water availability [50, 51], which may suppress vegetation growth, but it may benefit vegetation growth in some highlands [48, 49]. Owing to sufficient insolation in arid and semiarid China, $R_p$ is not decisive to vegetation growth, which was also confirmed by the weak correlations and the inconsistency of the spatial patterns of vegetation changes and that of the $R_p$ changes (figures 4 and S3) [23]. In drylands, wind plays an important role in vegetation growth by changing evapotranspiration, transporting surface materials, and affecting seed dispersals [52, 53]. Therefore, a decrease in wind speed from 1982 to 2015 may benefit vegetation restoration and decrease in DI in the region (figures 3 and S3). However, from 2001 to 2015, the intensified aeolian activities in regions covered by BSSCP may offset the positive effects of ecological programs and resulted in vegetation decline in some areas. Besides, elevated $[CO_2]$ can stimulate vegetation growth and productivity by enhancing mesophyll $CO_2$ diffusion and photosynthesis, increasing water-use efficiency and ameliorating water limitation, and indirectly reducing leaf stomatal conductance and evapotranspiration [54–56]. In arid and semiarid China, elevated $[CO_2]$ contributed large quantities to vegetation restoration from 1982 to 2015 (figure 4), which was also highlighted by previous studies [21].

Generally, with the implementation of ecological programs, vegetation restoration is expected in two ways: artificial plantation and natural restoration by removal of human interferences. The three vegetation indices individually showed that over 65% of the vegetated areas experienced overall vegetation restoration since 1982, and over 40% showed consistent restoration (figure 2, tables S2–S4), which seems to be in line with the governmental statistics [13] and previous studies [25, 47]. However, despite that more ecological programs were launched around 2000, areas of continuous vegetation restoration still decreased largely after 2000 (figure 2), and remote sensing data also suggested large decreases in forest and grassland areas from 1980 to 2015 in the region (table S8). In some pilot regions, e.g. Loess Plateau, vegetation restored with the implementation of ecological programs [25, 27], but massive artificial afforestation is gradually depleting the soil moisture, which highly increases the risks of desertification [27, 57]. Grazing prohibition and enclosures enable vegetation restored naturally. After grazing prohibition, the community structure and vegetation coverage did improve quickly in the degraded grasslands [58, 59], and precipitation amplified vegetation restoration processes [58]. Interestingly, statistics showed that the livestock numbers (indicating the grazing intensity) continuously increased from 1982 to 2015 (figure S4), but there was no corresponding ecological deterioration occurred in arid and semiarid China [5, 21, 25]. Control of desertification and dust storm are key objectives of these ecological programs [5, 6].

The changes in DI seem to be in line with the implementation of ecological programs. The DI significantly decreased all over the arid and semiarid China after the launch of GGWP (figure 3(c)), but this area was much bigger than the cumulative afforestation area. It is unlikely to fully attribute the reduction of DI to the implementation of the GGWP [6, 14]. There was also no obvious reduction in DI after more ecological programs being launched around 2000 (figure 3(d), table S6), which is in line with the decrease of consistent vegetation restoration area after 2000 (figure 2(l)). Changes in wind speed and precipitation may be the direct causes of the reduction of DI [6, 60] (figure S3). Studies also suggested that over 26.4% of the afforestation areas have degraded and only about 14.9% play a role in the control of desertification and dust storm in the region [13], which is lower than what the GGWP program was expected. Besides, traditionally the rural communities took plant as one source of fuels, such means have been changed with the electrical energy and natural gas being popularized (table S10), which also benefited the vegetation restoration in the region. Therefore, the above analysis shows that ecological programs may have limited effects on vegetation restoration, which follows the contribution rate given in our results.

5. Conclusions

Over the past decades, several large-scale ecological programs being launched by Chinese governments have played a controversial role in desertification combating, dust storm controlling, and the ecological environment improving in arid and semiarid China. If the ecological programs are the key controls of vegetation restoration, it is hard to estimate the level of degradation in ecological environments in arid and semiarid China when the government stops investing huge funds on the ecological programs. Results from this study suggest that in arid and semiarid China, climate change (precipitation, temperature, solar radiation, and wind speed) and elevated $[CO_2]$ contributed more than 50% to vegetation restoration from 1982 to 2015 in contrast to about 20% was attributed to the effects of ecological programs. The results of this study may provide crucial guidance for decision-makers when considering the necessary and appropriateness of huge investments in launching ecological programs.

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Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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