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Original Research

Coupled Influences and Lagged Effects of Climate and Topography on Vegetation Dynamics in Yiliang County

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Abstract

In order to further study the spatiotemporal dynamic changes of vegetation in Yiliang County, explore the multiple factors affecting vegetation coverage and the hysteresis of precipitation and temperature on NDVI, the Landsat8 dataset from 2014 to 2024 was selected to calculate the annual, seasonal, and monthly mean values of NDVI using the mean method and explore the interannual change trend and vegetation coverage changes in Yiliang County in the past 10 years. The coupling changes of NDVI and influencing factors were analyzed using the correlation coefficient method, and the hysteresis effect of temperature and precipitation on NDVI was explored by cross-correlation analysis. The annual mean NDVI value of Yiliang County from 2014 to 2024 was 0.5949. The seasonal mean NDVI was highest in autumn and lowest in spring, reaching a peak in August and a minimum in March. The area of vegetation increase in Yiliang County was greater than the area of vegetation decrease, and vegetation growth generally improved. The vegetation coverage rate at an altitude of 1,900-2,000 m was the highest, at 17.23%, and the largest NDVI proportion occurred at slopes of 10°-15°, at 19.42%. The area of positive correlation was larger than the area of negative correlation. Increased precipitation and a moderate increase in temperature both promote vegetation growth, and there is a lag in the effects of precipitation and temperature on NDVI.

Keywords: normalized difference vegetation index (NDVI), Yiliang County, influencing factors, correlation analysis, cross-correlation analysis

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Introduction

Vegetation is an important component of terrestrial ecosystems and plays a key role in regulating regional climate, soil, and water conservation, and environmental quality [1-3]. The results demonstrate that climatic factors, particularly temperature and precipitation, serve as the primary drivers of vegetation dynamics [4-7]. Changes in seasonal temperature and precipitation patterns exert direct influence on vegetation growth and spatial distribution [8, 9]. The normalized difference vegetation index (NDVI) is an important remote sensing indicator reflecting the dynamic changes in vegetation, offering a synthesized representation of vegetation types, coverage levels, and growth conditions. Its application holds significant implications for assessing ecosystem stability [10, 11]. A substantial body of international research has been dedicated to investigating the spatiotemporal dynamics of NDVI and their underlying driving mechanisms. Nooni et al. [12] utilized long-term NDVI time series data from equatorial Africa alongside multi-source climate data. By integrating trend analysis and partial correlation methods, they identified minimum temperature and precipitation as the dominant factors driving regional vegetation change. Sonia et al. [13] employed the Mann-Kendall trend test and wavelet multiscale analysis in arid regions of India, revealing that soil moisture and evapotranspiration exert significantly stronger control over NDVI than air temperature. This underscores the dominant role of water constraints in arid zones. Eisfelder et al. [14] employed causal analysis methods based on 30 years of seasonal NDVI data across Europe to identify the dominant roles of climatic factors such as precipitation and saturated vapor pressure deficit within different biogeographic regions. Jeong et al. [15] constructed a globally consistent NDVI dataset with enhanced temporal coherence through cross-sensor radiation calibration and machine learning fusion. Their analysis revealed a persistent greening trend across the globe over the past four decades, highlighting the critical importance of data consistency for identifying vegetation changes and their underlying drivers. These studies conducted across diverse climate zones and spatial scales demonstrate that vegetation coverage is collectively influenced by multiple factors, including temperature, precipitation, altitude, and human activities. Consequently, systematic analysis of vegetation dynamics and their driving factors is of significant importance for understanding ecological environmental evolution and providing scientific foundations for ecological conservation and sustainable development [16].

Traditional methods for acquiring vegetation fractional coverage predominantly rely on field-based surveys and on-site measurements, which, while achieving high accuracy, entail substantial costs, significant labor inputs, and face challenges in supporting long-term monitoring over extensive areas [17]. With the advancement of remote sensing technology, utilizing multi-source remote sensing data for large-scale, long-term vegetation monitoring has become a crucial means to overcome the limitations of traditional manual observation [18, 19]. Against the backdrop of building a Beautiful China, research on vegetation cover changes in representative regions holds significant practical importance [20]. Current research on vegetation coverage and its spatial patterns in Yiliang County, Yunnan Province, remains relatively limited, with a persistent lack of comprehensive data and systematic analysis. To address this research gap, this study employs remote sensing data to analyze the spatiotemporal variation characteristics of NDVI in Yiliang County between 2014 and 2024, while further investigating the influence of climatic factors on vegetation cover dynamics [21, 22]. This study aims to provide theoretical support for enhancing regional vegetation coverage, improving vegetation growth conditions, and reducing soil erosion, while also offering scientific references for local ecological environment protection and land-use planning.

Survey Area

Yiliang County (N24°30′36″-N25°17′2″; E102°58′22″ -E103°28′5″) lies in the central part of Yunnan Province (Fig. 1), the eastern part of Kunming City, and the center of the triangle formed by Kunming City, Qujing City, and Yuxi City. It borders two districts and seven counties, including Luliang County and Shilin County to the east; Mile City and Huaning County to the south; Chengjiang City, Chenggong District, and Guandu District to the west; and Songming County and Malong District of Qujing City to the north. Yiliang County is situated in the heartland of Central Yunnan Province, with terrain higher in the north and lower in the south, surrounded by mountains on the east and west sides. The middle part features flat terrain, making it highly suitable for farming and earning the reputation of "The Granary of Central Yunnan". A northern subtropical monsoon climate prevails, and temperatures are mild throughout the four seasons, with small annual temperature variations. The forest coverage rate is as high as 60%, and the air quality excellence rate remains above 98%. The Nanpan River traverses it and provides abundant water resources. The maximum horizontal distance spans 51.5 km from east to west, whereas the maximum longitudinal distance measures 85.3 km from north to south. The county occupies a total area of 1,913.53 km^2. The built-up urban area covers 11.4 km^2. The urban area is situated at an elevation of 1,536 m, with an annual mean temperature of 6ºC-17ºC and an annual precipitation of 965.7 mm. The terrain is relatively high in the north and relatively low in the south. The region enjoys winters without severe cold and summers without intense heat. As of 2024, the permanent resident population has reached 381,300, reflecting an urbanization rate of 57.79%.

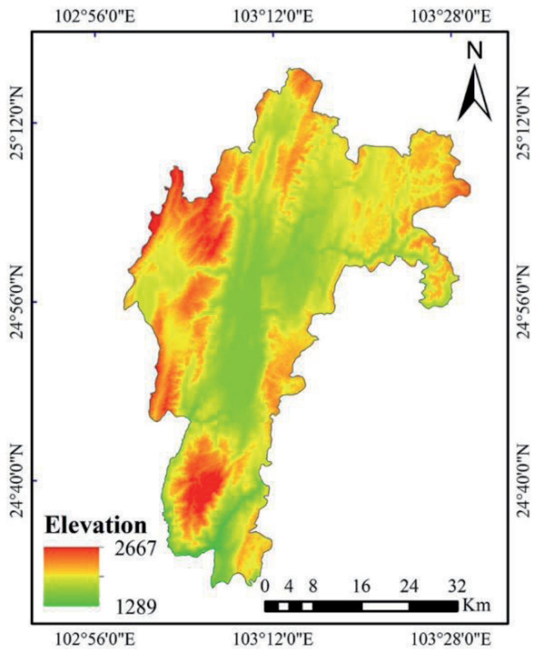

Fig. 1. Map of Yiliang County.

Materials and Methods

Data Sources

In this study, all the NDVI, precipitation, and temperature data were sourced from Google Earth Engine (GEE) (https://earthengine.google.com/). The Digital Elevation Model (DEM) and slope data were also acquired from GEE. The NDVI data were sourced from the Landsat 8 Collection 2 Level-2 dataset provided by GEE, with a spatial resolution of 30 m and a temporal resolution of 16 days. The coordinate system used was GCS_WGS_1984. Cloud layers and cloud shadows were processed to ensure the data were scientifically robust and reliable. The time series covered the period from 2014 to 2024. Precipitation data were obtained from the CHIRPS dataset, featuring a spatial resolution of 0.05° and a temporal resolution of one day. Temperature data were retrieved from the ERA5-Land dataset provided by ECMWF, with a spatial resolution of 0.1° and a temporal resolution of one hour. Finally, the NDVI data were clipped according to the vector boundary of the county. Detailed dataset information and key spatiotemporal resolutions are provided in Table 1.

Research Methods

This study explores how vegetation growth responds to environmental conditions by combining Pearson correlation and cross-correlation analyses (Fig. 2). Pearson correlation is first used to measure the strength of the simultaneous relationships between NDVI and four environmental variables: elevation, slope, precipitation, and temperature. The resulting correlation coefficients describe the linear association between each factor and NDVI and are used to identify the main environmental controls on the spatial pattern and seasonal behavior of vegetation. On this basis, cross-correlation analysis is further employed to elucidate the lag effects of precipitation and temperature on the Normalized Difference Vegetation Index (NDVI). Given the disparity in original spatial resolution between Landsat NDVI (30 m) and gridded climate datasets (CHIRPS and ERA5-Land), this study first standardizes all variables into regional-scale monthly, seasonal, and annual time series to ensure scale consistency and facilitate correlation analysis. Within each county boundary, the regional average NDVI, regional average temperature, and regional cumulative precipitation are computed on a monthly basis to construct corresponding matched regional series. Pearson correlation analysis is conducted at monthly, seasonal, and annual scales, with further cross-correlation analysis performed at the monthly scale to identify potential lag effects. This method is based on a monthly time series from January 2014 to December 2024. After applying first-order differencing, correlation coefficients are computed for lag times from 0 to 12 months, and their significance is evaluated with the Bartlett approximation at the 95% confidence level, allowing the optimal lag and persistence of meteorological influences on vegetation growth to be determined. Together, these two complementary approaches capture both synchronous and lagged relationships and thus clarify the mechanisms linking vegetation dynamics to environmental drivers in the study area. NDVI levels were classified as follows: –1 to 0.1 (bare soil or water bodies), 0.1 to 0.3 (low vegetation coverage), 0.3 to 0.5 (moderate vegetation

Table 1. Inventory of remote sensing and reanalysis data sources.

Data type	Data Name	Data source institution	Data ID	Spatial resolution	Temporal resolution
NDVI	Landsat 8 C2 T1 L2	USGS/NASA	LANDSAT/LC08/C02/T1_L2	30 m	16 days
DEM	SRTM DEM	NASA	USGS/SRTMGL1_003	30 m	Year
Precipitation	CHIRPS	UCSB Climate Disaster Center	UCSB-CHG/CHIRPS/DAILY	0.05°	Daily
Temperature	ERA5-Land	ECMWF	ECMWF/ERA5_LAND/ HOURLY	0.1°	Every hour

coverage), 0.5 to 0.7 (high vegetation coverage), and 0.7 to 1 (very high vegetation coverage). The interannual change trend levels were categorized as follows: –0.08 to –0.02 a^{-1}, implying a significant decrease; –0.02 to –0.006 a^{-1}, indicating a slight decrease; –0.006 to 0.006 a^{-1}, denoting almost no change; 0.006 to 0.02 a^{-1}, indicating a slight increase; and 0.02 to 0.08 a^{-1}, indicating a marked increase.

Calculation of the Coefficient of Variation

The stability of the vegetation indices was assessed by the coefficient of variation (CV), where a higher CV indicated poorer data stability. The calculation formula was as follows:

$$CV = \frac{SD}{Mean} \times 100\% \tag{1}$$

where SD represents the standard deviation and Mean represents the average value.

Correlation Analysis

The relationships between the NDVI and precipitation/temperature were subjected to Pearson correlation analysis and partial correlation analysis via the following formula:

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

where: x_i and y_i represent the i-th observed values of the two variables, respectively; $\bar{x}$ and $\bar{y}$ represent the mean values of variables x and y, respectively, and n is the number of observed values. The value of the Pearson correlation coefficient ranged between

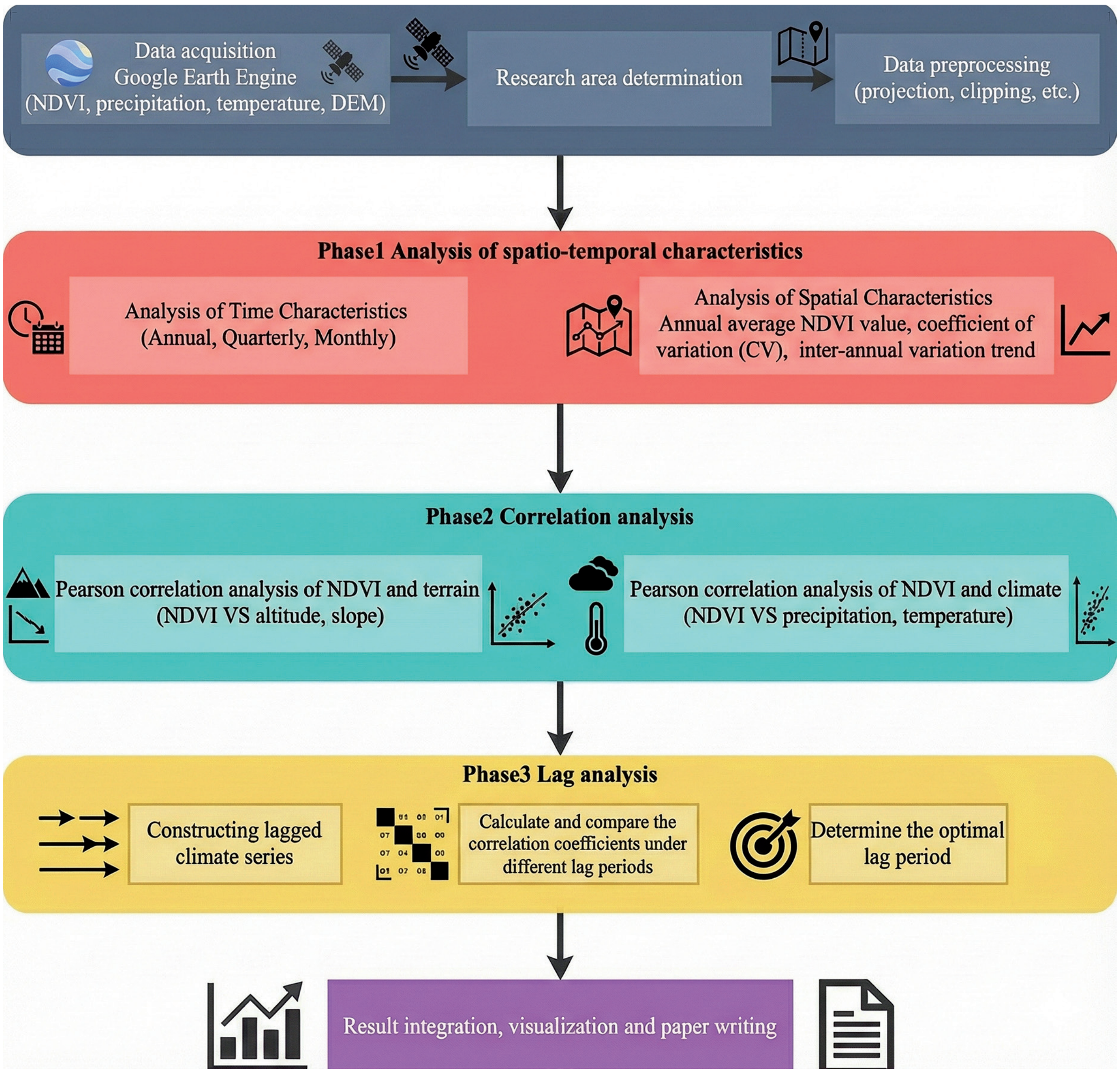

Fig. 2. Technical roadmap.

–1 and 1. r = 1 indicates a positive correlation, whereas r = –1 indicates a negative correlation, and r = 0 indicates no linear correlation. Therefore, a higher r value signifies a stronger correlation.

Cross-Correlation Analysis

The cross-correlation coefficient with a lag period of k month(s) was calculated via the following formula:

$$r_k = \frac{\sum_{t=1}^{n-k}(X_t)(Y_{t+k}-\bar{Y})}{\sqrt{\sum_{t=1}^{n}(X_t-\bar{X})^2}\sqrt{\sum_{t=1}^{n}(Y_t-\bar{Y})^2}} \quad (3)$$

where X_t is the value of the independent variable (precipitation or temperature) at time t; Y_{t+k} is the value of the dependent variable (NDVI) at time t+k; $\bar{X}$ and $\bar{Y}$ are the mean values of the two time series, respectively, and n is the length of the time series.

The following formula was used to calculate the significance threshold:

$$\text{Threshold} = \pm\frac{1.96}{\sqrt{n}} \quad (4)$$

where 1.96 is the critical value of the normal distribution at the 95% confidence level, and where n is the sample size. A correlation coefficient with an absolute value exceeding the threshold indicates statistical significance.

Results

Temporal Changes in the NDVI

From 2014 to 2024, the mean NDVIs fluctuated between 0.5626 and 0.6348 (Fig. 3); the maximum fluctuation amplitude of this value was 0.0722. Among the years surveyed, the annual mean NDVI (0.6348) was the highest in 2022 and the lowest (0.5626) in 2023. The mean NDVI over this decade was 0.5949. The years of 2020 and 2021 experienced a maximum increase rate of 6.24% in this index, and the years 2022 and 2023 experienced a maximum decrease rate of 11.06%. A linear fitting analysis revealed that the annual mean NDVIs exhibited an overall upward trend, with an annual average growth rate of 0.0017/a. In general, the mean NDVI in Yiliang County fluctuated between 2014 and 2024, showing a pattern of initially increasing, then decreasing, increasing yet again, and finally declining. The mean NDVI was subjected to large fluctuations but rose slowly during these fluctuations.

Spatial Distribution of NDVI

The linear fitting results of the seasonal mean NDVIs calculated for different months each year are shown in Fig. 4. The seasonal mean value reached the highest value (0.6728) in autumn, followed by those (0.6714 and 0.5405) in summer and winter, respectively, and reached the lowest value (0.4927) in spring. The seasonal mean value in autumn fluctuated slightly, whereas that in spring exhibited the greatest fluctuation. Those in autumn and winter displayed an increasing trend. That in summer demonstrated a downward trend, but the vegetation coverage remained high. As shown by the linear fitting equations in Fig. S1, the linearly fitted seasonal mean NDVI reached the highest value in autumn and then decreased in winter, spring, and summer, with R^2 values of 0.0635, 0.0209, 0.0025, and 0.0018, respectively. The fitting effects for winter, spring, and summer were poorer than those for autumn. Fig. 4 presents the nonlinear fitting results of monthly mean NDVIs in Yiliang County. The monthly mean NDVI exhibited an increasing trend from March to

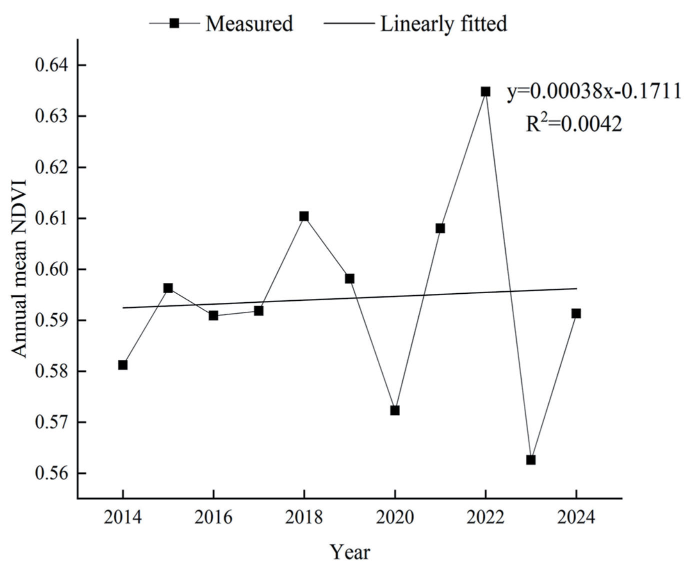

Fig. 3. Annual mean NDVIs in Yiliang County from 2014 to 2024.

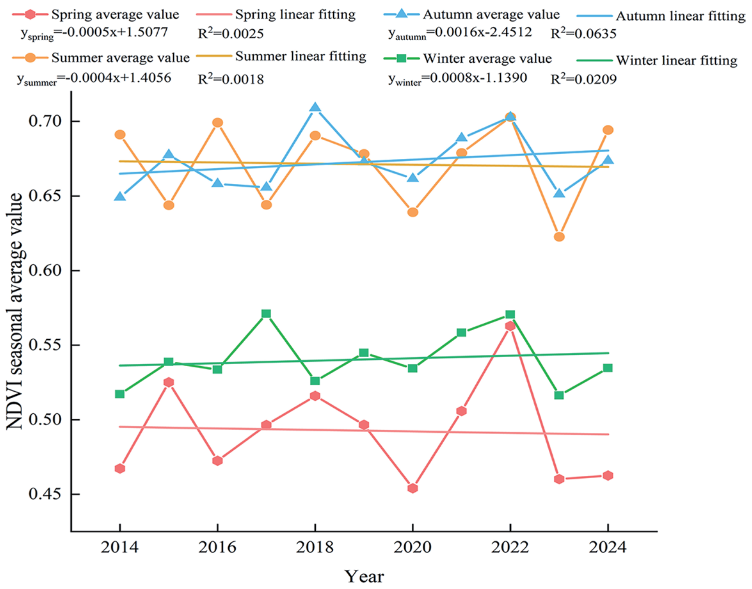

Fig. 4. Fitted seasonal mean NDVIs in Yiliang County from 2014 to 2023.

August, reaching a peak of 0.7245 in August. The rainy season extended from May to August, during which precipitation accounted for more than half of the annual total, creating favorable conditions for plant growth and development. Following September, the monthly mean NDVI began to decline, with vegetation coverage decreasing until February of the subsequent year and reaching its lowest value (0.4841) in March.

As illustrated in Fig. 5a), over 60% of the survey area had spatial NDVIs above 0.5. The areas with very high vegetation coverage (NDVI: 0.7-1) occupied 23.88% of the total survey area; the areas without vegetation coverage constituted only 1.08% (partial water areas of Yangzonghai Lake in western Yiliang County); and the areas with low vegetation coverage were mainly concentrated in densely populated areas in the central part of the county. Generally, this county has good vegetation coverage. As calculated for the CVs of the NDVI in the county over the surveyed ten years (Fig. 5b)), the mean CV was 20.72%, indicating a small range of variation. The areas with CVs less than 50% accounted for almost 84%, whereas those with CVs less than 15% accounted for 33.34%, and those with CVs greater than 50% accounted for only 1.4%. This implied a stable overall change trend in the NDVI in this county during the ten years. Furthermore, the interannual change trend of the NDVI in Yiliang County from 2014 to 2024 was calculated (Fig. 5c)). The results revealed a small overall change trend in the NDVI, but the change trends across various regions varied. According to the statistics of the NDVI change trends (Fig. S2), the areas with significant decreases and slight decreases in the NDVI accounted for 2.61% and 8.90% of the total survey area, respectively. As shown in Fig. 5c) (the distribution of interannual change trends), the areas with decreased NDVIs were predominantly concentrated

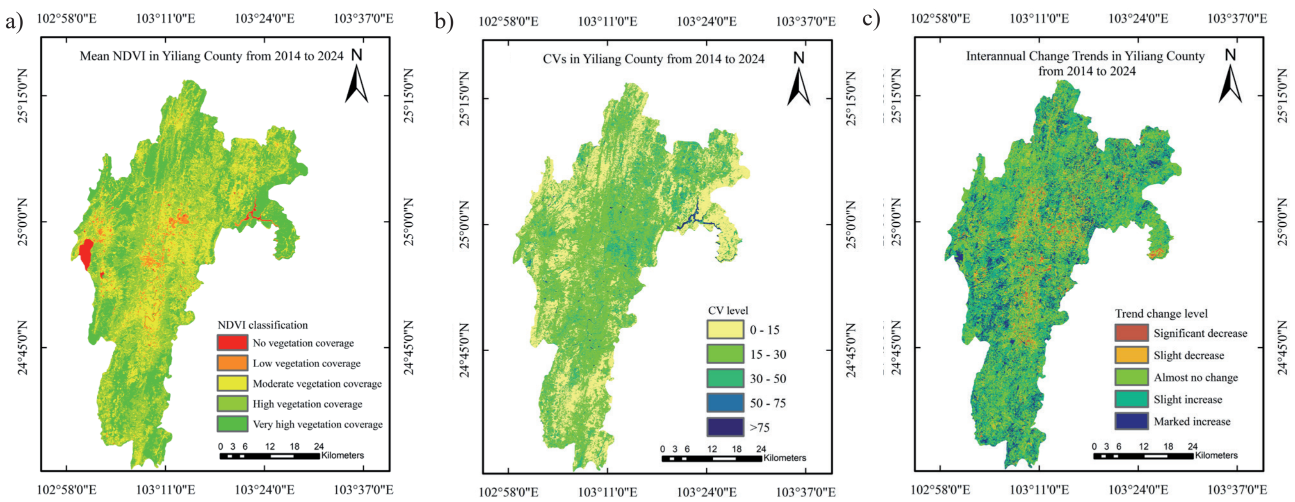

Fig. 5. Spatial distribution maps of the mean NDVIs, CVs, and interannual change trends in Yiliang County from 2014 to 2024.

in the economically developed central regions (including Beigucheng Town, Kuangyuan Subdistrict, Nanyang Subdistrict, and Goujie Town); the areas with almost no change in NDVI accounted for 34.69%, whereas the areas with an increasing trend in NDVI surpassed 50%. The areas with notably increased NDVIs accounted for 11.03%. Overall, Yiliang County experienced more increases than decreases in NDVI, with the increases mainly slight. Overall, vegetation conditions improved.

Influencing Factors for Vegetation

Landform factors

Elevation

Yiliang County has elevations ranging from 1,289 m to 2,667 m. In this study, the county DEM was classified into eight elevation levels: 1,289-1,500 m, 1,500-1,600 m, 1,600-1,700 m, 1,700-1,800 m, 1,800-1,900 m, 1,900-2,000 m, 2,000-2,200 m, and 2,200-2,667 m. Based on this classification, vegetation coverage was calculated for each elevation level, with the results presented in Table 2. As shown, the vegetation coverage area was smallest (1.47%) at the 1,289-1,500 m level and largest (17.23%) at the 1,900-2,000 m level. The highest proportion of areas with very high vegetation coverage (5.87%) was also found at the level of 1,900-2,000 m, whereas those with high, moderate, low, and no vegetation coverage (9.43%, 6.68%, 1.51%, and 0.7% of the total area, respectively) were observed at levels of 1,800-1,900 m, 1,500-1,600 m, 1,500-1,600 m, and 1,700-1,800 m, respectively. Generally, the mean NDVI increased with elevation. The county had 95.57% of the areas with at least moderate vegetation coverage, reflecting a high vegetation coverage rate and a favorable ecological environment in the county.

In addition, the relationship between the interannual NDVI change trend and elevation in the survey area was analyzed based on the spatiotemporal variation characteristics of the NDVI (Fig. S3). At all the elevation levels, the increasing trend in the NDVI was greater than the decreasing trend. At levels 1 to 5, the proportion of areas with an increasing trend in the NDVI increased with elevation and peaked at 12.39%. At all eight elevation levels, the proportion of areas exhibiting a decreasing trend in the NDVI was less than 4%. At the 1,500-1,600 m level, the areas with an increasing trend in NDVI reached the highest proportion (3.18%). Across the entire study area, regions with increasing and decreasing trends in NDVI accounted for 54.29% and 11.64%, respectively. These findings indicate that vegetation across all elevation levels in the county has improved over the past ten years.

Fig. 6a) shows the correlation between the NDVI and elevation in the county as analyzed via the Pearson correlation coefficient method pixel by pixel. The correlation coefficients between the NDVI and elevation were maintained between –1 and 1 and were averaged at 0.2144. Areas with positive and negative correlations accounted for 62.84% and 37.16% of the total area, respectively, whereas areas with significant positive correlations and extremely significant positive correlations accounted for 9.15% and 22.35%, respectively. As seen in the spatial distribution map of the correlation between the NDVI and elevation, the positively correlated areas were concentrated in the central and northern regions of the county, including Beigucheng Town, Kuangyuan Town, Goujie Town, and Zhushan Town. In addition, a statistical analysis was conducted on the proportion of areas with a correlation between each elevation level and the NDVI (Fig. 7). As illustrated, the largest proportion of positively correlated areas (11.01%) was at the level of 1,900-2,000 m; the smallest proportion of negatively correlated areas (0.49%) was at the level of 2,200-2,667 m; and the level of 1,500-1,600 m presented the maximum difference between the proportions of positively correlated areas (10.68%) and negatively correlated areas (2.43%) among the eight levels.

Table 2. Elevation levels and NDVI changes in Yiliang County.

Elevation level (m)	Mean NDVI	Proportion of no vegetation coverage (%)	Proportion of low vegetation coverage (%)	Proportion of moderate vegetation coverage (%)	Proportion of high vegetation coverage (%)	Proportion of very high vegetation coverage (%)
1,289-1,500	0.5417	0.00	0.02	0.46	0.90	0.09
1,500-1,600	0.4480	0.20	1.51	6.68	4.42	0.31
1,600-1,700	0.5207	0.07	0.56	4.57	6.08	1.12
1,700-1,800	0.5320	0.70	0.38	4.73	7.65	2.95
1,800-1,900	0.5700	0.07	0.51	6.41	9.43	5.03
1,900-2,000	0.6055	0.02	0.24	4.01	7.11	5.87
2,000-2,200	0.6389	0.01	0.10	2.19	4.91	5.62
2,200-2,667	0.6721	0.00	0.03	0.71	1.45	2.87

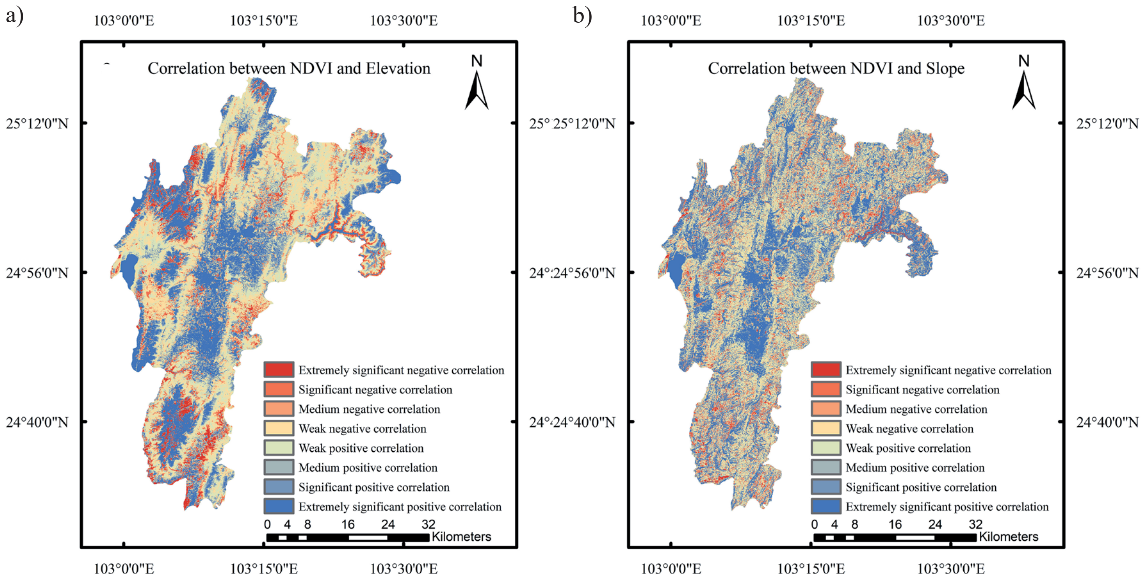

Fig. 6. Spatial distribution map of correlations between the NDVI and elevation/slope in Yiliang County from 2014 to 2024.

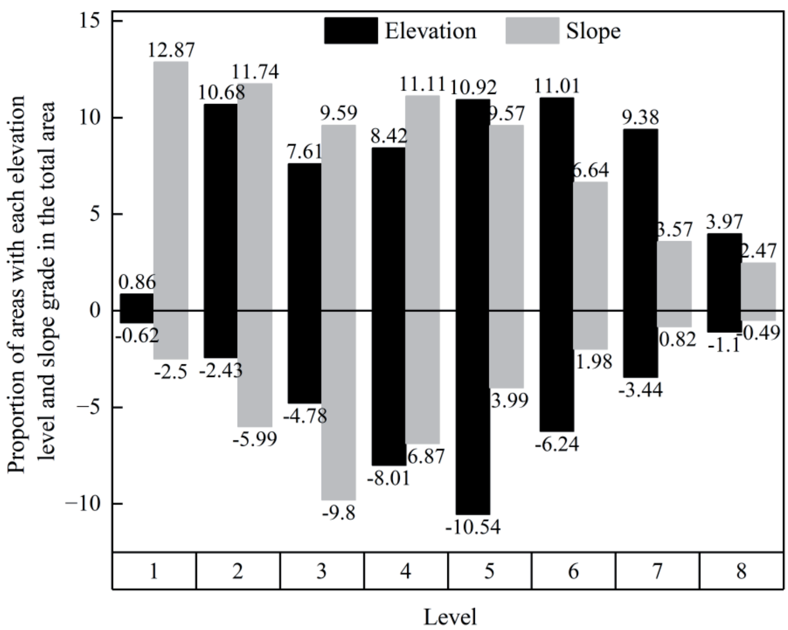

Fig. 7. Proportions of correlated areas at each elevation level and slope grade.

Slope

The slopes in Yiliang County were classified into eight grades: 0-5°,5°-10°, 10°-15°, 15°-20°, 20°-25°, 25°-30°, 30°-35°, and 35°-90° (Table 3). The largest proportion of vegetation coverage area (19.42%) was observed at the 10°-15° slope grade, followed by the 15°-20° and 20°-25° grades, accounting for 17.85% and 17.72%, respectively. As the slope increased, the vegetation coverage rate initially increased and then decreased; the mean NDVI showed a rising trend with increasing slope grades. However, when the slope exceeded 30°, the vegetation coverage rate declined sharply. At the 30°–35° slope grade, vegetation coverage accounted for 4.38% of the area. When the slope was greater than 35°, the proportion of areas with vegetation coverage fell to only 3.16%. Overall, 95.57% of the areas had at least moderate vegetation coverage according to the NDVI, but most of them were distributed in regions with small slopes. This demonstrated that the NDVI initially increased but then decreased as the slope increased. In other words, steep slopes are unfavorable for plant growth and development, hence resulting in a subsequent decline in vegetation coverage.

As revealed through an analysis of the correlation between the interannual NDVI change trend and slope (Fig. S3), the increasing trend was greater than the decreasing trend at each slope grade. At grades 1-3,

Table 3. Slope levels and NDVI changes in Yiliang County.

Slope grade (°)	Mean NDVI	Proportion of no vegetation coverage (%)	Proportion of low vegetation coverage (%)	Proportion of moderate vegetation coverage (%)	Proportion of high vegetation coverage (%)	Proportion of very high vegetation coverage (%)
0-5	0.4172	0.84	1.51	8.37	4.08	0.57
5-10	0.5084	0.11	1.00	7.78	6.73	2.12
10-15	0.5659	0.06	0.45	6.06	8.48	4.33
15-20	0.6038	0.03	0.20	3.93	8.24	5.48
20-25	0.6274	0.02	0.10	2.10	6.40	4.85
25-30	0.6449	0.01	0.06	0.92	4.18	3.44
30-35	0.6552	0.00	0.02	0.35	2.17	1.84
35-90	0.6557	0.00	0.01	0.21	1.68	1.26

the proportion of areas with an increasing trend gradually increased. Once the slope exceeded 15°, the proportion of areas with an increasing trend began to decrease with increasing slope. As the slope increased continuously, the proportion of areas with a decreasing trend decreased from a maximum of 3.55% to 0.16%. In the survey area, the percentages of areas with an increasing trend and a decreasing trend were 54.17% and 11.63%, respectively. This suggested that vegetation tended to grow across the different slope grades over the ten years and that vegetation growth improved.

Furthermore, a correlation analysis was performed between the mean NDVI over the ten-year period and slope, resulting in a spatial distribution map of the correlation coefficients between NDVI and slope (Fig. 6b)). The correlation coefficients ranged from –1 to 1, with an average value of 0.2736. The proportions of positively and negatively correlated areas were 67.56% and 32.44%, respectively; 35.84% of the areas exhibited at least significant positive correlations, primarily concentrated in certain regions in the central and western parts of the county, including Beigucheng Town, Kuangyuan Town, and Goujie Town. A statistical analysis of the proportion of correlated areas at each slope grade (Fig. 7) revealed that positively correlated areas accounted for about 10% of the area at slope grades 1 to 5. The highest proportion of positively correlated areas (12.87% of the total area) was found at slope grades of 0°-5°. At slope grades of 10°-15°, the negatively correlated area was greater than the positively correlated area; however, at the remaining slope grades, the positively correlated areas exceeded the negatively correlated areas.

Climatic Factors

Unary linear regression analysis was carried out to determine the change trends of annual precipitation and annual mean temperature in Yiliang County over the surveyed ten years. The results are provided in Fig. 8a) and b). As illustrated in the curves, both the annual precipitation and annual mean temperature fluctuated without a regular pattern. Overall, the annual precipitation showed a decreasing trend, whereas the

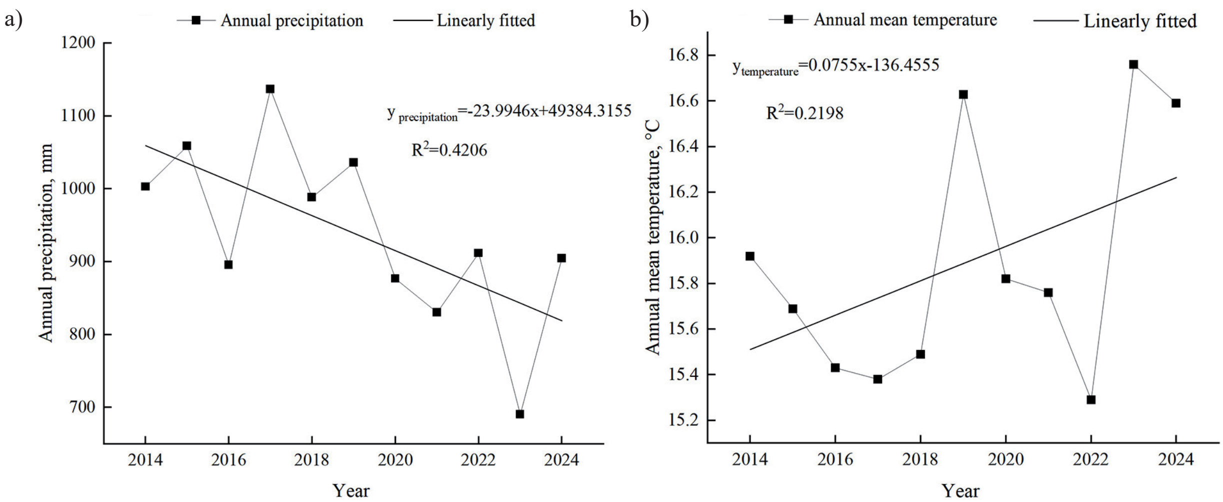

Fig. 8. Annual precipitation and annual mean temperature in Yiliang County from 2014 to 2024.

annual mean temperature displayed an increasing trend. Specifically, the average rate of decrease in precipitation was –23.99 mm/a, whereas the average rate of increase in temperature was 0.0984°C/a. On certain time scales, precipitation and temperature exhibited synchronous change trends. Both the mean precipitation and mean temperature increased from 2018 to 2019 but decreased from 2019 to 2020.

On an annual scale, the correlation coefficients between NDVI and precipitation and between NDVI and temperature were 0.008 and –0.321, respectively (Fig. S4), indicating no significant correlations. The increase in precipitation contributed slightly to plant growth, while variations in precipitation did not result in significant changes in NDVI. The annual mean temperature exhibited a negative correlation with NDVI, suggesting that rising annual temperatures inhibited plant growth. On a seasonal scale, the mean NDVIs increased as the precipitation and temperature increased from spring to summer. After summer, both the precipitation and temperature decreased, and the mean NDVI decreased. The correlation coefficients between the seasonal mean NDVI and precipitation, as well as between the seasonal mean NDVI and temperature, were 0.648 and 0.325, respectively, reflecting positive correlations (Fig. S4). On a monthly scale, the mean NDVI varied with precipitation and temperature, with correlation coefficients of 0.605 and 0.303, respectively, with precipitation and temperature. Both of these correlations were positive, which indicated that vegetation growth was significantly driven by increases in precipitation or temperature.

Regardless of the scale, the mean NDVI lagged behind the changes in both precipitation and temperature due to the growth characteristics of the plants. When the precipitation or temperature markedly changed, the corresponding changes in the NDVI did not occur in time because plant growth requires a certain amount of time and cycle. Additionally, a cross-correlation analysis was conducted on the NDVI data from 2014 to 2024 to probe the dynamic impacts of precipitation and temperature on the NDVI. The results revealed that the correlation between precipitation and NDVI had significant phased features (Fig. 9a)). The first was a positive correlation in the short term (with lag periods of 0 to 2 months), with correlation coefficients of 0.3598, 0.4476, and 0.2276, respectively, implying an immediate promoting effect of precipitation on vegetation growth. The second showed no significant correlation in the medium term (with lag periods of 3 to 4 months). That is, there was not a marked linear correlation between precipitation and NDVI. The third was a negative correlation in the long term (with lag periods of 6 to 9 months), with a correlation coefficient as low as –0.3858. These findings suggest that excessive precipitation or saturated soil might suppress vegetation growth. The fluctuation range of correlation occurred at lag periods of 7 months and 10 to 11 months.

When the lag period was 7 months, the correlation coefficient was –0.1644, which did not reach a significant level; similarly, at lag periods of 10 and 11 months, the correlation coefficients were –0.0487 and 0.1249, respectively, and also did not reach significance. These results indicate that the linear correlation between precipitation and NDVI was weak during these lag periods. However, when the lag period extended to 12 months, the correlation coefficient increased to 0.2440, suggesting that precipitation exerted an annual periodic influence on vegetation growth. Regarding the correlation between temperature and NDVI (Fig. 9b)), the relationship demonstrated a pattern of early-stage promotion followed by later-stage inhibition. At a lag of 0 months, the correlation coefficient was 0.1689, not exceeding the significance threshold. Thus, temperature variations in the current month had no observable direct effect on NDVI. Within lag periods of 1 to 4 months, the correlation coefficients fluctuated between 0.2016 and 0.4442, indicating that rising temperatures

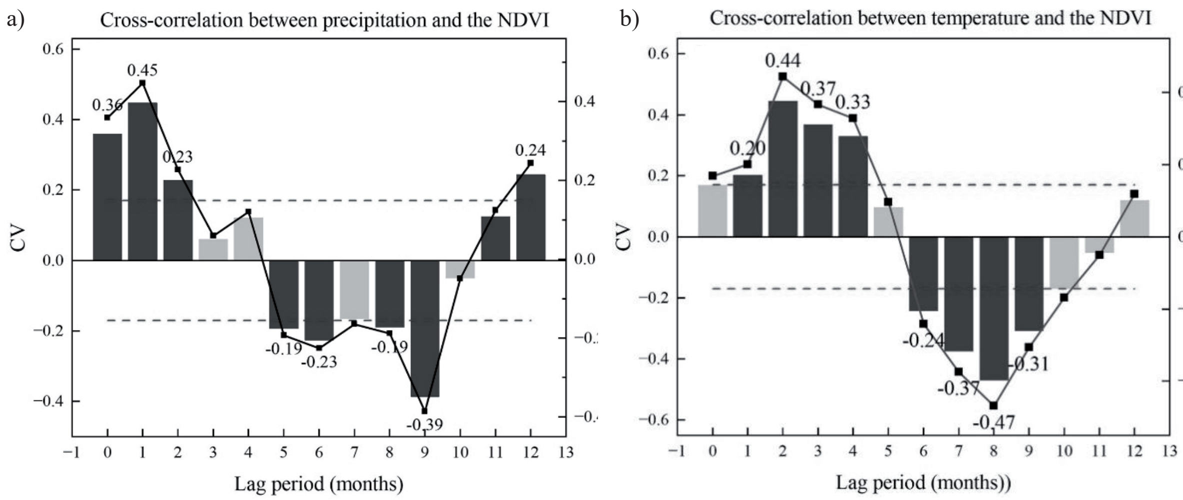

Fig. 9. Results of a cross-correlation analysis between precipitation/temperature and the NDVI.
Note: The red dashed line represents the significance threshold (±0.171); the dark-colored bars indicate significant correlations ($p<0.05$).

significantly promoted vegetation growth. However, when the lag period extended to 6 to 9 months, the correlation coefficient declined sharply to –0.4683, reflecting the negative effects of high-temperature stress or phenological changes on vegetation growth. Correlations within lag periods of 10 to 12 months were insignificant.

Discussion

This study employed NDVI data obtained from GEE to examine the changes and spatial distribution of vegetation coverage in Yiliang County [23]. Correlation analysis and cross-correlation analysis were performed to quantitatively assess the change trends in NDVI and the interactions among the factors influencing its distribution. NDVI-based assessments are widely used in international vegetation monitoring, which makes the findings comparable to studies in other regions [24]. The results revealed that NDVI in Yiliang County from 2014 to 2024 exhibited an uneven spatiotemporal distribution, characterized by an overall upward trend with fluctuations and distinct seasonal variations. The NDVI changes generally followed a pattern of peaking in late summer (August) and decreasing in winter and spring. The monthly mean NDVI peaked in August and reached a minimum in March.

With respect to the relationships between the NDVI and landform factors such as elevation and slope, high vegetation coverage was found at elevations of 1,900-2,000 m. This finding reflected that this elevation level was suitable for vegetation growth. At an elevation above 2,200 m, the vegetation coverage decreased sharply. This occurred because the increase in elevation led to changes in temperature, precipitation, and sunshine duration, which are unfavorable for plant growth and development [25]. Similar "mid-elevation optimum" patterns are also reported in many mountainous regions, where heat and moisture conditions are jointly favorable at intermediate elevations [26]. At the slope grade of 10°-15°, the proportion of vegetation coverage area reached the largest value. As the slope increased, the vegetation coverage rate first increased but then decreased [27]. Overall, the NDVI was significantly correlated with elevation and slope. Specifically, the positively correlated area was significantly larger than the negatively correlated area at the elevation level of 1,500-1,600 m and slope grade of 0°-5°. This indicated that within a certain range, the vegetation coverage area expanded with elevation and slope.

Temperature and precipitation are two key climatic factors influencing the growth and distribution of vegetation. As revealed through the climatic factor analysis, precipitation and temperature were generally positively correlated with the NDVI, suggesting that climate change was conducive to improving vegetation growth. In addition, precipitation had a greater impact on the vegetation NDVI than did temperature. This implies that vegetation growth during key periods may be relatively more constrained by water availability, particularly in water-limited regions [28, 29]. An analysis of the correlation between temperature and precipitation and the annual, seasonal, and monthly mean NDVI revealed that temperature and precipitation were notably correlated with the seasonal and monthly mean NDVIs.

Further, a cross-correlation analysis was conducted to investigate the lag effects of precipitation and temperature on NDVI. The results revealed that the correlations between NDVI and precipitation/temperature exhibited distinct phased characteristics. The effect of precipitation on NDVI was positive in the short term, insignificant in the medium term, and negative in the long term; the effect of temperature on NDVI demonstrated a pattern of early-stage promotion followed by late-stage inhibition. However, changes in precipitation and temperature did not lead to immediate changes in vegetation, as vegetation requires time to absorb precipitation through the root system, resulting in a lag effect [30]. Soil moisture "memory" and delayed leaf development may also contribute to this lag [31]. In addition to being closely related to precipitation and temperature, vegetation growth is also influenced by factors such as sunlight, humidity, and human activity, which were not addressed in this study. Another limitation is that CHIRPS/ERA5-Land are coarser than Landsat NDVI; although we mitigated this by using region-aggregated time series, microclimatic/topographic heterogeneity may still be smoothed, introducing uncertainty in the estimated NDVI–climate relationships.

Conclusions

Based on the NDVI remote sensing images and climatic data of Yiliang County from 2014 to 2024, this study examined the spatiotemporal dynamic changes of NDVI and the influencing factors. The results indicated that over the ten years, the mean NDVI was 0.5949, exhibiting an overall upward trend with fluctuations. Seasonally, the mean NDVI was highest in autumn and lowest in spring. On a monthly scale, the mean NDVI peaked in August and reached its lowest point in March. Spatially, the NDVI changes tended to stabilize; the increase in vegetation coverage exceeded the decrease, which was primarily characterized by a slight increase. Overall, vegetation growth improved.

Elevation and slope are crucial for vegetation growth. The highest vegetation coverage was observed at the elevation level of 1,900-2,000 m, accounting for 17.23% of the total survey area. The largest proportion of vegetation occurred at slope grades of 10°-15°, covering 19.42% of the total area. In general, the areas with positive correlations between the NDVI and elevation/slope were larger than the areas with negative correlations. As the elevation increased and the slope steepened, the mean NDVI gradually increased, with the vegetation coverage area initially expanding but then declining.

An increase in both precipitation and temperature could promote vegetation growth; however, this effect exhibited a lag. The lag effect of precipitation on NDVI was positive in the short term, insignificant in the medium term, and negative in the long term. The effect of temperature on NDVI showed a pattern of early-stage promotion followed by late-stage suppression.

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Conflict of Interest

The authors declare no conflict of interest.

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Supplementary Material

link to the material: https://www.pjoes.com/SuppFile/217904/1/