Separating the Contributions of Human Activities and Climate Change to Vegetation Dynamics on the Loess Plateau Using Machine Learning

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Abstract. Against the dual backdrop of climate change and ecological restoration projects, vegetation on the Loess Plateau has experienced rapid recovery. However, the relative contributions of climate change and human activities to these vegetation changes remain controversial. This study employs the Leaf Area Index (LAI) as an indicator of vegetation greenness, identifies the onset of significant ecological restoration effects in different regions using change-point detection, and separates the contributions of human activities and various climate factors through machine learning and segmented residual analysis. The results indicate that the LAI of the Loess Plateau exhibits a fluctuating upward trend. The timing of significant ecological restoration effects shows pronounced spatial heterogeneity, with an average onset year of 2013. The machine learning model, which considers the optimal 3-month cumulative rainfall scale, achieves an average R^2 of 0.87. Based on this model and residual trend analysis, human activities are found to dominate 69.6% of the vegetation changes, while climate change contributes 30.4%. After 2010, the promoting effect of human activities became more pronounced, whereas climate change shifted from a promoting role before the change-point to an inhibiting role afterwards. This study systematically analyzes the mechanisms of vegetation change on the Loess Plateau, providing a scientific basis for formulating regional ecological management policies.

Keywords: Loess Plateau; Leaf Area Index (LAI); climate change; human activities; relative contribution.

1. Introduction

Vegetation serves as a key indicator for assessing ecological environment quality and plays an indispensable role in maintaining ecosystem balance, supporting the stability of natural ecosystems and the order of human production and life. Regional vegetation dynamics result from the combined effects of climate and human activities, both of which have dual impacts on vegetation evolution. Temperature, precipitation and net radiation influence plant structural attributes, physiological processes, and the decomposition and transformation of soil organic carbon by regulating effective accumulated temperature and soil water supply, thereby affecting long-term vegetation dynamics and spatial distribution patterns [1]. Human activities such as slope management, gully-slope joint management, small watershed comprehensive management, and gully land reclamation, particularly the Grain for Green Program (GGP) implemented since 1999, have not only promoted vegetation restoration but also supported socio-economic development [2]. The Loess Plateau faces significant challenges, including soil erosion, population pressure and low productivity [3], making it a typical ecologically fragile zone in China and a key implementation area for national ecological restoration projects, holding strategic importance in maintaining national ecological balance and promoting ecological construction.

The Leaf Area Index (LAI), defined as half the total green leaf area per unit horizontal ground surface area, is an important biophysical parameter for characterizing canopy structure and plant biomass [4]. Numerous scholars worldwide have conducted extensive research on LAI data using various statistical methods to investigate vegetation greenness dynamics, spatial distribution characteristics, vegetation properties under different land cover types, and the intrinsic relationships between LAI and vegetation health status. Due to differences in research methods, LAI data sources, and relatively short time series, research conclusions vary considerably. For instance, Yi Lang et al. [5] used the Mann-Kendall method and residual analysis to identify human-induced abrupt changes but did not quantify the relative contributions of climate change and human activities. Wang Guangfang et al. [6] applied linear regression and multiple residual analysis, concluding that LAI changes on the Loess Plateau over the past forty years were mainly influenced by climate change with predominantly positive effects, while human activities mainly showed inhibitory effects; however, they did not employ segmented linear regression to account for differences in human activities. Fan et al. [7] used difference-in-differences and change-point detection methods, arguing that climate change was the main driver of vegetation restoration with human activities playing a secondary role. Li et al. [8] applied correlation analysis and residual trend analysis, concluding that climate change contributed 62% to net primary productivity changes while human activities contributed 38%. Guo Famia et al. [9] and Zhang Leyi et al. [10] used methods similar to Li et al. [8] and concluded that human activities rather than climate change were the primary drivers of vegetation restoration on the Loess Plateau. While these studies have paid considerable attention to natural factors like climate change and soil properties, and to some extent considered changes in human activities, they did not account for spatial differences in the years when ecological restoration became significantly effective, leading to uncertainties in quantifying the contribution of human activities.

This study focuses on the Loess Plateau, utilizing long-term high-precision remote sensing LAI data (GIMMS 4g) and the China Meteorological Forcing Dataset (CMFD) to comprehensively characterize vegetation greenness dynamics from 1982 to 2018. By employing change-point detection to divide human activity impacts into periods before and after the implementation of key policies and ecological projects, and combining machine learning with segmented residual analysis and scenario differencing methods, we evaluate the relative contributions of climate change and human activities to vegetation changes on the Loess Plateau, revealing vegetation responses to climate change. This provides scientific support for ecological restoration and sustainable economic development in the region.

2. Study Area

The Loess Plateau is located in the core area of the middle and upper reaches of the Yellow River, with geographical coordinates between 33°43′–41°16′N and 100°54′–114°33′E. It stretches from the Taihang Mountains in the east to the Riyue Mountains in Qinghai in the west, the Qinling Mountains in the south, and the Ordos Plateau in the north. The average elevation ranges from 500 to 2000 meters, covering a total area of approximately 640,000 km² and spanning seven provinces: Henan, Qinghai, Ningxia, Gansu, Shaanxi, Shanxi, and Inner Mongolia, including 45 prefecture-level cities such as Xi’an.

This region spans semi-humid and semi-arid climate zones along an east-west gradient. Vegetation types exhibit a zonal transition from northwest to southeast, shifting from warm-temperate deciduous broadleaf forests in the southeast to forest steppes, dry steppes, and finally temperate desert steppes in the northwest. The Loess Plateau boasts rich and diverse vegetation. However, in recent years, global climate change has led to warmer and wetter conditions on the Loess Plateau, directly affecting vegetation growth.

Meanwhile, the rapid development of urban agglomerations such as the Guanzhong Plain, the Central Shanxi Urban Agglomeration, and the Lanzhou-Xining Urban Agglomeration has intensified human activities in the region. From 1982 to 2018, the rural population continued to grow, and economic development brought about resource exploitation and environmental changes. Human activities such as reclamation, grazing, and urban expansion have continuously altered land-use patterns on the Loess Plateau.

3. Data

3.1 LAI Data

We used the Global Inventory Modeling and Mapping Studies Leaf Area Index (GIMMS LAI 4g) spatiotemporally consistent dataset (1982–2020) (V1.2) to characterize vegetation dynamics [11]. The dataset covers the study period from 1982 to 2018, with a spatial resolution of 8 km and a temporal resolution of 15 days. The LAI data were resampled to 0.1 degrees using bilinear interpolation to match the spatial resolution of the meteorological forcing data. Monthly averages were calculated by aggregating the 15-day interval LAI data to a monthly scale.

3.2 Climate Data

The China Meteorological Forcing Dataset (CMFD) was used to obtain temperature, precipitation, and net radiation as key climate variables for vegetation dynamics [12]. The dataset spans 40 years (1979–2018), with a spatial resolution of 0.1 degrees and a temporal resolution of 3 hours. Precipitation was aggregated to a monthly scale by cumulative summation, while temperature and radiation were aggregated by monthly averaging.

4. Methodology

4.1 Trend Analysis

Univariate linear regression was used to simulate each grid cell's trend, reflecting the region's spatiotemporal evolution. The formula is as follows:

$$LAI = a \times year + b \quad (1)$$

where a is the slope of the linear regression equation. A positive a indicates an increasing trend in LAI, while a negative a indicates a decreasing trend. The variable "year" represents the time, and b is the intercept.

4.2 Mutation Test

Although ecological restoration projects began in 2000, the actual implementation and effectiveness varied across regions, leading to differences and delays in the onset of human-induced impacts. The Pettitt test [13] was employed to identify the starting point of human activities. For each grid cell, the LAI time series x1,x2……xn，was analyzed, where n is the length of the data. The cumulative statistic Sk was calculated for each data point xi. The specific calculation method is as follows: From i=1to n for each i, then traverse from j=1 to i−1. If xi>xj, then let s=s+1; if xi<xj, then let s=s−1; if xi=xj, then s=s+0. Find the value of k that makes Sk reach the maximum value, denoted as k0. The test statistic U=Sk0. Use the approximate formula to calculate the p-value:

$$p = 2\exp\left(\frac{-6U^2}{n^3 + n^2}\right) \quad (2)$$

The p-value is used to determine whether the mutation is significant. Compare the p-value with the pre-set significance level (0.05). If the p-value is less than the significance level, it is considered that there is a significant mutation point in the time series at k0.

4.3 Machine Learning Model Driven Solely by Climate

For each grid, the period before the mutation point was considered as the period without human activities, and a machine learning model of LAI and climatic variables was established. A random forest model was constructed with climatic data such as precipitation, temperature, and net radiation as independent variables and the LAI index as the dependent variable. Since the impact of precipitation on LAI has a lag effect, the optimal cumulative scale of precipitation was calculated during the research, and precipitation over a certain time span was considered cumulatively. The data were divided into a training set and a test set at a ratio of 7:3, and the optimal hyperparameters were found using the GridSearch technique in Python. With this model, the predicted LAI values driven only by climate could be calculated.

4.4 Residual Trend Analysis for Quantifying Absolute and Relative Contributions

The monthly rainfall, monthly temperature and monthly radiation in the period after the mutation point are utilized to drive the optimal machine learning model, thereby obtaining the vegetation dynamics without the influence of human activities. The residual between the actual LAI and the simulated LAI [14] is regarded as the impact of human activities.

$$LAI_{res} = LAI_{obs} - LAI_{pred} \quad (3)$$

where LAI_{res} is the residual value of LAI, LAI_{obs} is the observed value of LAI, and LAI_{pred} is the predicted value of LAI. When LAI_{res}, human activities have a positive contribution to LAI; otherwise, the contribution is negative. The slope of LAI_{pred} in the post-mutation period is calculated as the absolute contribution of climate change AC_{cli}; the slope of LAI_{res} is calculated as the absolute contribution of human activities AC_{hum}. The relative contributions of climate change and human activities are calculated based on the relative proportions of the absolute contributions, as shown in equations (4-7) respectively:

$$AC_{cli}=slope(LAI_{pred}) \quad (4)$$

$$AC_{hum}=slope(LAI_{res}) \quad (5)$$

$$RC_{cli} = \frac{AC_{cli}}{AC_{cli} + AC_{hum}} \times 100\% \quad (6)$$

$$RC_{hum} = \frac{AC_{hum}}{AC_{cli} + AC_{hum}} \times 100\% \quad (7)$$

where RC_{cli} and RC_{hum} represent the relative contributions of climate change and human activities, respectively.

4.5 Separating the Contributions of Each Climatic Variable through Scenario Differencing

The contributions of each climatic variable are separated through scenario differencing. The contributions of each climatic variable are calculated by comparing the differences between the predicted values under different scenarios and the original predicted values [14]. The scenario differencing experiment is set up as follows: In the S0 scenario, the original climatic data such as precipitation, temperature, and net radiation are input into the machine-learning model, and the predicted LAI value is taken as the baseline scenario. In the S1 scenario, only the precipitation data is detrended and input into the model together with other untreated climatic data to obtain the predicted LAI value. The difference between S0 and S1 represents the contribution of precipitation. Similarly, in the S2 scenario, only the temperature data is detrended, and in the S3 scenario, only the net radiation data is detrended. They are respectively input into the model together with other untreated climatic data to obtain the predicted LAI values. The differences between S0 and S2, S3 represent the contributions of temperature and net radiation, respectively.

5. Results and Discussion

5.1 Long-term Vegetation Trends and Spatial Patterns

Overall, the average greenness of vegetation on the Loess Plateau increases from the northwest to the southeast. The average LAI in the northern region is below 0.5, while it is significantly higher in the southern region, reaching 3.0 in some areas (Figure 1). The trends of LAI changes in the northwest and southeast regions are relatively significant, while LAI changes in the central part are less obvious.

Temporally, the vegetation on the Loess Plateau increased significantly from 1982 to 2018 (slope = 0.014, $p < 0.05$). Especially after 2000, the LAI increased rapidly (slope = 0.043, $p < 0.05$).

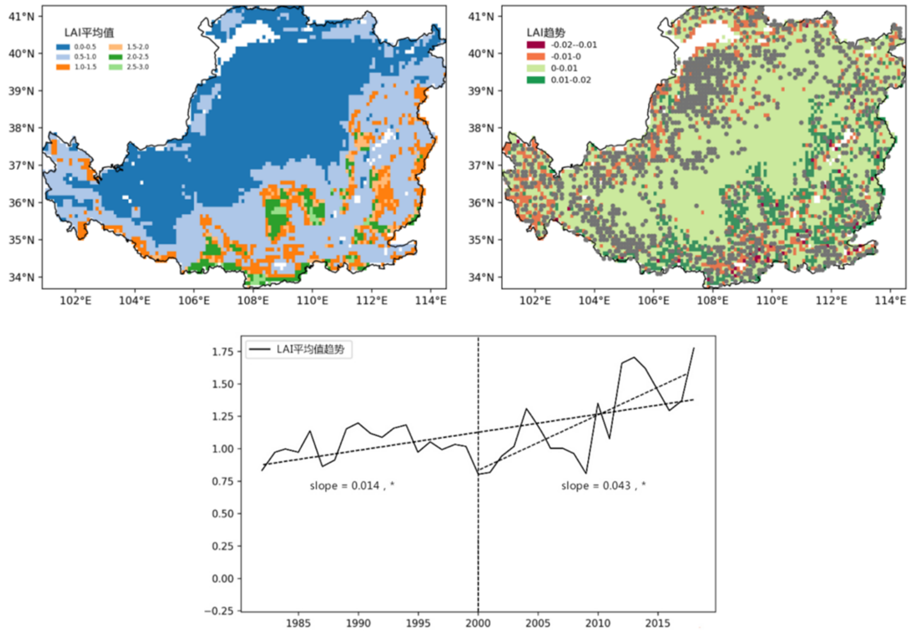

Figure 1. Average LAI and trends in the Loess Plateau region from 1982 to 2018

5.2 Years of Vegetation Mutation

The Pettitt test (Figure 2) reveals that in most areas of the central Loess Plateau, the mutation of human activities occurred between 2010 and 2018, with an average of 2013. It is speculated that this is because the second-phase project of the Grain-for-Green Program began to be implemented in the Loess Plateau region in 2013. During this period, the relatively concentrated population and economic activities in the central part prompted people to intensify ecological restoration efforts. A large amount of land originally used as farmland was returned to forest and grassland, further promoting the positive evolution of vegetation.

The mutation times in the border areas of the Loess Plateau vary greatly. This may be due to the uneven population distribution in the border areas, and the more complex terrain compared to the central region, resulting in different traffic conditions. There are differences in the human resources and resource supply for ecological restoration in different places. In addition, the climatic and soil conditions in the border areas also differ from those in the central region, leading to variations in the response time of vegetation restoration.

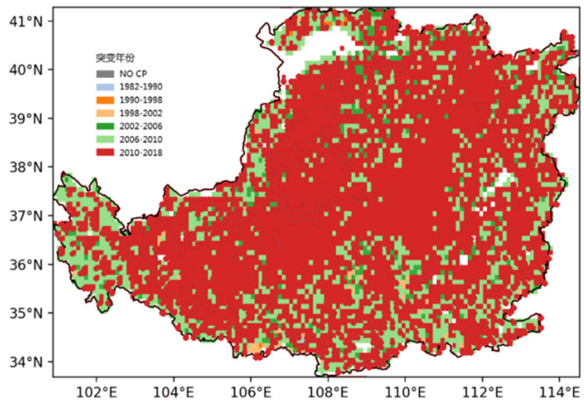

Figure 2. Pettitt test and the years of mutation of human activities identified by its significance

5.3 Machine Learning Model Driven by Climate

By considering the cumulative scale of precipitation, a machine learning model was established to predict and map the optimal cumulative precipitation (Figure 3). It can be concluded that in most areas of the Loess Plateau, the optimal time scale of cumulative precipitation is 3 months. Only in some southeastern and northern areas of the Loess Plateau do small fluctuations occur. This may be because the topography and monsoon conditions in these areas have changed the distribution and flow paths of precipitation, resulting in differences in the cumulative effect of precipitation compared with other regions [15].

The machine learning model was used to fit the LAI, precipitation, temperature, and net radiation before and after the mutation point. The average value of R2 in most areas is 0.87, and in most areas, it can reach 0.95, indicating that this model is applicable in most areas of the Loess Plateau. However, in the southern and northwestern regions, the fitting degree of this model is lower than 0.7. Differences in topography, soil conditions, and changes in other climatic factors in different regions will all lead to differences in the model fitting.

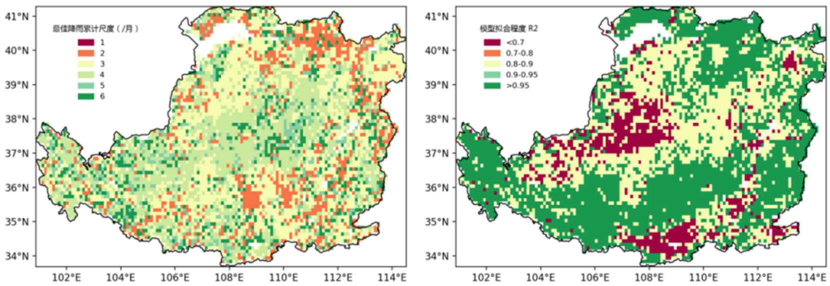

Figure 3. Optimal Precipitation Accumulation Scale and Model Fitting Value R^2

5.4 Contributions of Climate Change and Human Activities

There is spatial heterogeneity in the impacts of climate change and human activities on the vegetation changes in the Loess Plateau (Figure 4). The roles of these two factors in the vegetation changes of the Loess Plateau vary greatly. In approximately 90% of the areas in the Loess Plateau, climatic factors have promoted the vegetation change index of the Loess Plateau, which is mainly distributed in the central, eastern, and northern parts of the Loess Plateau region. This indicates that temperature, precipitation, and net radiation jointly promote vegetation restoration. The areas with less inhibition and those basically unaffected account for a relatively small proportion, which are mainly distributed around Yan'an City and in the border areas of the Loess Plateau.

Human activities promote development in most areas of the central and southeastern parts of the Loess Plateau region, especially having an obvious promoting effect in northern Shaanxi Province. However, human activities have a restraining effect in the western and northern border areas and some urban areas in the south. According to relevant research and analysis, this may be due to the relatively developed urban development and agriculture in the Lanzhou-Xining Urban Agglomeration [16].

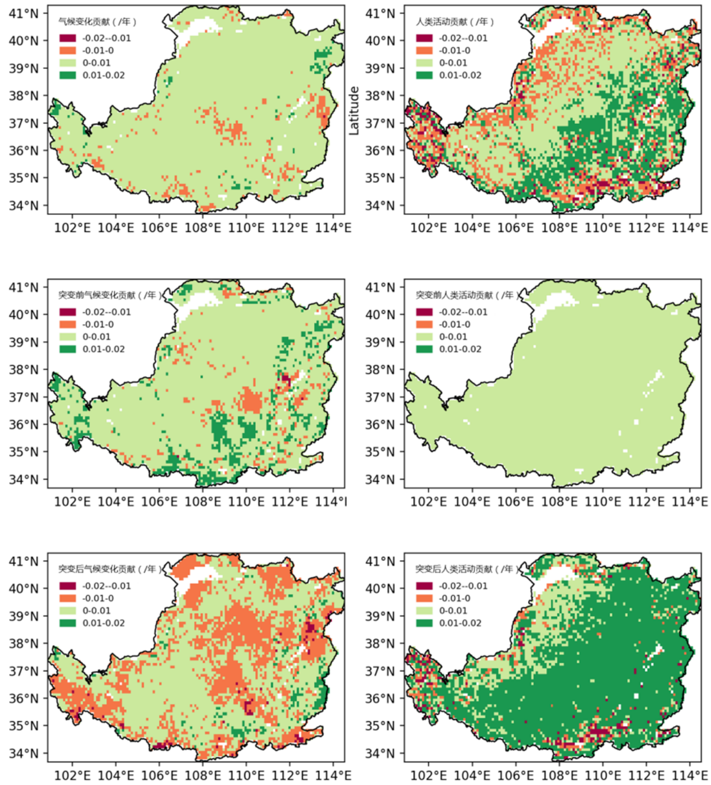

Figure 4. Absolute Contributions of Climate Change and Human Activities

By comparing the contributions of climate change and human activities to the LAI index before and after the mutation point, it can be concluded that: Before the mutation point, the impact of human activities on LAI can be regarded as negligible. Climate change has a positive impact on LAI in more than 90% of the areas, and only has a negative impact in a small part of the central region. After 2000, human activities began to intervene, and a series of measures related to vegetation restoration in the Loess Plateau region, such as returning farmland to forests, were carried out. Human activities have played an obvious promoting role in most areas, especially in the central and northeastern regions. From 2000 to 2018, climatic factors had a restraining effect on LAI in about 45% of the areas, especially in the central and western parts of the Loess Plateau, and had a promoting effect in the remaining areas, but not as significant as the promoting effect of human activities.

By calculating the relative contributions of climate change and human activities to LAI (Figure 5), it can be obtained that during the overall study period from 1982 to 2018, climate change played a dominant role in the change of LAI, with a relative contribution of 56.92%, while human activities accounted for the remaining 43.08%. However, after the mutation of human activities, in the vast majority of areas mainly in the central part of the Loess Plateau, the impact of human activities on LAI is greater than that of climate change. The relative contribution of human activities reaches 69.58%, and the relative contribution of climate change is 30.42%. This indicates that in addition to the direct impact brought by the ecological restoration project, with the economic development and the gradual improvement of human environmental protection awareness, in urban and surrounding areas, the process of urban greening and ecological environment restoration has also had a certain degree of impact on LAI.

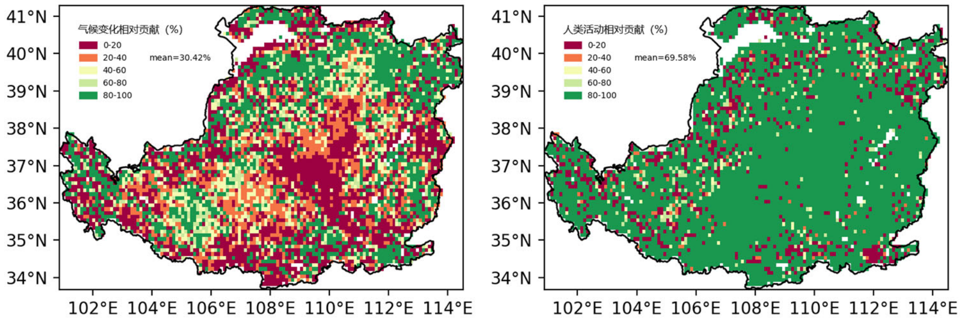

Figure 5. Relative Contributions of Climate Change and Human Activities

5.5 Correlation between Climatic Variables and Vegetation

By separating the individual contributions of the three climatic variables of precipitation, temperature, and net radiation to LAI from 1982 to 2018 through scenario differencing, it is found that: Among various climate change indicators (Figure 6), net radiation and temperature have a restraining effect on the vegetation coverage in the southern part of the Loess Plateau, and show a promoting effect in the remaining parts of the region. Precipitation has a promoting effect on LAI in most areas, and only has a negative effect in a few scattered areas. Overall, climate change has a positive impact on the vegetation in the Loess Plateau. From the perspective of a single climatic factor, precipitation has a positive impact in most areas. Temperature and net radiation promote LAI in the northern region, but have a restraining effect in the southern region.

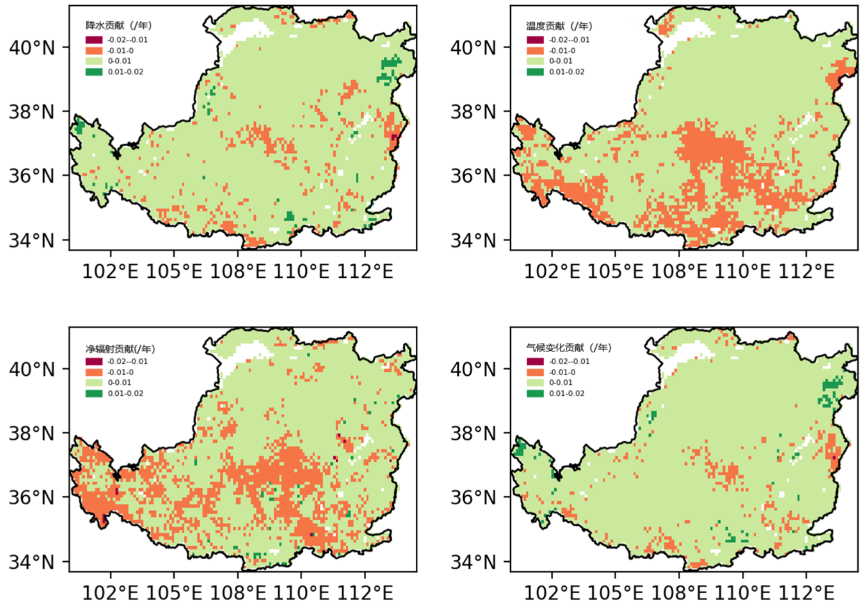

Figure 6. Contributions of Various Climatic Factors

6. Conclusion

Based on the spatiotemporally consistent dataset (1982-2020) (V1.2) of the Global Inventory Modeling and Mapping Studies Leaf Area Index (GIMMS LAI4g) and the high-resolution meteorological driving dataset for the Chinese region (CMFD), this paper employs methods such as machine learning, mutation test, residual trend analysis, and scenario differencing to study the variation characteristics of the Leaf Area Index (LAI) in the Loess Plateau from 1982 to 2018 and its response patterns to changes in climatic factors and human activities. The conclusions are as follows:

(1) Spatial distribution and change trend of LAI

In terms of spatial distribution, the vegetation greenness in the southeastern part of the Loess Plateau is higher than that in the western and northern regions. During the period from 1982 to 2018, the vegetation in the Loess Plateau showed a fluctuating upward trend. Among them, before 2000, the growth of LAI fluctuated greatly and was not obvious, while after 2000, the LAI increased significantly.

(2) Relative contributions of human activities and climate change

There is obvious spatial heterogeneity in the impacts of human activities and climate change on the changes of LAI of the vegetation in the Loess Plateau. Throughout the entire period, climatic factors promoted the vegetation change index in 90% of the areas in the Loess Plateau, which were mainly distributed in the central, eastern, and northern regions. After 2006, in the vast majority of areas mainly in the central part of the Loess Plateau, the relative contribution of human activities (69.58%) to LAI was greater than that of climate change (30.42%). Only in some areas in the western and northern regions, the relative contribution of climate change was larger. In addition, climate change had a restraining effect on LAI in about 45% of the areas.

(3) Individual contributions of climatic factors

Among various climatic factors, there are obvious differences in the impacts of precipitation, temperature, and net radiation on LAI. Precipitation has a promoting effect on LAI in most areas, and only a restraining effect in a few scattered areas; net radiation and temperature have a restraining effect on the vegetation coverage in the southern part of the Loess Plateau, and a promoting effect in the remaining parts of the region.

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