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Ecological Engineering Projects Shifted the Dominance of Human Activity and Climate Variability on Vegetation Dynamics

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Abstract: Global greening and its eco-environmental outcomes are getting mounting international focus. The important contribution of China to the global greening is highly appreciated. However, the basic driving forces are still elusive. The Loess Plateau (LP) and Three-River Source Region (TRSR) were chased as study areas in Northern China. The prior one represents the region experiencing intensive human interventions from ecological engineering projects, while the latter is a typical region that is experiencing faster climate change. Hypothesized to be driven by a disproportionate rate of human activities and climates, also being regions of typical large-scale ecological engineering projects, the study goal is to identify the actual driving forces on vegetation dynamics in these two regions. Trend analysis, correlation analysis, and residual trend-based method (RESTREND) were utilized to understand the relationships between climate variability, human activities, and vegetation dynamics. The spatiotemporal variations of vegetation from 1982 to 2019 were evaluated and the respective impacts of climatic and anthropogenic factors on vegetation dynamics were disentangled. Indicating apparent vegetation restoration in LP and TRSR, the results depict that annual LAI has remarkably increased during the 38 years. Temperature and precipitation promoted vegetation growth, whereas the solar radiation and vapor pressure deficit hampered it. After implementing the ecological engineering projects, the primary climatic factor changed from temperature to precipitation. Meanwhile, human activities act as the major driving factor in vegetation greening in the entire study area, with a contribution rate exceeding 70%. This information highlights that ecological engineering can significantly reduce the risks of ecosystem degradation and effectively restore vegetation, especially in ecologically sensitive and vulnerable areas.

Keywords: vegetation dynamics; LAI; RESTREND; ecological restoration projects; Loess Plateau; Three-River Source Region

1. Introduction

As an indispensable part of the terrestrial ecosystem, vegetation works as a bridge between land and the atmosphere for carbon, water, and energy exchanges, providing food, fiber, fuel, habitat, and other ecosystem services [1–3]. Vegetation dynamics are a typical sign measuring plant health and ecosystem stability, which are highly linked to sustainable development [4,5]. Global vegetation is undergoing major changes driven by climate variability and human activities [6–9]. Climate variability affects vegetation dynamics by affecting their growing environment [10–12]. Moreover, human activities such as farming, grazing, and ecological engineering also strongly impact vegetation growth [13–15]. Monitoring vegetation dynamics and attributing their underlying driving
forces is critical to global vegetation regeneration and conservation in the face of increased human involvement and continued climate change.

Global greening has been plentifully reported. China mainly contributes to global greening, particularly for those regions under the several large-scale ecological engineering projects, such as croplands for grassland and vegetation reforestation on the Loess Plateau (LP) [16]. In the last few decades, the vegetation coverage on the LP has increased by more than 20 percent [17]. A typical combination of human activities and climate variabilities involving vegetation greening within the same type and vegetation type transitions caused this increase. Many studies have concluded that this vegetation greening is mainly caused by human activities [15,18]. Although the impact of ecological engineering on vegetation dynamics seems to be visually clear [18,19], the relative contribution from human activity and climate variability is still exposed to high uncertainties when they are estimated by various methods. To deepen our understanding of the actual driving forces, simultaneously investigating several regions hypothesized to be driven by distinct magnitudes of human activities and climate variabilities is necessary.

Satellite-based remote sensing is an essential means to detect large-scale vegetation dynamics both spatially and temporally compared with ground-based observations [20]. To improve the accuracy of monitoring, selecting favorable remote sensing products is crucial for evaluating vegetation dynamics and their growth conditions. Although the satellite-based normalized difference vegetation index (NDVI) has been largely utilized as a proxy to assess the greenness of the global land surface [21,22], there are several limitations inherent in remote sensing, such as their low sensitivity to vegetation dynamics for dense vegetation cover [23]. Compared with NDVI, the leaf area index (LAI, described as one-half of the total area projected relative to the horizontal size) has a more straightforward physical interpretation. It is also directly connected to the vegetation growth environment [1,24].

Quantitative models have been commonly utilized in recent years to simulate and disentangle the effects of climate variabilities and human activities on vegetation dynamics [25,26]. Frequently used methods include the rain use efficiency (RUE) [27,28], the coefficient of variation method [29], the residual trend (RESTREND) method [30], and the biophysical model-based method [31]. Among them, the RESTREND has been depicted to be an effective approach at large spatial scales [32], and it is commonly accepted due to the practicality, convenience, and universality of its parameters. The RESTREND separates the effects of non-climate factors on vegetation dynamics by calculating actual and simulated vegetation trends based on the relationship model between vegetation and climate factors. However, there are still uncertainties in this method. For example, RESTREND is highly dependent on the established climate-vegetation relationship. Most of the past RESTREND are mainly focused on temperature and precipitation in terms of climates [33] while neglecting some other factors crucial to vegetation growth, such as solar radiation and vapor pressure deficit [34–36]. These omissions may significantly impair the effectiveness of the RESTREND.

The LP and Three-River Source Region (TRSR) are fragile and sensitive to climate variabilities and human activities interventions. Significant climate variations have occurred in these areas, which may promote or inhibit vegetation growth [37]. Several studies have revealed that global warming stimulates vegetation growth by extending the growing season and promoting summer photosynthesis. Enhanced precipitation can alleviate drought limitation to some extent, and a higher vapor pressure deficit normally causes inhibitory effects on vegetation growth. Solar radiation can also play a crucial role in vegetation growth [34,35,38–40]. On the other hand, on steep slopes overgrazing, deforestation, and other human activities have caused a series of ecological problems over the LP and TRSR, such as vegetation degradation, soil and water loss, and desertification. The Chinese government has invested heavily in launching several large-scale ecological engineering projects to recover and protect environments, such as the Grain for Green (GFG) Project over the LP in 1999 [41] and the Project of Ecological Protection and Construction of the Three-River Source Nature Reserve (EPCP) over the TRSR in 2005 [42]. Propelled by these
endeavors, varying degrees of vegetation recovery have occurred in both areas, and land cover in the LP has dramatically changed [43].

Adjacent to the LP, the TRSR is a critical part of the Tibetan Plateau and serves as the water sources region of the three main rivers in China. The ecological engineering projects in the TRSR have been chiefly about grazing for greening, and vegetation coverage change is primarily shaped by natural vegetation growth, which can be hypothesized to be more influenced by natural climates. On the LP, ecological engineering projects consist of a variety of measures, including reforestation and croplands for grassland and forest. Using the TRSR as a reference, we attempt to have a more comprehensive perception of the driving forces on vegetation greening in the two regions.

We will quantify the relative contribution of climate variabilities and human activities to vegetation greening on the LP and TRSR using the RESTREND built on the comprehensive effects of four climate factors (including temperature, precipitation, vapor pressure deficit, and solar radiation). This study aims to: (1) detect the spatial-temporal patterns of vegetation dynamics in the LP and TRSR; (2) explore the relationship between vegetation dynamics and climate variation; (3) quantify the relative contributions of climate variabilities and human activities to vegetation greening and reveal the magnitude differences between LP and TRSR. As global climate variations and human activities intensify, the attribution of vegetation dynamics becomes complex. Improved understanding of the relationships between climate variabilities, human activities, and vegetation dynamics implies utmost importance to climate change mitigation and vegetation restoration.

2. Materials and Methods

2.1. Study Area

Considering the distinct proportion of climate variations and ecological engineering effects on vegetation, we chose two specific regions located in northern-central China as the study area, namely Loess Plateau (LP) and Three-River Source Region (TRSR) (Figure 1). More specifically, LP (100°54′–114°33′ E, 33°43′–41°16′ N) is situated in the middle reaches of the Yellow River and covers parts of Inner Mongolia, Qinghai, Gansu, Ningxia, Shaanxi, Henan, and Shanxi provinces, with a total area of more than 620,000 km². The terrain in this region is high in the west and low in the southeast, with numerous ravines and fragmented landforms. The LP is prevailed by an arid and semi-arid climate, transiting from the warm temperate to the cold temperate climate from south to north. The regional climates are characterized as being dry, strong solar radiation and high evaporation in the LP. The TRSR (89°22′–102°26′ E, 31°36′–37°12′ N) is located in the south of Qinghai province with an area of approximately 363,000 km². This region is the headstream of the Yellow River, the Yangtze River, and the Lantang River, which is also known as the ‘Chinese water tower’ [42]. The terrain in TRSR rises from east to west, with an altitude range of 2579–6824 m. The TRSR features a typical continental plateau climate characterized as being cold, dry, and intense radiation.
2.2. GLOBMAP LAI Data

The GLOBMAP LAI version 3 dataset (1981–2019) was generated through a fusion of Moderate Resolution Imaging Spectroradiometer (MODIS) LAI and Advanced Very High Resolution Radiometer (AVHRR) LAI data quantitatively, at 8 km resolution and on a Geographic grid [44]. Based on MODIS land surface reflectance data (MOD09A1), the MODIS LAI series was produced by the GLOBCARBON LAI algorithm [45]. The relationships between AVHRR observations (GIMMS NDVI) and MODIS LAI were established pixel by pixel during their overlapped period (2000–2006) [46]. Then the AVHRR LAI back to 1981 was generated by combining historical AVHRR observations and the established pixel-level relationships. Validated by field measurements and fine resolution LAI, this long-term LAI could explain 71% of the variability in the ground LAI over global sites covering all major vegetation types and is biased by 0.81 LAI on average. More detailed descriptions of the algorithm and data evaluation can be found in Liu’s article [44]. Compared with other LAI products, the GLOBMAP LAI exhibits high reliability over China ($R^2 = 77\%$) and the low LAI area [47,48]. In addition, this LAI product is the most intra-consistent over time and has a longer time coverage [49]. Its applicability in detecting and attributing terrestrial vegetation greenness has been well-documented at regional and global scales [7,26].

In this study, the GLOBMAP LAI datasets were averaged over the entire year to obtain the annual LAI from 1982 to 2019. We used the annual LAI to reflect vegetation dynamics rather than using growing season LAI, as the prior one is more applicable to our study regions with different growing season lengths. The annual LAI possesses the advantages of being simple and being capable of capturing vegetation greening due to
extended vegetation growing season or heightened amplitude of vegetation growth. The annual LAI can further avoid the limitations of growing season LAI, i.e., the subjective thresholds set to define growing season start and end dates [16].

2.3. Meteorological Data

Monthly average temperature (TMP) and total precipitation (PRE) with a spatial resolution of 1 km from 1982 to 2019 were produced by the Loess Plateau science data center, National Earth System Infrastructure of China [50]. Monthly average shortwave down surface radiation (RAD) and vapor pressure deficit (VPD) was obtained from the TerraClimate dataset [51], with a resolution of 4 km. To make them comparable, all meteorological data products were uniformly resampled to the same spatial (8 km) and temporal resolution (annual).

2.4. Auxiliary Data

Digital elevation model (DEM) data with a spatial resolution of 30 m was provided by the Geospatial Data Cloud site, Computer Network Information Center, Chinese Academy of Science (http://www.gscloud.cn (accessed on 28 September 2020)). Land use and cover data in 1980, 2000, 2005, and 2018 were obtained from the Resources and Environment Data Cloud Platform (http://www.resdc.cn (accessed on 30 September 2020)) with a spatial resolution of 1 km. The land was reclassified into cropland, forest, shrubland, grassland, waterbodies, urban and desert.

2.5. Trend Analysis

Trends of LAI, TMP, PRE, RAD, and VPD over the past 38 years were assessed based on simple linear regressions. Ecological engineering projects were launched in 2000 over the LP and 2005 over the TRSR. We split the entire study period (1982–2019) into the first period (1982–1999 for the LP and 1982–2004 for the TRSR) and the second period (2000–2019 for the LP and 2005–2019 for the TRSR) following Xiu [41] and Zhai [52]. The trend slope in a multi-year regression equation represents interannual changes and can be solved using the ordinary least squares method (OLS). The equation is as follows:

$$\beta = \frac{n \times \sum_{i=1}^{n} i \times x_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} i}{n \times \left(\sum_{i=1}^{n} i^2 - \left(\sum_{i=1}^{n} i\right)^2\right)}$$

(1)

where $\beta$ represents the interannual trend of $x_i$ for each pixel, $n$ is the number of years, and $x_i$ represents the value of $x$ in the $i$th year. $\beta > 0$ suggests an increasing trend, while $\beta < 0$ suggests a decreasing trend. The significances of the trends were determined using a $t$-test at a significance level of 0.05.

2.6. Correlation Analysis

Relationships between LAI and climate factors were assessed utilizing simple parametric correlations of the Pearson product-moment linear correlation coefficients ($r$ values ranging from $-1$ to 1) as follows:

$$r = \frac{n \sum_{i=1}^{n} x_i y_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{\sqrt{n \sum_{i=1}^{n} x_i^2 - \left(\sum_{i=1}^{n} x_i\right)^2} \times \sqrt{n \sum_{i=1}^{n} y_i^2 - \left(\sum_{i=1}^{n} y_i\right)^2}}$$

(2)

where $r$ represents the Pearson correlation coefficient, $n$ is the number of years, $x_i$ refers to LAI in the $i$th year, and $y_i$ represents climate factor in the $i$th year. The significance of the correlations was assessed by $t$-test at significance levels of 0.05.

2.7. Residual Trend Analysis

Due to the lack of long-term spatially explicit data about human activities such as grazing, mining, and land use management, it is normally assumed that effects of human
activities are the residual after climate variabilities effects are accounted for, which can be disentangled by RESTREND [53–55]. This study thoroughly considered the complexity of the multi-layer background features. We established the relationship model between vegetation dynamics and climate factors by taking TMP, PRE, RAD, and VPD as independent variables and LAI as the dependent variable. The RESTREND method works as follows:

Step 1: Establish a multiple linear regression between LAI and climate factors as follows:

\[
\text{LAI}_{\text{pre}} = A \times T + B \times P + C \times R + D \times V + E
\]

where, \( \text{LAI}_{\text{pre}} \) represents the simulation value of LAI. \( T \) represents the TMP, \( P \) represents the PRE, \( R \) represents the RAD, \( V \) represents the VPD. \( A, B, C, \) and \( D \) are the slopes of the linear regression between the LAI and TMP, PRE, RAD, and VPD, respectively. \( E \) is a constant.

Step 2: Calculate the residual difference between \( \text{LAI}_{\text{actual}} \) and \( \text{LAI}_{\text{pre}} \), and define the residual differences as \( \text{LAI}_{\text{res}} \) as follows:

\[
\text{LAI}_{\text{res}} = \text{LAI}_{\text{actual}} - \text{LAI}_{\text{pre}}
\]

where \( \text{LAI}_{\text{res}} \) represents the residual, \( \text{LAI}_{\text{actual}} \) represents the actual value of LAI proxied by satellite products, \( \text{LAI}_{\text{pre}} \) represents the simulation value of LAI.

Step 3: In this study, we calculated the trends of \( \text{LAI}_{\text{actual}}, \text{LAI}_{\text{pre}} \) and \( \text{LAI}_{\text{res}} \) using the simple linear regression according to Equation (1). The trends of \( \text{LAI}_{\text{pre}} \) represent the impact of climate variabilities, and the trends of \( \text{LAI}_{\text{res}} \) measure the effects of human activities.

Step 4: Set the division rule of driving factors on vegetation greening as shown in Table 1. Based on this, the contribution of climate variabilities and human activities to vegetation greening before and after the implementation of ecological engineering was calculated.

| Vegetation Greening | Determination Criteria | Contribution (%) |
|---------------------|------------------------|------------------|
| \( \text{LAI}_{\text{actual}} \) Trend | \( \text{LAI}_{\text{pre}} \) Trend | \( \text{LAI}_{\text{res}} \) Trend | Climate Variabilities | Human Activities |
| >0 | >0 | >0 | \( \text{Slope(\text{LAI}_{\text{res}})} \) | \( \text{Slope(\text{LAI}_{\text{actual}})} \) | \( \text{Slope(\text{LAI}_{\text{actual}})} \) | \( \text{Slope(\text{LAI}_{\text{actual}})} \) |
| <0 | >0 | <0 | 0 | 100 |
| >0 | <0 | <0 | \( \text{Slope(\text{LAI}_{\text{pre}})} \) | \( \text{Slope(\text{LAI}_{\text{actual}})} \) | \( \text{Slope(\text{LAI}_{\text{actual}})} \) | \( \text{Slope(\text{LAI}_{\text{actual}})} \) |
| <0 | <0 | <0 | 100 | 0 |

3. Results

3.1. Spatial-Temporal Patterns of Vegetation Dynamics

The annual average LAI trends from 1982–2019 revealed that vegetation growths in the LP and the TRSR have experienced significant amelioration (Figure 2). Various ecological engineering projects have different implementation timelines, we set the separation line as 1999–2000 for the LP and 2004–2005 for the TRSR. In the LP, the annual LAI depicted a substantial upward trend at a rate of 0.0050 year\(^{-1} \) \(( p < 0.01)\) from 1982 to 2019. The LAI trend in 1982–1999 exhibited a non-significant increase (0.0014 year\(^{-1} \), \( p > 0.05)\), but it sharply increased in 2000–2019 with a rate of 0.0133 year\(^{-1} \) \(( p < 0.01)\). In the TRSR, the background annual LAI is low and showed a fluctuating upward trend during 1982–2019 with a rate of 0.0012 year\(^{-1} \) \(( p < 0.01)\). The annual LAI fluctuation in 2005–2019 was more noticeable than in 1982–2004.
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![Figure 2](image_url)

**Figure 2.** The trends in the LAI values over the LP and TRSR for the entire period (1982–2019); two stages were set according to the initiation timing of the ecological engineering project (1982–1999 and 2000–2019 for the LP; 1982–2004 and 2005–2019 for the TRSR).

Vegetation dynamics in the study areas exhibited high spatial heterogeneity (Figure 3a). The annual LAI in 97.5% of the LP and 86.0% of the TRSR showed increasing trends, with 91.4% and 65.3% of each region showing a significant trend (\(p < 0.05\)), respectively (Table 2). The noticeable upward trends (more than 0.01 year\(^{-1}\)) occurred mainly in the southeastern LP region dominated by forests. The decreasing trend accounted for 2.5% of the LP and 14.1% of the TRSR. However, the area exhibiting significant decreasing trends was small (only 0.5% of the LP and 3.5% of the TRSR), dispersed in the southern region of LP and the central and south parts of TRSR.

**Table 2.** Summary of LAI trends in the study regions.

| Regions | Periods     | Increased Area (%) | Significantly Increased Area (%) | Decreased Area (%) | Significantly Decreased Area (%) |
|---------|-------------|--------------------|----------------------------------|--------------------|----------------------------------|
| LP      | 1982–2019   | 97.5               | 91.4                             | 2.5                | 0.5                              |
|         | 1982–1999   | 80.3               | 23.3                             | 19.7               | 0.9                              |
|         | 2000–2019   | 98.9               | 94.7                             | 1.1                | 0.3                              |
| TRSR    | 1982–2019   | 86.0               | 65.3                             | 14.1               | 3.5                              |
|         | 1982–2004   | 66.2               | 26.4                             | 33.8               | 3.9                              |
|         | 2005–2019   | 70.5               | 17.0                             | 29.5               | 2.6                              |

Vegetation trends varied considerably before and after implementing the ecological engineering project (Figure 3b,c). LAI showed an increasing trend in 80.3% of the LP and 66.2% of the TRSR before the implementation, with 23.3% and 26.4% of the total being significantly increased, respectively. The area with major vegetation improvements was mostly distributed in the northern region of LP and the northwestern region of TRSR; 0.9% of the LP and 3.9% of the TRSR suffered a certain degree of vegetation degradation, mainly around the area with rapid urbanization. LAI exhibited a significant increase for almost the entire LP after the implementation, and 51.1% of the LP demonstrated a steeper increasing slope (more than 0.01 year\(^{-1}\)). On the other hand, only 17.0% of the TRSR showed a significant increasing trend, and decreasing trends were mainly found in the central and southeastern regions, accounting for 2.6% of the TRSR. During the second period, in the LP, the area of significant increasing trends expanded by 71.4%, and the area exhibiting significant decreasing trends shrank by 3.6%. However, in the TRSR, the area showing significant increasing and decreasing LAI trends shrank by 9.4% and 1.3% after 2004, respectively. Overall, vegetation showed a greening trend during 1982–2019, and
the area exhibiting a greening trend expanded after the implementation of the ecological engineering project, especially in the LP.

![Figure 3](image)

**Figure 3.** Spatial distributions of the LAI trends over the study areas during the three periods: 1982–2019 (a), before the implementation of the ecological engineering project (b), and after the implementation of the ecological engineering project (c). The inset panels show the pixels where LAI trends are statistically significant at $p < 0.05$.

### 3.2. Climate Variability in the Study Area

The annual mean temperature across the LP and TRSR has been increasing at a significant pace of $0.0363 \, ^\circ C/\text{year}$ ($p < 0.01$) and $0.0256 \, ^\circ C/\text{year}$ ($p < 0.01$) over the past 38 years (Figure 4). The annual total precipitation increased significantly in the LP and exhibited a weak increase in the TRSR. The annual RAD and VPD showed opposite trends between the LP and TRSR during 1982–2019. In the LP, the RAD exhibited non-significant trends, and VPD increased at a rate of $0.0039 \, \text{kPa/year}$ ($p < 0.01$). However, in the TRSR, the RAD showed a significantly declining trend with a rate of $-1.672 \, \text{W/m}^2/\text{year}$ ($p < 0.01$), and the VPD decreased non-significantly.
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![Graphs showing temperature, precipitation, shortwave radiation, and vapor pressure deficit trends](image)

Figure 4. Interannual changes in annual mean climatic variables (TMP, PRE, RAD, and VPD) during 1982–2019. TMP, PRE, RAD, and VPD represent temperature, precipitation, downward surface shortwave radiation, and vapor pressure deficit, respectively.

The climate variability in the study area exhibited high spatial and temporal heterogeneities (Figure 5). Before implementing the ecological engineering project, almost the whole area showed increasing TMP and VPD in the LP. In contrast, 68.3% of the area showed a decreasing PRE and 41.3% of the area exhibited an increase in RAD. Approximately 70% of the LP showed warming and drying climates during 1982–1999. However, nearly 80% of the LP slowed its warming and became wetting from 2000 to 2019. In the TRSR, the west part showed warming and wetting climates while the east showed warming and drying during 1982–2004. The climate of the whole TRSR then reversed as it transitioned from the first to the second period, as seen by cooling and drying conditions in about 80% of the area.
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Figure 5. Spatial patterns of the trends in annual mean climatic variables (TMP, PRE, RAD, and VPD) for the three periods: 1982–2019 (a1–d1), before the implementation of ecological engineering project (a2–d2), after the implementation of ecological engineering project (a3–d3). TMP, PRE, RAD, and VPD represent temperature, precipitation, downward surface shortwave radiation, and vapor pressure deficit, respectively.

3.3. The Relationship between Vegetation Dynamics and Climate Variability

Due to the tremendous spatial heterogeneity of the climate variability in the study area, the relationship between vegetation dynamics and climate variability also exhibited substantial spatial and temporal patterns (Figure 6). During 1982–2019, the correlation coefficient between LAI and TMP was positive in 96.65% of the LP and 90.05% of the TRSR, with 72.09% of the LP and 57.09% of the TRSR being significant, respectively (Table 3). The rising TMP had a positive effect on vegetation growth in the whole period. In almost 85% of the study area, after implementing the ecological engineering project, the correlation between LAI and TMP remained positive. The correlation coefficients between PRE and LAI in the majority of the study area (92.74%) were positive during 1982–2019. Compared with the first period, the correlation shifted from negative to positive in the second period. The positive influence of PRE on LAI became stronger. Averaged over the past 38 years, the correlation between LAI and RAD was gradually changed from negative in the west to positive in the east. The RAD had a positive effect on LAI in about 50% of the LP during the three periods, while in the TRSR, the RAD mainly had a negative impact (about 80% of the area) on LAI. Between 1982–2019, the VPD was positively correlated with LAI in the LP (80.24%) and the linkage became negative in the TRSR (73.29%). However, in 83.34% of the LP, the correlation between LAI and VPD changed to negative after implementing the
ecological engineering project. Compared with 1982–2004, the positive correlation area of the TRSR between LAI and VPD expanded by 23.6% during 2005–2019.

According to the coefficients of correlation and their significances between LAI and climatic drivers, we draw maps showing the spatial separation of dominant climatic constrain on LAI (Figure 6e1–e3). From 1982 to 2019, temperature was the dominant climatic factor in over 50% of the entire study area. More than 10% of the area is dominated by precipitation, mainly in the eastern part of the TRSR and the western part of the LP. After implementing the ecological engineering project, vegetation growth in the study area changed from temperature to precipitation constraints. The area of RAD dominance increased in the TRSR, and the impact of VPD in the LP was enhanced and spatially more concentrated.

**Figure 6.** Spatial patterns of the correlation coefficients between LAI and TMP (first column), PRE (second column), RAD (third column), VPD (fourth column), and spatial patterns of dominant climatic constraint on LAI (fifth column). They were estimated for 1982–2019 (a1–e1), before the implementation of the ecological engineering project (a2–e2), after the implementation of ecological engineering (a3–e3), respectively. TMP, PRE, RAD, and VPD represent temperature, precipitation, downward surface shortwave radiation, and vapor pressure deficit, respectively.
Table 3. Summary of the correlations between LAI and TMP, PRE, RAD, and VPD in the study regions.

| Between Relationship | LP 1982–2019 | LP 1982–1999 | LP 2000–2019 | TRSR 1982–2019 | TRSR 1982–2004 | TRSR 2005–2019 |
|----------------------|--------------|--------------|--------------|----------------|----------------|----------------|
| LAI-TMP              |              |              |              |                |                |                |
| Positive area (%)    | 96.65        | 71.52        | 88.62        | 90.05          | 81.25          | 70.61          |
| Significant positive area (%) | 72.09 | 8.99          | 6.50          | 57.09          | 17.56          | 3.55           |
| Negative area (%)    | 3.35         | 28.48        | 11.38        | 9.95           | 18.75          | 29.39          |
| Significant negative area (%) | 0.22 | 0.32          | 0.01          | 0.80           | 0.25           | 0.41           |
| LAI-PRE              |              |              |              |                |                |                |
| Positive area (%)    | 95.24        | 71.95        | 95.00        | 88.11          | 41.82          | 82.57          |
| Significant positive area (%) | 42.37 | 6.67          | 35.17        | 30.94          | 1.25           | 15.46          |
| Negative area (%)    | 4.76         | 28.05        | 5.00         | 11.89          | 58.18          | 17.43          |
| Significant negative area (%) | 0.19 | 1.35          | 0.04         | 0.25           | 1.81           | 0.17           |
| LAI-RAD              |              |              |              |                |                |                |
| Positive area (%)    | 55.26        | 36.52        | 56.98        | 11.71          | 45.72          | 15.54          |
| Significant positive area (%) | 9.67 | 1.80          | 2.70         | 0.08           | 0.98           | 0.17           |
| Negative area (%)    | 44.74        | 63.48        | 43.02        | 88.29          | 54.28          | 84.46          |
| Significant negative area (%) | 11.02 | 3.82         | 0.36         | 20.64          | 2.03           | 12.58          |
| LAI-VPD              |              |              |              |                |                |                |
| Positive area (%)    | 80.24        | 47.43        | 16.66        | 26.71          | 21.90          | 45.50          |
| Significant positive area (%) | 26.98 | 4.01         | 0.19         | 0.31           | 0.46           | 2.36           |
| Negative area (%)    | 19.76        | 52.57        | 83.34        | 73.29          | 78.10          | 54.50          |
| Significant negative area (%) | 1.69 | 4.13          | 12.01        | 13.44          | 10.51          | 1.33           |

3.4. Land Cover Changes before and after the Implementation of Ecological Engineering

Before implementing ecological engineering, the areas of cropland, forest, and urban on the LP increased, while the areas of other land cover types reduced (Table 4). Grassland was the main source of increase in the area of other land cover types, with 3364.03 km² of grassland converted to cropland and 1568.61 km² converted to desert. In the TRSR, the areas of cropland, forest, urban, and desert increased, whereas others decreased. Land cover change in the TRSR was relatively weak before the implementation of ecological engineering, with mainly grassland (924.35 km²) and waterbodies (485.08 km²) converting to desert.

Table 4. Transfer matrix of different land cover types from 1980 to 2018 in the study regions (unit: km²).

| Period     | Type    | Cropland | Forest | Shrubland | Grassland | Waterbodies | Urban | Desert |
|------------|---------|----------|--------|-----------|-----------|-------------|-------|--------|
| 1980–2000  | LP      | 201,270.44 | 148.80 | 93.41     | 3364.03   | 792.36      | 8.89  | 608.26 |
| 2000–2018  | LP      | 117,484.22 | 6639.21 | 4311.61   | 54,293.92 | 2315.97     | 7088.91 | 2599.08 |
| 2000–2005  | TRSR    | 7993.59   | 30,779.40 | 3830.02  | 11,692.15 | 238.07      | 285.35 | 566.68 |
| 2018–2019  | TRSR    | 5051.89   | 3719.19  | 19,705.75 | 10,686.85 | 119.63      | 92.60  | 325.40 |
| 1980–2000  | TRSR    | 57,769.81 | 9927.44  | 10,364.27 | 164,034.37 | 1857.11     | 1972.09 | 12,574.92 |
| 2000–2018  | TRSR    | 2391.27   | 263.56   | 154.34    | 2028.06   | 2921.85     | 231.08 | 652.60 |
| 2005–2019  | TRSR    | 13,686.50 | 918.06   | 383.51    | 5605.51   | 539.48      | 4870.88 | 919.56 |
| 2018–2019  | TRSR    | 1235.32   | 37.49    | 5.01      | 242.13    | 34.64       | 13,126.32 | 32.19 |
| 2019–2020  | TRSR    | 319.47    | 8.18     | 43.28     | 1568.61   | 243.71      | 0.00   | 40,431.11 |

| Period     | Type    | Cropland | Forest | Shrubland | Grassland | Waterbodies | Urban | Desert |
|------------|---------|----------|--------|-----------|-----------|-------------|-------|--------|
| 1980–2000  | TRSR    | 745.28   | 4.25   | 0.00      | 86.00     | 2.34        | 0.00  | 2.87   |
| 2000–2018  | TRSR    | 0.00     | 312.88  | 34.14     | 21.83     | 1.00        | 0.00  | 1.03   |
| 2005–2019  | TRSR    | 3.24     | 18.80   | 37.51     | 237,798.15 | 312.44      | 2.33  | 192.60 |
| 2018–2019  | TRSR    | 2.56     | 0.00    | 2.62      | 68.14     | 16,626.61   | 0.00  | 94.05  |
| 2019–2020  | TRSR    | 4.35     | 0.00    | 0.00      | 4.66      | 1.82        | 61.80 | 0.00   |
| 2020–2021  | TRSR    | 2.59     | 0.00    | 2.38      | 924.35    | 485.08      | 0.00  | 78,932.47 |
Table 4. Cont.

| Period | Type     | Cropland | Forest | Shrubland | Grassland | Waterbodies | Urban | Desert   |
|--------|----------|----------|--------|-----------|-----------|-------------|-------|----------|
| 2005–2018 TRSR | Cropland | 456.31   | 19.00  | 29.67     | 335.21    | 29.27       | 8.06  | 29.52    |
|       | Forest   | 23.07    | 1578.30| 194.96    | 1257.71   | 23.96       | 0.40  | 94.47    |
|       | Shrubland| 18.58    | 194.49 | 4763.10   | 5716.53   | 49.71       | 3.25  | 221.99   |
|       | Grassland| 284.39   | 1318.76| 5828.42   | 210,490.87| 4350.73     | 36.93 | 30,601.93|
|       | Waterbodies| 32.60    | 23.13  | 44.43     | 4524.10   | 10,457.73   | 2.78  | 2470.63  |
|       | Urban    | 17.60    | 3.12   | 6.47      | 68.64     | 4.99        | 16.97 | 6.22     |
|       | Desert   | 2.77     | 20.32  | 159.95    | 15,382.96 | 1793.67     | 1.62  | 46,636.25|

The areas of cropland and desert on the LP significantly decreased after implementing ecological engineering, covering the areas of 11,550 km$^2$ and 4298 km$^2$, respectively. The reduced cropland area was mainly changed into grassland, urban, and forest, whereas the reduced desert area was mainly converted into cropland and grassland. In the TRSR, the areas of grassland and waterbodies increased significantly and the area of desert decreased significantly, accompanied by the non-significant area changes of other land cover types. The area of grassland mainly increased, stemming mainly from the desert. During this period, the waterbodies area increased, stemmed from grassland and desert with a total of 7000 km$^2$. Despite the area of flow between grassland, forest, and shrubland being large, the transfer in and out was basically balanced, so the areas of forest and shrubland remained stable.

3.5. Contributions of Climate and Human Factors to Vegetation Greening

In this study, we quantitatively identified the contributions of climate variabilities and human activities to vegetation greening by using a linear regression model. Figure 7 showed the linear regression coefficients between LAI and TMP, PRE, RAD, and VPD. During 1982–2019, climate variabilities and human activities jointly contribute to vegetation greening (Figure 8). The average contributions of climate variabilities to vegetation greening were 59.91% in the LP and 52.92% in the TRSR, both slightly higher than the contributions of human activities. Moreover, climate variabilities dominated vegetation greening accounting for 81.23% and 52.33% of the LP and TRSR, respectively. On a long-timescale, climate variability contributed more to vegetation greening than human activity.

![Figure 7](Image1.png)
Nevertheless, the relative contribution of climate variabilities and human activities shifted considerably between the two time periods, divided by the initiation of the ecological engineering projects. Before implementing the projects, climate variabilities controlled 81.52% of vegetation greening area on the LP, and the positive effect of human activities on vegetation was small. In the TRSR, the western side was mainly influenced by climate change and the eastern side by human activities. Furthermore, the impact of climate variabilities (50.58%) was weakly higher than that of human activities. These indicated that vegetation greening in the study regions was mainly dominated by climate variabilities. After the projects’ implementation, the area of vegetation greening mainly caused by human activities increased significantly from 6.69% to 74.62% in the LP and from 27.62% to 93.67% in the TRSR. The patches dominated by human activities (approximately 430,208 km$^2$) were concentrated and large in the LP, while those in the TRSR (approximately 39,744 km$^2$) were small and scattered.

4. Discussion
4.1. Vegetation Greening

This study analyzed spatial-temporal patterns of vegetation dynamics across different periods over the past 38 years, and the characteristics of the LP and TRSR were compared. We detect significant vegetation greening in the LP (91.4%) and TRSR (65.3%) during 1982–2019, with considerable greening mainly distributed in the eastern TRSR and southeastern LP. These findings are in line with earlier studies which show that vegetation conditions of the study regions have improved [15,17,56]. Although LAI decreased in some parts of the study region, the decreasing trend was mostly not statistically significant. The areas where LAI decreased significantly were consistent with the distribution of urban land, indicating that the significant decrease in LAI was mainly related to human activities such as urbanization. However, the distribution of non-significant decreases changed from sporadic to clustered after 2005, reflecting heightened fluctuation of the LAI trend [43].
suggested that the vegetation of TRSR has generally improved, but vegetation degradation still highly exists.

Although both LP and TRSR exhibit significant greening from 1982–2019, their specific change characteristics differ greatly. First, the rate of vegetation greening on the LP is about four times higher than that of the TRSR, which may be related to therein high background vegetation coverage and the extensive ecological engineering project implementation [42]. According to previous studies, more than 20,000 km² of cropland has been converted to grassland and forests after the GFG implementation [57,58], as well as the afforestation area on the LP, reached 28,300 km² in 2018 alone [59]. Second, vegetation dynamics show different trends between the two regions prior to and posterior to the ecological engineering projects. After implementing the ecological engineering projects, the vegetation greening accelerated, and the greening area extended obviously in the LP. By contrast, only 17% of the TRSR exhibited significant greening trends, much lower than 94.7% of the LP. The faster vegetation greening rate on the LP is highly related to the more favorable climate conditions and the types of ecological engineering measures on the LP. On the LP, the combinations of precipitation and temperature produce environmental conditions breeding higher vegetation productivity than on the TRSR. Moreover, ecological engineering projects on the LP are mainly about afforestation and grassland recovery from croplands, which accommodate higher productivity ecosystems than the alpine grasslands on the TRSR.

### 4.2. Climate Variability and Its Relationship with Vegetation Dynamics

There is no doubt that climate variability is a factor essential for vegetation dynamics [19]. Besides temperature and precipitation, solar radiation and vapor pressure are increasingly included in climate variability and anthropogenic activity differentiation studies [60–62]. Our results show that vegetation growth on the LP and TRSR was mainly influenced by temperature, followed by precipitation, vapor pressure deficit, and lastly by solar radiation. For nearly 10% of our study area, vegetation dynamics are primarily influenced by solar radiation and vapor pressure deficit. Our model has significantly improved the variations explained by adding solar radiation and VPD to the statistical model (R² = 85.3%), as compared to the previous TP-based LAI model (R² = 65.6%), which considered only temperature and precipitation, our model has significantly improved the variations explained by adding solar radiation and VPD to the statistical model (R² = 85.3%). Other climate parameters were not included in this analysis, considering the risk of multicollinearity and marginal improvements on explained variations [63,64].

Our study confirms previous reports that vegetation growth is mainly limited by regional hydrothermal conditions in the LP and TRSR [6,36,65]. Temperature rises may promote photosynthesis and extend vegetation growing season, thereby benefiting dry matter accumulation [39,66]. Precipitation favors vegetation growth in both LP and TRSR, which are both classified as semi-regions and enhanced precipitation can alleviate drought limitation to some extent [18,67,68]. Nevertheless, in areas such as southeast LP and central TRSR, precipitation is negatively correlated with vegetation growth. This downplaying effect may be related to the artificial irrigation that makes vegetation not sensitive to precipitation in some parts of the LP [69]. In cold and the relatively humid TRSR, precipitation may decrease temperature and solar radiation, resulting in inhibiting vegetation growth [70]. Temperature and precipitation have similar impacts on vegetation dynamics in most of the studied locations, while the effects of solar radiation and vapor pressure deficit are regionally diverse. On the eastern side of the LP, solar radiation benefits vegetation growth via its promotion of photosynthesis [18,71]. However, in the TRSR and western part of the LP, high-altitude areas with sufficient solar radiation, increased solar radiation leads to more evapotranspiration, thereby inhibiting vegetation growth [72]. The higher VPD normally shows inhibitory effects on vegetation growth because leaf and canopy photosynthetic rates decrease due to stomatal closure [35]. However, VPD and vegetation greening are positively correlated in the LP. The unusual relationship might be caused by
the particular soil moisture conditions on the LP. The intervention of human management might be another contributing factor.

The relationship between climates and vegetation adjusted after the ecological engineering projects. In the LP, climate variations shifted from warming-drying to warming-humid after 2000. Although the warming rate becomes slower, precipitation and solar radiation shift from decreasing to increasing in the LP, and vapor pressure deficit changes from increasing to decreasing [41,73]. The LP’s environment becomes more favorable to vegetation growth. However, in the TRSR, warming slowed down after 2005 and the trend was even reversed in some regions. Reduced precipitation, stronger solar radiation, and increased vapor pressure deficit make the climate conditions more unfavorable for vegetation growth in the TRSR [74]. Precipitation has substituted temperature as the dominant climate factor affecting vegetation growth in many regions [75].

In a word, climate variability and its relationship with vegetation dynamics exhibit similarities and disparities between LP and TRSR. After the ecological engineering projects, the dominant climate factor changes from temperature to precipitation in both LP and TRSR, which indicates that human activities might significantly modify the regional hydrological conditions. After the ecological engineering projects, climate conditions in the LP improved while degraded in the TRSR. The progressively unfavorable climate conditions in the TRSR make it more challenging to implement ecological engineering projects in the TRSR.

4.3. Ecological Engineering Drives Vegetation Greening

This study quantifies the relative contribution of climate variabilities and human activities to vegetation greening ($p < 0.05$) using the RESTREND method. However, both human activities and climate factors are contained in the residual. Some of these climate factors (such as soil texture) are relatively stable on the time dimension, and their impact on vegetation dynamics can be neglected. Human variables are usually assumed to account for a considerable amount of the residual. Furthermore, in the LP and TRSR, most human activities positively impacting vegetation growth are stemmed from ecological engineering projects. Our results identified a significant increase in the contribution of human activities after implementing ecological engineering projects, which are in line with the series of government launched large-scale projects in these two regions. In addition, the changes in land cover before and after the ecological engineering was considered, and the results also confirmed the increased contribution of human activities to vegetation greening.

During 1982–2019, vegetation greening on the LP and TRSR was driven by a combination of climate variabilities and human activities, with the contribution of climate variabilities slightly higher than human activities. This is consistent with prior research findings. [18,52]. However, in the TRSR, the contribution of climate variabilities is lower than human activities in both the two split periods. The explanation for this could be that the relationships between vegetation dynamics and climate are more stable in an extended period, while human activities are exposed to wider fluxes [30,61].

The human activity contribution has been intensified with time elapsing. The GFG project, also known as the Conversion of Cropland to Forests and Grassland Program, was launched in 1999 on the Loess Plateau and has played a significant role in vegetation greening directly or indirectly. The primary measures include converting agricultural lands into forest or grassland, afforestation, artificial irrigation, and so on. From 2000–2014, there were afforested areas of $2.39 \times 10^4$ km$^2$ in the northern Shaanxi Province alone. It was reported that the correlation coefficients between the NDVI time series and cumulative afforestation areas in some areas of the LP reached 0.978 [76]. These findings suggest that human activities have been the primary factor in vegetation improvement in the LP. Our results also show that after the GFG project, the greening area primarily driven by human activities on the LP increased from 6.7% to 74.7%. This result reveals that the implementation of ecological restoration projects and the economic incentives given to the local farmers have made a remarkable contribution to vegetation greening.
Intense human intervention has altered the land surface state in the LP, regional climates, and their relationships with vegetation dynamics. Some studies have noticed that the conversions of unused land and rainfed cropland into forest or grassland have contributed to the increasing precipitation trends after 1999 [17]. At the same time, it has raised concerns about local food shortages. However, in Shaanxi Province, the fastest-greening province, the crop production area decreased by 21.34% while the total yield and yield per unit area increased by 12.60% and 43.14% from 2000–2018 [15]. The increased yield per unit area and the optimization of crop structure compensated for the yield loss caused by the reduction of cropland area.

In the TRSR, the first phase (2005–2012) of EPCP comprises reducing livestock, banning grazing, delaying grazing, ecological migration, controlling desertification, rodent pest control, and returning farmland to forests and grasslands [77,78]. The second phase was launched in 2013, and it adheres to the primary principle of reducing human interventions and investing more in natural vegetation recovery. Animal husbandry is the main industry in the TRSR, and the number of livestock has an important impact on vegetation dynamics. Therefore, the change in livestock numbers can reflect the effect of EPCP to some extent. According to the statistical annals of the Qinghai government, livestock numbers in the TRSR have decreased by 15.34% since the implementation of the EPCP [74]. Our results also show that human activities dominated proportion increased from 27.6% to 93.7% for those greening areas on the TRSR. Whereas, climate conditions in the TRSR become increasingly unfavorable for vegetation growth as mentioned above. After the EPCP, vegetation greening is not significant in many areas of the TRSR under the interacted human activities and natural climates. Notably, some protective measures are not as effective as expected. Thus, more appropriate adaptation strategies should be adopted to address climate change in the future.

A high disparity was identified between the LP and TRSR in terms of the contribution rates of climate variabilities and human activities to vegetation greening. Although the vegetation greening rate in the TRSR is smaller than in LP, the ecological engineering project’s contribution rate is higher in the TRSR. Our results, together with other relevant studies, raise the importance of paying more attention to the contribution of artificial vegetation construction and agricultural technology innovation to regional vegetation greening [79–82]. Thereby, for ecologically fragile areas, vegetation recovery can incline more on natural recovery, but a balanced natural recovery and human interventions are also necessary.

The entire investigation made several improvements and bridged some gaps based on existing studies. Firstly, RESTREND can capture the enhancement of the anthropogenic contribution to vegetation greening after implementing ecological engineering projects in the study areas, and the inclusion of suitable climate factors can make this method more applicable locally. Secondly, by comparing the relationship between vegetation, climate, and human activities before and after the ecological engineering projects, it was unexpectedly found that climate variabilities in the TRSR after 2005 mainly inhibited vegetation growth, and vegetation greening was dominated by human activities. Thirdly, it was easy to overestimate the contribution of human activities because climate effects on vegetation are difficult to detect over shorter time spans. Thus, two typical regions need to be compared in order to have a more accurate assessment of the anthropogenic contribution. Finally, through comparison, it was found that the effects of implementing ecological engineering projects varied greatly in different areas, with the LP exhibiting obvious results while the TRSR exhibited fewer ones. In implementing ecological engineering projects, close attention should be paid to climate variations and timely adjustments to the specific measures of ecological engineering projects, such as increasing human intervention when climate conditions are not suitable for the natural recovery of vegetation.
5. Conclusions

The present study analyzed the spatial-temporal patterns of vegetation dynamics over the LP and TRSR from 1982 to 2019. The relative contributions of climate variabilities and human activities on vegetation greening were quantified using RESTREND based on the LAI-climate model. The following conclusions were drawn: (1) On an overall basis, there was a significant vegetation greening trend in the entire study area. Vegetation greening rate and magnitude were greater on the LP than on the TRSR; (2) Increasing TMP and PRE mainly promote vegetation growth in the entire study area, while higher RAD and VPD mainly play an inhibiting role; (3) Ecological engineering projects have adjusted the relationship between climate and vegetation. The primary climatic factor changed from temperature to precipitation after implementing the series of ecological engineering projects; (4) The most notable vegetation greening primarily stems from the ecological engineering projects. Counterintuitively, the area percentage of human activities dominated region is higher in the TRSR (91.73%) than in the LP (68.02%); and (5) Compared with the Loess Plateau, the results of ecological engineering are more challenging to maintain in the TRSR. This study can further enhance our understanding of the relationship between climate variabilities, human activities, and vegetation dynamics for the large-scale ecological engineering project affected regions.

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