Quantitative Analysis of Vegetation Dynamics in Response to Climatic Factors and Human Activities in Southwest China

Cuiping Yang (✉ yang_cuiping@nwafu.edu.cn)

Northwest A&F University

Yongqiang Wang

Northwest A&F University

Jiujiang Wu

Northwest A&F University

xiaoyi ma

Northwest A&F University

Research Article

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Posted Date: December 27th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-1165782/v1>

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Quantitative analysis of vegetation dynamics in response to climatic factors and human activities in southwest China

Cuiping Yang^a, Yongqiang Wang^a, Jiujiang Wu^a, Xiaoyi Ma^{a,*1}

(A Key Laboratory of Agricultural Soil and Water Engineering in Arid Area of Ministry of Education, Northwest A&F University, Yangling 712100, China)

Abstract: We determined the time scale of normalized difference vegetation index (NDVI) response to drought and used trend and correlation analyses to explore the spatial and temporal variability characteristics of the NDVI and SPEI and their sensitivity to climatic factors in southwest China from 2000 to 2020. We used a partial derivative approach to calculate the contributions of six climatic factors and human activities to the interannual variation in the NDVI. The results demonstrated that from 2000 to 2020, the annual mean NDVI in southwest China showed a slight decreasing trend at a rate of 0.0001 y^{-1} . The NDVI had the highest sensitivity to the standardized precipitation and evapotranspiration index on a 12-month time scale. The NDVI exhibited a 1-year delayed response to drought. The SPEI has the highest sensitivity to precipitation. The percentage of pixels with a positive correlation between NDVI and precipitation, mean temperature, temperature difference, mean relative humidity, mean wind speed, and sunshine duration in the study area was 31.73%, 46.81%, 35.49%, 25.76%, 39.36%, and 39.89%, respectively. The average contributions of these six climatic factors to the interannual variation of NDVI were 0.00029, 0.00046, -0.00007 , 0.00007, 0.0008, and 0.00001 y^{-1} , respectively. The NDVI had the highest sensitivity to mean temperature and the lowest sensitivity to mean relative humidity. The average contributions of climatic factors and human activities to interannual variability in southwest China were 0.00156 and 0.00012 y^{-1} , respectively. The positive influence of climatic factors on the NDVI was stronger than that of human activities. This study provides a theoretical basis for the sustainable management of the regional ecological environment.

Keywords: Normalized difference vegetation index (NDVI); Standardized precipitation and evapotranspiration index (SPEI); driving factors; factor contribution; Sobol' global sensitivity; southwest China

¹ Author: Cuiping Yang, E-mail: yang_cuiping@nwfau.edu.cn; Corresponding author: Xiaoyi Ma, E-mail: xma@nwfau.edu.cn.

1 Introduction

Vegetation is an important component of ecosystems ([Lizaga et al., 2018](#); [Christopher et al., 2019](#)), with significant sensitivity to climatic factors and human activities. Vegetation growth responds to changes in environmental factors ([Zhao et al., 2019](#)). In particular, drought can affect the change in vegetation growth on a regional scale. Changes in vegetation growth have been explored to reveal the characteristics of regional ecological changes and their response mechanisms to environmental factors and human activities ([Zhang et al., 2018](#); [Nijssen et al., 2016](#)) and to provide a theoretical basis for the formulation of reasonable ecological and environmental management policies.

The normalized difference vegetation index (NDVI) has been widely used to quantify vegetation growth and cover status. Climatic factors directly influence vegetation growth and cover change. Numerous domestic and international studies have focused on two driving factors, precipitation and temperature. [Keisling et al. \(2016\)](#) reported that with the gradual increase in temperature, vegetation growth at high latitudes showed early greening. [Turco et al. \(2016\)](#) demonstrated that the correlation coefficient between the NDVI and precipitation was high in southern Israel. [Ayana et al. \(2016\)](#) reported a significant correlation between NDVI values and mean precipitation in spring in eastern Africa. [Mo et al. \(2019\)](#) demonstrated that the growth of different types of vegetation in southwest China is increasing and is significantly influenced by environmental factors such as temperature and precipitation. [Huang et al. \(2016\)](#) used a distribution index to reveal significant differences in the characteristics of vegetation change between different seasons in southwest China. [Han et al. \(2019\)](#) and [Fu et al. \(2014\)](#) determined that the annual mean NDVI values in southwest China exhibited an increasing trend and were significantly correlated with both temperature and precipitation. The influence of climatic factors on evapotranspiration has been evaluated based on the partial derivative method, which quantifies the contribution of each driving factor ([Yang et al., 2012](#); [Meng et al., 2012](#)). In addition to precipitation and temperature, the contribution of other drivers of climatic factors (relative humidity, solar radiation and wind speed) to vegetation growth is undisputed, but unfortunately, there are fewer relevant studies in this area.

Vegetation growth is more sensitive to climatic factors than human activities ([Mu et al., 2013](#)).

And the impact of human activities on vegetation growth varies from region to region. And vegetation growth in southwest China correlated best with autumn precipitation and summer temperatures and that human activities contributed to vegetation growth (Li et al., 2015). The impact of human activities on the vegetation of the Loess Plateau and Qinling Mountains was demonstrated to be two-sided, but the positive effects were greater than the negative effects (Shi et al., 2020; Liu et al., 2016). The effects of human activities and vegetation growth are reciprocal, with urbanization leading to a decrease in the area of suburban vegetation on the one hand and an increase in the area of urban greenery on the other (Yao et al., 2018; Gong et al., 2017). Analysis of residuals is commonly used in such studies to analyze the relationship between vegetation and drivers, but this method cannot accurately quantify the contribution of climatic factors and human activities to vegetation, especially in distinguishing and comparing the effects of individual climatic factors on vegetation, while the partial derivative method can compensate for this shortcoming (Qu et al., 2018; Yan et al., 2019).

The study of vegetation change characteristics in southwest China is crucial for ecological security. Current studies mainly focus on vegetation cover change monitoring and attribution; studies on the influence of climatic factors on the NDVI mainly concern the influence of temperature and precipitation on the NDVI. Few studies have been conducted to separately quantify each driver affecting regional vegetation growth. Therefore, the purpose of this paper is to explore (1) temporal variations of the NDVI, the standardized precipitation and evapotranspiration index (SPEI), and climatic factors from 2000 to 2020; (2) response characteristics of vegetation to drought on different time scales; (3) the sensitivity of interannual variation trend of NDVI to climatic factors in southwest China from 2000 to 2020; and (4) the contributions of six climatic factors and human activities to the interannual variation of the NDVI based on the partial derivative method. This study provides a scientific basis for the planning of ecological projects in southwest China by elucidating the response mechanisms of vegetation dynamics to drought on different time scales and quantifying the contribution of different drivers to the NDVI.

2 Materials and methods

2.1. Study region

Southwest China includes Yunnan Province, Guizhou Province, Sichuan Province, Guangxi

90 Zhuang Autonomous Region, and Chongqing Municipality, with an area of approximately $1.37 \times$
 91 10^6 km² (Fig. 1). The region is located between 20°54'-34°19'N and 97°21'-112°04'E. The western,
 92 northwestern, and central-eastern parts of the study region are mountainous and hilly and account
 93 for more than two-thirds of the total area of the region. The rest of the region is mostly plains and
 94 plateau. The region is in the climate transition zone of the Qinghai-Tibet Plateau, with a generally
 95 warm and sunny climate. The average annual temperature is 14–24 °C and the average annual
 96 precipitation is 600–2300 mm, with precipitation mainly concentrated in the summer and autumn
 97 (80%–90%; Zhao, 1997). Precipitation is largely characterized by a decreasing distribution from
 98 the southeast to northwest (Zhu et al., 2017), ranging from more than 2500 mm on the northern
 99 coast of the Beibu Gulf (Guangxi Zhuang Autonomous Region) to less than 700 mm in
 100 northwestern and northeastern Yunnan (Li et al., 2019).

113 **Fig. 1** The study region comprises four provinces, Yunnan, Guizhou, Sichuan, and Guangxi , and a
 114 municipality, Chongqing.

2.2 Data source and processing

2.2.1 Meteorological data

Meteorological data were obtained from 108 meteorological station datasets provided by the China Meteorological Data Sharing Service Center (<http://cdc.cma.gov.cn>). Datasets included daily precipitation, maximum temperature, minimum temperature, average wind speed, light hours, and average relative humidity data from 2000 to 2020. Datasets from 32 stations that had data missing for more than one year were excluded; the remaining 96 stations were distributed as shown in Fig 1. To facilitate the correlation analysis between the NDVI and SPEI, the SPEI calculated using station meteorological data was interpolated as raster data using inverse distance weights, with the spatial resolution resampled to 1 km.

2.2.2 Remote sensing data

MODIS NDVI data were derived from the MOD13Q1 dataset (<https://lpdaac.usgs.gov/products/mod13q1v006/>) from the MODIS Terra satellite sensor data from 2000 to 2020. The spatial resolution was 500 m and the temporal resolution was 16 d. NDVI data were synthesized into monthly values using the maximum value composite method (Cong et al., 2012; Zhao et al., 2017). The NDVI data were also resampled to a spatial resolution of 1 km.

2.3 Methods

2.3.1 NDVI

As an important remote sensing parameter reflecting vegetation status, NDVI is an indicator of plant growth status and spatial distribution density. The NDVI was defined as follows:

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad (1)$$

where *NIR* is the near-infrared reflectance and *RED* is the visible reflectance. Regions with an $NDVI > 0.1$ are generally considered vegetated, and an increase in NDVI indicates an increase in green vegetation; an $NDVI < 0.1$ indicates the lack of detectable vegetation on the surface, which could mean human settlement, bare soil, desert, water bodies, or clouds.

2.3.2 SPEI

Vicente-Serrano et al. (2010) proposed the SPEI. Compared with the standardized precipitation index, the SPEI considers the effect of potential evapotranspiration and uses the FAO

Penman–Monteith formula to calculate potential evapotranspiration (ET_0), which can more accurately characterize the drought condition, especially in regions with significant warming (Zhang et al., 2015). The specific calculation method is found in Ruspini et al. (1965).

2.3.3 Trend analysis

To quantitatively reflect the spatial and temporal variation of the NDVI in the study region, interannual trends in the NDVI were calculated at the pixel level using least squares regression, and the F-test was used to determine the significance of each pixel. The calculation equation was as follows:

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

where λ_{slope} is the slope of regression, n is the total number of years monitored ($n = 21$), and C_i is the mean NDVI value in year i . When $\lambda_{slope} > 0$, the NDVI had an increasing trend during the study period; otherwise, it had a decreasing trend.

2.3.4 Correlation analysis

The correlation between NDVI and SPEI and the correlation between NDVI and climate factors were evaluated by calculating Pearson correlation coefficients of all pixels. The calculation equation was as follows:

$$R = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \sum_{i=1}^n (y_i - \bar{y})^2}} \quad (3)$$

where x_i and y_i represent the values of the SPEI (or climatic factors) and the NDVI in year i , respectively, and $\bar{x}$ and $\bar{y}$ are the average values of the SPEI (or climatic factors) and the NDVI over time.

2.3.5 Sobol' sensitivity analysis of the SPEI to climatic factors

In this study, the Sobol global sensitivity analysis method (Aovk, et al., 2017), which analyzes the independent and total sensitivity of the SPEI to meteorological factors, was selected as a global

sensitivity analysis method based on variance assignment. The model is first decomposed as a function of individual variables and combinations between variables, and then, the total variance of the model output is decomposed as a combination of individual input variables and correlations between variables as follows:

$$V = \sum_i V_i + \sum_{i < j} V_{ij} + \sum_{i < j < m} V_{ijm} + \Lambda V_{1,2,\Lambda,k} \quad (4)$$

where V is the total variance value of the model output, V_i is the variance value caused by the input variables, and V_{ij} is the variance value caused by the correlation between the input variables i and j .

The formula for calculating the sensitivity coefficient is as follows:

$$S_i = \frac{V_i}{V} \quad (5)$$

$$S_{ij} = \frac{V_{ij}}{V} \quad (6)$$

$$S_{\pi} = \frac{V_i + \sum_i V_{ij} + \sum_{j < m} V_{ijm} + \Lambda V_{i,j,\Lambda,k}}{V} \quad (7)$$

where Eq. (5) is used to calculate the first-order sensitivity coefficient, which represents the independent sensitivity of SPEI to meteorological factors, Eq. (6) is used to calculate the second-order sensitivity coefficient, which represents the correlation between meteorological factors, and Eq. (7) is used to calculate the total order sensitivity coefficient, which represents the total sensitivity of the SPEI to meteorological factors. The variance of these equations was estimated by approximating Monte Carlo values. S_{Pre} , S_{Tem} , $S_{Tmax-Tmin}$, S_{Rh} , S_{Ws} , and S_{Sd} represent the sensitivity coefficients of the SPEI to precipitation, mean temperature, temperature difference, mean relative humidity, mean wind speed, and sunshine duration, respectively.

2.3.6 Contribution of each driver to the interannual variation of the NDVI

The partial derivative method has been widely used to quantify the contribution of climatic factors to evapotranspiration (Meng et al., 2012; Li et al., 2017a). It is increasingly applied to vegetation analysis (Yan et al., 2019; Zhang et al., 2016). We applied this method to quantitatively estimate

the contribution of different drivers to changes in the NDVI. We assumed that climatic factors (precipitation, average temperature, temperature difference, average relative humidity, average wind speed, and sunshine duration) and nonclimatic factors are the complete set of environmental factors that contribute to NDVI variation. The contribution of each factor to the interannual variability of NDVI was calculated as follows:

$$\begin{aligned}\lambda_{slope} &= Con(Pre) + Con(Tem) + Con(T \max - T \min) + Con(Rh) + Con(Ws) + Con(Sd) + UF \\ &= \frac{\partial NDVI}{\partial Pre} \times \frac{\partial Pre}{\partial t} + \frac{\partial NDVI}{\partial Tem} \times \frac{\partial Tem}{\partial t} + \frac{\partial NDVI}{\partial T \max - T \min} \times \frac{\partial T \max - T \min}{\partial t} + \frac{\partial NDVI}{\partial Rh} \times \frac{\partial Rh}{\partial t} + \\ &\quad \frac{\partial NDVI}{\partial Ws} \times \frac{\partial Ws}{\partial t} + \frac{\partial NDVI}{\partial Sd} \times \frac{\partial Sd}{\partial t} + UF \\ &= CF + UF\end{aligned}\quad (8)$$

where λ_{slope} is the interannual variability of NDVI, which is obtained from Equation (2), and precipitation, mean temperature, temperature difference, mean relative humidity, mean wind speed, and sunshine duration are expressed by Pre , Tem , $Tmax - Tmin$, Rh , Ws , and Sd , respectively.

$Con(Pre)$, $Con(Tem)$, $Con(Tmax - Tmin)$, $Con(Rh)$, $Con(Ws)$, and $Con(Sd)$ denote the contributions of precipitation, mean temperature, temperature difference, mean relative humidity, mean wind speed, and sunshine duration to the interannual variation of the NDVI, respectively; t

is time. $\frac{\partial NDVI}{\partial Tem}$, $\frac{\partial NDVI}{\partial T \max - T \min}$, $\frac{\partial NDVI}{\partial Rh}$, $\frac{\partial NDVI}{\partial Ws}$, $\frac{\partial NDVI}{\partial Sd}$ denote the slopes of linear regressions between the NDVI and precipitation, mean temperature, temperature difference, mean relative humidity, mean wind speed, and sunshine duration, respectively.

$\frac{\partial Pre}{\partial t}$, $\frac{\partial Tem}{\partial t}$, $\frac{\partial T \max - T \min}{\partial t}$, $\frac{\partial Rh}{\partial t}$, $\frac{\partial Ws}{\partial t}$, $\frac{\partial Sd}{\partial t}$ denote the slope of linear regression of precipitation, mean air temperature, temperature difference, mean relative humidity, mean wind speed, and sunshine duration at time t , respectively. CF and UF denote the contributions of climatic and nonclimatic factors to the interannual variability of the NDVI, respectively, where CF is the sum of $Con(Pre)$, $Con(Tem)$, $Con(Tmax-Tmin)$, $Con(Rh)$, $Con(Ws)$, and $Con(Sd)$, and UF is the residual between the rate of NDVI change and the contribution of climatic factors. In this study, the contribution of other unknown natural factors was ignored, and UF was considered to be the contribution of human activities to the NDVI. A positive contribution of the driver to the

interannual variation of the NDVI indicated that the driver promoted an increase in the NDVI.

3 Results and analysis

3.1 Temporal variation of climatic factors and drought indices in southwest China

The results of the linear trend analysis demonstrated that the mean NDVI value in southwest China decreased slightly with a slope of -0.0001 from 2000 to 2020; the NDVI curve fluctuates widely, with the minimum value of 0.36 appearing in 2012 (Fig. 2). The slope of the SPEI was 0.0037 , which indicates a slightly wet trend in the climate of the southwest between 2000 and 2020, with the minimum value of -0.66 occurring in 2011. Based on the time of the minimum values of the NDVI and SPEI, the NDVI response to drought lagged by up to 1 year. The mean values of precipitation, mean temperature, temperature difference, mean relative humidity, mean wind speed, and sunshine duration in the southwest from 2000 to 2020 were 1142.33 mm, 15.94°C , 9.48°C , 73.39%, 1.64 m s^{-1} , and 1606.96 h, respectively. Mean temperature and mean wind speed exhibited a significant increasing trend ($P < 0.05$), with increases of $0.0222^{\circ}\text{C y}^{-1}$ and $0.00171\text{ m}\cdot\text{s}^{-1}\cdot\text{y}^{-1}$, respectively. Precipitation, mean relative humidity, and sunshine duration exhibited a nonsignificant increasing trend ($P > 0.05$), with increases of 4.3316 mm y^{-1} , $0.0086\%\text{ y}^{-1}$, and $0.3031\text{ h}\cdot\text{y}^{-1}$, respectively. Temperature difference exhibited a decreasing trend, with a rate of $0.0108^{\circ}\text{C y}^{-1}$. The temperature difference gradually decreased and temperature showed an increasing trend. The temperature change in southwest China responded to the global warming trend.

Fig. 2 Trends of the normalized difference vegetation index (NDVI), climatic factor, and standardized precipitation and evapotranspiration index (SPEI) changes in southwest China from 2000 to 2020. The shaded areas indicate the confidence intervals of the NDVI, climatic factor, and SPEI changes, respectively.

3.2 Response of the NDVI to the SPEI on different time scales

[Fig. 3](#) illustrates the spatial pattern of the correlation between the NDVI and SPEI on different time scales in southwest China from 2000 to 2020. The correlation coefficients between the NDVI and SPEI were significantly spatially heterogeneous across the study area, but the correlations between the NDVI and SPEI on different time scales were spatially homogenous. The areas with high correlation coefficients between the NDVI and SPEI were located primarily in northeastern Sichuan Province, Chongqing City, eastern Yunnan Province, and central Guangxi Province, with a maximum value of 0.91, whereas the areas with low correlation coefficients were located primarily in western Sichuan Province and western Yunnan Province (Hengduan Mountains), with a minimum value of -0.51 . Overall, the highest correlation between the NDVI and drought in southwest China was in the central region, followed by the eastern and western regions. The proportion of pixels that passed the significance test for the correlation between the NDVI and the SPEI on the time scales of 1 month (SPEI-1), 3 months (SPEI-3), 6 months (SPEI-6), and 12 months in southwest China was 5.93%, 6.20%, 7.44%, and 9.89%, indicating that the correlation between vegetation growth and wet and dry conditions in these regions was high. The sensitivity of the NDVI to SPEI-12 was the highest, and the time scale of the response to drought was longer.

Fig. 3 Correlation coefficients of the normalized difference vegetation index (NDVI) with the standardized precipitation and evapotranspiration index (SPEI) of different time scales in southwest China from 2000 to 2020. (a–d) The correlation coefficients of the NDVI with the SPEI on the time scales of 1 month (SPEI-1), 3 months (SPEI-3), 6 months (SPEI-6), and 12 months (SPEI-12). The inset in the upper right corner shows the regions in the southwest that passed the significance test ($P < 0.05$) for the pixel class. The pie inset shows the proportion of pixel area (%) that passed the significance test for the correlation analysis of the NDVI and SPEI.

3.3 Sensitivity analysis of SPEI and NDVI to climate factors in southwest China

3.3.1 Global sensitivity analysis of SPEI to climate factors

To further investigate the influence of climatic change on vegetation, this study used the Sobol' global sensitivity method to analyze the sensitivity of the SPEI to precipitation, mean temperature, temperature difference, mean relative humidity, mean wind speed, and sunshine duration in southwest China (Fig. 4). We determined that the first-order sensitivity and total sensitivity

coefficients of the relationship between the SPEI and the six climatic factors were nearly identical, that is, the SPEI had the highest sensitivity to precipitation, followed by average relative humidity, and the lowest sensitivity to sunshine duration. The maximum value of 0.45 of the first-order precipitation sensitivity coefficient occurred in July and the minimum value of 0.06 occurred in February, indicating a considerable seasonal difference. The difference between the total intra-annual sensitivity coefficients and the first-order sensitivity coefficients of precipitation, mean air temperature, temperature difference, mean relative humidity, mean relative wind speed, and sunshine duration was 0.54, 0.54, 0.31, 0.42, 0.12, and 0.09, respectively, indicating that the SPEI was more sensitive to the effects of average temperature and precipitation and the least sensitive to sunshine hours, which differs from the sensitivity of the NDVI to individual climatic factors. This demonstrates that the constraint affecting drought in the study area was precipitation.

Fig. 4 Intra-annual variation of first-order sensitivity and total sensitivity of the standardized

precipitation and evapotranspiration index to climatic factors in southwest China

(Pre[precipitation]; Tem[mean temperature]; Tmax – Tmin [temperature difference]; Rh [mean relative humidity]; Ws [mean wind speed]; Sd [sunshine duration])

3.3.2 Sensitivity of the NDVI to climatic factors

A combination of factors affects the healthy growth of vegetation. Both climate change and land use change are key factors affecting the spatial and temporal patterns of vegetation growth (Mao et

al., 2012). We analyzed the correlation between the NDVI and climatic factors (Fig. 5). Positive and negative correlations between the NDVI and precipitation, mean air temperature, temperature difference, mean relative humidity, mean relative wind speed, and sunshine duration coexisted; the proportion of pixels with positive correlations between the NDVI and the six climatic factors in the study area was 31.73%, 46.81%, 35.49%, 25.76%, 39.36%, and 39.89%, respectively, which indicates that the NDVI was most sensitive to mean temperature, followed by sunshine hours; the NDVI was least sensitive to mean relative humidity. Therefore, temperature was the most important factor limiting vegetation growth in southwest China during the study period. The proportion of pixels that passed the significance test ($P < 0.05$) for the correlation between the NDVI and precipitation, mean air temperature, temperature difference, mean relative humidity, mean relative wind speed, and sunshine duration in the study area was 6.93%, 15.69%, 8.31%, 5.85%, 16.06%, and 6.67%, respectively. The areas of high correlation between the NDVI and temperature were located primarily in southeastern Sichuan, western Guizhou, and southern Guangxi, with a wide distribution; northwestern Sichuan (Ruoerge Plateau) is at a high altitude with low vegetation cover, so the correlation with temperature was low. The influence of precipitation on the NDVI in the study area was relatively small, which is a result of the differing surface vegetation cover and elevation topography in the southwest and the large difference in precipitation correlation. The regions with a significant correlation ($P < 0.05$) between mean annual NDVI and mean annual precipitation were mainly located in southeastern Sichuan and northeastern Yunnan (central and western Yunnan–Guizhou Plateau), which is explained by the fact that in mountainous or humid areas where precipitation is abundant, the water conditions required for plant growth can be met, whereas excessive precipitation can reduce light and affect photosynthesis, thus affecting plant growth (Li et al., 2009). By contrast, the correlation between the NDVI and precipitation was lower in the Sichuan basin than in the surrounding areas because the region is an agricultural area where crops are well watered because of irrigation and other tillage practices and require less natural precipitation. The areas with a high correlation between

the NDVI and mean wind speed were mainly in northeastern Sichuan (Sichuan Basin), which is related to the special topography of the basin. The NDVI was significantly correlated with sunshine duration mainly in Guizhou Province. The correlation between the NDVI and mean relative humidity was negative in most areas.

Fig. 5 Spatial distribution of the correlation coefficients between the NDVI and climatic factors (precipitation, mean temperature, temperature difference, mean relative humidity, mean wind speed, and sunshine hours) in southwest China. The inset in the upper right corner shows the regions in the southwest where the pixel level passed the significance test ($P < 0.05$) for the

correlation analysis of the NDVI and climatic factors. The pie inset shows the proportion of pixel areas (%) that passed the significance test.

3.4 Quantitative analysis of the drivers of vegetation dynamics in southwest China

3.4.1 Contribution of climatic factors to the interannual variation of the NDVI

The correlation coefficients describe the sensitivity of vegetation to climatic factors but cannot quantify the effect of climatic factors on the interannual variation of the NDVI. To quantify the effects of climatic factors on the NDVI, this study compared the contributions of each climatic factor to the NDVI of southwest China from 2000 to 2020 at the regional and pixel levels (Fig. 6) and analyzed the relationships between the NDVI, each climatic factor, and human activities. The average contributions of the six climatic factors to the NDVI were mainly positive. The average contributions of precipitation, average temperature, temperature difference, average relative humidity, average wind speed, and sunshine duration to the NDVI were 0.00029, 0.00046, -0.00007 , 0.00007, 0.0008, and 0.00001 y^{-1} , respectively. Mean wind speed contributed the most to the NDVI, followed by mean temperature and precipitation; the mean contribution of temperature difference to the NDVI was negative. At the pixel level, the positive contributions of precipitation, mean temperature, temperature difference, mean relative humidity, mean wind speed, and sunshine duration to the interannual variation of the NDVI were 45.24%, 53.39%, 32.79%, 38.83%, 52.45%, and 34.07%, respectively, for the study area, which indicated a strong positive contribution of temperature to the NDVI. And we determined that temperature difference and sunshine hours had the strongest negative contributions to the NDVI for the southeastern part of southwest China (Guizhou and Guangxi provinces). Mean wind speed made the largest contribution to the interannual variation of the NDVI in northeastern Sichuan, with a maximum value of 0.0139 y^{-1} . Precipitation made a relatively small contribution to the NDVI in southwest China. In conclusion, the NDVI in southwest China was most sensitive to temperature and relatively sensitive to mean wind speed and precipitation.

Fig. 6 Contribution of climatic factors to the interannual variation of the NDVI in southwest China from 2000 to 2020.

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3.4.2 Contribution of different drivers to the interannual variation of the NDVI

The total contribution of climatic and nonclimatic factors to the interannual variation of the NDVI in southwest China is illustrated in Fig. 7. The interannual rate of change of the NDVI in southwest China from 2000 to 2020 was 0.00168 y^{-1} , of which the contribution of climatic factors was 0.00156 y^{-1} and that of UF was 0.00012 y^{-1} , which indicates that both climatic and nonclimatic factors had a positive influence on the NDVI. Climatic factors mainly contributed to the NDVI in eastern Sichuan and southern Guangxi, regions which are mostly flatter crop-growing areas sensitive to climatic factors. The contribution from climatic factors was relatively small for northwestern Sichuan (Ruoerge Plateau). Pixels in which climatic factors and human activities made positive contributions to the NDVI in southwest China accounted for 80.52% and 52.49% of the region, respectively. The positive influence of climatic factors on the NDVI was stronger than that of human activities.

Fig. 7 Interannual trends of the normalized difference vegetation index (NDVI) and the contribution of climatic factors and human activities to the NDVI in southwest China

4 Discussion

4.1 Relationship between NDVI and multi-scale drought

On longer time scales (6 and 12 months), the area with relatively high correlation coefficients between the NDVI and SPEI in southwest China was extended, with 9.89% of the total pixels passing the significance test for correlation on the 12-month scale (Fig. 2d), a phenomenon that may result from soil conditions and vegetation type. Southwest China is predominantly mountainous and the vegetation is dominated by trees and scrub, whose roots can draw deep groundwater to resist drought (Davidson et al., 2000; Wu et al., 2018). The correlation between the NDVI and SPEI on different time scales reflects the time sensitivity of vegetation to drought. If the correlation between the NDVI and short time-scale SPEI is higher, vegetation responds to drought faster; if the correlation between the NDVI and long time-scale SPEI is higher, vegetation responds to drought slower, indicating that biomes are more resistant to drought.

The response of vegetation to drought varied with time scale. In this study, we determined that the NDVI had the slowest response to the SPEI-12 and the fastest response to the SPEI-1 (Fig. 2). In previous studies, the response of vegetation to drought has been reported to differ among regions. Compared with other regions in China, vegetation in the Loess Plateau arid zone was the most sensitive to the SPEI (Zhao et al., 2018). The NDVI in North China was more sensitive to drought on short- and medium-term time scales (Zhang et al., 2016). The Mediterranean region was more sensitive to drought on short- and medium-term scales (Gouveia et al., 2016). Vegetation in southwest China is more sensitive to drought on medium- and long-term scales. Therefore, precipitation and evapotranspiration are not the only factors that influence vegetation response to

drought; other factors include plant species, topographic features, and soil texture.

4.2 Interannual sensitivity response of SPEI to climate factors

The sensitivity of potential evapotranspiration to meteorological factors has been well studied (Wang et al., 2019; Remus et al., 2019), but the sensitivity of the drought index to meteorological factors has been less studied. Liu et al (2011) demonstrated that the sensitivity of the drought index to meteorological factors was as follows: precipitation > maximum temperature > wind speed > minimum temperature. Zhang et al. (2019) reported that the sensitivity of potential evapotranspiration in the Taohe basin to meteorological factors was as follows: average temperature > precipitation > relative humidity > wind speed > temperature difference > solar radiation. These studies are generally consistent with our findings. Table 1 lists the interannual first-order and total sensitivity coefficients of the SPEI to the six climatic factors. In our study, the total interannual sensitivity of the SPEI to meteorological factors in southwest China was as follows: precipitation > average temperature > average relative humidity > temperature difference > average wind speed > sunshine duration. The abnormal climate driving factors make the ecosystem exceed the climate tolerance threshold and lead to drought disaster, which leads to the increase of vegetation mortality, forest fire and unpredictable changes of vegetation community, and finally has a negative impact on NDVI (Beguería et al., 2014; Gremer et al., 2015).

Table 1 Interannual sensitivity coefficients of the standardized precipitation and evapotranspiration index to climatic factors in southwest China

Sensitivity coefficient	S_{Pre}	S_{Tem}	$S_{Tmax-Tmin}$	S_{Rh}	S_{Ws}	S_{Sd}
First order sensitivity coefficient	0.25	0.01	0.05	0.12	0.10	0.01
Total order sensitivity coefficient	0.79	0.55	0.35	0.54	0.22	0.10

Note: S_{Pre} , S_{Tem} , $S_{Tmax-Tmin}$, S_{Rh} , S_{Ws} , and S_{Sd} represent the sensitivity coefficients of the SPEI to precipitation, mean temperature, temperature difference, mean relative humidity, mean wind speed, and sunshine duration, respectively.

4.3 Response of vegetation to climatic and nonclimatic factors

Our study results indicated that the NDVI had the highest sensitivity to temperature throughout the

study area (Fig. 4). However, the contribution of mean wind speed to the NDVI was the largest at 0.0008 y^{-1} , and the effect of mean wind speed on the interannual trend of the NDVI in the study area was significantly spatially heterogeneous, with the largest effect mainly in eastern Sichuan (Sichuan basin) and southern Guangxi (Guangxi hills) (Fig. 5-e). This may be related to the topographic characteristics of those regions; the Sichuan basin and Guangxi hills are low, the topography is relatively flat, so the climate change is susceptible to wind. And the southern part of Guangxi is close to the sea in the south, which brings water vapor and precipitation through the wind, which in turn affects vegetation growth (Peng et al., 2019; Zha et al., 2016). Human activities had a strong negative contribution to the NDVI in most of Sichuan (Sichuan Basin) and northwestern Yunnan (Hengduan Mountains; Fig. 6c). The large population size and urban expansion in Sichuan province have led to a reduction in vegetation area, so human activities have had a suppressive effect on vegetation growth there, whereas in northwestern Yunnan, which is dominated by plateaus and mountains, the ecology is fragile and vulnerable to the negative effects of human activities (Bounmans et al., 2015). The large difference in the average contributions of the two drivers stems from the short duration and strong effect of human activities on vegetation growth, for example, ecological restoration projects have noticeable effects in the short term, whereas climatic factors have a slow and stable effect on vegetation.

This study quantified the contribution of each driver to vegetation growth in southwest China based on the partial derivative method, but the limited time span may lead to some limitations in our understanding of the effects of different drivers on vegetation dynamics. In addition, plant growth is also influenced by soil type, community characteristics, and other factors. Future research could elucidate the mechanisms of interaction between human activities, climatic factors, and changes in vegetation growth and subdivide and quantify the effects of various nonclimatic factors.

5 Conclusions

From 2000 to 2020, the average NDVI in southwest China fluctuated but generally showed a

slight decreasing trend with a rate of -0.0001 y^{-1} . However, the SPEI showed an increasing trend at a rate of 0.0037 y^{-1} , with a nonsignificant wetting trend in the southwest. The NDVI had a delayed response to drought, with a lag time of up to 1 year. The NDVI was most correlated with drought in the central region, followed by the eastern region; the western region had the lowest correlation. Pixels with positive correlations between the NDVI and precipitation, mean temperature, temperature difference, mean relative humidity, mean relative wind speed, and sunshine duration accounted for 31.73%, 46.81%, 35.49%, 25.76%, 39.36%, and 39.89% of the study area, respectively, which indicated that the NDVI was most sensitive to mean temperature, followed by sunshine duration; the NDVI had the lowest sensitivity to mean relative humidity. Therefore, temperature was the most important factor limiting vegetation growth in southwest China. The average contributions of precipitation, mean temperature, temperature difference, mean relative humidity, mean wind speed, and sunshine duration to the NDVI were 0.00029, 0.00046, -0.00007 , 0.00007 , 0.0008 , and 0.00001 y^{-1} , respectively. Mean wind speed had the greatest influence on the interannual variation of the NDVI in southwest China, contributing the most to eastern Sichuan (Sichuan Basin). The average contributions of climate factors and human activities to interannual variability in southwest China were 0.00156 and 0.00012 y^{-1} , respectively, throughout the study period. Pixels with positive correlations between the NDVI and climate factors and human activities accounted for 80.52% and 52.49% of the study area, respectively. Climatic factors had the strongest positive effect on the change in the NDVI.

Author Contribution

Cuiping Yang: Data curation, Writing-Original draft preparation. Yongqiang Wang, Jiujiang Wu: Conceptualization, Methodology, Software. Xiaoyi Ma: Reviewing and Editing.

Fundings

This study was financially supported by The National Natural Science Foundation of China, grant

number 51279167; Distributed Monitoring and Forecasting Technology of Soil Moisture in Irrigation District (No.2017YFC0403202)

Data Availability Statement

All data generated or analysed during this study are included in this published article.

Conflicts of Interest

The authors declare no conflict of interest.

References

- Aovk* , B S K , B N S, (2017). Constrained Global Sensitivity Analysis: Sobol' indices for problems in non-rectangular domains. *Computer Aided Chemical Engineering*, 40:151-156.
- Ayana E K, Ceccato P, Fisher J, et al., (2016). Examining the relationship between environmental factors and conflict in pastoralist areas of East Africa. *Science of the Total Environment*, 557-558:601-611.
- Beguiría S, Vicente-Serrano S M, Reig F, et al., (2014). Standardized precipitation evapotranspiration index (SPEI) revisited: Parameter fitting, evapotranspiration models, tools, datasets and drought monitoring. *Int. J. Climatol*, 34: 290-301.
- Boumans R, Roman J, Altman I, Kaufman L, (2015). The Multiscale Integrated Model of Ecosystem Services(MIMES): Simulating the interactions of coupled human and natural systems. *Ecosyst. Serv.*, 12: 30-41.
- Christopher E, Ndehedehe V G, Ferreira N O, et al., (2019). Hydrological controls on surface vegetation dynamics over West and Central Africa. *Ecological Indicators*, 103:494-508.
- Cong N, Piao S, Chen A, Wang X, Lin X, et al., (2012). Spring vegetation green-up date in China inferred from SPOT NDVI data: a multiple model analysis. *Agric For Meteorol*, 165:104-113.
- Davidson E A, Verchot L V, Cattanio J, et al., (2000). Effects of soil water content on soil respiration in forests and cattle pastures of eastern Amazonia. *Biogeochemistry*, 48: 53-69.
- Fu X, Tang C, Zhang X, et al., (2014). An improved indicator of simulated grassland production based on MODIS NDVI and GPP data: A case study in the Sichuan province, China. *Ecological Indicators*, 40:102-108.
- Gong Z N, Zhao S Y, Gu J Z, (2017). Correlation analysis between vegetation coverage and

531 climate drought conditions in North China during 2001-2013. *Geogr. Sci.* 27: 143-160.

532 Gouveia C M, Trigo R M, Beguería S, et al., (2017). Drought impacts on vegetation activity in the
533 Mediterranean region: An assessment using remote sensing data and multi-scale drought
534 indicators. *Global and Planetary Change*,151: 15-27.

535 Gremer J R, Bradford J B, Munson S M, Duniway M C, et al., (2015). Desert grassland responses
536 to climate and soil moisture suggest divergent vulnerabilities across the southwestern United
537 States. *Glob. Chang. Biol*, 21: 4049-4062.

538 Han Z, Song W, (2019). Spatiotemporal variations in cropland abandonment in the
539 Guizhou-Guangxi karst mountain area, China. *Journal of Cleaner Production*, 238:1-15.

540 Huang W, Ho H C, Peng Y, et al., (2016). Qualitative risk assessment of soil erosion for karst
541 landforms in Chahe town, Southwest China: A hazard index approach. *Catena*, 144:184-193.

542 Keisling B A, Castañeda I S, Brigham G J, et al., (2017). Hydrological and temperature change in
543 Arctic Siberia during the intensification of Northern Hemisphere Glaciation. *Earth and
544 Planetary Science Letters*,457:136-148.

545 Li G, Zhang F, Jing Y, Liu Y, Sun G, (2017a). Response of evapotranspiration to changes in land
546 use and land cover and climate in China during 2001-2013. *Sci.Total. Environ.* 596:256-265.

547 Li L N, (2009). Study on spatial Variation of Temperature and Precipitation and its Correlation
548 with NDVI in Shaanxi Province. Shaanxi: Doctoral Dissertation of Northwest University,
549 56-60.

550 Lizaga I, Gaspar L, Quijano L, et al., (2018). NDVI, ¹³⁷Cs and nutrients for tracking soil and
551 vegetation development on glacial landforms in the Lake Parón Catchment (Cordillera
552 Blanca, Perú). *The Science of the total environment*,651:250-260.

553 Li Z, Chen Y N, Li W H, Deng H J, Fang G H, (2015). Potential Impacts of Climate Change on
554 Vegetation Dynamics in Central Asia. *Geophys. Res. Atmos.*, 120, 2045-2057.

555 Liu X F, Zhu X F, Pan Y Z, Li S S, et al., (2016). V egetation dynamics in Qinling-Daba
556 Mountains in relation to climate factors between 2000 and 2014. *Geogr. Sci.* 26:45-58.

557 Li X Y, Li Y, Chen A P, et al., (2019).The impact of the 2009/2010 drought on vegetation growth
558 and terrestrial carbon balance in Southwest China. *Agricultural and Forest Meteorology*,
559 269:239-248.

560 Liu C M, Zhang D, et al., (2011). Spatial-temporal variation of sensitivity to potential
 561 evapotranspiration over China. *Acta geographica sinica*, 66(5):579-588.
 562 Mao D H, Wang Z M, Han J X, et al., (2012). Spatio-temporal Pattern of Net Primary Productivity
 563 and Its Driven Factors in Northeast China in 1982-2010. *Scientia Geographica Sinica*, 32(9):
 564 1106-1111.
 565 Meng D, Mo X, (2012). Assessing the effect of climate change on mean annual runoff in the
 566 Songhua River basin, China. *Hydrological Processes*, 26(7):1050-1061.
 567 Mo K, Chen Q, Chen C, et al., (2019). Spatiotemporal variation of correlation between vegetation
 568 cover and precipitation in an arid mountain-oasis river basin in northwest China. *Journal of*
 569 *Hydrology*, 574:138-147.
 570 Mu S J, Yang H F, Li J L, Chen Y Z, et al., (2013). Spatio-temporal dynamics of vegetation
 571 coverage and its relationship with climate factors in Inner Mongolia, China. *J. Geogr. Sci.*,
 572 23,231-246.
 573 Nijssen B, Lettenmaier D P, Mu X, et al., (2016). Drought in the Pacific Northwest, 1920-2013.
 574 *Journal of hydrometeorology*, 17(9):2391-2404.
 575 Peng W, Kuang T, Tao S, (2019). Quantifying influences of natural factors on vegetation NDVI
 576 changes based on geographical detector in Sichuan, western China. *Journal of Cleaner*
 577 *Production*, 233: 353-367.
 578 Qu S, Wang L, Lin A, et al., (2018). What drives the vegetation restoration in Yangtze River basin,
 579 China: Climate change or anthropogenic factors? *Ecological Indicators*, 90:438-450.
 580 Remus B, A Prvlie, et al., (2019). Spatio-temporal changes of the climatic water balance in
 581 Romania as a response to precipitation and reference evapotranspiration trends during
 582 1961–2013. *Catena*, 172:295-312.
 583 Ruspini E H, (1965). A new approach to clustering. *Information and Control*, 1969, 15(1):22-32.
 584 Shi S Y, Yu J J, Wang F, et al., (2020). Quantitative contributions of climate change and human
 585 activities to vegetation changes over multiple time scales on the Loess Plateau. *Science of*
 586 *The Total Environment*, 755:1-14.
 587 Turco M, Levin N, Tessler N, et al., (2016). Recent changes and relations among drought,
 588 vegetation and wildfires in the Eastern Mediterranean: The case of Israel. *Global & Planetary*

589 Change, 151:28-35.

590 Vicente-Serrano M, Beguería S, López-Moreno J I, (2010). A multiscalar drought index sensitive
591 to global warming: the standardized precipitation evapotranspiration index. Journal of
592 Climate, 23(7) : 1696-1718.

593 Wang Z, Ye A, Wang L, et al., (2019). Spatial and temporal characteristics of reference
594 evapotranspiration and its climatic driving factors over China from 1979-2015. Agricultural
595 Water Management, 213:1096-1108.

596 Wu X C, Liu H Y, Li X Y, et al., (2018). Differentiating drought legacy effects on vegetation
597 growth over the temperate Northern Hemisphere. Global Change Biology, 24: 504-516.

598 Yang H, Yang D, (2012). Climatic factors influencing changing pan evaporation across China
599 from 1961 to 2001. Journal of Hydrology, (s414/415):184-193.

600 Yan Y, Liu X, Wen Y, et al., (2019). Quantitative analysis of the contributions of climatic and
601 human factors to grassland productivity in northern China. Ecological indicators,
602 103:542-553.

603 Yao R, Wang L C, Huang X, et al., (2018). Less sensitive of urban surface to climate variability
604 than rural in Northern China. Sci. Total Environ. 629:650-660.

605 Zha B, Wei S A, (2016). Abandoned cropland: Patterns and determinants within the Guangxi Karst
606 Mountainous Area, China. Applied Geography, 122:245-256.

607 Zhang H, Fan J, Wang J, et al., (2018). Spatial and temporal variability of grassland yield and its
608 response to climate change and anthropogenic activities on the Tibetan Plateau from 1988 to
609 2013. Ecological Indicators, 95:141-151.

610 Zhang B, Wang Z, Chen G, et al., (2017). A Sensitivity Study of Applying a Two-Source Potential
611 Evapotranspiration Model in the Standardized Precipitation Evapotranspiration Index for
612 Drought Monitoring. Land Degradation & Development, 28(2):783-793.

613 Zhang J, Qiao Z, et al., (2016). Assessing the remotely sensed Drought Severity Index for
614 agricultural drought monitoring and impact analysis in North China. Ecological Indicators,
615 143:387-396.

616 Zhang Q, Qi T Y, Singh V P, Chen Y D, Xiao M Z, (2015). Regional frequency analysis of
617 droughts in China: a multivariate perspective. Water Resources Management, 2015, 29(6):

618 1767-1787.

619 Zhang Y, Zhang C, Wang Z, Chen Y, et al., (2016). Vegetation dynamics and its driving forces
620 from climate change and human activities in the Three River Source Region, China from
621 1982 to 2012. *Sci. Total. Environ.* 563, 210-220.

622 Zhao A, Zhang A, Liu H, Liu Y, Wang H, Wang D, (2017). Spatiotemporal variation of vegetation
623 coverage before and after implementation of Grain for Green Project in the Loess Plateau. *J*
624 *Nat Resourc* 32:449-460.

625 Zhao A Z, Zhang A B, Cao S, et al., (2018). Responses of vegetation productivity to multi-scale
626 drought in Loess Plateau, China. *Catena*, 163: 165-171.

627 Zhao G J, Mu X M, Jiao J Y, Gao Peng, et al., (2018). Assessing response of sediment load
628 variation to climate change and human activities with six different approaches. *The Science*
629 *of the total environment*, 639: 773-784.

630 Zhao J, 1997. *Physical Geography of China*. 4th Ed. Beijing: Higher Education Press.

631 Zhu G, Qin D, Liu Y et al, (2017). Accuracy of TRMM precipitation data in the southwest
632 monsoon region of China. *Theoretical and Applied Climatology*, 129(1/2): 353-362.