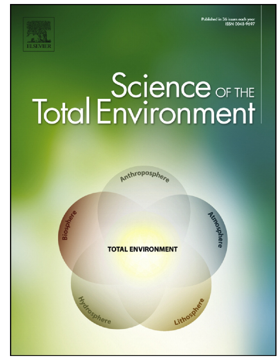
Journal Pre-proof



Human activity vs. climate change: Distinguishing dominant drivers on LAI dynamics in karst region of southwest China

Jian Peng, Hong Jiang, Qinghua Liu, Sophie M. Green, Timothy A. Quine, Hongyan Liu, Sijing Qiu, Yanxu Liu, Jeroen Meersmans

PII: S0048-9697(20)37828-1

DOI: https://doi.org/10.1016/j.scitotenv.2020.144297

Reference: STOTEN 144297

To appear in: *Science of the Total Environment*

Received date: 5 September 2020

Revised date: 26 November 2020

Accepted date: 29 November 2020

Please cite this article as: J. Peng, H. Jiang, Q. Liu, et al., Human activity vs. climate change: Distinguishing dominant drivers on LAI dynamics in karst region of southwest China, *Science of the Total Environment* (2020), https://doi.org/10.1016/j.scitotenv.2020.144297

Human activity vs. climate change: Distinguishing dominant drivers on LAI dynamics in karst region of southwest China

Jian Peng[a,*], Hong Jiang[b], Qinghua Liu[b], Sophie M. Green[c], Timothy A. Quine[c], Hongyan Liu[a], Sijing Qiu[a], Yanxu Liu[d], Jeroen Meersmans[e]

[a] Laboratory for Earth Surface Processes, Ministry of Education, College of Urban and Environmental Sciences, Peking University, Beijing 100871, China

[b] Key Laboratory for Environmental and Urban Sciences, School of Urban Planning & Design, Shenzhen Graduate School, Peking University, Shenzhen 518055, China

[c] Geography, CLES, University of Exeter, Exeter EX4 4SB, United Kingdom

[d] State Key Laboratory of Earth Surface Processes and Resource Ecology, Faculty of Geographical Science, Beijing Normal University, Beijing, 100875, China

[e] TERRA Teaching and Research Centre, Gembloux Agro-Bio Tech, University of Liège, Gembloux 5030, Belgium

Abstract: Studying the impacts of climate change and human activities on vegetation is of great significance to the sustainable development of terrestrial ecosystems. However, most studies focus on the overall impact over a period of time and only a very few studies have examined the time-lag effect of vegetation's response to climate factors when determining the driving mechanisms of vegetation dynamics. In this study, we identified key areas driven by either positive or negative human activities and climate change. Taking the three karst provinces of southwest China as study area, a Leaf Area Index (LAI) - climate model was constructed by quantifying the time-lag effect. Subsequently the associated residual threshold was calculated to identify the vegetation change areas dominated by human activities and climate change. The results show that, during the implementation period of ecological restoration projects from 1999 to 2015, dominant impact areas of human activities present a spatial clustering. Positive impact areas of human activities are mainly distributed among the implementation areas of ecological restoration projects, accounting for 5.61% of the total area, while decreasing since 2012. For another, the negative impact areas are mainly distributed across the mountainous area of Yunnan province, accounting for 1.30% of the total area. Karst landforms are having the greatest influence on the areas dominated by positive human activities, whereas both topography and karst landform both affect significantly the areas dominated by negative human activities. The degree of urban development has the greatest impact on the regions dominated by climate change. In the present study we were able to delineate vegetation dynamics zones. Moreover, by assessing the importance of different factors, the influences of social and natural factors on the zoning were determined. Hence, the outcome of this study provides scientific support for the sustainable development of ecological restoration projects.

Keywords: Vegetation dynamics; Dominant impact factors; Climate change; Human activities; Karst region; Residual threshold

1 Introduction

Vegetation, as an important part of terrestrial ecosystems and the natural link between soil, water and the environment, is very sensitive to global environmental change (Lunetta et al., 2006; Solomon and Shugart, 1993). Vegetation dynamics are not only representing the dynamic characteristics of terrestrial ecosystem, but also reflect the change of the environment (Reed et al., 1993). Hence, changes in environmental factors such as climate and human activities can both affect vegetation dynamics (Brandt et al., 2017; Mendoza-Ponce et al., 2018). This is particular true as many recent studies underline the importance of climate change affecting, the structure and function of vegetation

(Gottfried et al., 2012; Kruhlov et al., 2018; Zeng et al., 2018). Moreover, intensified human activities are also having a crucial impact on vegetation dynamics, including large-scale artificial surface construction on the urban scale and the change in ecosystem structure at the regional scale, which threatening the regional ecological security (Hao et al., 2018; Pricope et al., 2013). Many countries around the world have implemented ecological restoration projects, which have made great contributions towards vegetation restoration (Peng et al., 2019; Heilmayr et al., 2020). As a consequence, many studies have focused on the impacts of these projects and climate change (Chen et al., 2014; Robinson et al., 2018) and made an attempt to separate the impacts of both key factors (Jiang et al., 2020; Zhou et al., 2018).

Although many studies have explored the separation of the two factors, the methods used have some limitations. For one thing, the commonly used residual trend analysis method, which represent the impacts of factors other than climate change by analyzing residuals' trend in vegetation dynamics (Evans and Geerken, 2004; Jiang et al., 2017; Li et al., 2012), can only identify the overall residual trend within the study period, and cannot identify the inter-annual fluctuation of the impact of human activities on vegetation dynamics. In order to solve this problem, we propose a new method in this study. For another, an increasing number of studies have found that the response of vegetation to climate has a time-lag effect (Davis, 1989; Vicente-Serrano et al., 2013), because the water and heat conditions will not only affect the current but also the future vegetation dynamics (Chen et al., 2014; Kuzyakov and Gavrichkova, 2010). However, few studies have considered the time-lag effect of vegetation's response to climate change, which increases the uncertainty of the associated research outcomes (Peng et al., 2013; Zhang et al., 2016). Therefore, we take time-lag effect into account when constructing LAI-climate model to obtain a more accurate model.

Yunnan, Guizhou and Guangxi Provinces have received a lot of attention since eighty-two percent of China's karst landforms are located here, which are all characterized by fragile environment, broken high topographical complexity (including steep mountain topography) and poor soil conditions (Jiang et al., 2014). As a consequence of early agricultural activities, serious land degradation and extensive ecological problems have occurred in this region (Qiu et al., 2020; Wang et al., 2004). To tackle this problem China has undertaken large-scale ecological restoration projects, contributing to the greening of China (Chen et al., 2019; Deng et al., 2017; Tong et al., 2017). In order to reverse the ecological degradation across the karst region of southwest China, the government has set-up projects to control rocky desertification. This has improved the vegetation coverage and alleviated the deterioration of ecological environments through measures such as the Grain-to-Green Program and the Natural Forest Protection (Brandt et al., 2018; Liu et al., 2014). At the same time, rapid urbanization (since 2000) of large areas of vegetation have been transformed into construction land, which had a negative impact on the regional vegetation growth. Hence, as a consequence of the combined impacts of climate change, urbanization and ecological restoration projects, vegetation dynamics in the karst region of southwest China showed significant spatial differences (Tong et al., 2018). Although it is crucial to explore the dominant factors driving these vegetation dynamics, ecological restoration projects are rarely based on the identification of these dominant factors, either caused by human activities or climate change (Zheng et al., 2019).

LAI (Leaf Area Index) has been widely considered as an important indicator in order to quantify the effectiveness of ecological restoration projects across forest ecosystems (Tong et al., 2018; Zhu et al., 2016), and is impacted by climate change, human positive and negative impacts. Climate change affects vegetation growth by changing water and heat condition, thus affecting LAI (Nemani et al., 2003; Ciais et al., 2005). Specifically, at the individual plant level, temperature and precipitation affect plant growth processes (e.g. photosynthesis, respiration, etc.), resulting in changes in LAI. At the plant community level, climatic conditions affect the vegetation structure (e.g. dry conditions may make the plant composition of the community become drier, thus causing changes in LAI). "Human positive impact" is caused by the implementation of ecological restoration projects, which promote vegetation restoration through measures such as "closing hill for afforestation" and "Grain-for-Green" projects. Human negative impact refers to the impact of vegetation degradation caused by urbanization, reclamation, etc. The objective of this study is to (i) characterize vegetation dynamics with long LAI sequences obtained from remote sensing data, (ii) identify the dominant impact factors of vegetation dynamics using the newly proposed residual threshold method, and (iii) explore how various natural and social factors determine the spatial distribution of the dominant factors of vegetation dynamics. The results of this study can provide support for evaluation and implementation of ecological restoration projects. For areas dominated by negative impact of human activities, governance may be needed. For areas where the impact of human activities changed from positive to negative, focus attention and governance should be placed to curb this change. What's more, to cope with the risks of climate change, projects to address climate change should be carried out in the vegetation degradation dominated by climate change.

2 Study area and data sources

2.1 Study area

Yunnan, Guizhou and Guangxi provinces located in Southwest China were chosen as study area, of which 38.6% of the area is karst, (i.e. 0.3 million km^2 accounting for 82% of the total karst landform area in China). The vegetation coverage of the study area is high with a proportion of forest land and grassland equaling to 76.4%, whereas construction land covers only a small part (i.e. 1.3%) (Fig. 1). The altitude declines from west to east, with a mean of 1275m. The study area is dominated by subtropical monsoon climate, with an average annual precipitation of 1021 mm and an average annual temperature of 17.6℃ (Tong et al., 2017) and is characterized by a high vegetation type diversity of evergreen species (Wang et al., 2008). However, serious land degradation problems were reported, because inappropriate land management decisions across the fragile ecological environment of the karst region triggered the degradation of vegetation and soil, causing rocky landscapes and threatening the sustainable development of the region (Wang et al., 2004; Zhao and Hou, 2019). The government initiated the "Grain-for-Green" project in 1999, the regional ecological environment significantly improved as a result of the increase in vegetation growth and coverage (Tong et al., 2018).

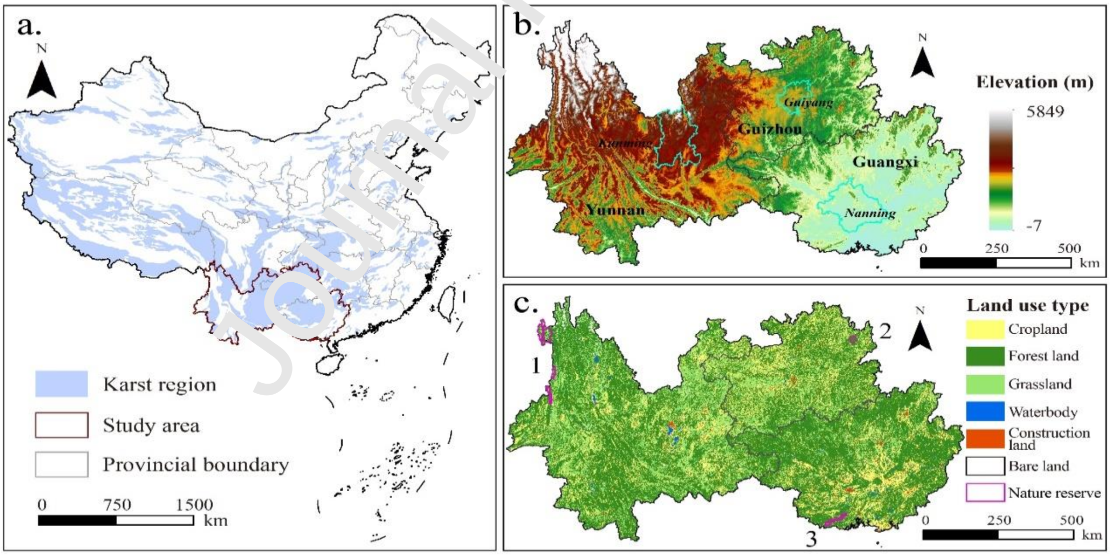


Fig. 1. Geographical location and information of the study area. (a) Location of the study area in China and distribution of karst landforms in the study area. (b) Elevation of the study area. (c) Land use map and location of three nature reserves (1. Gaoligong mountain national nature reserve in Yunnan province (established in 1983), 2. Fanjing mountain national nature reserve in Guizhou

Province (established in 1978), 3. Shiwandashan Mountain National Natural Reserve in Guangxi province (established in 1982)).

2.2 Data and processing

The following datasets are used in this paper and were transformed into Albers equal area projection (Snyder and Voxland, 1989).

(1) Global Land Surface Satellite (GLASS) LAI data products from Beijing normal university (http://glass-product.bnu.edu.cn/) from 1983 to 2015 with spatial resolution of 0.05° in order to characterize the surface vegetation cover condition; Average annual LAI is used to represent yearly growth state of vegetation;

(2) Monthly temperature and precipitation data covering the period from October 1982 to December 2015 obtained from the China meteorological data service center (http://data.cma.cn/) was rasterized after applying the commonly used kriging interpolation technique (Jeffrey et al., 2001; Tong et al., 2017);

(3) DEM data, from Geospatial data clouds (http://www.gscloud.cn/) to create slope maps;

(4) Geological data from the Institute of Karst Geology, Chinese Academy of Geological Sciences to map karst landform data;

(5) Inter-annually adjusted nighttime light data from NOAA (http://ngdc.noaa.gov/) between 1999 and 2012;

(6) Land use type data, from Resource and environment data cloud platform (http://www.resdc.cn/).

3 Methods

3.1 Research framework

The Grain-to-Green project was implemented by the Chinese government from 1999 (Naeem et al., 2020). Before this, the urbanization level in the study area was quite low. The main causes of ecological problems are the complex terrain, the widespread distribution of karst landform, and the poor soil conditions. Human activities were mainly long-term agricultural behaviors, which have little impact on vegetation dynamics (Wang et al., 2019). Therefore, from 1983 to 1998, anthropogenic activities in this area were weak. Vegetation dynamics in the study area were mainly impacted by climate change. From 1999 to 2015, due to the acceleration of urbanization and the implementation of large-scale ecological restoration projects, human activities significantly enhanced, which became the main impact factor of vegetation dynamics in some areas (Delang & Yuan, 2015). To separate the impacts of climate change and human activities on vegetation dynamics, we divide the whole research period into two parts, i.e.

(1) The reference period from 1983 to 1998. Vegetation dynamics are almost affected by climate change. We construct the multiple regression LAI-climate models.

(2) The experimental period from 1999 to 2015. Vegetation dynamics are affected by climate change and human activities. We use the LAI-climate models to analyze the impacts of climate change and human activities on vegetation dynamics.

The research process includes four parts, which are carried out according to the flow presented in Fig. 2, i.e.

(1) The quantification of the time-lag effect.

The response of LAI to climate factors in the study area has a time-lag effect (Wu et al., 2015). In order to ensure the scientific establishment of LAI-climate model, the time-lag effect is firstly analyzed, which is used to modify the climate factors in the model.

(2) The specification of the LAI-climate model.

Due to the existence of spatial heterogeneity, climate factors of different grids may have different impacts on vegetation (Piao et al., 2019; Zhu et al., 2016). So, we construct the model in a spatial explicit format, i.e. raster-based.

(3) The identification of the dominant factor of vegetation dynamics.

By comparing the LAI residuals corresponding to the reference period and the experimental period, a threshold value was obtained based on the mean and standard deviation of residuals considering the reference period. Subsequently, the residuals were analyzed to identify the dominant factors of LAI dynamics.

(4) The assessment of the impact of topography, landform and urban development on the zoning results of dominant impact factors of LAI dynamics.

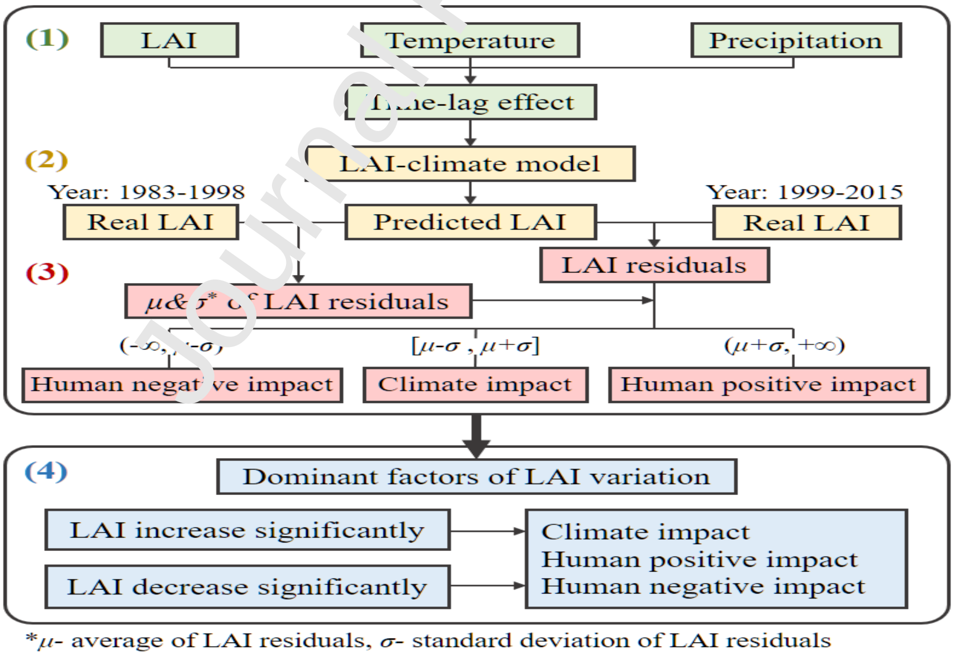


Fig. 2. Research framework.

3.2 Time-lag effect quantification

Climate change mainly affects the vegetation growth of terrestrial ecosystems through temperature and precipitation (Ye et al., 2019), but this is characterized by a time-lag effect. Due to the existence of the spatial heterogeneity in environmental and climatological factors, this time-lag effect differs depending on latitude. For example, Wu et al. (2015) showed that the correlation between vegetation growth and temperature for a given month is the highest in mid- to high latitudes (i.e. 30°N - 90°N, 30°S - 90°S), whereas there is a clear time-lag effect between vegetation growth and temperature in the low latitudes (30° S - 30 °N), which is often more than one month. Recent studies have shown that varying time-lags also exists between precipitation and water uptake by trees at mid and high latitudes (Juhlke et al.,2021). Furthermore, studies have shown that Normalized Difference Vegetation Index (NDVI) was strongest correlated with the cumulative precipitation of the current as well as two previous months (Herrmann et al., 2005; Nicholson et al., 1990), indicating the existence of a time-lag effect of climate factors on vegetation productivity between zero and three months. In the present study, we quantify the time-lag effect defined as follow:

$$Temp_{lag-n}^{i} = \frac{Temp_i + Temp_{i-1} + \cdots + Temp_{i-n}}{n+1} \quad (1)$$

$$Pre_{lag-n}^{i} = \frac{Pre_i + Pre_{i-1} + \cdots + Pre_{i-n}}{n+1} \quad (2)$$

where $Temp_{lag-n}^{i}$ and Pre_{lag-n}^{i} refer to the time-lagged temperature and precipitation data, calculated as the mean value of temperature or precipitation of the current month and the *n* previous months; $Temp_i$ and Pre_i refer to temperature and precipitation of the i^{th} month.

The average LAI and the corresponding time-lagged data of climate factors of each month from 1983 to 1998 are linearly fitted. From this analysis the optimal fitting results are used to determine the time-lag effect of the corresponding climate factors.

3.3 LAI-climate model specification

The LAI-climate model is constructed under the assumption of natural conditions without human activities, allowing the model to make LAI prediction considering only climatic factors. In order to do so, firstly, a surface trend of LAI is calculated by applying a linear regression filter to reflect the spatial and temporal patterns of vegetation. More precisely, the associated slope of the linear regression is calculated in each grid cell as follow:

$$slope = \frac{n \times \sum_{i=1}^{n} i \times L_i - \sum_{i=1}^{n} i \sum_{i=1}^{n} L_i}{n \times \sum_{i=1}^{n} i^2 - \left(\sum_{i=1}^{n} i\right)^2} \quad (3)$$

where *slope* refers to the trend in annual average LAI; L_i represents LAI of the i^{th} year, n refers to the length of the time series; *i* refers to the number of the year. Hence, when the slope is greater than 0, the annual average LAI shows an increasing trend.

Before establishing a LAI-climate model that can be used to predict climate factors dominated LAI, it is necessary to determine the correlation between LAI and climate factors. Hence, in the present study partial correlation coefficients were calculated in order to analyze the correlation between temperature, precipitation and LAI. The significance of the partial correlation coefficients was tested by using *t* statistics. Taking temperature as an example, the partial correlation coefficient between LAI and temperature is defined as follow:

$$r_{LAI—Temp} = \frac{r_{LAI \cdot temp} - r_{LAI \cdot pre} \cdot r_{temp \cdot pre}}{\sqrt{1 - r_{LAI \cdot pre}^2}\sqrt{1 - r_{temp \cdot pre}^2}} \quad (4)$$

Through multiple linear regression of LAI and time-lagged climate data from 1983 to 1998, gridded LAI-climate model is established:

$$LAI(i,j) = a_i \times TEMP(i,j) + b_i \times PRE(i,j) + c_i \quad (5)$$

where i refers to the i^{th} grid cell; j refers to the j^{th} month; a_i and b_i are the multiple linear regression slope coefficients of temperature and precipitation, respectively; c_i is a constant. The resulting R^2 – values and associated levels of significance (i.e. p-value) of each grid-cell are used to evaluate the overall performance of the model.

3.4 Residual threshold analysis

The results of the presented residual trend analysis method reflect the trend of the impact of human activities on vegetation throughout the study period (Yan et al., 2020; Wu et al., 2020). At the same time, it is difficult to identify the impact of human activities within a relatively short period of time. To solve this problem, we analyzed the distribution of LAI residuals, and found that the residuals tend to be normally distributed, which supports the validity to apply the residuals threshold method. The method consists of three main steps, i.e. (i) calculating the LAI residual, (ii) demarcating the LAI residual threshold, and (iii) identifying the dominant impact area of LAI dynamics.

First, according to the LAI-climate model, the predicted LAI not affected by human activities (under ideal conditions) is calculated as follow:

$$LAI_{pre}(i) = a_i \times TEMP(i,j) + b_i \times PRE(i,j) + c_i \quad (6)$$

where i refers to the i^{th} grid cell; j refers to the j^{th} month, LAI_{pre} refers to LAI obtained by the LAI-climate model; $TEMP$ and PRE represent temperature and precipitation, respectively.

Taking the GLASS LAI data as the real LAI under the impact of climate and human activities, we name it LAI_{real}. Therefore, the residual of LAI can be defined as follow:

$$LAI_{residual} = LAI_{real} - LAI_{pre} \quad (7)$$

LAI residuals represent the impact of factors other than climate, including human activities and other environmental factors. In this study, the impacts of these environmental factors are considered as random errors, so the residuals of LAI values corresponding to the period 1983 to 1998 are theoretically distributed following a normal distribution. The distributions of residuals in each grid cell are different due to the difference in soil conditions across the study area. For each grid cell, the sequence of monthly LAI residuals is obtained, and the mean and standard deviation are calculated in order to verify whether the residuals conform to the theoretical normal distribution.

To explore the distribution of LAI residuals of the time window 1983 to 1998, we have used ranges corresponding to 0.5, 1, 1.5 and 2 times the standard deviation. Without the impact of human activities, the residual distribution is within the range of *n* (equals to 0.5, 1.0, 1.5 or 2.0) times the standard deviation of the average value. However, with the impacts of human activities, LAI residuals for units affected by human activities jump out of the range. The associated mean and standard deviation values of LAI residual from 1983 to 1998 in the corresponding grid cells are denoted by μ and σ respectively. The annual mean residuals of LAI from 1999 to 2015 are used to identify the areas in which climate change or human activities significantly impact according to the following formula:

$$Factor_{domin} = \begin{cases} human\ \ activity(negative)\ LAI_{residual} < \mu - \mathrm{n} * \sigma \\ \ \ climate \qquad\qquad\quad \mu - \mathrm{n} * \sigma < LAI_{residual} < \mu + \mathrm{n} * \sigma \\ human\ activity(positive)\ \ LAI_{residual} > \mu + \mathrm{n} * \sigma \end{cases} \quad (8)$$

For each grid, if the LAI residual falls within the range (i) (μ+n*σ, +∞), it is identified as a positive impact area of human activities, (ii) (-∞, μ-n*σ), it is identified as a negative impact area of human activities. (iii) [μ-n*σ, μ+n*σ], it is identified as a climate impact area.

3.5 Geographical Detector

In order to explore the effects of natural and socio-economic factors, the geographical detector approach developed by Wang et al. (2010) is applied. This allows us to detect the spatial heterogeneity of the driving forces behind these effects (Ran et al., 2019). The risk detector identifies whether there are significant differences among the independent variables and across the different layers as well as associated t statistic tests, whereas the factor detector identifies the spatial structure of the dependent variable (Eq. 9), and the degree to which the independent variable explains the dependent variable. By combining the two results (i.e. risk detector and factor detector), we can analyze the influence mechanism of different social and natural factors on human activities and climate.

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} = 1 - \frac{SSW}{SST} \quad (9)$$

$$SSW = \sum_{h=1}^{L} N_h \, \sigma_h^2 \quad (10)$$

$$SST = N\sigma^2 \quad (11)$$

where h refers to the number of layers in which the independent variable is located; N_h and N refer to the number of cells in layer h across the whole region, respectively; σ_h^2 and σ^2 represent the variance of layer h and the whole region, respectively. q refers to the degree to which the independent variable explains the dependent variable, ranging between 0 and 1 (i.e. the closer q is to 1, the stronger the independent variable explains the dependent variable. The closer q is to 0, the weaker the independent variable explains the dependent variable).

Taking county-level administrative regions as the research unit, 295 county units are divided into five levels according to the equal-division method, which includes topography, landform and urban development speed. Since slope affects the way and intensity of land use by humans, the average slope of the research unit is used to characterize the influence of the topography factor, with a five-level grading standard of 0.21º - 2.86º, 2.86º - 4.00º, 4.00º - 5.14º, 5.14º - 7.09º, 7.09º - 15.87º corresponding to level I to V, respectively. The distribution of karst landform affects the vulnerability of the ecological environment. Since karst landform is characterized by broken landform and poor soil, and rocky desertification problems are easy to occur. Therefore, karst regions are the key implementation areas of ecological restoration projects. At the same time, vegetation growth is also affected by karst landform due to the difference in vegetation structure and growth process between karst and non-karst landforms. To explore whether the positive impact of human activities more significant in areas with a higher proportion of karst landforms, the landform zones of level I to V are respectively set as 0% - 6.26%, 6.26% - 26.29%, 26.29% - 53.32%, 53.32% - 73.73%, 73.73% - 100%, according to the proportion of karst landform area. The speed of urban development affects the intensity of human activities and also the regional climate. Using the average growth amount of nighttime light intensity, urban development zones of level I to V are 0.07 - 0.66, 0.66 - 1.41, 1.41 - 2.10, 2.10 - 3.58, 3.58 - 20.31, respectively. The grades of three indicators are taken as independent variables, whereas the dependent variables are the area of “positive impact of human activities”, “negative impact of human activities” and “impact of climate change”.

4 Results

4.1 Time-lag effect in Yunnan, Guizhou and Guangxi provinces

The results of time-lag effect analysis show that the fitting of LAI with temperature and precipitation data is optimal with a two-month time-lag (Table 1), which is consistent with the results of existing studies (Herrmann et al., 2005; Wu et al., 2015). Therefore, we use the climate factors with a lag effect of 2 months to calculate climate dominated LAI.

Table 1. Correlation between LAI and time-lagged climate factors.

R^2	0 month	1 months	2 months	3 months
Temperature	0.75	0.91	0.94	0.85
Precipitation	0.57	0.74	0.80	0.67

4.2 LAI trends

Trend analysis shows that the dynamics trend of LAI in the study area presents significant spatial heterogeneity, and there is an obvious difference between the reference period and the experimental period. During the reference period (i.e. between 1983 and 1998), there is no significant change in LAI in 87.11% of the region. 9.74% of the area shows a significant increasing trend, mainly distributed in Yunnan province with high vegetation coverage. 3.16% has a significantly decreasing trend and seems to be rather randomly scattered across the entire study area, but mainly in Guizhou and Guangxi (Fig. 3a). During the experimental period, the area characterized by a significant changing trend increased from 12.89% to 23.18%, of which 12.48% with an increasing trend and 10.70% with a decreasing trend (Fig. 3b). Moreover, the spatial distribution of significantly increased areas changed considerably over times with many more regions across the border of three provinces as well as in the southern part of Yunnan province, which may be the result of human activities. Hence, this result indicates that from 1999 to 2015, climate change, urbanization and ecological restoration projects together led to drastic changes in vegetation dynamics.

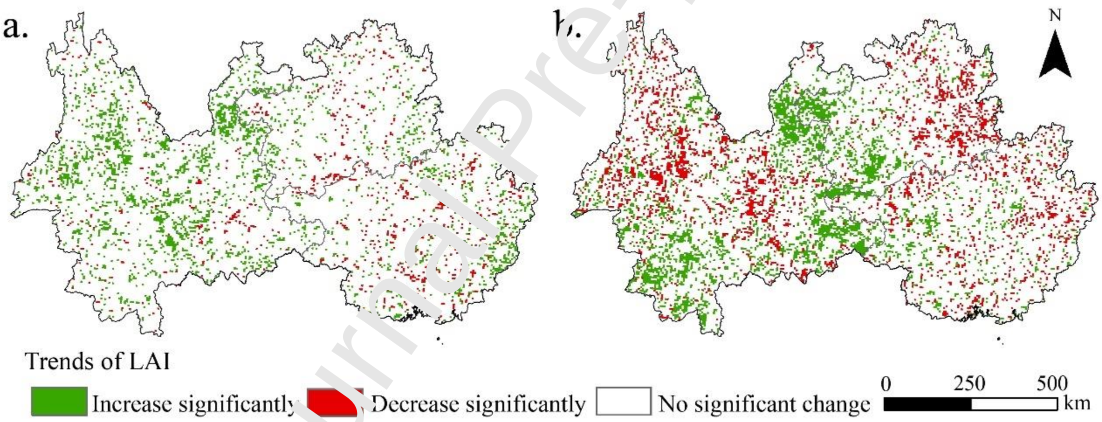


Fig. 3. Vegetation trends for different periods based on yearly average LAI time series. (a)1983 -1998. (b)1999 - 2015.

4.3 LAI-climate model

The partial correlation degree between LAI and temperature gradually decreases from east to west, and the correlation coefficient in most areas is positive and higher than 0.25 (Fig. 4a). The correlation between LAI and precipitation shows a distribution with generally higher values in the west and lower values in the east due to the land and sea location (Fig. 4b). The results of the significance test show that (i) the southwestern part of the study area is only significantly influenced by precipitation, (ii) the west part is only significantly influenced by temperature and (iii) the central part is significantly influenced by both temperature and precipitation (Fig. 4c, d). While the central and southern regions of Yunnan province have low latitude and abundant heat, so LAI is more sensitive to changes in precipitation.

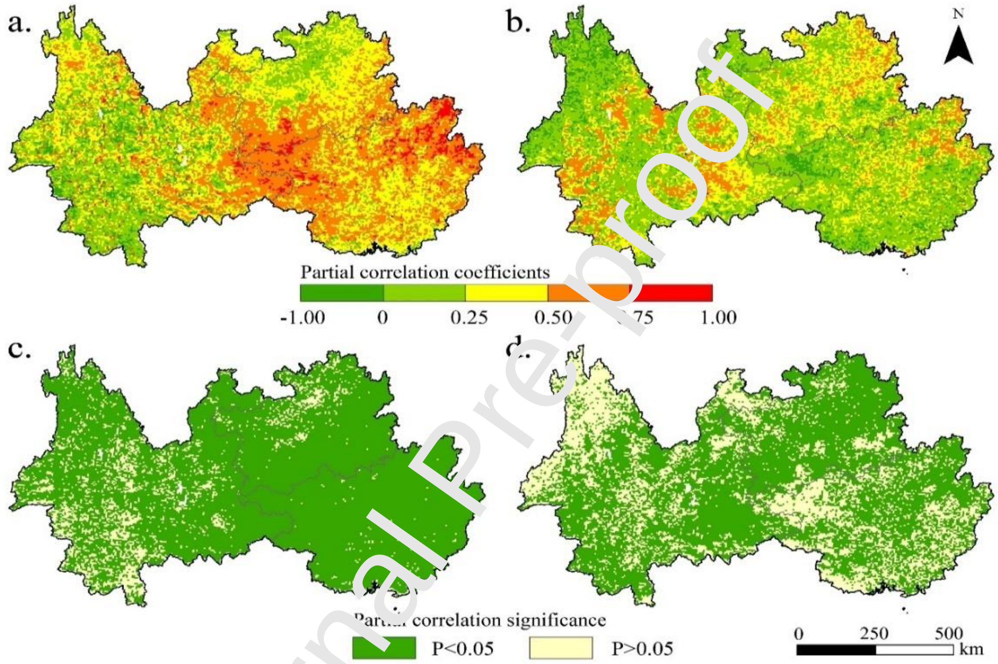


Fig. 4. Partial correlation analysis results of LAI and climate factors for the period of 1983 - 1998. (a) Partial correlation coefficients of LAI and temperature. (b) Partial correlation coefficients of LAI and precipitation. (c) P value of LAI and temperature. (d) P value of LAI and precipitation.

From 1983 to 1998, LAI in the study area is jointly affected by two climate factors, namely, temperature and precipitation, so a LAI-climate model can be constructed at the grid level. The model is typically characterized by R^2 values above 0.6 in most of the regions. However, the goodness of fit in central and western Yunnan is lower, but basically higher than an R^2 value of 0.2 (Fig. 5). In general, the LAI-climate models in most areas of the study area have a high degree of goodness of fit and pass the significance test (i.e. 99.14% of the regions in the study area passed the significance test), indicating that the proposed approach is reliable.

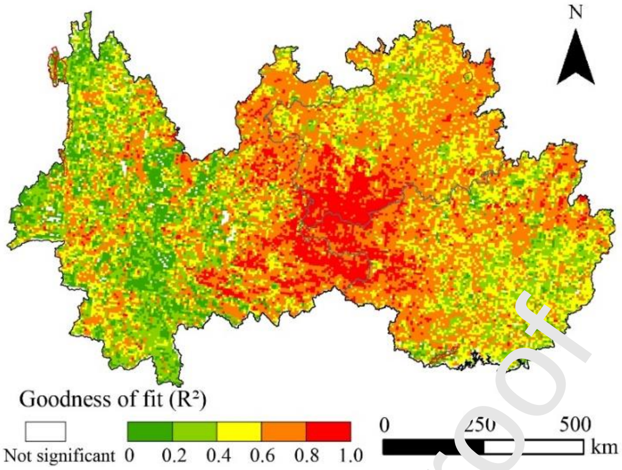


Fig. 5. Goodness of LAI-Climate Model (At the significance level of 0.05).

4.4 Spatial distribution of dominant factors

Time-lagged temperature and precipitation data from 1983 to 2015 are used to fit the LAI-climate model and obtain a LAI prediction considering the impact of climate factors. Fig. 6 compares the real LAI and predicted LAI values on a monthly basis. The predicted LAI before January 1999 is basically consistent with the real LAI, however since January 1999, the predicted value and the real value began to show a much larger deviation.

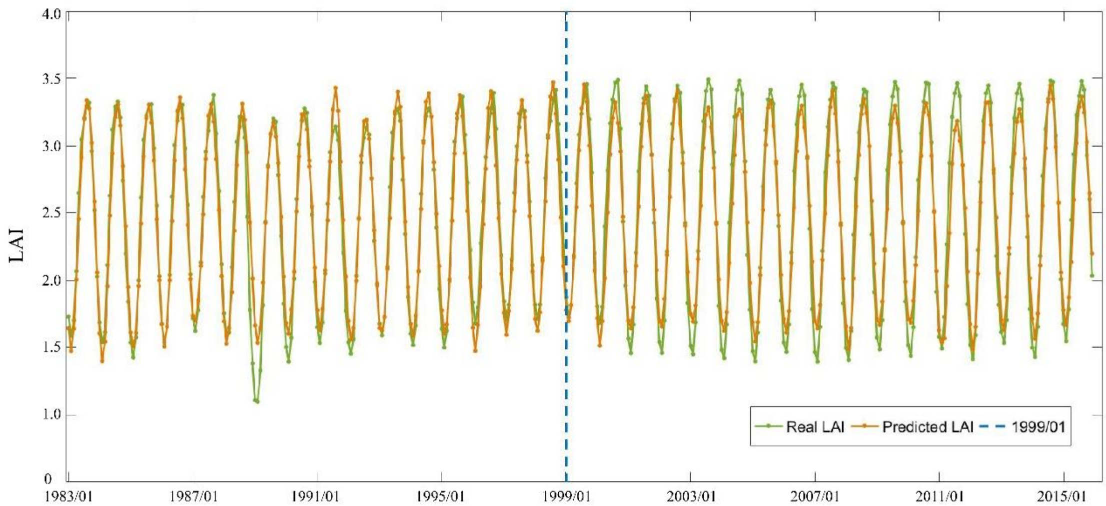


Fig. 6. Average of real LAI and predicted LAI of each month for the period of 1983 - 2015.

When verifying whether LAI residuals from 1983 to 1998 care normally distributed, the results confirm that 82.54% of pixels are subject to normal distribution (Fig. 7a). The pixels which do not follow a normal distribution are scattered in the research area without obvious spatial clusters. By comparing the potential using of 0.5, 1, and 2 times the standard deviation in order to identify residuals and the impact of human activities, it is found that 1 times standard deviation performed best. For each pixel, the proportion of residual distribution within one standard deviation is found to be within the range of 60% to 80% (Fig. 7b). Therefore, one standard deviation above and below the average are used as the threshold for residual analysis, which means *n* in Eq. (9) is equal to 1. Based on this, the dominant impact areas of human activities and climate change are identified (Fig. 8a). In 1999, there are no obvious spatial clusters or patterns of impact areas dominated by human activities, which is probably due to the fact that the ecological restoration projects were still in an early stage. Since 2000, the impact area of human activities begins to appear, and by 2004, it has formed a relatively obvious and stable impact area of human activities. Positive impact of human activities mainly distributes at the junction of the three provinces, while negative impact is mainly distributed in the central and western parts of Yunnan province. In order to verify the accuracy of the results, we selected a large-scale nature reserve in each province (Fig. 1), and the results show that the LAI in the three nature reserves have been dominated by climate impact. The spatial distribution and area ratio of the dominant factors were analyzed (Fig. 8b). Since the beginning of the ecological restoration projects in 1999, the positive and negative impact areas of human activities in the study area have shown an overall increasing trend. Since 2012, the area affected by positive human activities has been significantly reduced, indicating that the benefits of ecological restoration projects have begun to weaken.

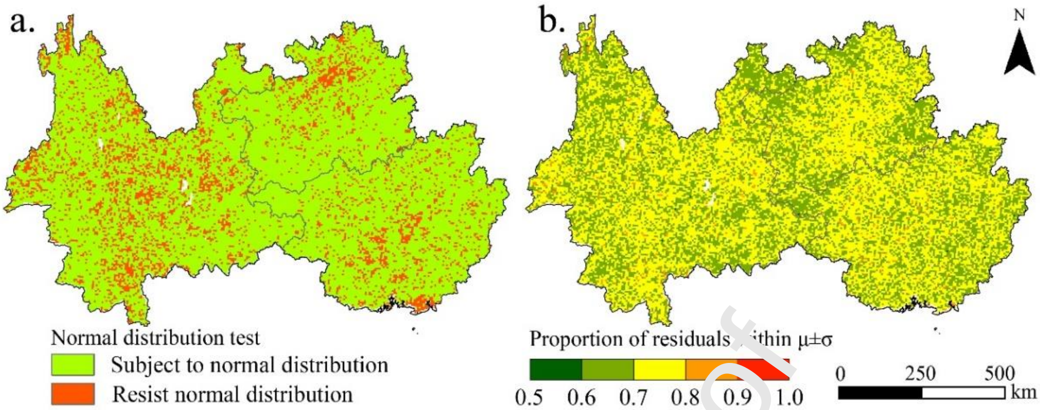


Fig. 7. Residual threshold analysis. (a) Result of normal distribution test. (b)Proportion of residuals within [μ-σ, μ+σ].

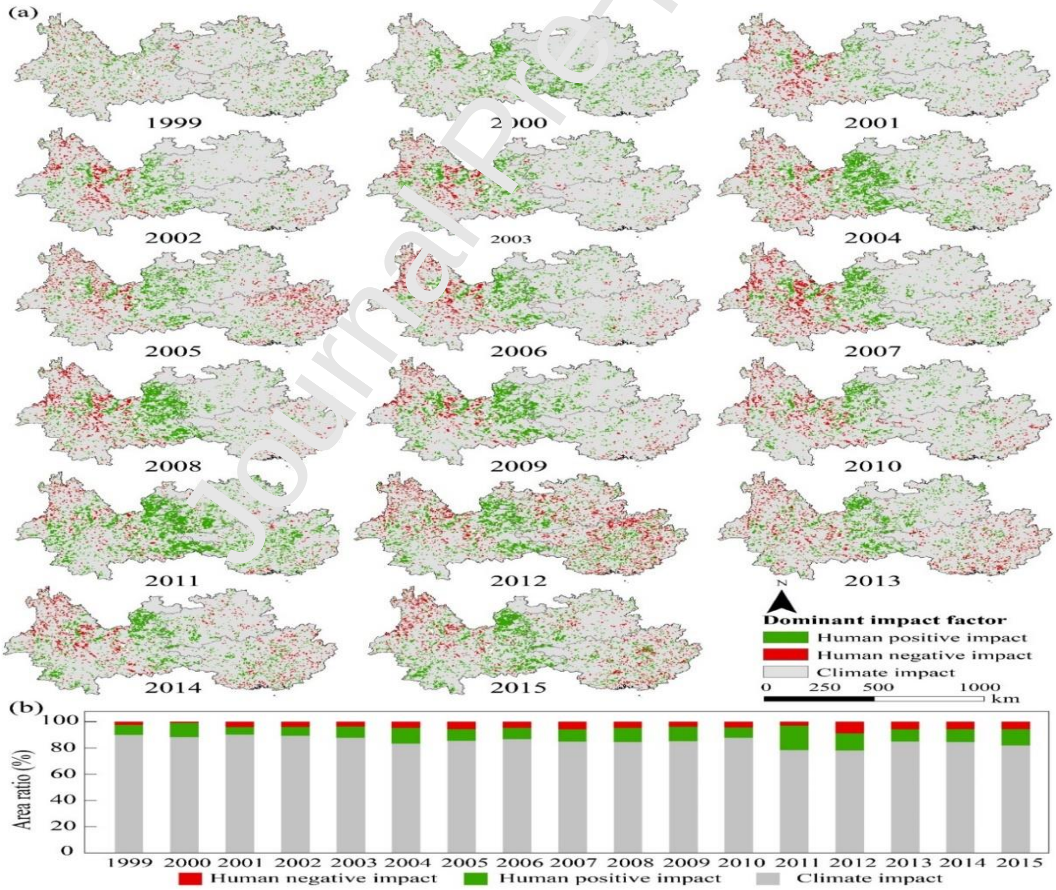


Fig. 8. Spatial distribution (a) and area ratio (b) of dominant factors of LAI dynamics from 1999 to 2015.

In order to analyze the leading factors of vegetation dynamics as a whole, comprehensive leading factors of LAI dynamics from 1999 to 2015 were identified (Fig. 9a). The proportions of area under the positive impact of human activities, negative impact of human activities and climate impact are 5.61%, 1.30% and 93.09%, respectively. The spatial distribution of the affected areas is similar to the results of multi-year identification, but the affected areas of human activities significantly decrease. This is because the impact of human activities in many areas alternates between positive and negative, so the impact of human activities is not obvious, and as such climate is recognized as the dominant factor. The positive impacts of human activities are mainly distributed around the junction of the three provinces as well as parts of central and northern Yunnan, which is the key implementation area of ecological restoration projects, indicating that these projects had a significant positive effect on LAI. The negative impact areas of human activities are mainly distributed across the mountainous areas of the Yunnan province, which may be disturbed by urban development strategies such as "low-slope hilly" in Yunnan province (Liu et al., 2018).

We also superimpose the result of the identified dominant impact areas with the layer displaying significant dynamics of LAI (Fig. 9b). For the pixels characterized by significant dynamics in LAI, the error rate of dominant impact identification is 0.2% (i.e. pixels with either (i) significant increases in LAI but identified as negative impact of human activities or (ii) significant decreases in LAI but identified as positive impact of human activities). This indicates that the identification results as regards the dominant impact factors are reliable. 82.54% of the pixels with significantly increased LAI are climate-dominated, while 16.95% are positively impacted by human activities. For the pixels with significantly decreased LAI, 94.76% are climate-dominated and 3.33% are dominated by a negative impact of human activities. It can be seen that in most areas with significant dynamics of LAI, the impact of human activities is not as high as considered. Furthermore, the results show that in the mountainous areas of Yunnan province there is no significant dynamics in vegetation, despite the negative impact of human activities in this particular region. As a whole, from 1999 to 2015, the vegetation dynamics in the karst region of southwest China are mainly dominated by climate change. Dominant areas of positive impact of human activities are mainly distributed across the implementation area of ecological restoration projects near the junction of the three provinces.

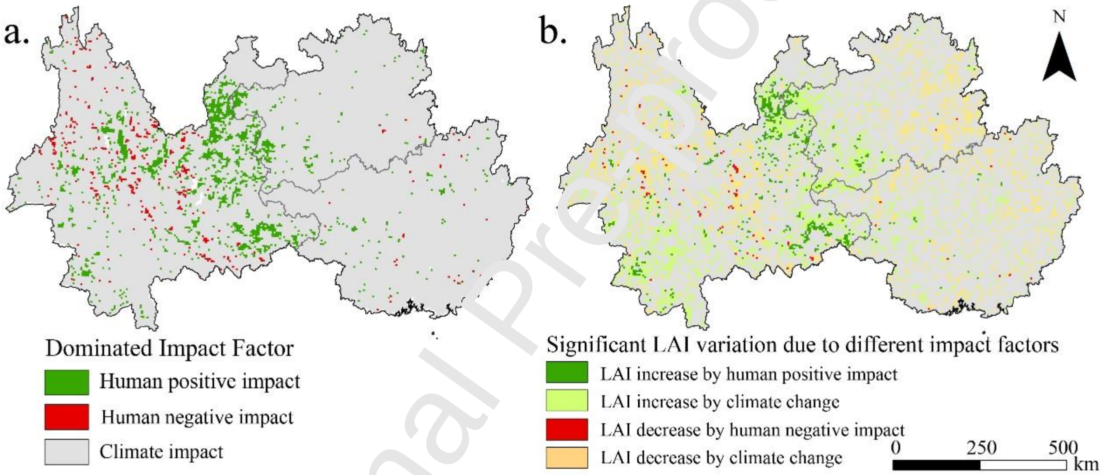


Fig. 9. (a) Spatial distribution of dominant factors of LAI dynamics for the period of 1999 - 2015. (b) Spatial distribution of significant LAI dynamics due to different factors for the period of 1999 - 2015.

5 Discussion

5.1 Influencing factors of the dominant drivers' distribution

For the areas dominated by positive impact of human activities, only landform zoning has been identified by the significance test as having a significant influence on the restoration effects due to ecological restoration projects. This is because karst landform areas are more sensitive to disturbance and therefore more prone to ecological degradation, and hence, are considered as key areas of ecological restoration projects. For the areas dominated by negative impact of human activities, the influence of topographic and landform zoning passes the significance test. More precisely, the influence degrees are significantly higher than that of urban development zoning. Human activities such as agricultural and urban construction are restricted by topography factors, and therefore, are resulting in significant spatial patterns as regards the negative disturbance of vegetation depending on the topography settings, such as slope angle. For another, the distribution of karst landform affects the degree of agricultural development, and hence, also the degree of disturbance to natural vegetation. However, for regions mainly affected by climate change, the influence of urban development passes the significance test. The latter can be explained by the fact that the overall impact of human activities is relatively weak for climate-dominated regions, resulting in a high sensitivity to the degree of urban development. At the same time, the influence of slope is also significant, because the magnitude of slope determines the intensity of soil erosion. As the slope increases, the topography gradually becomes more complex, and different topographic sections of the landscapes (defined below as a topography zoning) receive different amounts of solar radiation, causing a spatial heterogeneity in water vapor as well as supply of heat and water across the landscape (Gallardo-Cruz et al., 2009; Holland and Steyn, 1975).

Table 2. Results of the factor detector analysis. Explanatory ability of natural and social factors to the distribution of dominant factors in LAI dynamics.

	Positive human impacts			Negative human impacts			Climate change impacts		
	TZ	LZ	UDZ	TZ	LZ	UDZ	TZ	LZ	UDZ
q	0.021	0.069	0.022	0.142	0.130	0.026	0.043	0.029	0.140

p	0.189	<0.001	0.184	<0.001	<0.001	0.117	0.016	0.077	<0.001

Note: q represents the degree to which the independent variable explains the dependent variable. p represents degree of confidence. TZ: Topography zoning. LZ: Landform zoning. UDZ: Urban development zoning.

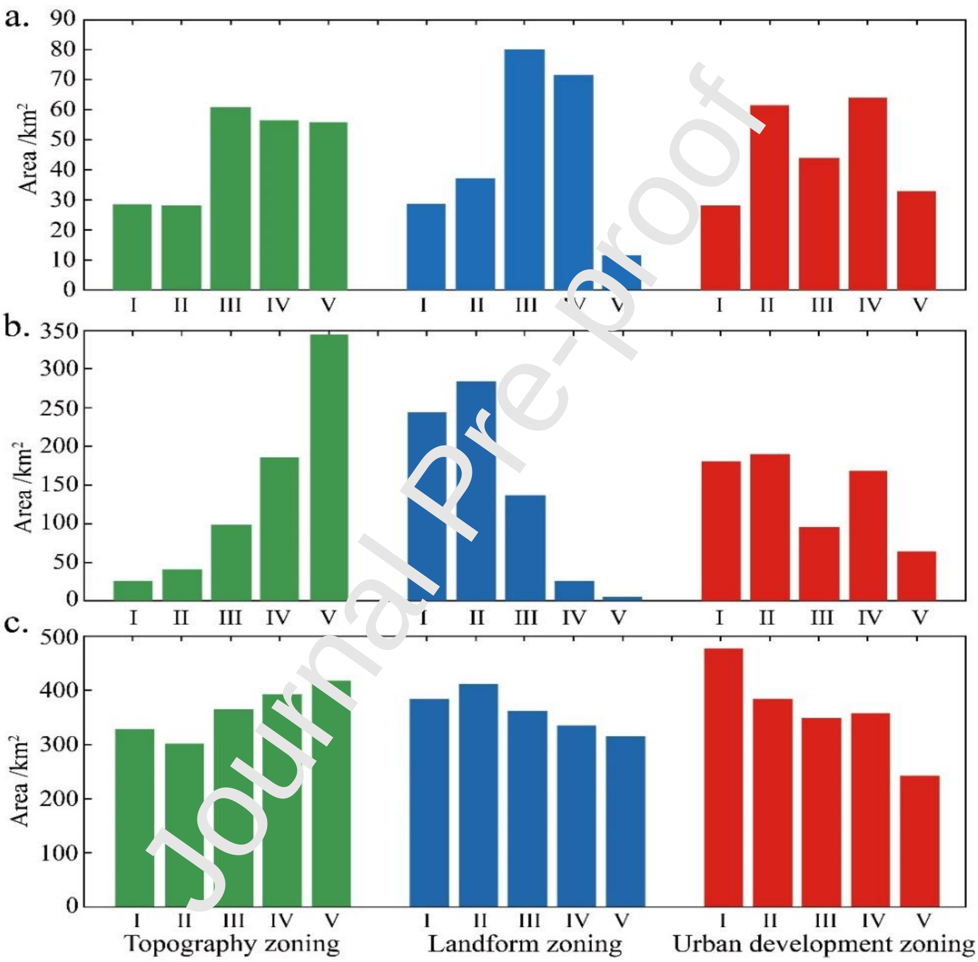


Fig. 10. Results of risk detector. (a) Average area of human positive impact in different zones. (b) Average area of human negative impact in different zones. (c) Average area of climate change impact in different zones.

According to the results of the risk detector analysis, the positive impact area of human activities (i.e. landform zones are III and IV) is significantly larger, indicating that the vegetation restoration effect is optimal when the relative spatial proportion of karst landform is between 26.29% and 73.73% (Fig. 10). However, it is important to recognize that it is difficult to restore ecology in the area characterized by a large proportion of karst landform, in particular when considering a short period time. When considering the negative impact of human activities, the area increases with increasing slope angle and decreases with increasing relative proportion of karst landform. This is because the range of average slopes in the research unit is between 0.21º and 15.87º, which is generally suitable for human activities. When the slope angle exceeds this range, human activities are more intense and will have a strong negative impact on vegetation. However, these steep sloped areas are less suitable for human activities. Moreover, the area characterized by a high proportion of karst landform tend to have more serious ecological problems, which means that these areas are also less suitable for human activities. As mentioned above, the latter areas are considered as key areas for the implementation of ecological restoration projects, with the objective to control the negative impact on vegetation. Consequently, the negative impact area of human activities is gradually decreased. Finally, it can be noted that for the regions under the impact of climate change, the faster the city develops, the lower the impact degree of climatic factors will be.

5.2 Methodological considerations

The time-lag effect of vegetation's response to climate factors has been ignored in most current studies, however, it may cause high uncertainty (Wen et al., 2019; Ding et al., 2020). Hence, we comprehensively analyzed the results of other studies at similar latitude to our study area in order to illustrate the effect of time-lag. In essence, when the time-lag effect is ignored, the impact of climate is not correctly estimated. The most direct result is that the R^2 of vegetation-climate model is low, and part of the impact of climate change is misclassified as that of human activities, and hence, the results are biased and cannot truly reflect the distribution of dominant impact factors.

Most of the existing studies ignored the time-lag effect. Wang et al. (2015) took 114 countries (cities and districts) across Southwest China as study area, and directly used annual NDVI and annual mean values of climate factors in order to carry-out a correlation analysis. The significant increase of vegetation around the junction of the Yunnan, Guizhou and Guangxi provinces is consistent with our results. However, the coefficient of partial correlation analysis was rather low, indicating that the climate factors did not explain the vegetation development (represented by NDVI) well without considering the time-lag effect. With respect to Yunnan, Guangxi and Guizhou provinces, Tong et al. (2017) used LAI data at an 8km grid covering the period 1982 – 2011 to calculate vegetation trends. They showed a significant positive impact of human activities. Our results indicate that the impact of human activities in Guangxi was mostly positive before 2011, whereas after 2011, the negative influence began to appear, which reduced the positive influence area of human activities in the final identification results. This also reminds us to pay attention to the long-term maintenance of effects after the implementation of ecological restoration projects. Wang et al. (2008) chose eight karst provinces (cities) in southwest China as study area. Without considering the time-lag effect, the partial correlation analysis results of NDVI and NPP with climate factors were found to be insignificant. In our study, when taking time-lag effect into account, fitting R^2 of LAI with temperature and precipitation were found to be mostly significant, as ranging from 0.75 to 0.94 and from 0.57 to 0.80, respectively (Table 1). Generally speaking, as an important effect of vegetation's response to climate factors, time-lag effect has a great impact on the results through modeling LAI (Zhao et al., 2020). Therefore, the time-lag effect should be considered when analyzing vegetation dynamics in order to ensure the authenticity of the results.

Residual trend analysis is a commonly used method to identify dominant factors of vegetation dynamics. However, this method cannot truly reflect the impacts of climate change and human activities (Wu et al., 2020), nor can it analyze the inter-annual changes of such impacts. Wang et al. (2015) used the residual trend method to explore the dominant factors of vegetation dynamics in southwest China, and found that from 2000 to 2010, the residuals showed an obvious upward trend indicating that ecological restoration projects were effective. This is consistent with our results, but did not reflect the annual impact distribution. Tong et al. (2017) analyzed the dominant factors of vegetation dynamics from 2001 to 2011 using the residual trend method, and found that the positive effects of human activities were concentrated in Guangxi. In our results, before 2011, the vegetation dynamics in Guangxi was dominated by positive impact of human activities, but the subsequent negative impact of human activities, such as urban development, offset the previous positive impact. To solve the problems of residual trend method, many studies have proposed new methods. Yan et al. (2020) used the second-order partial correlation analysis model to identify the dominant factors. Wu et al. (2020) used partial derivatives to quantify the impacts of climate change and human-induced NPP dynamics. Our study provides an additional perspective to identify the dominant factors of vegetation dynamics.

Moreover, in terms of potential applications, by determining the dominant factors of vegetation dynamics, as well as their variation over a period of time, our study can support afforestation and reforestation monitoring, and integrated governance of social-ecological development. Although land use policies have significantly improved the environment and the ecosystem functions, they are not stable (Tong et al., 2020). Analyzing the spatial distribution and temporal changes of ecological restoration projects' impacts can help us find the changes and take measures on time. The first stage of ecological restoration projects began in 1999 and ended in 2007, after which the increase in vegetation cover leveled off (Brandt et al., 2018). What’s more, vegetation growth was impeded by abnormally dry years until 2011 (Brandt et al., 2018; Jiang et al., 2014), after 2011, the impact of climate change increased significantly, which replaced human activities’ positive impact as the dominant factor. Our study can help to achieve the greatest value for money, while avoiding costly and simplistic plantings by analyzing the change of ecological restoration projects’ impact (Menz et al., 2013).

5.3 Limitations and future research

In this study, we considered the time-lag effect of vegetation’s response to climate change and proposed a new residual threshold analysis method to separate climate change and human activities' impacts on vegetation dynamics in karst region of southwest China. However, there are still some limitations in this study, which may be the direction of future research. Firstly, we use kriging interpolation technique to interpolate with temperature and precipitation data from meteorological stations all over China. However, there are also some other interpolation methods that could be applied, such as Thin Plate Spline (TPS) (Hutchinson et al., 1995). Secondly, we did not further quantitatively analyze the time limitation of the ecological restoration projects' effect to come up with a concrete plan to maximize the benefits of ecological restoration projects. This may be an important direction for future research. Thirdly, based on the assumption of normal distribution, we choose n=1 to determine the threshold of LAI residuals to separate the impacts of climate change and human activities. However, the results is sensitive to the choice of n, which needs to cooperate statistical results and background knowledge together to determine. And there may be differences in the sensitivity to n in different regions. This needs to be discussed more in future researches. Finally, we do not consider the changes in plant species and the nonlinear process of vegetation's response to climate factors, especially the limitation of water. This needs a deeper discussion in the future researches.

6 Conclusions

In this study, we take the time-lag effect on vegetation's response when establishing LAI-climate model, and propose a new residual threshold analysis method to separate the impacts of climate change and human activities on vegetation dynamics across the three provinces in the karst region of southwest China. Our results indicate that the ecological restoration projects induced a significant positive impact of human activities, which promoted the growth of vegetation but this influence began to decrease from 2012 onwards. We identified that (i) dominant areas of positive impact of human activities are mainly distributed along the implementation areas of ecological restoration projects, and (ii) the dominant areas of negative impact are mainly situated in the mountainous area of Yunnan province. In the respect of influencing factors of dominant factors' distribution, it is worth noting that the relative spatial proportion of karst landform has a remarkably big influence on the spatial pattern of areas characterized by positive impact of human activities on vegetation development. However, when the proportion of karst landform exceeds 73.73%, the positive impact area of human activities significantly decreases. Therefore, the implementation of ecological engineering should be strengthened in the area where karst landform is widely distributed. The results also indicate that the positive impact of human activities brought by ecological restoration projects may be offset by the negative impact and gradually weakens over time. Hence, it is crucial to restrict human activities in zones with degraded vegetation and pay attention to the long-term implementation effects of ecological restoration projects.

Acknowledgments

This work was jointly financed by the National Science Foundation of China (Grant No. 41571130044), the National Environmental Research Council of the UK and the Newton Foundation (Grant No. NE/N007603/1 & NE/N007530/1).

References

Brandt, M., Rasmussen, K., Penuelas, J., Tian, F., Schurgers, G., Verger, A., Mertz, O., Palmer, J.R.B., Fensholt, R. (2017) Human population growth offsets climate-driven increase in woody vegetation in sub-Saharan Africa. Nature Ecology & Evolution 1, 6. https://doi.org/10.1038/s41559-017-0081.

Brandt, M., Yue, Y.M., Wigneron, J.P., Tong, X.W., Tian, F., Jepsen, M.R., Xiao, X.M., Verger, A., Mialon, A., Al-Yaari, A., Wang, K.L., Fensholt, R. (2018) Satellite-Observed Major Greening and Biomass Increase in South China Karst During Recent Decade. Earths Future 6, 1017-1028. https://doi.org/10.1029/2018EF000890

Chen, C., Park, T., Wang, X.H., et al. (2019) China and India lead in greening of the world through land-use management. Nature Sustainability 2, 122-129. https://doi.org/10.1038/s41893-019-0220-7.

Chen, T., de Jeu, R.A.M., Liu, Y.Y., van der Werf, G.R., Dolman, A.J. (2014) Using satellite based soil moisture to quantify the water driven variability in NDVI: A case study over mainland Australia. Remote Sensing of Environment 140, 330-338. https://doi.org/10.1016/j.rse.2013.08.022.

Ciais, P., Reichstein, M., Viovy, N., et al. (2005) Europe-wide reduction in primary productivity caused by the heat and drought in 2003. Nature 437, 529-533. https://doi.org/10.1038/nature03972.

Davis, M.B. (1989) Lags in vegetation response to greenhouse warming. Climatic Change 15, 75-82. https://doi.org/10.1007/BF00138846.

Delang, C.O., & Yuan, Z. (2015). China’s grain for green program. Cham: Springer International.

https://doi.org/10.1007/978-3-319-11505-4.

Deng, L., Liu, S.G., Kim, D.G., Peng, C.H., Sweeney, S., Shangguan, Z.P. (2017) Past and future carbon sequestration benefits of China's grain for green program. Global Environmental Change-Human and Policy Dimensions 47, 13-20. https://doi.org/10.1016/j.gloenvcha.2017.09.006.

Ding, Y. X., L, Z., Peng, S.Z. (2020) Global analysis of time-lag and -accumulation effects of climate on vegetation growth. International Journal of Applied Earth Observation and Geoinformation, 92, 102179. https://doi.org/10.1016/j.jag.2020.102179.

Evans, J., Geerken, R. (2004) Discrimination between climate and human-induced dryland degradation. Journal of Arid Environments 57, 535-554. https://doi.org/10.1016/S0140-1963(03)00121-6.

Gottfried, M., Pauli, H., Futschik, A. et al (2012) Continent-wide response of mountain vegetation to climate change. Nature Climate Change 2, 111-115. https://doi.org/10.1038/nclimate1329.

Hao, L., Pan, C., Fang, D., Zhang, X.Y., Zhou, D.C., Liu, P.L., Liu, Y.Q., Sun, G. (2018) Quantifying the effects of overgrazing on mountainous watershed vegetation dynamics under a changing climate. Science of the Total Environment 639, 1408-1420. https://doi.org/10.1016/j.scitotenv.2018.05.224.

Heilmayr, R., Echeverría, C., Lambin, E.F. (2020) Impacts of Chilean forest subsidies on forest cover, carbon and biodiversity. Nature sustainability, 3, 701-709. https://doi.org/10.1038/s41893-020-0547-0.

Herrmann, S.M., Anyamba, A., Tucker, C.J. (2005) Recent trends in vegetation dynamics in the African Sahel and their relationship to climate. Global Environmental Change - Human and Policy Dimensions 15, 394-404. https://doi.org/10.1016/j.gloenvcha.2005.08.004.

Hutchinson, M.F. (1995) Interpolating mean rainfall using thin plate smoothing splines. International Journal of Geographical Information Systems, 9, 385-403.

https://doi.org/10.1080/02693799508902045.

Jeffrey, S.J., Carter, J.O., Moodie, K.B., Beswick, A.R. (2001) Using spatial interpolation to construct a comprehensive archive of Australian climate data. Environmental Modelling & Software, 16, 309-330. https://doi.org/10.1016/S1364-8152(01)00008-1.

Jiang, H.L., Xu, X., Guan, M.X., Wang, L.F., Huang, Y.M., Jiang, Y. (2020) Determining the contributions of climate change and human activities to vegetation dynamics in agro-pastural transitional zone of northern China from 2000 to 2015. Science of the Total Environment 718, 14. https://doi.org/10.1016/j.scitotenv.2019.134871.

Jiang, L.L., Jiapaer, G., Bao, A.M., Guo, H., Ndayisaba, F. (2017) Vegetation dynamics and responses to climate change and human activities in Central Asia. Science of the Total Environment 599, 967-980. https://doi.org/10.1016/j.scitotenv.2017.05.012.

Jiang, Z.C., Lian, Y.Q., Qin, X.Q. (2014) Rocky desertification in Southwest China: Impacts, causes, and restoration. Earth-Science Reviews 132, 1-12. https://doi.org/10.1016/j.earscirev.2014.01.005.

Juhlke, T.R., Geldern, R.V., Barth, J.A.C. et al. (2021) Temporal offset between precipitation and water uptake of Mediterranean pine trees varies with elevation and season. Science of the Total Environment 755, 142539. https://doi.org/10.1016/j.scitotenv.2020.142539.

Kruhlov, I., Thom, D., Chaskovskyy, O., Keeton, W.S., Scheller, R.M. (2018) Future forest landscapes of the Carpathians: vegetation and carbon dynamics under climate change. Regional Environmental Change 18, 1555-1567. https://doi.org/10.1007/s10113-018-1296-8.

Kuzyakov, Y., Gavrichkova, O. (2010) REVIEW: Time lag between photosynthesis and carbon dioxide efflux from soil: a review of mechanisms and controls. Global Change Biology 16, 3386-3406. https://doi.org/10.1111/j.1365-2486.2010.02179.x.

Li, A., Wu, J.G., Huang, J.H. (2012) Distinguishing between human-induced and climate-driven vegetation changes: a critical application of RESTREND in inner Mongolia. Landscape Ecology 27, 969-982. https://doi.org/10.1007/s10980-012-9751-2.

Liu, Q.H., Liu, Y.X., Peng, J., Zhang, T., Li, Y.R., Hu, Y.N. (2018) Linking GRNN and neighborhood selection algorithm to assess land suitability in low-slope hilly areas. Ecological Indicators 93, 581-590. https://doi.org/10.1016/j.ecolind.2018.05.008.

Liu, Y., Huang, X.J., Yang, H., Zhong, T.Y. (2014) Environmental effects of land-use/cover change caused by urbanization and policies in Southwest China Karst area A case study of Guiyang. Habitat International 44, 339-348. https://doi.org/10.1016/j.habitatint.2014.07.009.

Lunetta, R.S., Knight, J.F., Ediriwickrema, J., Lyon, J.G., Worthy, L.D. (2006) Land-cover change detection using multi-temporal MODIS NDVI data. Remote Sensing of Environment 105, 142-154. https://doi.org/10.1016/j.rse.2006.06.018.

Mendoza-Ponce, A., Corona-Nunez, R., Kraxner, F., Leduc, S., Patrizio, P. (2018) Identifying effects of land use cover changes and climate change on terrestrial ecosystems and carbon stocks in Mexico. Global Environmental Change - Human and Policy Dimensions 53, 12-23. https://doi.org/10.1016/j.gloenvcha.2018.08.004.

Menz, M.H.M., Dixon, K.W., Hobbs, R.J. (2013) Hurdles and Opportunities for Landscape-Scale Restoration. Science, 339: 526-527. DOI: 10.1126/science.1228334.

Naeem, S., Zhang, Y., Tian, J., Qamer, F.M., Latif, A., Paul, P.K. (2020) Quantifying the Impacts of Anthropogenic Activities and Climate Variations on Vegetation Productivity Changes in China from 1985 to 2015. Remote Sensing 12, 1113-1141. https://doi.org/10.3390/rs12071113.

Nemani, R.R., Keeling, C.D., Hashimoto, H., et al. (2003) Climate-Driven Increases in Global Terrestrial

Net Primary Production from 1982 to 1999. Science 300, 1560-1563. DOI: 10.1126/science.1082750.

Nicholson, S.E., Davenport, M.L., Malo, A.R. (1990) A comparison of the vegetation response to rainfall in the Sahel and East-Africa, using normalized difference vegetation index from NOAA AVHRR. Climatic Change 17, 209-241. https://doi.org/10.1007/BF00138369.

Peng, J., Hu, Y., Dong, J., Mao, Q., Liu, Y., Du, Y., Wu, J., Wang, Y. (2019) Linking spatial differentiation with sustainability management: Academic contributions and research directions of physical geography in China. Progress in Physical Geography: Earth and Environment 44, 14-30. https://doi.org/10.1177/0309133319878107.

Peng, S.S., Piao, S.L., Ciais, P., et al. (2013) Asymmetric effects of daytime and night-time warming on Northern Hemisphere vegetation. Nature 501, 88-92. https://doi.org/10.1038/nature12434.

Piao, S.L., Wang, X.H., Park, T., et al. (2019) Characteristics, drivers and feedbacks of global greening. Nature Reviews Earth & Environment 1, 14-27. https://doi.org/10.1038/s43017-019-0001-x.

Pricope, N.G., Husak, G., Lopez-Carr, D., Funk, C., Michaelsen, J. (2013) The climate-population nexus in the East African Horn: Emerging degradation trends in rangeland and pastoral livelihood zones. Global Environmental Change - Human and Policy Dimensions 23, 1525-1541. https://doi.org/10.1016/j.gloenvcha.2013.10.002.

Qiu, S., Peng, J., Dong, J., Wang, X., Ding, Z., Zhang, H., Mao, Q., Liu, H., Quine, T.A., Meersmans, J. (2020) Understanding the relationships between ecosystem services and associated social-ecological drivers in a karst region: A case study of Guizhou Province, China. Progress in Physical Geography: Earth and Environment 44, 1-17. https://doi.org/10.1177/0309133320933525.

Ran, Q.W., Hao, Y.B., Xia, A.Q., Liu, W.J., Hu, R.H., Cui, X.Y., Xue, K., Song, X.N., Xu, C., Ding, B.Y., Wang, Y.F. (2019) Quantitative Assessment of the Impact of Physical and Anthropogenic Factors on

Vegetation Spatial-Temporal Variation in Northern Tibet. Remote Sensing 11, 22. https://doi.org/10.3390/rs11101183.

Reed, R.A., Peet, R.K., Palmer, M.W., White, P.S. (1993) Scale dependence of vegetation-environment correlations - A case-study of a north-Carolina piedmont woodland. Journal of Vegetation Science 4, 329-340. https://doi.org/10.2307/3235591.

Robinson, M., De Souza, J.G., Maezumi, S.Y., Cardenas, M., Pessenda, L., Prufer, K., Corteletti, R., Scunderlick, D., Mayle, F.E., De Blasis, P., Iriarte, J. (2018) Uncoupling human and climate drivers of late Holocene vegetation change in southern Brazil. Scientific Reports 8, 10. https://doi.org/10.1038/s41598-018-24429-5.

Snyder, J.P., Voxland, P.M. (1989) An album of map projections. United States Govt Printing Office.

Solomon, A.M., Shugart, H. (1993) Vegetation Dynamics & Global Change. Springer, Boston, US.

Tong, X., Brandt, M., Yue, Y., et al. (2018) Increased vegetation growth and carbon stock in China karst via ecological engineering. Nature Sustainability 1, 44-50. https://doi.org/10.1038/s41893-017-0004-x.

Tong, X.W., Wang, K.L., Yue, Y.M., Brandt, M., Liu, B., Zhang, C.H., Liao, C.J., Fensholt, R. (2017) Quantifying the effectiveness of ecological restoration projects on long-term vegetation dynamics in the karst regions of Southwest China. International Journal of Applied Earth Observation and Geoinformation 54, 105-113. https://doi.org/10.1016/j.jag.2016.09.013.

Tong X., Brandt M., Yue, Y., et al. (2020) Forest management in southern China generates short term extensive carbon sequestration. Nature Communications 11:129. DOI: 10.1038/s41467-019-13798-8.

Vicente-Serrano, S.M., Gouveia, C., Julio Camarero, J., et al. (2013) Response of vegetation to drought time-scales across global land biomes. Proceedings of the National Academy of Sciences of the

United States of America 110, 52-57. https://doi.org/10.1073/pnas.1207068110.

Wang, J., Meng, J.J., Cai, Y.L. (2008) Assessing vegetation dynamics impacted by climate change in the southwestern karst region of China with AVHRR NDVI and AVHRR NPP time-series. Environmental Geology 54, 1185-1195. https://doi.org/10.1007/s00254-007-0901-9.

Wang, J., Wang, K.L., Zhang, M.Y., Zhang, C.H. (2015) Impacts of climate change and human activities on vegetation cover in hilly southern China. Ecological Engineering 81, 451-461. https://doi.org/10.1016/j.ecoleng.2015.04.022.

Wang, J.F., Li, X.H., Christakos, G., Liao, Y.L., Zhang, T., Gu, X., Zheng, X.Y. (2010) Geographical Detectors-Based Health Risk Assessment and its Application in the Neural Tube Defects Study of the Heshun Region, China. International Journal of Geographical Information Science 24, 107-127. https://doi.org/10.1080/13658810802443457.

Wang, K.L., Zhang, C.H., Chen, H.S., et al. (2019) Karst landscapes of China: patterns, ecosystem processes and services. Landscape Ecology 34, 2743-2763. https://doi.org/10.1007/s10980-019-00912-w.

Wang, S.J., Liu, Q.M., Zhang, D.F. (2004) Karst rocky desertification in southwestern China: Geomorphology, landuse, impact and rehabilitation. Land Degradation & Development 15, 115-121. https://doi.org/10.1002/ldr.592.

Wen, Y.Y., Liu, X.P., Yang, J., Lin, K., Du, G.M. (2019) NDVI indicated inter-seasonal non-uniform time-lag responses of terrestrial vegetation growth to daily maximum and minimum temperature. Global and Planetary Change 177, 27-38. https://doi.org/10.1016/j.gloplacha.2019.03.010.

Wu, D.H., Zhao, X., Liang, S.L., Zhou, T., Huang, K.C., Tang, B.J., Zhao, W.Q. (2015) Time-lag effects of global vegetation responses to climate change. Global Change Biology 21, 3520-3531.

https://doi.org/10.1111/gcb.12945.

Wu, L.H., Wang, S.J., Bai, X.Y., et al. (2020) Climate change weakens the positive effect of human activities on karst vegetation productivity restoration in southern China. Ecological Indicators 115, 106392. https://doi.org/10.1016/j.ecolind.2020.106392.

Yan, X.X., Li, J., Shao, Y., et al. (2020) Driving forces of grassland vegetation changes in Chen Barag Banner, Inner Mongolia. GIScience & Remote Sensing 57, 753-769. https://doi.org/10.1080/15481603.2020.1794395.

Ye, Z.X., Cheng, W.M., Zhao, Z.Q., Guo, J.Y., Ding, H., Wang, N. (2019) Interannual and Seasonal Vegetation Changes and Influencing Factors in the Extra-High Mountainous Areas of Southern Tibet. Remote Sensing 11, 20. https://doi.org/10.3390/rs11111392.

Zeng, B., Zhang, F.G., Yang, T.B., Qi, J.G., Ghebrezgabher, M.G. (2018) Alpine sparsely vegetated areas in the eastern Qilian Mountains shrank with climate warming in the past 30 years. Progress in Physical Geography 42, 415-430. https://doi.org/10.1177/0309133318765196.

Zhang, Y., Zhang, C.B., Wang, Z.Q., Chen, Y.Z., Gang, C.C., An, R., Li, J.L. (2016) Vegetation dynamics and its driving forces from climate change and human activities in the Three-River Source Region, China from 1982 to 2012. Science of the Total Environment 563, 210-220. https://doi.org/10.1016/j.scitotenv.2016.03.223.

Zhao, L.S., Hou, R. (2019) Human causes of soil loss in rural karst environments: a case study of Guizhou, China. Scientific Reports 9. https://doi.org/10.1038/s41598-018-35808-3.

Zhao, J., Huang, S.Z., Huang, Q., et al. (2020) Time-lagged response of vegetation dynamics to climatic and teleconnection factors. CATENA 189, 104474. https://doi.org/10.1016/j.catena.2020.104474.

Zheng, K., Wei, J.Z., Pei, J.Y., Cheng, H., Zhang, X.L., Huang, F.Q., Li, F.M., Ye, J.S. (2019) Impacts of climate change and human activities on grassland vegetation variation in the Chinese Loess Plateau. Science of the Total Environment 660, 236-244. https://doi.org/10.1016/j.scitotenv.2019.01.022.

Zhou, X., Yamaguchi, Y., Arjasakusuma, S. (2018) Distinguishing the vegetation dynamics induced by anthropogenic factors using vegetation optical depth and AVHRR NDVI: A cross-border study on the Mongolian Plateau. Science of the Total Environment 616, 730-743. https://doi.org/10.1016/j.scitotenv.2017.10.253.

Zhu, Z.C., Piao, S.L., Myneni, R.B., et al. (2016) Greening of the Earth and its drivers. Nature Climate Change 6, 791–795. https://doi.org/10.1038/nclimate3004.

Declaration of competing interests

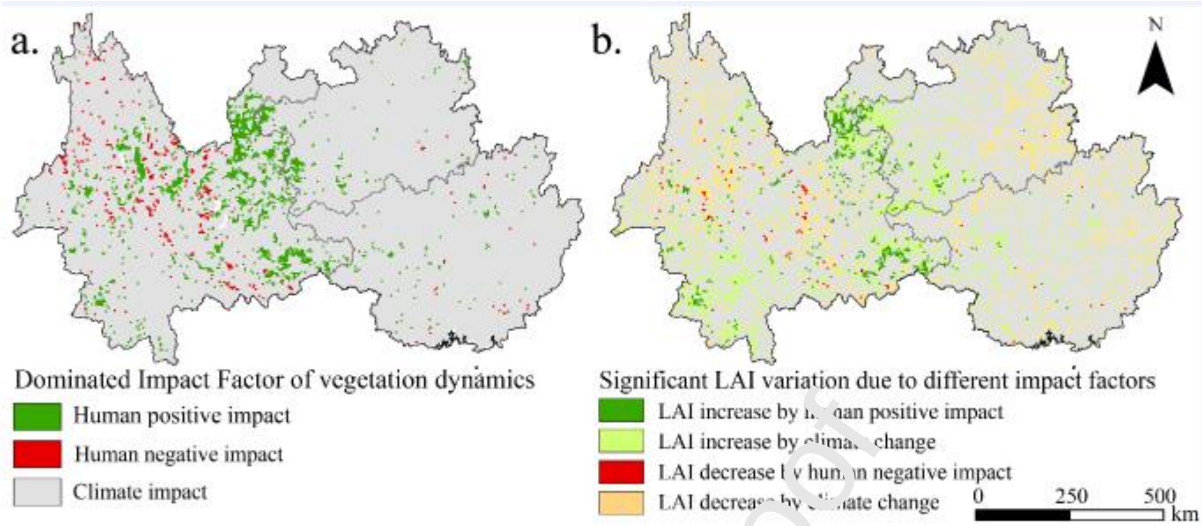
☑ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

CRediT authorship contribution statement

Jian Peng: Conceptualization, Methodology, Writing- Original draft preparation, Writing- Reviewing and Editing. **Hong Jiang:** Data curation, Methodology, Writing- Original draft preparation. **Qinghua Liu:** Data curation, Writing- Original draft preparation. **Sophie M. Green:** Writing- Reviewing and Editing. **Timothy A. Quine:** Writing- Reviewing and Editing. **Hongyan Liu:** Writing- Reviewing and Editing. **Sijing Qiu:** Writing- Reviewing and Editing, Resources. **Yanxu Liu:** Writing- Reviewing and Editing. **Jeroen Meersmans:** Writing- Reviewing and Editing.

Graphical abstract



Highlights

· We consider the time-lag effect when establishing the LAI-climate model.

· We use residual threshold to separate the impacts of climate and human activities.

· LAI changed significantly from 1999 to 2015.

· Dominant impact areas of climate change and human activities are identified.

· Karst landform affects the distribution of human's positive impact most.