Satellite View of Vegetation Dynamics and Drivers Over Southwestern China

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1 Satellite view of vegetation dynamics and drivers over Southwestern China

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17 **Abstract:**

18 **Background:** Vegetation is a key component of terrestrial ecosystems. The dynamics of
19 vegetation can be used as an indicator of vegetation health and ecosystem stability. However, the
20 dynamics and responses of vegetation in Southwestern China remain unclear.

21 **Methods:** Both monotonic and turning point approaches were used in trend analysis to understand
22 the dynamics of vegetation. We applied partial correlation analysis and the relative importance of

climatic factors to determine the drivers of vegetation dynamics. Residual trend analysis was applied to distinguish other drivers.

Results: The annual mean NDVI generally increased at a rate of 0.0011 year^{-1} from 1982 to 2015, but much of the study area showed the opposite trend before and after the turning point during this period. The vegetation in the western part of the study area was degraded and increased significantly in the eastern part of the study area. An increasing trend that continued to an increasing trend (II) and a decreasing trend that changed into an increasing trend (DI) were two of the largest patterns of vegetation trends, and they were mainly distributed in the eastern part of the study area. An increasing trend that changed into a decreasing trend (ID) was mainly distributed in the western part of the study area, where the vegetation types were mainly evergreen needle-leaved and grassland. Temperature was the dominant climatic factor and had a positive correlation with vegetation in the eastern part of the study area. Temperature also had some negative correlations with vegetation in western mountainous areas where surface soils are prone to droughts. Solar radiation had a positive correlation with vegetation in the western part of the study area. In addition, the regions with more intensity human activities than other areas were concentrated in the eastern part of the study area.

Conclusions: The spatial distribution and trend showed high heterogeneity over Southwestern China. Temperature was the dominant climatic factor. In the eastern part of the study area, human activities played an important role in vegetation greening.

Keywords: Normalized difference vegetation index (NDVI), vegetation dynamics, climate, human activities, turning point analysis

1. Introduction

As a key component of terrestrial ecosystems (Peng et al. 2016), vegetation plays a vital role in regulating cycles of carbon, water, and energy (Cao and Woodward, 1998; Foley et al. 2000; Zoran et al. 2016; Tong et al. 2016), affecting the global climate (Pei et al. 2018), and providing food, fiber and wood production (Liang et al. 2015). Vegetation in an ecosystem is influenced by synergistic effects of climatic change and human activities (Qu et al. 2020; Chu et al. 2019; Hua et al. 2017). The dynamics of vegetation can be used as an indicator of vegetation health and ecosystem stability. Over recent decades, increasing attention has been paid to the observed responses of vegetation dynamics to climate change and human activities (Wang et al. 2020; Zhao et al. 2020; Wang et al. 2020; Jiang et al. 2017; Qu et al. 2018). Therefore, monitoring and attributing the spatiotemporal dynamics of vegetation are critical for understanding the interaction between terrestrial ecosystems and the atmosphere and also for assessing the benefits of strategies and policies for ecosystem restoration (Liu et al. 2019).

Accounting for spatial and temporal heterogeneity, satellite remote sensing provides a great opportunity to map global vegetation information from the Earth's surface (Huete, 2016). The normalized difference vegetation index (NDVI) is widely used as a proxy of vegetation production to track the spatiotemporal dynamics of vegetation (Li et al. 2019). Based on satellite-derived NDVI, numerous studies have been conducted to explore and attribute the dynamics of vegetation at various scales (Jeong et al. 2011; Li et al. 2018; Shen et al. 2018; Guo et al. 2018; Jiang et al. 2017).

Precipitation and temperature are generally regarded as the two most important climatic factors driving vegetation dynamics (He et al. 2015). Previous studies have shown that increasing temperatures prolong the growing season, thus promoting vegetation productivity (Piao et al. 2006;

Suzuki et al. 2007). Meanwhile, divergent vegetation responses to droughts have been founded. Droughts may promote vegetation growth and carbon absorption in early summer and may lead to a decline in NDVI in spring and winter (Song et al. 2019; Tang and Dubayah, 2017). However, solar radiation has often been neglected. Studies have shown that sufficient solar radiation supplies enough energy for vegetation photosynthesis (Zhang et al. 2016; Fang et al. 2019), and it has some influence on soil moisture (Li et al. 2015; Yang et al. 2015), which may affect vegetation growth (Yao et al. 2017). In addition, increasing attention has been paid to the influence of anthropogenic activities on vegetation change. With the expansion of urbanization, the growth of urban vegetation is affected by the urban heat island effect, human management and other factors, and urbanization may promote or inhibit vegetation growth (Zhong et al. 2019; Liu et al. 2015). The Grain for Green Program has greatly increased vegetation cover and improved the ecological environment of China, especially in the Loess Plateau region (Zhao et al. 2019; Xiao, 2014).

Southwestern China (Fig. 1), including the municipality of Chongqing and the provinces of Sichuan, Yunnan, Guizhou and Guangxi, plays an important role in maintaining biodiversity and state ecosystem security. The western part of this area is mostly dominated by alpine grassland with obvious seasonal and spatial vegetation heterogeneity (Yin et al. 2020; Fu et al. 2014; Rao et al. 2016; Peng et al, 2012). The eastern part is mostly dominated by subtropical vegetation and has formed China's largest terrestrial carbon sink over the last three decades (Piao et al. 2009; Liu et al. 2016). There is a contrasting distribution of the intensity of anthropogenic activities, most of which are concentrated in the eastern part of Southwestern China. Although there are many studies of vegetation dynamics in Southwestern China, many of those studies focused on parts of the study area, such as Yunnan, Guizhou (Hou et al. 2015; Liu et al. 2018), or Sichuan (Peng et al. 2019; Li

et al. 2020). Almost no studies have investigated all of Southwestern China, and the dynamics and responses of vegetation in this area remain unclear. Additionally, relatively less attention has been paid to anthropogenic activities when attributing vegetation dynamics, and the potential influences of human activities on vegetation growth in Southwestern China are poorly understood.

Fig. 1. Location of Southwestern China and a digital elevation model (DEM)

In this study, we used satellite-based NDVI to analyze the spatiotemporal vegetation dynamics and their response to climatic and anthropogenic factors in Southwestern China. Both monotonic approaches and turning point methods were used in the trend analysis of vegetation. The purposes of this study are as follows: (1) to investigate the NDVI and climate factor characteristics of interannual spatiotemporal changes in Southwestern China, (2) to analyze the correlation between NDVI and climatic factors and identify the main drivers at pixel scales and (3) to distinguish other potential drivers of NDVI changes, including human activities and natural disturbance.

2. Data and methods

2.1 Study area

Southwestern China extends from western Sichuan Plateau to the Beibu Gulf, with an area of 1.37 million km², accounting for approximately 14.34% of China's land area (Fig. 1). The elevation varies from -25-7148 m and generally increases from east to west. The terrain is complex and includes the Hengduan Mountains, Sichuan Basin, Yunnan-Guizhou Plateau and Guangxi Hills. From east to west, the study area is characterized by a subtropical monsoon climate, tropical seasonal rainforest climate and plateau climate. The monsoon effects and topography together shaped the unevenly distributed climatic factors. The annual mean temperature varies from -11.1-24.56°C and decreases from southeast to northwest. The annual mean precipitation varies from 454.55-2731.91mm, and its spatial distribution is generally similar to that of the temperature. The annual mean solar radiation ranges from 115.17-221.62 W/m² and increases with increasing elevation. The main vegetation types of the study area include cropland, evergreen broad-leaved forest, deciduous broad-leaved forest, evergreen needle-leaved forest and grassland (Fig. 2a). The population is unevenly distributed and is mainly concentrated in the eastern part (Yu et al. 2018).

Fig. 2. (a) Spatial distribution of vegetation types and (b) interannual change in mean NDVI in

Southwestern China over the period 1982-2015. Vegetation types included rainfed and irrigated cropland (CRO); mixed cropland and natural vegetation, cropland > 50% (MCR); mixed natural vegetation and cropland, natural vegetation > 50% (MNV); evergreen broad-leaved forest (EBF); deciduous broad-leaved forest (DBF); evergreen needle-leaved forest (ENF); grassland (GRA); mixed tree, shrub and herbaceous vegetation, tree and shrub > 50% (MTS); shrubland (SHR); wetland, settlement, bare area and water (other).

2.2 Data

2.2.1 Satellite NDVI

Advanced Very High Resolution Radiometer (AVHRR) series of satellites record the longest normalized difference vegetation index (NDVI) datasets dating back to 1981 (Tucker et al. 2005). In this study, the NDVI dataset derived from the third generation Global Inventory Monitoring and Modeling System (GIMMS NDVI3g) was adopted to monitor long-term vegetation dynamics. This dataset has a long time span (from 1982 to 2015), its temporal resolution is 15 days, and its spatial resolution is approximately 8 km. The annual NDVI was averaged from May to October, this period is the wet and main growing season for the study area.

2.2.2 Land cover and DEM

Land cover map with a 300 m spatial resolution was acquired from the European Space Agency (ESA) Climate Change Initiative (CCI). Based on this data, different vegetation covers were classified into ten types: rainfed and irrigated cropland (CRO); mixed cropland and natural vegetation, cropland > 50% (MCR); mixed natural vegetation and cropland, natural vegetation > 50% (MNV); evergreen broad-leaved forest (EBF); deciduous broad-leaved forest (DBF); evergreen needle-leaved forest (ENF); grassland (GRA); mixed tree, shrub and herbaceous vegetation, tree

and shrub > 50% (MTS); shrubland (SHR); wetland, settlement, bare area and water (other) (Fig. 2a).

The digital elevation model (DEM) dataset was provided by the Resource Environmental Science Data Center of the Chinese Academy of Sciences with a spatial resolution of 90 m. We resampled the spatial resolution to 8 km to keep the same resolution as NDVI.

2.2.3 Climate data

Climatic datasets, including air temperature, precipitation, and solar radiation, were developed by the Data Assimilation and Modeling Center for Tibetan Multi-spheres, Institute of Tibetan Plateau Research, Chinese Academy of Sciences (<http://westdc.westgis.ac.cn/>). With a resolution of 10 km and a long time span from 1979-2015, the dataset is based on existing international Princeton reanalysis data, Global Land Data Assimilation System (GLDAS) data, Global Energy and Water Cycle Experiment-Surface Radiation Budget (GEWEX-SRB) products, and Tropical Rainfall Measuring Mission (TRMM) precipitation data as background fields, combining the routine meteorological observation data of the China Meteorological Administration (He et al. 2020). The monthly average temperature, cumulative precipitation and average solar radiation were resampled to 8 km for further analysis.

2.2.4 Human footprint pressure map

We used a human footprint pressure dataset (<https://www.nature.com/articles/sdata201667>) to analyze the effects of human activities on vegetation growth. This dataset has a spatial resolution of 1 km covering both 1993 and 2009. It uses eight variables, including the extent of built environments, population density, electric infrastructure, croplands, pasture lands, roads, railways and navigable waterways, to measure the direct and indirect human pressures on the environment and has been

used to investigate the impact of human activities on environmental change, such as biodiversity conservation (Venter et al. 2016a) and vegetation dynamics (Li et al. 2018). We used human footprint data for 1993 and 2009 and calculated the difference between 1993 and 2009 to quantify the intensity of human activities.

2.3 Methods

2.3.1 Trend analysis

Trend analysis was applied to analyze interannual time series data of NDVI. We used least-squares linear regression (Eq. 1) to detect the trend of NDVI and climatic factor at the pixel scale.

$$slope = \frac{n \sum_{i=1}^n i \times Y_i - \sum_{i=1}^n i \sum_{i=1}^n Y_i}{n \sum_{i=1}^n i^2 - (\sum_{i=1}^n i)^2} \quad (1)$$

where Y_i is NDVI in i ; i is the year; and n is the total number of years, which is equal to 34; $slope$ is the annual mean increase in NDVI; and $slope > 0$ indicates that NDVI had an increasing trend, and vice versa.

Vegetation growth is influenced by climate fluctuations and human activities, and there can be a turning point in vegetation change over a long period. The trend based on least-squares linear regression does not reflect the change characteristics of vegetation in each stage. Therefore, a piecewise linear regression model (Tom and Lesperance, 2003) that has been applied to vegetation dynamics analysis in recent years to further analyze the trend of vegetation change (Eq. 2).

$$y = \begin{cases} \beta_0 + \beta_1 t + \varepsilon & t \leq \alpha \\ \beta_0 + \beta_1 t + \beta_2 (t - \alpha) + \varepsilon & t > \alpha \end{cases} \quad (2)$$

where y is NDVI, t is the year, α is the turning point in the trend of NDVI changes, β_0 is the intercept, β_1 is the trend before the turning point, $\beta_1 + \beta_2$ is the trend after the turning point, and ε is the residual error. Therefore, we can obtain the turning point and the trend before and after the turning point of each pixel. Four types of NDVI changes were observed: an increasing trend that continued to an

increasing trend (II), an increasing trend that changed into a decreasing trend (ID), a decreasing trend that changed into an increasing trend (DI), and a decreasing trend that continued to a decreasing trend (DD).

2.3.2 Relationship analysis between NDVI and climatic factors

Two methods were applied to analyze the relationship between vegetation dynamics and climate change. We applied partial correlation analysis in the R environment with the package “ppcor” to reflect the relationship between NDVI and climatic factors more realistically. Then, to determine the control factors of vegetation dynamics at the pixel scale, we used the Lindeman-Merenda-Gold (LMG) approach to calculate the relative importance of temperature, precipitation and solar radiation to NDVI in multiple linear regression in the R environment with the package “relaimpo” (Gromping, 2006). LMG is based on unweighted averages over sequential R^2 values of each variable to avoid the order effects of regressors. These metrics decompose R^2 into nonnegative contributions that automatically sum to the total R^2 . When the focus of the research is causal, LMG is more appropriate than other metrics. The relative importance of the three factors was normalized, and the RGB combination was derived to reflect drivers of NDVI change for each pixel.

2.3.3 Residual trend (RESTREND) analysis

Human activities is an important driver of vegetation dynamics, like climatic factors. RESTREND analysis can be used to eliminate NDVI changes due to climate change to further analyze vegetation changes caused by human activities. We used precipitation, temperature, and solar radiation to build a multiple linear regression model to obtain a predicted NDVI, and the residuals are the difference between the predicted NDVI and observed NDVI. Using trend analysis to analyze the multiyear residuals, the regions with significant changes may be affected by human

activities, and vegetation changes in areas where the residual changes are not significant can be explained by climate variables (Eq. 3).

$$NDVI_{pred_i} = a * prec_i + b * temp_i + c * sradi_i + d \quad (3)$$

Where i is the year; $NDVI_{pred_i}$ is the predicted NDVI in i ; $prec_i$, $temp_i$, and $sradi_i$ represent the precipitation, temperature and solar radiation in i , respectively; a , b and c are regression coefficients; and d is the constant (Eq. 4).

$$NDVI_{resi_i} = NDVI_{obse_i} - NDVI_{pred_i} \quad (4)$$

Where i is the year, $NDVI_{pred_i}$ is the predicted NDVI in i , $NDVI_{obse_i}$ is the observed NDVI in i , and $NDVI_{resi_i}$ is the NDVI residual in i .

3. Results

3.1 Vegetation dynamics over the study area

For the whole study area, the annual mean NDVI showed an increasing trend with a rate of 0.0011 year^{-1} ($R^2=0.41$, $P<0.01$) from 1982 to 2015. The annual mean NDVI of Southwestern China ranged from 0.60 in 1991 to 0.68 in 2013 (Fig. 2b). The spatial distribution of NDVI showed high heterogeneity over Southwestern China. The value of NDVI varied from 0.06 to 0.86 and increased from northwest to southeast, and the regions with high values of NDVI (0.8-0.9) were distributed in southern Yunnan, which were MTS, MNV and EBF (Fig. 2a and 3a). The regions with low values of NDVI (0-0.4) were distributed in western Sichuan. The NDVI of most pixels ranged from 0.5 to 0.7, mainly distributed in Sichuan Basin, northern Guizhou and southern Guangxi, which were occupied by CRO and MCR.

The trend of the spatial distribution of NDVI showed spatial heterogeneity in the study area (Fig. 3b), and NDVI generally increased from 1982 to 2015, with increasing NDVI occupying 82.09%

of the total study area. In addition, more than half of the pixels (52.54%) of the total increased significantly, and the trend of the annual NDVI was as high as 0.016 year^{-1} , including CRO in Chongqing, Sichuan and Guizhou, EBF and CRO in Guangxi, and ENF in eastern Yunnan. We also found a small part of regions (17.91%) in which the NDVI decreased that were located in the Hengduan Mountains and the transition zone of western Sichuan Plateau and Sichuan Basin, which were ENF and GRA. In general, the vegetation in the western part of the study area was degraded and increased significantly in the eastern part of the study area.

Fig. 3. Spatial distribution of (a) the annual mean NDVI and (b) the NDVI trend over the period 1982-2015.

3.2 Turning points in vegetation trends

We applied a piecewise linear regression model to further identify turning point years of vegetation trends for each pixel. The turning points that occurred between 2004 and 2005 accounted for 52.02% of the total pixels and were mainly distributed in the eastern part of the study area and some parts of Yunnan. Moreover, turning points that occurred between 1992 and 1993 also accounted for a large percentage (13.65%) and were mainly distributed in transition zones between mountains and basins (Fig. 4a).

246

247 **Table 1** The percentage of different vegetation types among various NDVI change types

Vegetation type	NDVI change types			
	II	ID	DI	DD
	Percentage(%)			
CRO	31.81	8.36	21.28	11.26
MCR	13.84	4.26	12.38	4.10
MNV	9.66	8.65	12.19	11.26
EBF	16.49	7.46	19.05	8.87
DBF	2.77	1.73	3.45	0.68
ENF	13.78	32.11	18.32	39.25
MTS	4.42	4.64	6.15	4.44
GRA	6.55	32.33	6.38	19.11
SHR	0.67	0.47	0.80	1.02
Sum	100.00	100.00	100.00	100.00

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249 II and DI were two of the largest patterns, and their percentages were 37.40% and 35.49%,
 250 respectively (Fig. 4b), and their vegetation types were mainly CRO, EBF and ENF (Table 1). II was
 251 mainly distributed in Sichuan Basin and southern Guangxi. DI was concentrated in the southern part
 252 of Sichuan and karst area of Yunnan, Guizhou and Guangxi, and the vegetation growth in these areas
 253 improved significantly. ID was mainly distributed in the western part of the study area, where the
 254 vegetation types were mainly ENF and GRA, with an area percentage of 25.44%. DD accounted for

only 1.67% of the total pixels and the vegetation types were mainly GRA and ENF.

Table 2 The percentage of different NDVI change types among various vegetation types

NDVI change type	Vegetation type								
	CRO	MCR	MNV	EBF	DBF	ENF	MTS	GRA	SHR
	Percentage(%)								
II	54.66	48.27	34.99	41.19	38.24	25.16	32.47	18.49	37.29
ID	9.77	10.10	21.30	12.68	16.18	39.88	23.18	62.04	17.80
DI	34.70	40.99	41.89	45.15	45.17	31.76	42.89	17.07	42.37
DD	0.86	0.64	1.82	0.99	0.42	3.20	1.46	2.41	2.54
Sum	100	100	100	100	100	100	100	100	100

There was a significant variation in the trend of the vegetation change before and after the turning point in some areas. Before the turning point, 62.84% of the study area showed an increasing trend, and a decreasing trend was concentrated in the eastern part of the study area (Fig. 4c). After the turning point, the vegetation browned over 27.11% of the study area, mainly concentrated in western Sichuan Plateau and Hengduan Mountains (Fig. 4d). Vegetation significantly greened in Sichuan Basin and karst areas of Yunnan, Guizhou and Guangxi.

Except for ENF and GRA, all the other vegetation types were observed to have a greening trend after the turning point, and the proportion of II exceeded 50% for CRO (Table 2). A relatively uniform distribution of II, ID and DI were found in ENF. The proportion of ID is as high as 62.04% for GRA, indicating management and restoration are urgent in this area.

Fig. 4. Spatial distribution of (a) the turning point year, (b) four types of NDVI changes: an increasing trend that continued to an increasing trend (II), an increasing trend that changed into a decreasing trend (ID), a decreasing trend that changed into an increasing trend (DI), a decreasing trend that continued to a decreasing trend (DD), (c) NDVI trend before that turning point year and (d) NDVI trend after that turning point year.

3.3. Relationship between climatic factors and vegetation dynamics

3.3.1 Driving effects of climatic factors

The trends of climatic factors had spatial heterogeneity from 1982 to 2015 (Fig. 5a-c). The temperature increased significantly in the most pixels (81.88%). However, precipitation and solar

radiation did not show significant trends. A partial correlation between NDVI and climatic factors was calculated at the pixel scale from 1982 to 2015 (Fig. 6a-c). We observed that 71.68% of the total pixels showed a positive correlation with temperature. These pixels were mainly distributed in the eastern part of the study area, and 24.00% of the total pixels reached a significant level. In addition, 60.80% of the NDVI showed a positive correlation with solar radiation, and 8.31% of the total pixels reached a significant level. They were mainly distributed in the western part of the study area. Further, 57.30% of the total pixels showed a positive correlation with precipitation, but only 6.22% of the total pixels reached a significant level and were mainly concentrated in western Chongqing and eastern Guangxi. There were also some negative correlations with climatic factors, mainly in western mountainous areas and eastern karst areas, where surface soils are prone to droughts.

Fig.5. Spatial distribution of (a) the precipitation trend, (b) temperature trend, (c) solar radiation trend over the period 1982-2015; (d) the precipitation trend, (e) temperature trend, (f) solar radiation trend before the turning point; (g) the precipitation trend, (h) temperature trend, and (i) solar radiation trend after the turning point.

3.3.2 Dominant climatic factors over the study area

We further calculated the relative importance of precipitation, temperature, and solar radiation to the NDVI. Overall, the dominant climate driver of NDVI varied widely across the study area. Regions where temperature was the dominant factor accounted for 47.02% of the total pixels, while precipitation and solar radiation accounted for 16.82% and 22.85%, respectively (Fig. 6d).

Temperature was observed to be important for farmland (CRO and MCR) and EBF in eastern study area and also had some restrictive effect on grasslands. The regions where solar radiation was the main dominant factor were mainly located at the junction of Yunnan and Sichuan, where the vegetation types were MNV and ENF. The regions where precipitation was the main dominant factor were scattered, and the vegetation types were CRO, MNV, EBF and ENF. At the junction of Sichuan and Chongqing, where the vegetation type was CRO, temperature and precipitation were significantly correlated with NDVI, but the relative importance of temperature was higher than precipitation. Similar results were also showed in eastern Guangxi.

Fig. 6. Spatial distribution of partial correlations between (a) mean NDVI and precipitation, (b)

mean NDVI and temperature, (c) mean NDVI and solar radiation and (d) climate drivers of NDVI interannual variability.

3.4 Effects of human activities on vegetation dynamics

In addition to climatic factors, the impact of human activities on vegetation growth should also be considered. Based on multilinear regression, we analyzed the annual NDVI and climatic factors to calculate the variation trend of NDVI residuals. Residuals represent parts of NDVI that are not explained by precipitation, temperature, or solar radiation. The regions with significant residual variation could not be well explained by the multivariate linear model fitted by temperature, precipitation and solar radiation, and the vegetation changes may be attributed to human activities. In areas where the residuals did not change significantly, vegetation changes were driven by climate variables.

Only 0.72% of the total pixels residuals decreased significantly, while 29.69% of the total pixels residuals increased significantly, including in eastern Sichuan, northern Guizhou, western Guangxi and northern Yunnan (Fig. 7a-b). The vegetation types were farmland (CRO, MCR) and EBF. We further analyzed the proportion of the residual variation of different vegetation types (Fig. 7c). We found that 46.02% of the CRO, 40.30% of the MCR and 34.34% of the EBF showed significant residual increases. The proportion of areas with insignificant changes in the residual ENF and GRA was 82.24% and 88.05%, respectively. These two vegetation types were mainly controlled by climatic factors. Overall, the regions with significant changes in residuals were concentrated in the eastern part of the study area, indicating that human activities played an important role in vegetation growth. In these areas, human afforestation and agriculture activities were intensifying, which lead to the increasing trend of vegetation.

Fig. 7. Spatial distribution of (a) NDVI residual trend and (b) residual trend types; (c) the percentage (%) of different types of residual trend among vegetation types.

4. Discussion

4.1 Climatic factors behind changing patterns of vegetation dynamics

With the longest period of observing global vegetation on satellite, AVHRR series datasets have more than 30 years continuous data to analyze vegetation dynamics. However, it is hard to fully understand the dynamics merely rely on monotonic trend analysis. Recently, more and more non-monotonic methods were used to further elucidate vegetation dynamics, such as piecewise linear regression models (Cao et al. 2017), breaks for additive seasonal and trend (BFAST) analysis (Fang

et al. 2018) and Ensemble empirical mode decomposition (EEMD; Pan et al. 2018). It is necessary to fully consider the differences between different periods in the whole study time to describe vegetation dynamics and drivers accurately and completely.

As to our study, 60.93% of the regions showed opposite changing trends (ID and DI) before and after the turning point, which indicate that the vegetation dynamics in Southwestern China over 34 years were temporal heterogeneity. Drivers behind the turning point of vegetation dynamics are the changing of climatic factors. In the western and the southern parts of the study area, NDVI had a relatively significant turning point, and ID and DI NDVI changes occurred. In western Sichuan Plateau and northern Yunnan, the NDVI increased before the turning point and decreased after the turning point (ID). In this region, vegetation growth was mainly controlled by temperature and precipitation. After the turning point, precipitation in most areas changed from increasing trend to decreasing trend, especially in northern Yunnan (Fig. 5d and g). The region that temperature increased was broader than before the turning point (Fig. 5e and h). The rapid warming and reduced precipitation caused drought, especially from autumn 2009 to spring 2010 (Wu et al. 2019; Jia et al. 2018; Zhang et al. 2017). Droughts caused by *El Niño* in 2009-2010 and *La Niña* in 2012-2013 had a strong impact on vegetation growth (Wang et al. 2015; Wang et al. 2010). In northwestern Yunnan, precipitation decreased, high-quality forests decreased and water storage capacity declined (Xiong et al. 2018). Droughts have emerged in areas that were not dry in the past and may expand over the next 30 years (Zhao et al. 2013). Due to the steep slope of the Hengduan Mountains, precipitation cannot be adequately stored for plant growth, although precipitation has increased in this area.

In southern Sichuan, DI changes of NDVI were observed and were controlled by solar radiation before and after the turning point. Before the turning point, the solar radiation decreased exceeded

0.8 W·m²/yr, limiting vegetation growth (Fig. 5f). After the turning point, the solar radiation increased exceeded 0.8 W·m²/yr (Fig. 5i) and no longer restricted vegetation growth. In areas where precipitation is not a limiting factor, solar radiation may become the main influential factor (Huete et al. 2006). Karnieli et al. (2010) found that in high latitude and high altitude areas of North America, solar radiation as a control factor of vegetation growth is generally considered to control the beginning or ending of the growing season, mainly affecting the length of the growing season, while temperature was the main control factor in the growing season.

Besides, in the eastern part of the study area, where II NDVI changes occurred, vegetation growth was mainly controlled by temperature. From 1982 to 2015, the temperature increased exceeded 0.03°C/year (Fig. 5b), and the NDVI increased due to the increasing temperature, which advanced the start of the growing season (Shen et al. 2019; Wu et al. 2016).

4.2 Effects of human activities and limitations of RESTREND

The population is concentrated in the eastern part of the study area (Yu et al. 2018), where the economy and urbanization has been rapidly developed, and plantation and farmland are strongly affected by human activities. By contrast, the climate in the western part of the study area is dry and cold (Feng et al. 2020), where the development of economic is slow, and the impact of humans on vegetation is weak (Qu et al. 2020; Liu et al. 2018). The results of RESTREND analysis also revealed that human activities had a stronger influence on vegetation growth in the eastern part of the study area than in the western part (Fig. 7), which showed a similar spatial pattern with the human footprint pressure map (Fig. 8; Venter et al. 2016b). The high value of the human footprint was mainly concentrated in the central city and radiated in all directions. Because of the mountainous landscape in the western part of Sichuan, the human footprint mainly extended to the

eastern part. Since 2000, with the implementation of ecological projects such as the Grain for Green Program and Natural Forest Protection Project, which has greatly affected vegetation growth, farmland has decreased, forests have increased, and humans have played an important role in vegetation improvement (Han et al. 2018). Similar results were also found in farmland areas in central and western Guizhou. The central part of Guizhou is a typical karst area, where vegetation is fragile, and the forest has been restored in recent years (Tong et al. 2017). In western Guizhou, the Hurst index exceeded 0.71, which indicated that the vegetation changed steadily, and the intensity of human agricultural activities in this region was relatively weak (Tian et al. 2017). In the past 20 years, approximately 40% of the original cultivated land was abandoned, which reduced the negative disturbance to the forest area and reduced pressure on the ecosystem (Han and Song, 2019; Cai et al. 2014; Li et al. 2016). In addition, some forest protection policies and the Karst Rocky Desertification Comprehensive Control and Restoration Project allowed revival of the vegetation (Cheng et al. 2017).

However, the human footprint pressure map and RESTREND analysis results were not completely consistent in some regions. Relevant to our results, in eastern Guangxi, the vegetation types are CRO and EBF, which have not changed significantly in 34 years. RESTREND did not detect the impact of human activities on vegetation growth. However, a large number of *Eucalyptus* trees were planted here (Lu et al. 2019; Zhang et al. 2019), and human activities are a driving factor of vegetation dynamics. Therefore, issues of RESTREND should be considered when using it to study effects of human activities on vegetation dynamics. One is that factors cannot be explained by climate variables are classified into human factors by RESTREND. Therefore, fires, floods, pests and diseases that cause vegetation dynamic could be mistaken for human activities (Liu et al. 2013;

407 Boever et al. 2019; Yuan et al. 2017). Another is RESTREND cannot detect human activities which
 408 driving vegetation throughout the study period. Besides, Due to the data quality and the selection of
 409 climatic factors, the regression model also has potential uncertainties. When using RESTREND, it
 410 is necessary to combine other data to identify the impact of human activities on vegetation, such as
 411 fire data (Chu et al. 2019), human footprint pressure, land use or relevant national policies (Jiang et
 412 al. 2017). Establishing a reasonable regression relationship between vegetation and climatic factors
 413 is also critical to identify human activities accurately (Ma et al. 2019). In our study, not only
 414 RESTREND but also human footprint map was used to fully detect the effects of human activities.
 415 This can better detect role of human in driving vegetation dynamics.

416

Fig. 8. Spatial distribution of (a) the human footprint map for 1993, (b) the human footprint map for 2009, (c) difference in the human footprint map between 1993 and 2009.

5. Conclusion

In view of satellite data, this study analyzed the temporal and spatial dynamics of vegetation across Southwestern China. Based on the results of NDVI trends and driving factors used to detect climate and human activities, several conclusions were drawn as follows. The spatial distribution and trend showed high heterogeneity over Southwestern China. The annual mean NDVI generally increased from 1982-2015, but much of the study area showed the opposite trend before and after the turning point during this period. II and DI were two of the largest patterns of vegetation trends and they were mainly distributed in the eastern part of the study area. Temperature was the dominant climatic factor. In the eastern part of the study area, human activities played an important role in vegetation greening.

Abbreviations

AVHRR: Advanced Very High Resolution Radiometer; NDVI: normalized difference vegetation index; CRO: rainfed and irrigated cropland; MCR: mixed cropland and natural vegetation, cropland > 50%; MNV: mixed natural vegetation and cropland, natural vegetation > 50%; EBF: evergreen broad-leaved forest; DBF: deciduous broad-leaved forest; ENF: evergreen needle-leaved forest; GRA: grassland; MTS: mixed tree, shrub and herbaceous vegetation, tree and shrub > 50%; SHR: shrubland; II: an increasing trend that continued to an increasing trend; ID: an increasing trend that changed into a decreasing trend; DI: a decreasing trend that changed into an increasing trend; DD: a decreasing trend that continued to a decreasing trend; RESTREND analysis: residual trend analysis

Declarations

Ethics approval and consent to participate

No applicable.

Consent for publication

No applicable.

Availability of data and materials

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

WY, HW & OJS conceived the study. WY analyzed the data. CJ, SJ & JA provided technical guidance. WY & HW wrote the paper. All authors read and approved the final manuscript.

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Figures

Figure 1

Location of Southwestern China and a digital elevation model (DEM) Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 2

(a) Spatial distribution of vegetation types and (b) interannual change in mean NDVI in Southwestern China over the period 1982-2015. Vegetation types included rainfed and irrigated cropland (CRO); mixed cropland and natural vegetation, cropland > 50% (MCR); mixed natural vegetation and cropland, natural vegetation > 50% (MNV); evergreen broad-leaved forest (EBF); deciduous broad-leaved forest (DBF); evergreen needle-leaved forest (ENF); grassland (GRA); mixed tree, shrub and herbaceous vegetation, tree and shrub > 50% (MTS); shrubland (SHR); wetland, settlement, bare area and water (other). Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 3

Spatial distribution of (a) the annual mean NDVI and (b) the NDVI trend over the period 1982-2015. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 4

Spatial distribution of (a) the turning point year, (b) four types of NDVI changes: an increasing trend that continued to an increasing trend (II), an increasing trend that changed into a decreasing trend (ID), a decreasing trend that changed into an increasing trend (DI), a decreasing trend that continued to a decreasing trend (DD), (c) NDVI trend before that turning point year and (d) NDVI trend after that turning point year. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 5

Spatial distribution of (a) the precipitation trend, (b) temperature trend, (c) solar radiation trend over the period 1982-2015; (d) the precipitation trend, (e) temperature trend, (f) solar radiation trend before the turning point; (g) the precipitation trend, (h) temperature trend, and (i) solar radiation trend after the turning point. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 6

Spatial distribution of partial correlations between (a) mean NDVI and precipitation, (b) mean NDVI and temperature, (c) mean NDVI and solar radiation and (d) climate drivers of NDVI interannual variability. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 7

Spatial distribution of (a) NDVI residual trend and (b) residual trend types; (c) the percentage (%) of different types of residual trend among vegetation types. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 8

Spatial distribution of (a) the human footprint map for 1993, (b) the human footprint map for 2009, (c) difference in the human footprint map between 1993 and 2009. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.