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Spatiotemporal Evolution of Vegetation and Its Climatic Driving Factors in Kezhou, Northwest China

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Abstract

Background: Understanding vegetation dynamics and their climatic drivers in arid regions is essential for ecological security in southern Xinjiang, a critical node of the Belt and Road Initiative. This study investigates the spatiotemporal evolution of vegetation and climate–NPP relationships in Kezhou (Kizilsu Kirgiz Autonomous Prefecture), Northwest China, from 2000 to 2020.

Methods: Based on MOD13Q1 and other MODIS products combined with meteorological observations, three vegetation parameters (NDVI, FVC and NPP) were retrieved for 2000–2020. FVC was estimated with the dimidiate pixel model, and NPP was simulated with the CASA model. Theil–Sen median trend analysis combined with the Mann–Kendall test was used to examine NPP trends, and pixel-wise Pearson correlation analysis was applied to explore temperature–precipitation–NPP relationships.

Results: (1) The regional mean growing-season NDVI increased at 0.0021 a^{-1} ; the 2011–2020 mean (0.141) was 12.8% higher than the 2000–2010 mean (0.125). (2) The FVC structure improved overall: moderate coverage (0.3–0.5) expanded from 10.9% to 17.93% and low coverage shrank from 7% to 2%, although relatively low coverage remained the dominant class. (3) NPP increased fluctuatingly to a peak of $5.1 \text{ g C m}^{-2} \text{ a}^{-1}$ in 2015 and then declined sharply by about 25.5% to $3.8\text{--}3.9 \text{ g C m}^{-2} \text{ a}^{-1}$ during 2017–2020; at the pixel scale, 88% of the area showed an insignificant increase over the full period. (4) The area with a positive precipitation–NPP correlation (50.3%) exceeded that for temperature (43.7%), indicating that water availability is the dominant constraint on vegetation productivity.

Conclusions: Vegetation in Kezhou improved slowly but remains fragile. The abrupt post-2015 NPP decline, asynchronous with the continuous FVC improvement, highlights water availability as the key productivity constraint. These findings provide a scientific basis for water-limited greening, differentiated restoration and climate-resilient ecosystem management in arid regions.

Keywords: Net Primary Productivity (NPP); Normalized Difference Vegetation Index (NDVI); Fractional Vegetation Cover (FVC); climate factors; arid region

1 Introduction

Over the past century, rapid global industrialization has caused massive CO₂ emissions, intensifying the greenhouse effect and global warming [1]. Arid landscapes, dominated by deserts, gobi and cultivated land [2], face severe challenges, as vegetation serves as a critical bridge connecting

ecosystems, the atmosphere, soil and water resources. Under global warming, reduced precipitation and intensified evapotranspiration have led to decreased vegetation coverage and ecosystem degradation [3]. For example, in the neighboring Kashi Delta, growing-season NDVI was negatively correlated with temperature but positively correlated with precipitation during 2000–2020, with precipitation playing the dominant role [41]. Arid regions cover approximately 40% of Earth's land surface and contribute about 40% of global vegetation NPP [5]. Vegetation NPP and NDVI are key indicators for assessing vegetation ecosystems, and their balance in arid regions is crucial for urban development and ecological security in the Belt and Road node cities of southern Xinjiang. Systematically analyzing spatiotemporal vegetation patterns and identifying climate driving mechanisms are core issues in global change research [6]. The United Nations Sustainable Development Goals (SDGs), particularly SDG 13 (Climate Action), SDG 15 (Life on Land) and SDG 2 (Zero Hunger), emphasize the urgent need to combat climate change, protect terrestrial ecosystems and ensure food security in vulnerable regions [7]. Northwest China, an ecologically fragile zone and a critical node of the Belt and Road Initiative, faces severe challenges in balancing economic development with environmental sustainability [8].

Since the 1980s, space-based remote sensing has developed rapidly, offering continuous spatiotemporal sequences, wide coverage and low cost for monitoring terrestrial vegetation [9–10]. Yin et al. found that vegetation cover in Northwest China showed an overall increasing trend from 2000 to 2019, with the lowest growth rate in the inland arid sub-region [35]. Zhang et al. reported a significant increase in fractional vegetation cover in the Yellow River Basin during 2000–2019, with obvious improvement in the central basin [36].

Previous studies [13] show that terrestrial vegetation in the arid regions of Northwest China has grown slowly over the past 20 years. However, differentiated research on the growth rates of NDVI, FVC and NPP remains insufficient. This study takes Kezhou, a typical arid region, as the study area and analyzes vegetation ecosystem evolution from three dimensions (NDVI, FVC and NPP), avoiding the pitfall that different underlying conditions may produce identical index values.

Under global warming, research on the response mechanisms and spatiotemporal heterogeneity of terrestrial ecosystems in arid regions has become a core scientific issue [14]. However, existing research mostly focuses on single vegetation indices or short-term monitoring, and systematic analysis of long-term NPP evolution is still lacking, particularly at the Pamir–Tianshan junction.

This study constructs a comprehensive framework of “multi-dimensional remote sensing monitoring–geomorphological gradient analysis–climate driving mechanism”. First, multi-source MODIS products were integrated to retrieve NDVI, FVC and NPP for 2000–2020. Second, Theil–Sen and Mann–Kendall analyses were applied to evaluate NPP evolution and its stability. Finally, coupled with meteorological data, pixel-wise Pearson correlation analysis was used to elucidate climate driving mechanisms and their spatial non-stationarity. The results deepen the understanding of carbon cycle processes and climate response mechanisms in arid ecosystems, providing decision-making support for green development in southern Xinjiang [15–16] and a theoretical basis for adaptive management and transboundary cooperation in arid regions.

2 Materials and Methods

2.1 Study Area

Kezhou (Kizilsu Kirgiz Autonomous Prefecture) is situated in southwestern Xinjiang, Northwest China, at the convergence of the Tianshan Mountains, the Pamir Plateau, the Kunlun Mountains and

the Tarim Basin (Fig. 1). Covering 72,500 km² with a 1,195 km border shared with Kyrgyzstan and Tajikistan, it comprises one city (Artux) and three counties (Akto, Wuqia and Aheqi), with a population of approximately 622,000, predominantly Kyrgyz. Mountainous terrain accounts for more than 90% of its area. The prefecture has a temperate continental arid climate with scarce precipitation, abundant sunshine and significant diurnal temperature variation, and is a notable fruit-producing region [17].

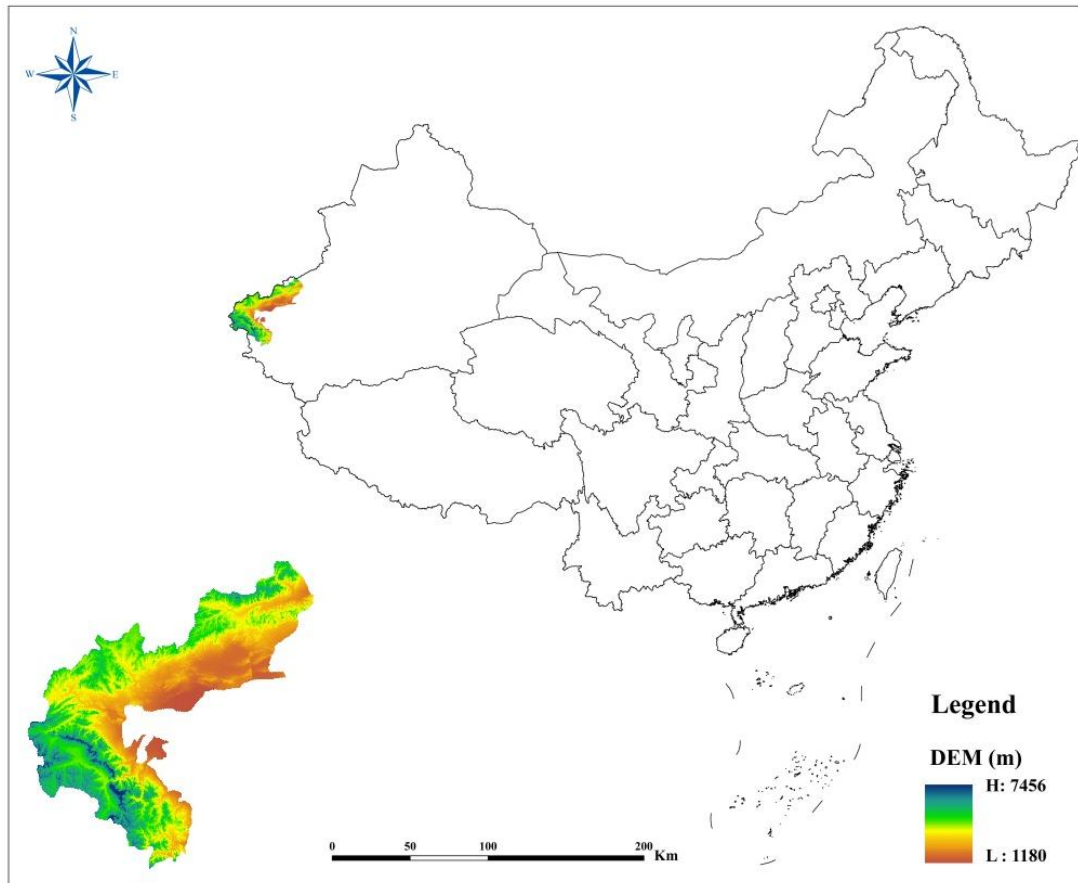


Fig. 1 Location and general situation of the study area

2.2 Data Sources and Preprocessing

The remote sensing data were obtained from the MODIS archive. NDVI was derived from the MOD13Q1 product (16-day, 250 m) for 2000–2020, and annual growing-season NDVI series were obtained by compositing the 16-day products. Vegetation NPP was estimated with the CASA model driven by the MOD13A1, MOD09A1 and MOD15A2H products together with meteorological data; the MOD17A3H annual NPP product was used for cross-validation of the CASA estimates (Table 1). Climate data (annual mean temperature and annual precipitation) from 21 meteorological stations in and around the study area were obtained from the National Meteorological Information Center [18].

Table 1. Usage data and sources

Product	Type	Temporal resolution	Spatial resolution	Data source
MOD13A1/Q1	NDVI	16 d	500 m/250 m	https://modis.gsfc.nasa.gov/
MOD09A1	Surface reflectance	8 d	500 m	https://modis.gsfc.nasa.gov/

MOD15A2H	FPAR/LAI	8 d	500 m	https://modis.gsfc.nasa.gov/
MOD17A3H	NPP (for validation)	annual	500 m	https://modis.gsfc.nasa.gov/
Temperature	TEM	annual	station	http://data.cma.cn/
Precipitation	PRE	annual	station	http://data.cma.cn/

2.3 Methods

2.3.1 Fractional Vegetation Cover Calculation

Fractional vegetation cover (FVC) is defined as the ratio of the vertically projected area of vegetation canopy to the total land area. FVC was calculated from MOD13Q1 NDVI using the dimidiate pixel (two-endmember) model [19]:

$$FVC = (NDVI - NDVI_s) / (NDVI_v - NDVI_s) \quad (1)$$

where NDVI is the normalized difference vegetation index of a pixel; $NDVI_s$ and $NDVI_v$ are the NDVI values of pure bare-soil and pure-vegetation pixels, respectively, determined from the cumulative frequency distribution of NDVI. Because the study area is located in an arid region, FVC was classified into five levels following the national standard for soil erosion classification (SL 190-2007) [37] (Table 2).

Table 2. FVC classification

FVC level	FVC value
High cover	$0.7 < FVC \leq 1.0$
Relatively high cover	$0.5 < FVC \leq 0.7$
Moderate cover	$0.3 < FVC \leq 0.5$
Relatively low cover	$0.1 < FVC \leq 0.3$
Low cover	$0 < FVC \leq 0.1$

2.3.2 Vegetation Net Primary Productivity

Net primary productivity (NPP) represents the total productivity of terrestrial plants that provides energy for autotrophs and other organisms, and can effectively assess vegetation health and terrestrial carbon cycling in arid regions. The Carnegie–Ames–Stanford Approach (CASA) model, proposed by Potter et al. in 1993 [34], has been widely used to simulate vegetation NPP by combining remote sensing, meteorological and plant physiological data [13], and has yielded reliable estimates in the Kashi region and the arid regions of Northwest China [12, 39].

In this study, NPP was estimated with the CASA model, which expresses NPP as the product of absorbed photosynthetically active radiation (APAR) and actual light use efficiency (ϵ):

$$NPP(x, m) = APAR(x, m) \times \epsilon(x, m) \quad (2)$$

where $NPP(x, m)$, $APAR(x, m)$ and $\epsilon(x, m)$ are the net primary productivity, absorbed photosynthetically active radiation and actual light use efficiency at pixel x in month m , respectively. Monthly NPP estimates were summed to annual values for subsequent analysis.

2.3.3 Trend Analysis and Significance Testing

The Theil–Sen median method (Sen slope) offers high computational efficiency and is insensitive to outliers, making it suitable for long-term time-series trend analysis [25]. The Mann–Kendall (M-K) test is a non-parametric significance test frequently used for long-term trends [26]. Combining Sen and M-K methods reduces noise interference and improves the robustness of trend detection for vegetation NPP [27]. The Sen slope is calculated as:

$$MI = \text{Median}((x_j - x_i) / (j - i)), \quad 2000 \leq i < j \leq 2020 \quad (3)$$

where x_i and x_j are the NPP values in years i and j , and MI is the median slope: $MI > 0$ indicates an increasing trend and $MI < 0$ a decreasing trend; the magnitude of MI represents the average rate of change [28-29].

The M-K test was used to detect the significance of NPP trends from 2000 to 2020 ($n = 21$). The test statistic S is:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(x_j - x_i) \quad (4)$$

where sgn is the sign function:

$$\text{sgn}(x_j - x_i) = \begin{cases} +1, & x_j - x_i > 0 \\ 0, & x_j - x_i = 0 \\ -1, & x_j - x_i < 0 \end{cases} \quad (5)$$

The standardized statistic Z is:

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{var}(s)}}, & S > 0 \\ 0, & S = 0 \\ \frac{S+1}{\sqrt{\text{var}(s)}}, & S < 0 \end{cases} \quad (6)$$

In Equation (7), $\text{var}(s)$ is the variance:

$$\text{var}(s) = \frac{n(n-1)(2n+5)}{18} \quad (7)$$

At the $\alpha = 0.05$ level, $|Z| > 1.96$ indicates a significant trend. Trends were classified into four types: significant increase ($S > 0, Z > 1.96$), insignificant increase ($S > 0, |Z| \leq 1.96$), insignificant decrease ($S < 0, |Z| \leq 1.96$) and significant decrease ($S < 0, Z < -1.96$).

2.3.4 Pearson Correlation Analysis

Pearson correlation analysis measures the strength of the linear relationship between two variables [30-31]. In this study, annual temperature and precipitation rasters with the same pixel size as NPP were generated year by year using inverse distance weighting (IDW) interpolation in GIS software, and pixel-wise correlations between annual NPP and the two climate factors were calculated in Matlab:

$$r = \frac{\sum_{i=1}^n (X - \bar{X})(Y - \bar{Y})}{\sqrt{\sum_{i=1}^n X^2 \sum_{i=1}^n Y^2}} \quad (8)$$

Where

$$\begin{aligned}\bar{X} &= X_i - \bar{X} \\ \bar{Y} &= Y_i - \bar{Y}\end{aligned}\quad (9)$$

where X_i is the vegetation index value (NPP) in year i , $\bar{X}$ is its multi-year mean (2000–2020), Y_i is the climate factor value (temperature or precipitation) in year i , and $\bar{Y}$ is its multi-year mean; r ranges within $[-1, 1]$. Following the correlation grading criteria commonly used in quantitative geography [38], correlations were classified as in Table 3. For $n = 21$, $|r| > 0.433$ corresponds to $p < 0.05$.

Table 3. Classification criteria for the correlation coefficient r

Correlation type	Criterion	Trend
High correlation	$ r \geq 0.8$	$r > 0$: positive
Moderate correlation	$0.5 \leq r < 0.8$	$r > 0$: positive
Low correlation	$0.2 \leq r < 0.5$	$r < 0$: negative
No correlation	$ r < 0.2$	—

3 Results and Analysis

3.1 Spatiotemporal Evolution Characteristics of NDVI

3.1.1 Temporal Evolution and Trends of NDVI

From 2000 to 2020, the regional mean growing-season NDVI of Kezhou fluctuated between 0.12 and 0.16, with an overall increasing rate of 0.0021 a^{-1} (Fig. 2). The multi-year mean NDVI was 0.132. Specifically, the mean NDVI for 2000–2010 was 0.125, while that for 2011–2020 was 0.141, an increase of 12.8% relative to the preceding decade.

During 2000–2010, the annual mean NDVI showed positive year-on-year growth in three years (2002, 2006 and 2009). During 2011–2020, positive growth occurred in six of the ten years (including 2012, 2015, 2016, 2017 and 2020), indicating markedly improved vegetation conditions in the recent decade.

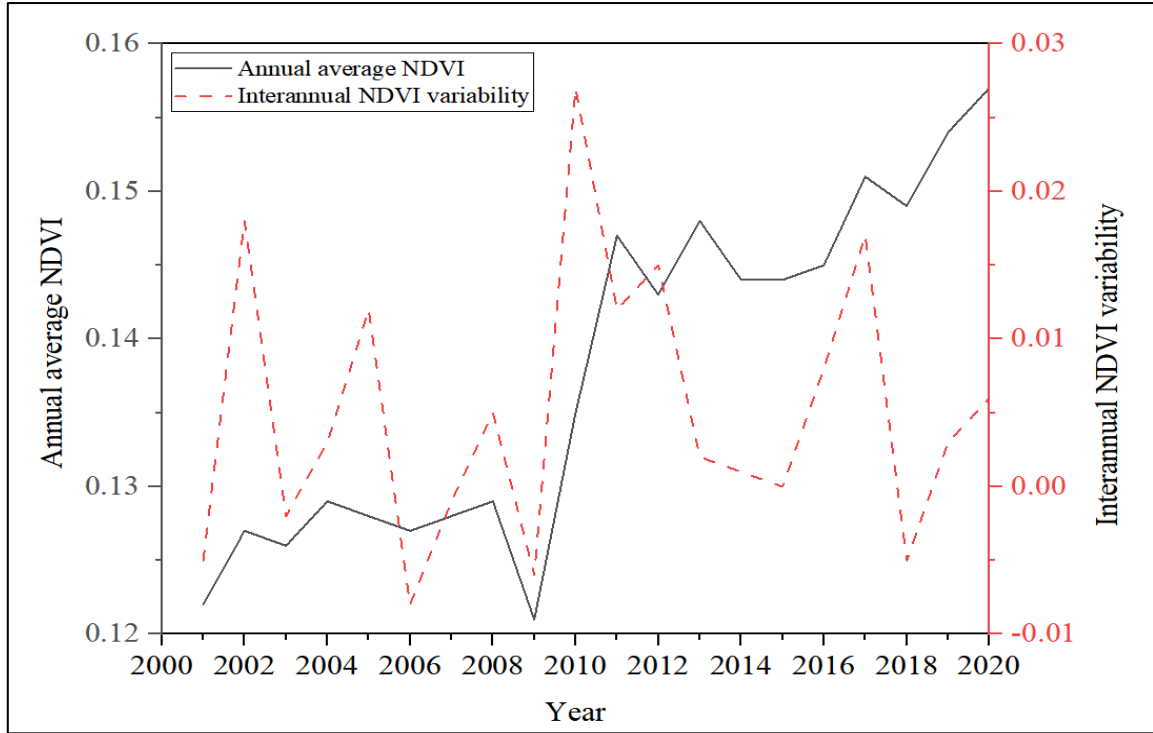


Fig. 2 Interannual variation and year-on-year change of mean NDVI in Kezhou (2000–2020)

3.1.2 Spatial Distribution Characteristics of NDVI

The mean NDVI spatial distribution (2000–2020) shows significant differentiation: high in the northwest and low in the southeast, with strip-shaped patterns along water systems and oases (Fig. 3). High NDVI areas (0.312–0.739) concentrate in the piedmont oasis belt at the southern Tianshan Mountains, the northeastern river valleys and intermountain basins. Relying on stable snow/ice meltwater and rivers (Kezhou and Gaizi), these areas form the main agricultural zones and natural oases with NDVI above 0.458, locally exceeding 0.7, demonstrating a distinct “oasis effect”. Medium NDVI regions (0.131–0.312) occur at oasis peripheries, river terraces and low mountain-hilly areas as ecological transition zones dominated by grasslands, shrubs and dryland farming. Low NDVI areas (0.008–0.131) cover the southern and central regions, including the Taklamakan Desert margin, gobi and bare rock, where sparse desert vegetation generally remains below 0.131.

Water resources constitute the core determinant of the NDVI pattern, while topography regulates distribution through precipitation and meltwater convergence. Human activities also significantly influence the spatial distribution: irrigated agricultural areas display higher NDVI than surrounding natural deserts, reflecting artificial oasis enhancement, whereas scattered desert-edge oases show lower cover due to limited water. Overall, the NDVI distribution reflects both the vulnerability of arid ecosystems and the regulatory roles of water resources and human activities.

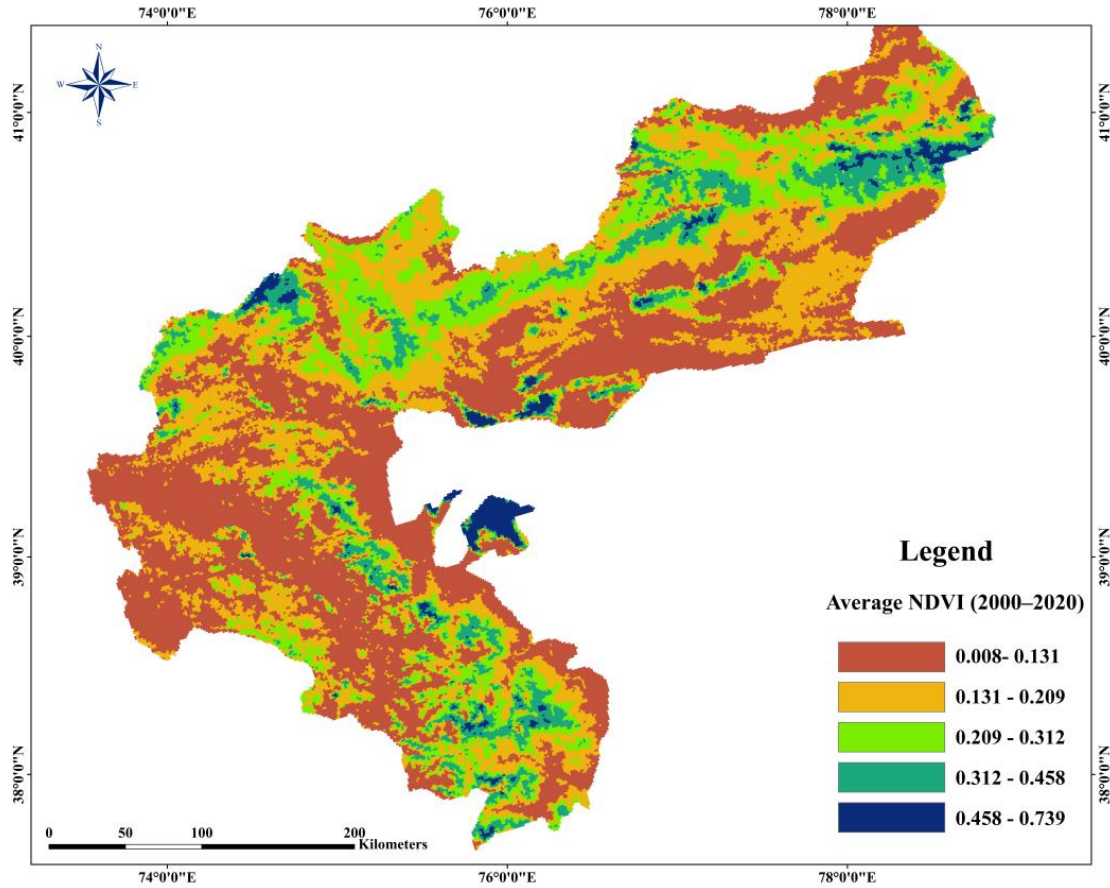


Fig. 3 Spatial distribution of mean annual NDVI in Kezhou (2000–2020)

3.2 Spatiotemporal Evolution Characteristics of FVC

Figure 4 presents the spatial distribution of FVC in 2000, 2005, 2010, 2015 and 2020. FVC shows an overall pattern of high values in the northwestern mountain-oasis belt and low values in the southeastern plains. From 2000 to 2020, vegetation coverage improved overall, characterized by the expansion of moderate and relatively high FVC areas. Improvement was modest during 2000–2005, while 2005–2015 witnessed the most significant improvement, with green areas expanding southeastward, indicating the positive effects of ecological restoration projects and climatic factors.

According to the annual FVC statistics (Fig. 5), low coverage (0–0.1) decreased consistently from 7% in 2000 to 2% in 2020. Moderate coverage (0.3–0.5) expanded from 10.9% to 17.93%, becoming the main contributor to the optimization of the cover structure. Relatively high and high coverage rose slowly, from 2% to 6% and from 1% to 3%, respectively, indicating the gradual expansion of high-grade vegetation areas. Relatively low coverage (0.1–0.3) remained the dominant class throughout the study period, indicating that the vegetation body is still dominated by sparse vegetation and grasslands.

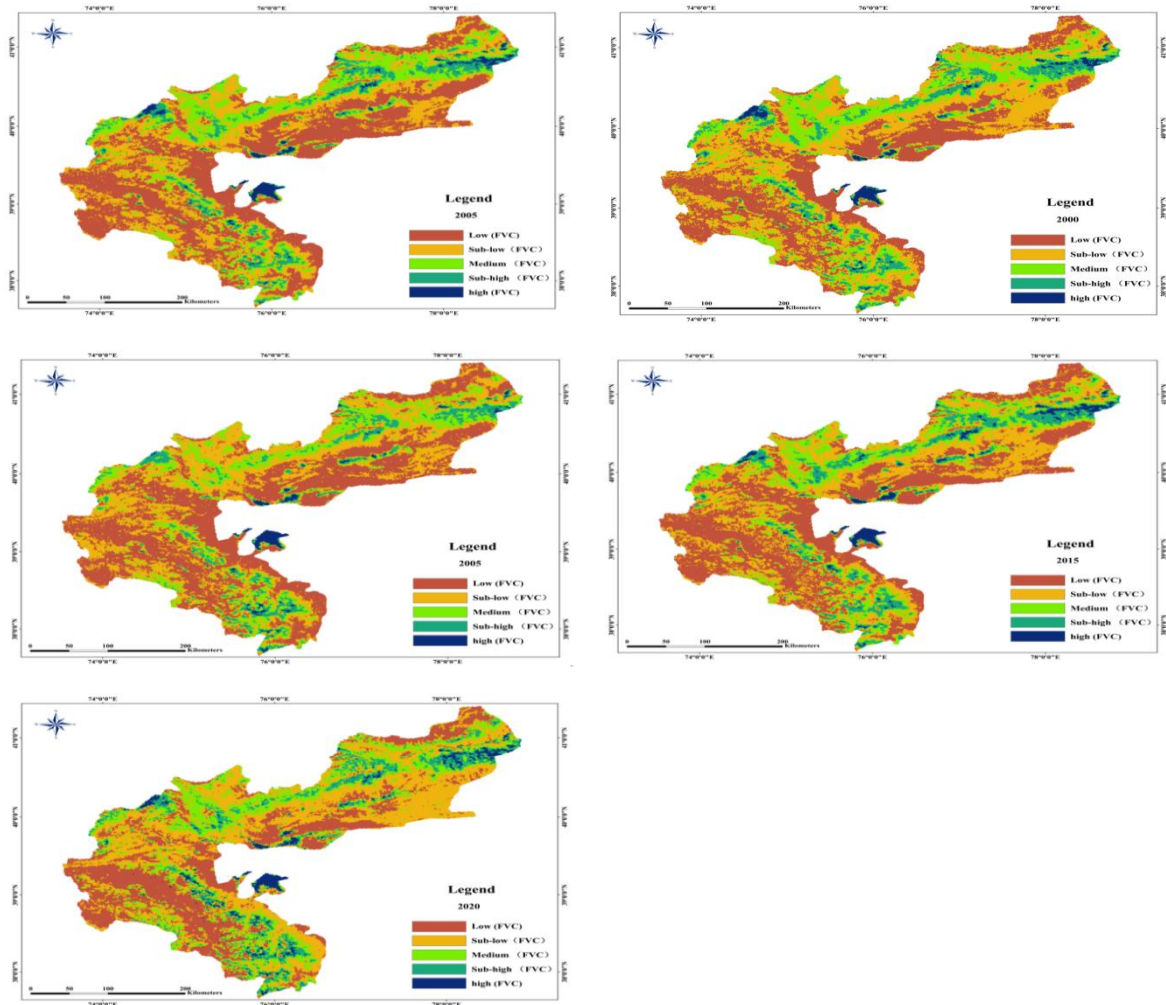


Fig. 4 Spatial distribution of FVC in Kezhou in 2000, 2005, 2010, 2015 and 2020

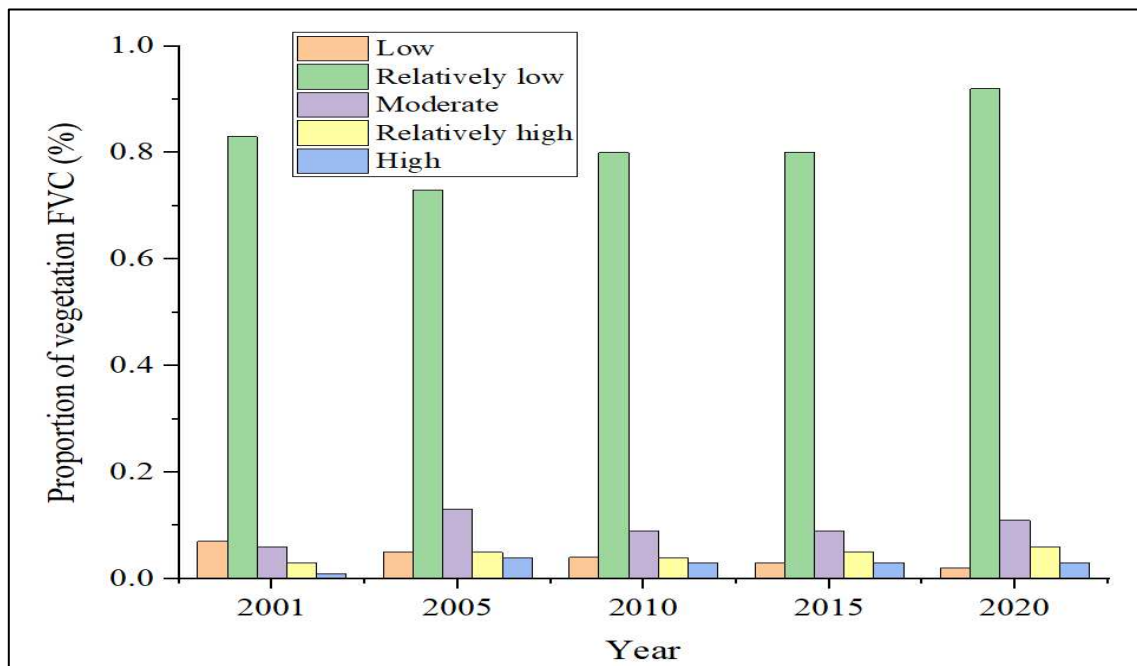


Fig. 5 Annual variation of FVC class proportions in Kezhou (2000–2020)

3.3 Spatiotemporal Evolution Characteristics of Vegetation NPP

3.3.1 Temporal Variation of NPP

From 2000 to 2020, vegetation NPP in Kezhou underwent a three-stage evolution of “fluctuating increase–sharp decline–low-level fluctuation” (Fig. 6). During 2000–2015, NPP showed an overall fluctuating upward trend, rising from about $4.2 \text{ g C m}^{-2} \text{ a}^{-1}$ in 2000, with brief declines during 2003–2004, adjustments during 2007–2008 and further fluctuations during 2011–2012, and reaching a peak of about $5.1 \text{ g C m}^{-2} \text{ a}^{-1}$ in 2015. The mean annual growth rate in this stage was about $0.06 \text{ g C m}^{-2} \text{ a}^{-1}$, possibly associated with ecological restoration projects and climate warming and wetting. After 2015, NPP declined sharply and remained at a low level of $3.8\text{--}3.9 \text{ g C m}^{-2} \text{ a}^{-1}$ during 2017–2020, about 25.5% below the 2015 peak.

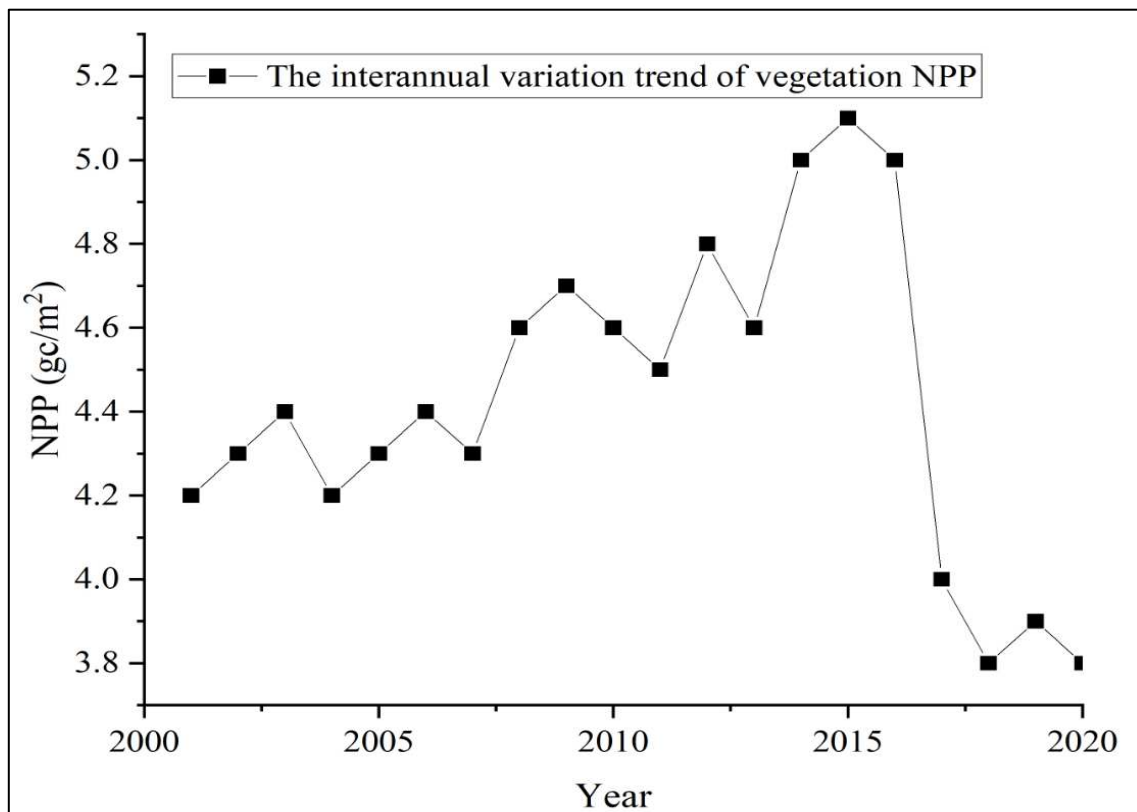


Fig. 6 Interannual variation of vegetation NPP in Kezhou (2000–2020)

3.3.2 Spatial Evolution Trends and Significance Testing of NPP

The mean NPP spatial distribution (2000–2020) exhibits significant heterogeneity, characterized by “high in the north and low in the south, and high in mountainous areas and low in plains” (Fig. 7). High NPP areas concentrate in the northern and northeastern mountains in strip distributions, where alpine meadows and forests show strong photosynthetic capacity. Two distinct high-NPP zones around water bodies appear in the east-central part, displaying “water body–oasis” synergistic characteristics of irrigated agriculture or riparian vegetation. Medium-high NPP areas appear patchily in the northwestern mountains, while the vast southwestern and southeastern plains are dominated by low NPP areas, indicating sparse vegetation constrained by extreme aridity and poor soil. Overall, NPP grades show gradient succession from north to south and from mountains to plains, with topography playing a decisive role; low-NPP areas occupy the absolute majority of the total area, while high-NPP areas show island-like distributions, indicating relatively low overall productivity and fragile ecological baseline

conditions.

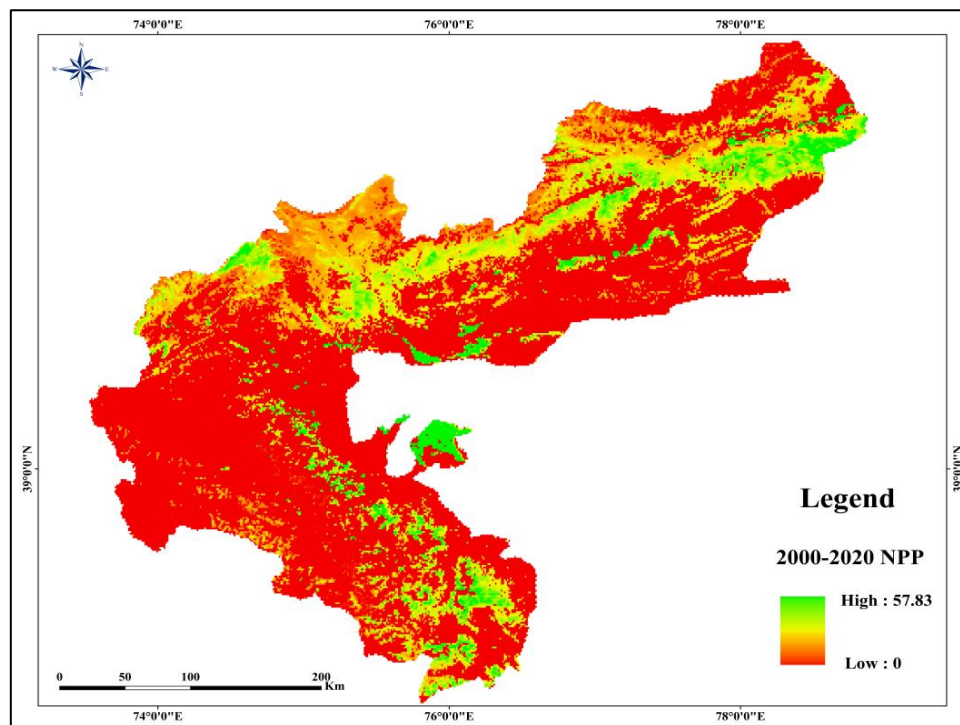


Fig. 7 Spatial distribution of mean vegetation NPP in Kezhou (2000–2020)

The Sen + M-K significance testing (Fig. 8, Table 4) shows that insignificant increase dominates at 88.0% of the area, extensively distributed across the south-central plains, eastern mountains and western areas, indicating stable or slowly improving ecosystems. Significant increase accounts for 6.5%, concentrated in the northwestern and central-northern mountainous zones with statistically reliable improvement. Insignificant decrease occupies 5.0%, embedded within the northeastern high-NPP baseline areas, while significant decrease is extremely rare (0.5%). Notably, significant increases mainly occur in areas with medium NPP baselines, whereas high-baseline areas show insignificant trends, implying that ecological restoration achieved more significant results in moderately conditioned areas.

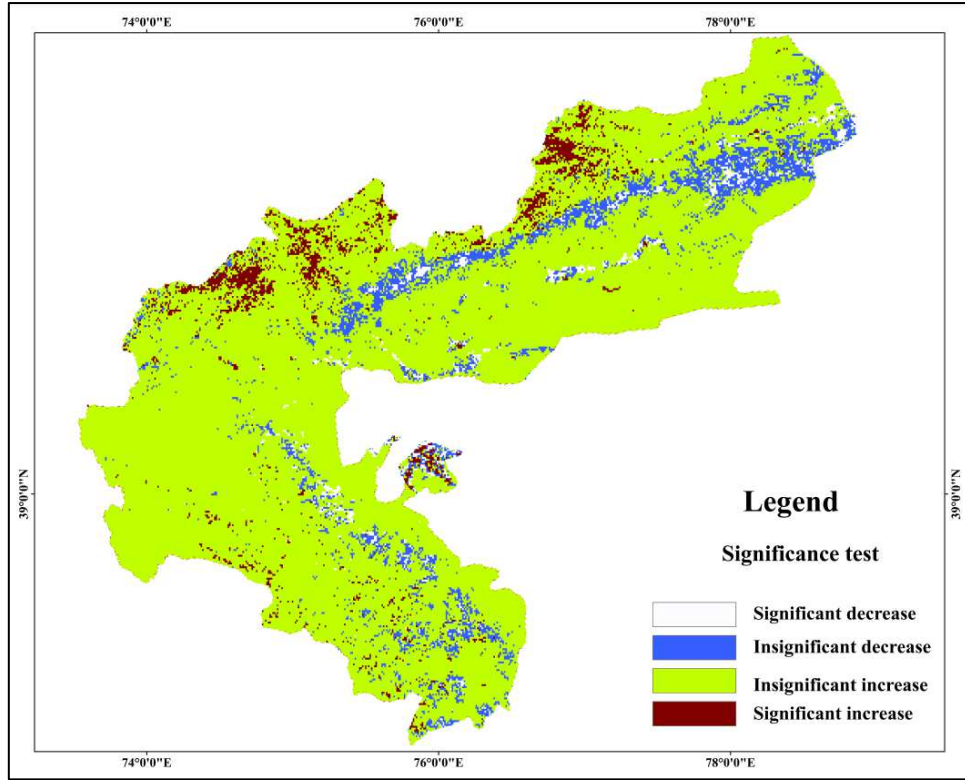


Fig. 8 Spatial distribution of NPP trends and M-K significance testing in Kezhou (2000–2020)

Table 4. Classification of Sen + M-K trend significance for NPP

Type of change	Classification criterion	Area percentage (%)
Insignificant decrease	$S < 0, Z \leq 1.96$	5.0
Significant decrease	$S < 0, Z < -1.96$	0.5
Insignificant increase	$S > 0, Z \leq 1.96$	88.0
Significant increase	$S > 0, Z > 1.96$	6.5

4 Discussion

4.1 Climate Drivers of Vegetation NPP and Their Spatial Heterogeneity

Pixel-wise Pearson correlation between annual NPP and annual climate factors (2000–2020) is shown in Fig. 9. The temperature–NPP correlation ranged from -0.792 to 0.875 : positive correlations covered 43.7% of the area (Fig. 9a), mainly in oasis agricultural areas (where irrigation enables effective heat utilization) and the southwestern plateau (where warming extends the growing season in high-altitude cold environments); negative correlations occupied 23.0%, concentrated in the central arid watersheds, where warming intensified evapotranspiration and insufficient precipitation caused vegetation water stress; the remaining 33.3% showed low or no correlation ($|r| < 0.2$). The precipitation–NPP correlation ranged from -0.81 to 0.86 : positive correlations covered 50.3% (Fig. 9b), exceeding that of temperature; 19.2% showed negative correlations, mainly in the central desert and gobi of the Tarim Basin margin, where increased precipitation may fail to convert into available soil moisture or may trigger runoff erosion; the remaining 30.5% showed low or no correlation.

The central arid regions exhibit “precipitation-positive dominance with temperature-negative correlation”, indicating that water availability is the core factor controlling vegetation productivity, while warming negatively affects productivity through enhanced evapotranspiration. In contrast, the southwestern plateau shows positive correlations with both factors: warming promotes alpine snow/ice melt, increasing river runoff and irrigation water and forming a “warm-humid” synergy, in contrast to the “warm-dry” stress in the central watersheds. This precipitation dominance is consistent with previous conclusions for Xinjiang grasslands, where the area positively correlated with precipitation exceeds that for temperature [40]. Overall, the NPP response to climate factors exhibits significant spatial heterogeneity, shaped jointly by water-heat conditions, topography and human activities, with water availability as the key explanatory variable.

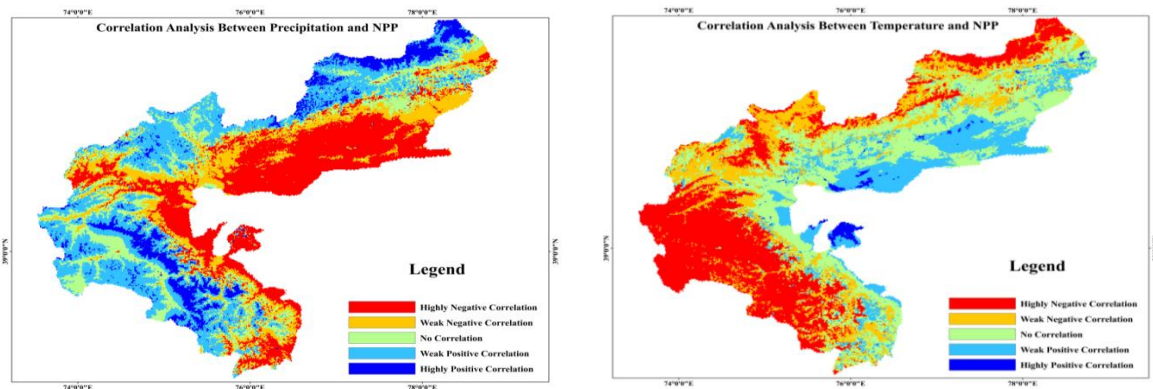


Fig. 9 Pixel-wise correlation between vegetation NPP and climate factors in Kezhou (2000–2020): (a) temperature; (b) precipitation

4.2 Evolution Characteristics of NDVI

The NDVI of Kezhou increased at 0.0021 a^{-1} during 2000–2020, showing slow improvement consistent with vegetation growth trends in Northwest China. This rate is slightly lower than the regional average of Northwest China (0.0027 a^{-1} for 2000–2019) but higher than that of its inland arid sub-region (0.0018 a^{-1}) [35], reflecting restoration difficulties in extremely arid zones. The mean NDVI of 2011–2020 (0.141) increased by 12.8% relative to 2000–2010 (0.125), and the number of positive-growth years rose from three to six, indicating significantly improved vegetation trends in the recent decade, probably related to the continued implementation of ecological projects such as the Grain for Green Program. The growth rate is also lower than that reported for the Yellow River Basin (0.0062 a^{-1}) [35–36], which is closely related to the local “three mountains sandwiching two valleys” topography: mountains exceed 90% of the area, usable oases are limited, and ecosystems are fragile, resulting in slow vegetation restoration.

Spatially, the “high northwest, low southeast” NDVI pattern along water systems and oases is consistent with research on Xinjiang’s ecological vulnerability [27]. High-value areas concentrate in the piedmont oasis belt of the southern Tianshan Mountains and in river valleys, exceeding 0.458 and demonstrating the “oasis effect”, while the southern Taklamakan Desert margin remains below 0.131. This differentiation is determined by hydrothermal conditions: the northwestern mountains receive abundant precipitation from orographic lifting plus snow/ice meltwater, whereas the southeastern plains suffer severe water stress from scarce precipitation and intense evaporation.

4.3 Evolution Characteristics and Ecological Significance of FVC

The FVC classification results reveal that the expansion of moderate-coverage vegetation was most significant from 2000 to 2020, increasing from 10.9% to 17.93% (a 64.4% relative growth) and becoming the main contributor to the optimization of the cover structure—similar to findings on the Loess Plateau [28], indicating that restoration in arid areas first manifests as the expansion of moderate-coverage regions. Low-coverage areas decreased from 7% to 2%, demonstrating improved ecological conditions and alleviated desertification pressure. However, the combined proportion of relatively high and high coverage remained low (about 9% in 2020) with slow growth, indicating that vegetation quality remains at a medium-to-low level, with sparse vegetation and grasslands of simple structure and insufficient stability. Future restoration should focus on improving cover quality and promoting conversion from low to moderate-high coverage. Spatially, 2005–2015 witnessed the fastest FVC improvement with southeastward green expansion, consistent with the rising NPP trend and reflecting the superimposed effects of ecological projects and climate warming and wetting; after 2015, improvement slowed, possibly related to ecosystem equilibration or intensified water-resource constraints.

4.4 The Post-2015 NPP Decline and Its Possible Mechanisms

Vegetation NPP in Kezhou exhibited a three-stage evolution of “fluctuating increase–sharp decline–low-level fluctuation”. After peaking in 2015 (about $5.1 \text{ g C m}^{-2} \text{ a}^{-1}$), NPP declined sharply and remained at $3.8\text{--}3.9 \text{ g C m}^{-2} \text{ a}^{-1}$ during 2017–2020. This contrasts with the continuous FVC improvement, revealing an asynchrony between vegetation coverage (quantity) and productivity (quality). The sharp decline may be attributed to the following factors:

(1) Climatic anomalies: periodic drought after 2015, featuring decreasing precipitation and rising temperatures, intensified evapotranspiration and vegetation water stress. Temperature shows a significant negative correlation with NPP in the central arid watersheds, which differs from conclusions that temperature has only weak effects on Xinjiang grassland vegetation [40], warranting further investigation.

(2) Water-heat combination effects: the southwestern plateau shows positive correlations with both factors (warming promotes snow/ice melt and increases runoff), forming a “warm-humid” synergy, whereas the central watersheds exhibit “warm-dry” stress. The precipitation-positive area (50.3%) exceeds the temperature-positive area (43.7%), indicating that water availability is the core control on productivity.

(3) Ecosystem threshold effects: the continuous increase before 2015 may have approached or exceeded the local water-resource carrying capacity, causing the subsequent productivity decline. This hypothesis requires direct testing (e.g., water-balance analysis) and should be regarded as a working hypothesis rather than a confirmed mechanism.

(4) The contrast between the abrupt post-2015 decline in the regional mean series and the dominance of insignificant pixel-scale trends (88% insignificant increase over the full period) suggests a step change rather than a gradual trend. In addition, the “middle breakthrough” pattern—significant increases (6.5%) concentrated in medium-baseline rather than high-baseline areas—implies that ecological projects achieve better results in moderately conditioned areas, providing a reference for differentiated restoration strategies.

4.5 Limitations and Prospects

This study has several limitations. (1) The CASA estimation did not fully consider soil types, CO_2

fertilization effects and human activities, which may bias estimates in agricultural areas, and the estimated absolute NPP values should be interpreted with caution pending systematic validation against MOD17A3H and field observations. (2) The meteorological stations are unevenly distributed—particularly sparse in the northwestern mountains—introducing uncertainty into the IDW interpolation. (3) Only temperature and precipitation were analyzed, excluding solar radiation, wind speed and human activities. (4) The interannual trends of temperature and precipitation themselves were not analyzed, which limits the attribution of the driving mechanisms. Future research should: (1) integrate multi-source remote sensing (Landsat, Sentinel-2) to improve spatial resolution; (2) employ Geodetector and multiple regression to quantitatively separate climatic and anthropogenic contributions; (3) couple NPP with ecosystem service values and carbon sequestration assessments to support the “dual carbon” goals; and (4) apply change-point detection (e.g., the Pettitt test or BFAST) to the NPP series to formally locate the post-2015 regime shift and exclude possible data artifacts.

5 Conclusions

Based on MODIS and meteorological data (2000–2020), this study employed Theil–Sen, Mann–Kendall and Pearson correlation analyses to reveal the spatiotemporal evolution of vegetation and its climatic drivers in Kezhou. The main conclusions are:

(1) NDVI increased at 0.0021 a^{-1} , with improvement accelerating after 2011. Spatially, NDVI shows a “high northwest, low southeast” pattern along water systems and oases, with high values (> 0.458) in the Tianshan piedmont oasis belt and low values (< 0.131) in the southern desert areas.

(2) The FVC structure optimized: moderate coverage expanded from 10.9% to 17.93% and low coverage decreased from 7% to 2%, while relatively high and high coverage rose slowly (to 6% and 3%, respectively) and relatively low coverage remained the dominant class.

(3) NPP followed a three-stage “rise-then-fall” trajectory: it peaked at about $5.1 \text{ g C m}^{-2} \text{ a}^{-1}$ in 2015 and then declined by about 25.5% to $3.8\text{--}3.9 \text{ g C m}^{-2} \text{ a}^{-1}$ during 2017–2020; at the pixel scale, 88% of the area showed an insignificant increase and only 6.5% a significant increase over the full period.

(4) Climatic responses show significant spatial heterogeneity: precipitation-positive areas (50.3%) exceed temperature-positive areas (43.7%), with “warm-dry” stress in the central watersheds and “warm-humid” synergy in the southwestern plateau, indicating that water availability is the dominant productivity constraint.

(5) The ecosystem is improving but remains fragile under climate warming and wetting. We recommend water-limited greening, differentiated restoration strategies for moderate-coverage areas, and transboundary water cooperation.

Declarations

Author Contributions: Wang Jianping wrote the original manuscript; Aynur Mamat and Aida Orozobekova designed the methodology; Almazbek Arzybaev revised the paper. All authors have read and agreed to the published version of the manuscript.

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Data Availability: The MODIS datasets (MOD13Q1 and related products) used in this study are publicly available from the NASA Land Processes Distributed Active Archive Center (<https://lpdaac.usgs.gov/>). The meteorological data were obtained from the China Meteorological Data

Service Centre (<http://data.cma.cn>). The processed datasets generated during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest: The authors declare no conflict of interest.

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