Influencing Factors of Spatiotemporal Changes in NDVI in the Lower Reaches of the Tarim River over the Past 30 Years

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Abstract

Vegetation is an important component of terrestrial ecosystems, and its spatiotemporal dynamics are highly sensitive to global change and human activities. The lower reaches of the Tarim River are located in a typical arid desert region of China. Clarifying the evolution patterns of regional vegetation cover and its main driving factors is of great significance for ecological protection and restoration. Based on long-term vegetation remote sensing data for the lower reaches of the Tarim River from 1990 to 2025, this study employed linear trend analysis and significance analysis to reveal the spatiotemporal variation patterns of the normalized difference vegetation index (NDVI). Furthermore, in combination with the optimal-parameters-based geographical detector model, the study systematically analyzed the independent explanatory power and interactions of natural factors such as temperature, precipitation, and solar radiation, as well as anthropogenic factors such as land use type, population density, and nighttime lights, and their influence patterns on the spatial distribution of vegetation. The results show that: (1) From 1990 to 2025, NDVI in the lower reaches of the Tarim River showed an overall phased and significant upward trend, but the growth rates differed markedly among periods. Before 2000, the vegetation index fluctuated upward; from 2001 to 2010, it increased rapidly; and thereafter it maintained a steady upward trend. (2) The spatial pattern exhibited an evolutionary mode of "continuous vegetation enhancement in the oasis core area and localized degradation in the peripheral desert," that is, vegetation cover along the river channel and in the oasis core area steadily increased and expanded toward the margins, while degradation occurred outside the oasis core area. (3) Factor detection results based on seven periods of time-series data from 1990 to 2020 indicate that land use type was consistently the dominant factor influencing the spatial differentiation of NDVI, with its explanatory power increasing from 0.23 to 0.74. The explanatory power of human-activity-related factors represented by population density and nighttime lights also showed a significant synchronous upward trend, and multifactor interactions further strengthened the joint shaping of vegetation patterns. This study quantifies the interactive mechanisms of natural factors and human activities, providing a scientific basis for a deeper understanding of the complex drivers of vegetation cover in arid regions. The analytical framework developed also offers methodological support for evaluating the comprehensive benefits of ecological restoration projects.

Full Text

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Influencing Factors of Spatiotemporal Changes in NDVI in the Lower Reaches of the Tarim River over the Past 30 Years

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Abstract: Vegetation is an important component of terrestrial ecosystems, and its spatiotemporal dynamics are highly sensitive to global change and human activities. The lower reaches of the Tarim River are located in a typical arid desert region of China. Clarifying the evolution patterns of regional vegetation cover and the major driving factors is of great significance for ecological protection and restoration. Based on long-term vegetation remote-sensing data for the lower reaches of the Tarim River from 1990 to 2025, this study used linear trend analysis and significance testing to reveal the spatiotemporal variation patterns of the normalized difference vegetation index (NDVI). In combination with the optimal-parameter GeoDetector model, it further systematically analyzed the independent explanatory power and interactions of natural factors such as temperature, precipitation, and solar radiation, as well as anthropogenic factors such as land-use type, population density, and nighttime lights, and their modes of influence on the spatial distribution of vegetation. The results show that: (1) From 1990 to 2025, NDVI in the lower reaches of the Tarim River showed an overall significant phased upward trend, but the growth rates differed markedly among periods: before 2000, the vegetation index increased with fluctuations; from 2001 to 2010, it grew rapidly; and thereafter it maintained a stable upward trend. (2) The spatial pattern exhibited an evolutionary mode of "continuous vegetation enhancement in the oasis core area and local degradation in the peripheral desert," namely, vegetation cover along the river channel and in the oasis core area steadily increased and expanded toward the margins, while degradation occurred outside the oasis core area. (3) Factor-detection results based on seven periods of time-series data from 1990 to 2020 show that land-use type has consistently been the dominant factor affecting the spatial differentiation of NDVI, with its explanatory power increasing from 0.23 to 0.74; the explanatory power of human-activity-related factors represented by population density and nighttime lights showed a significant upward trend, and multifactor interactions further strengthened their joint shaping of the vegetation pattern. This study quantifies the interactive influence mechanisms of natural factors and human activities, providing a scientific basis for an in-depth understanding of the complex drivers of vegetation cover in arid regions. The analytical framework constructed here also provides methodological support for

evaluating the comprehensive benefits of ecological restoration projects.

Keywords: lower reaches of the Tarim River; normalized difference vegetation index; influencing factors; spatiotemporal change; optimal-parameter GeoDetector

As the largest inland river in China, the Tarim River traverses the Tarim Basin in Xinjiang. It is not only the key water source sustaining the vast oasis belt from the southern foot of the Tianshan Mountains to the northern foot of the Kunlun Mountains, but also an important lifeline supporting socioeconomic development and ecological security in southern Xinjiang[1]. Native desert vegetation in the basin, such as *Populus euphratica* forests and *Tamarix* shrubs, effectively restrains the expansion of the Taklimakan Desert and plays an irreplaceable role in maintaining regional ecological balance[2]. Since the 1950s, owing to human factors such as increased agricultural water use in source-flow areas and low efficiency of canal-system water conveyance, inflow to the lower reaches of the Tarim River has decreased markedly, plunging from 12.0×10^8 m^3 in the 1950s to 2.5×10^8 m^3 in the 1990s. Long-term flow interruption led to shrinkage of the downstream river channel, decline of the groundwater table, ecological degradation, and extensive mortality of riparian natural vegetation. The ecological function of the downstream "green corridor" deteriorated sharply, and the risk of convergence between the Taklimakan Desert and the Kumtag Desert further intensified[2]. In response to this crisis, China launched the ecological water-conveyance project for the lower reaches of the Tarim River in 2000, gradually restoring downstream river flow, effectively raising the groundwater table, and ending 30 years of flow interruption in the lower reaches[3]. Meanwhile, with the advancement of the campaign to block the expansion of the Taklimakan Desert margin, multiple measures—including ecological water conveyance, sand-fixation afforestation, and photovoltaic sand control—have been implemented in coordination. These measures have significantly improved vegetation cover in the lower reaches of the Tarim River, mitigated wind-sand hazards, enhanced ecosystem stability, and achieved a shift from "desert advancing and people retreating" to "greenery advancing and desert retreating" [4]. However, the ecological environment of this region remains fragile, and the patterns and driving mechanisms of vegetation evolution are still unclear; in-depth investigation is therefore of great significance for ecological protection and sustainable development.

Vegetation is an important component of terrestrial ecosystems and has key functions such as conserving soil and water, preventing wind erosion and fixing sand, and improving the environment. The normalized difference vegetation index (NDVI) is commonly used to characterize vegetation cover, growth status, productivity level, and even to evaluate vegetation cover[5]. Studies have shown that vegetation changes in different regions

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the dominant factors differ: in some regions, vegetation change is controlled by natural factors (precipitation, air temperature, solar radiation)[6]; in some regions it is dominated by human activities (land development, population agglomeration, etc.)[7]; and in more regions it results from the combined effects of natural factors and human activities[8]. Therefore, clarifying the mechanisms by which climatic factors and human activities influence the spatiotemporal pattern of vegetation is of great scientific significance for environmental-quality assessment and ecosystem protection.

At present, many studies have been conducted on environmental change in the Tarim River Basin, but some deficiencies remain. Some studies have focused on river-channel buffer zones and have not fully covered the broader desert region[9]. With the advancement of ecological water conveyance projects in the lower reaches of the Tarim River, the groundwater level in the lower Tarim River Basin has risen, and shrubs have gradually grown in some previously unvegetated areas[3]. Focusing only on areas around the river channel makes it difficult to capture large-scale vegetation change. In addition, existing studies mostly use medium- to low-resolution remote-sensing data of 1 km or 250 m, which have limited ability to capture vegetation cover at small and medium scales[10–11]. Therefore, based on remote-sensing vegetation data for the lower reaches of the Tarim River from 1990 to 2025, this study systematically characterizes the spatiotemporal evolution of NDVI using linear regression and significance testing, and, with the aid of an optimal-parameters geographical detector model, quantitatively reveals the driving effects of natural factors and human-activity factors as well as their interaction effects.

1 Study Area Overview and Data Sources

1.1 Study Area Overview

This study takes the lower reaches of the Tarim River (39.5°–41.5°N, 86.5°–88.5°E) as the study area, mainly covering Korla City, Yuli County, Ruoqiang County, and surrounding related areas[12] (Fig. 1). The study area belongs to a typical temperate continental desert climate. The vegetation communities exhibit a typical desert riparian tree-shrub-herb structure. The main tree species is *Populus euphratica*; representative shrubs include *Tamarix ramosissima*, *Ly-*

cium ruthenicum, and *Halimodendron halodendron*; and the main herbaceous plants include *Phragmites australis*, *Poacynum hendersonii*, and *Alhagi sparsifolia*[13]. The distribution of regional water resources is closely related to human activities, making this a typical region for studying ecohydrological mechanisms in arid areas and the sustainable development of oases[14].

1.2 Data Sources and Processing

Based on the Google Earth Engine (GEE) platform, multi-temporal Landsat 5/7/8 imagery of the lower reaches of the Tarim River from 1990 to 2025 was preprocessed and composited to extract NDVI data at a spatial resolution of 30 m[15].

Visible labels in Fig. 1 include: national boundary; undemarcated boundary; provincial boundary; study-area extent; study-area boundary; county-level administrative boundary; grassland; cropland; wetland; water body; woodland; unused land; construction land; meteorological station; river; lake; elevation/m; Korla City; Yuli County; Ruoqiang County; 3700; 762; 0–300 km; 0–50 km; 0–40 km; N.

Note: The basemap was produced using the standard map from the National Platform for Common Geospatial Information Services; the map approval number is GS(2024)0650, and no modifications were made to the basemap boundaries. The same applies below.

Fig. 1 Overview map of the lower reaches of the Tarim River

(Table 1). The climate-factor data include mean precipitation, air temperature, and solar radiation. Among them, mean precipitation and air temperature were derived from the China 1 km-resolution monthly precipitation dataset (1901–2024) [16–17], and the solar-radiation data were from the China homogenized gridded climate dataset (1961–2022) released by the National Tibetan Plateau Data Center [18]. Monthly data were aggregated on the GEE platform to obtain annual totals (means). All meteorological data were uniformly resampled to a 1 km resolution by bilinear interpolation. ERA5-Land assimilates global multi-source data and has good spatial continuity, which can compensate for accuracy limitations in areas with sparse stations. Human-activity factors include land-use type, nighttime lights, and population density. The land-use data employed annual land-cover products for 1985–2025 (1 km resolution) [19]; the nighttime-light data used the long-term annual artificial nighttime-light dataset for China (1984–2020), which had undergone inter-sensor calibration and saturation correction [20]; and the population-density data comprised seven periods —1990, 1995, 2000, 2005, 2010, 2015, and 2020—at a resolution of 1 km (Table 1). Both nighttime-light and population-density data were extracted to the corresponding sample points by bilinear interpolation and spatially linked with the NDVI sample attribute table.

2 Research Methods

2.1 Spatial Analysis and Data Processing

Using the ArcGIS software platform, all spatial data were preprocessed, managed, and visually analyzed. Global and local spatial autocorrelation indices were calculated to identify the spatial clustering characteristics and distribution patterns of NDVI and various driving factors, thereby laying a spatial-statistical foundation for the subsequent analysis of driving mechanisms [21].

2.2 Analysis of Change Trends

In the temporal analysis, the linear trend method [22] was used to analyze the trend in maximum NDVI. The coefficient of determination (R^2) was used to evaluate the goodness of fit of the regression, and a t-test was used to detect the significance of changes. The calculation method is as follows:

$$Slope = \frac{n \times \sum_{i=1}^{n} i \times \overline{x_i} - \sum_{i=1}^{n} i \times \sum_{i=1}^{n} \overline{x_i}}{n \times \sum_{i=1}^{n} i^2 - \left(\sum_{i=1}^{n} i\right)^2} \tag{1}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(x_i - e_i)^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{2}$$

where *Slope* is the slope; i is the year (a); $\overline{x_i}$ is the value of each study element in year i; n is the length of the time series studied; x_i is the observed value of the study variable in year i; e_i is the simulated value of the study variable in year i; $\bar{x}$ is the mean of the observed values; and N is the number of data points.

To identify possible structural change points in the NDVI time series, the Pettitt nonparametric test method [23] was adopted. This method determines whether an abrupt change has occurred by testing the consistency of the cumulative frequency distributions of samples before and after the change point. It imposes no specific requirements on the distribution type of the sequence and is suitable for abrupt-change analysis of climatic, hydrological, and ecological time series. The annual mean maximum NDVI series for the study area from 1990 to 2025 was input into the test model, with the significance level set at $\alpha = 0.05$. When the test statistic exceeded the critical value and the corresponding P value was less than 0.05, the point was identified as a significant abrupt-change point.

2.3 Analysis of Change Significance

In the spatial analysis, the statistical significance of the trend was first determined [24]. For all pairs of time points (i, j), where $j > i$, the slope was calculated as follows:

$$Q_k = \frac{X_j - X_i}{j - i} \tag{3}$$

$$\beta = \mathrm{median}(Q_k) \tag{4}$$

where X_i and X_j are the observed values at the corresponding time points. β is the median of all Q_k values; $\beta > 0$ indicates an increasing trend, $\beta < 0$ indicates a decreasing trend, and $\beta = 0$ indicates no obvious trend. The Mann-Kendall trend test was then used to determine whether the trend was statistically significant [25]. The test statistic was calculated

Table 1 Data Sources

Tab. 1 Data source

Data type	Data	Data source
Normalized Difference Vegetation Index	NDVI data	Google Earth Engine (https://earthengine.google.com/)
Climate-factor data	Precipitation	Tibetan Plateau Scientific Data Center (https://doi.org/10.5281/zenodo.3114194.)
Climate-factor data	Air temperature	Tibetan Plateau Scientific Data Center (https://doi.org/10.5281/zenodo.3114194.)
Climate-factor data	Solar radiation	Tibetan Plateau Scientific Data Center (https://doi.org/10.5281/zenodo.3114194.)
Human-activity data	Land-use type	Resource and Environmental Science and Data Center (https://www.resdc.cn/DOI/doi.aspx?DOIid=54)
Human-activity data	Population density	Resource and Environmental Science and Data Center (https://www.resdc.cn/DOI/doi.aspx?DOIid=54)
Human-activity data	Nighttime-light value	Tibetan Plateau Scientific Data Center (https://data.tpdc.ac.cn/)

S and its variance $\mathrm{var}(S)$ are given as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \mathrm{sgn}\left(X_j - X_i\right) \tag{5}$$

$$\mathrm{var}(S) = \frac{n(n-1)(2n+5) - \sum_t t(t-1)(2t+5)}{18} \tag{6}$$

where sgn( ) is the sign function, and t is the number of observations with the same rank. The standardized test statistic is Z: when $S > 0$, $Z = (S-1)/\sqrt{\mathrm{var}(S)}$; when $S = 0$, $Z = 0$; and when $S < 0$, $Z = (S+1)/\sqrt{\mathrm{var}(S)}$. Given a significance level α, when $|Z| > Z_{1-\alpha/2}$, the trend is judged to be significant, and the direction of the trend is determined by the sign of Z.

2.4 Optimal-Parameter Geodetector

Traditional Geodetectors are relatively subjective when discretizing driving factors and can introduce uncertainty if the classification scheme is inappropriate. The optimal-parameter Geodetector, by contrast, can automatically select the best discretization method and breakpoint combination for each continuous variable[^26]. For continuous variables—including precipitation, air temperature, solar radiation, nighttime light intensity, and population density—five classification methods were adopted: the quantile method, natural breaks, equal interval, standard deviation, and geometric interval. The number of intervals was set from 4 to 10, and the parameter combination with the highest q value was selected for spatial discretization; categorical data were used directly according to their categories. The method mainly includes two core modules: (1) the factor detector, which calculates the explanatory power q value of each driving factor, quantifies the degree to which a single factor explains the spatial differentiation of NDVI, and determines the order of factor influence; and (2) the interaction detector, which identifies changes in explanatory power after two-factor coupling, determines the interaction type—such as bi-factor enhancement, nonlinear enhancement, or independent action—and analyzes the coordinated driving effects of multiple factors[^27].

In this study, seven periods of data at 5-year intervals from 1990 to 2020 were selected for detection. The data for all factors were uniformly resampled to a 1 km resolution and valid pixel samples were extracted. After invalid and anomalous values were removed, a complete panel dataset covering the seven years was constructed for analysis.

3 Results and Analysis

3.1 Spatiotemporal Variation Characteristics of NDVI in the Lower Reaches of the Tarim River

3.1.1 Temporal variation of NDVI in the lower reaches of the Tarim River

From 1990 to 2025, the annual maximum NDVI in the lower reaches of the Tarim River increased significantly at a rate of 0.00227 per year ($P < 0.001$) (Fig. 2d), indicating an overall improvement in regional vegetation cover. In particular, the 19th year was a significant abrupt change point in the evolution of the NDVI time series ($P < 0.001$) (Fig. 3). By stage, NDVI fluctuated upward during

1990–2000 ($P = 0.026$) (Fig. 2a); during 2001–2010, the annual increase was the fastest (0.0034, $P < 0.001$), and the vegetation recovery process accelerated (Fig. 2b); during 2011–2025, the annual growth rate slowed but still increased significantly (0.00204, $P < 0.001$), entering a period of stable growth (Fig. 2c).

Fig. 2 Temporal distribution of NDVI and its changes in each period from 1990 to 2025 in the lower reaches of the Tarim River

In-figure labels and fitted equations:

- (a) 1990–2000; y-axis: NDVI; x-axis: Year; $y = 0.00271x - 5.33288$; $R^2 = 0.44$, $P = 0.026$.
- (b) 2001–2010; y-axis: NDVI; x-axis: Year; $y = 0.0034x - 6.73281$; $R^2 = 0.79141$, $P < 0.001$.
- (c) 2011–2025; y-axis: NDVI; x-axis: Year; $y = 0.00204x - 3.98782$; $R^2 = 0.66798$, $P < 0.001$.
- (d) 1990–2025; y-axis: NDVI; x-axis: Year; $y = 0.00227x - 4.45105$; $R^2 = 0.8991$, $P < 0.001$.

In the figure: y-axis, NDVI; x-axis, Year; annotation, Change point (2008).

Fig. 3 Change-point detection of NDVI in the lower reaches of the Tarim River

3.1.2 Spatial distribution of NDVI in the lower reaches of the Tarim River

Vegetation cover in the lower reaches of the Tarim River showed marked improvement and spatial differentiation in its spatiotemporal pattern (Fig. 4). Temporally, the changes were clearly phased. From 1990 to 2000, changes were slow, and the area proportion of high vegetation cover zones (NDVI > 0.4) was only 0.02%–0.76% (Tab. 2). From 2001 to 2015, the range of vegetation improvement continued to expand, and the proportion of high vegetation cover zones increased from 3.75% to 6.89% (Figs. 4c–4e). After 2016, the vegetation pattern tended to stabilize; the proportion of high vegetation cover zones increased to 7.90% and showed spatial contiguity (Figs. 4f–4h). The spatial differentiation pattern was characterized by a typical configuration of "continuous vegetation enhancement in the oasis core area and localized degradation in the surrounding desert" (Fig. 4). The oasis core area was the vegetation-covered area; high-NDVI zones expanded outward, while medium- and low-value zones extended toward the desert margin. Low vegetation cover areas (NDVI < 0.1) shrank, with their proportion declining from 89.15% in 1990–1995 to 71.01% in 2021–2025 (Tab. 2). Bare land and extremely low-cover areas were continuously replaced by vegetation, indicating an improving ecological condition.

Tab. 2 Area percentage of NDVI spatial distribution in the lower reaches of the Tarim River during different periods from 1990 to 2025

Year	NDVI area percentage/% (<0)	NDVI area percentage/% (0–0.1)	NDVI area percentage/% (0.1–0.2)	NDVI area percentage/% (0.2–0.3)	NDVI area percentage/% (0.3–0.4)	NDVI area percentage/% (>0.4)
1990–1995	0.27	89.15	9.08	1.24	0.24	0.02
1996–2000	0.79	84.53	10.64	2.09	1.19	0.76
2001–2005	0.07	82.20	9.18	3.42	1.38	3.75
2006–2010	0.06	80.59	10.17	2.72	1.27	5.19
2011–2015	0.10	76.65	11.31	3.49	1.56	6.89
2016–2020	0.03	73.86	12.21	4.32	2.02	7.56
2021–2025	0.02	71.01	13.59	5.11	2.37	7.90
1990–2025	0.00	77.97	11.95	3.35	2.32	4.41

The NDVI change trend in the lower reaches of the Tarim River exhibited phased characteristics of "pronounced early fluctuations, strengthening recovery in the middle period, and spatial differentiation in the later period" (Fig. 5). During 1990–2000, the trend showed strong interannual fluctuations (Figs. 5a, 5b). Such short-term, large-scale trend reversals reflect the inherent sensitivity and vulnerability of arid-zone ecosystems to climate change. Since 2001, the trend has been significantly restructured spatially: the annual enhancement trend along the river channel and in the oasis core area (slope $> 2 \times 10^{-3}$) persisted and remained dominant (Figs. 5c–5e). After 2016, the area exhibiting degradation trends in the oasis periphery and downstream transition zone (slope < 0) expanded markedly, forming a spatially differentiated pattern of "continuous improvement in the oasis core area and localized degradation in marginal areas" (Figs. 5f, 5g, 5h; Tab. 3).

From 1990 to 2025, vegetation-cover change in the lower reaches of the Tarim River evolved in stages over time and showed clear spatial differentiation (Fig. 6). Significantly improved areas were dominant, accounting for 86.99% of the area (Tab. 4), and constituted the principal spatial change trend. By stage, the significance structure underwent an obvious shift. After 2016, the area proportion of regions with degradation trends (slight degradation and significant degradation) increased from 45.06% in 2016–2020 to 54.82% in 2021–2025, mainly distributed in the oasis periphery and parts of the downstream area (Fig. 6g), consistent with the "localized degradation in marginal areas" pattern identified in the trend analysis (Fig. 6b). The above significance pattern was synchronized with the NDVI trend stages (Fig. 5), jointly revealing the spatial differentiation of "overall improvement and localized degradation" in vegetation-cover change in arid zones, as well as the complexity of its dynamic evolution.

3.2 Exploration of driving factors of NDVI change in the lower reaches of the Tarim River

3.2.1 Relative importance of factors affecting NDVI change

The factor detection results indicate that land-use type was consistently the most important factor influencing the spatiotemporal pattern of NDVI. Its q value increased year by year from 0.23 in 1990 to 0.74 in 2020 (Fig. 7), indicating a progressively stronger explanatory power for the spatial heterogeneity of vegetation cover. The q values of population density and nighttime lights also increased markedly, from 0.13 and 0.01 to 0.31 and 0.2, respectively (Fig. 7), indicating that the influence of human activities on the spatial pattern of NDVI gradually strengthened. The q values of climatic factors (precipitation, temperature, and solar radiation) were overall lower than those of human-activity factors and changed only slowly (Fig. 7), suggesting that the direct constraints of climatic elements on the spatial differentiation of regional vegetation were relatively weak.

3.2.2 Analysis of interaction effects among driving factors of NDVI change

Data for seven periods from 1990 to 2020 show that the interactive effects of the driving factors on the spatial differentiation of NDVI strengthened significantly, and the explanatory power of interactions was generally higher than that of single factors (Fig. 8), indicating that multi-factor synergy had a more prominent influence on the spatial pattern of vegetation. The q values after interaction between any two factors were higher than those of their independent effects, and they increased markedly over time. Among all interaction combinations, factor pairs involving land-use type were the most significant; their interactive q values were generally the highest and showed the greatest increase (Fig. 8). 1990–

Fig. 4. Spatial distribution of NDVI values in different periods in the lower reaches of the Tarim River from 1990 to 2025

Subpanels: (a) 1990–1995; (b) 1996–2000; (c) 2001–2005; (d) 2006–2010; (e) 2011–2015; (f) 2016–2020; (g) 2021–2025; (h) 1990–2025.

Legend: NDVI: <0; 0–0.1; 0.1–0.2; 0.2–0.3; 0.3–0.4; >0.4. Scale: 0–80 km. North arrow: N.

Table 3. Area percentage of NDVI spatial distribution trends in the

lower reaches of the Tarim River during different periods from 1990 to 2025

Year	<−1	−1–0	0–1	1–2	2–3
1990–1995	1.86	0.66	0.93	1.32	2.00
1996–2000	54.11	12.80	10.36	6.97	4.13
2001–2005	9.32	3.15	4.21	6.11	9.63
2006–2010	6.40	0.86	1.09	1.49	2.29
2011–2015	14.36	4.12	5.50	7.53	10.17
2016–2020	30.04	15.22	20.32	12.29	5.61
2021–2025	39.93	15.04	14.33	9.34	4.84
1990–2025	2.72	4.96	9.63	21.95	47.55

Area percentage / %

By 2020, the interaction q value between land use and population density had increased from 0.3893 to 0.7939; the interaction q value between land use and nighttime light also rose from 0.2582 to 0.7644; and the interactions between land use and natural factors—precipitation, air temperature, and solar radiation—also increased substantially. The interactions among factors related to human activities likewise strengthened markedly: the interaction q value between population density and nighttime light increased from 0.1439 to 0.4216 (Fig. 8), indicating that human settlement and economic activities formed a positive synergy and jointly affected vegetation distribution. In terms of interaction types, the study period was dominated by "two-factor enhancement" and "nonlinear enhancement," and after 2010 the proportion of "two-factor enhancement" gradually increased (Fig. 8), with the linear enhancement effect becoming increasingly prominent. The interactions between natural factors and human-activity factors were also mainly enhancing; the interaction q values of precipitation and air temperature with nighttime light both increased severalfold. Overall, human-activity factors—especially land-use type—and their interactions with natural

Fig. 5. Spatial distribution of the change trends of NDVI in different periods from 1990 to 2025 in the lower reaches of the Tarim River

Subpanels: (a) 1990–1995; (b) 1996–2000; (c) 2001–2005; (d) 2006–2010; (e) 2011–2015; (f) 2016–2020; (g) 2021–2025; (h) 1990–2025.
Legend: change trend (10^{-3}): < -1, $-1 \sim 0$, $0 \sim 1$, $1 \sim 2$, $2 \sim 3$, > 3. Scale: 0–80 km. North arrow: N.

Tab. 4 Area percentage of the significance of NDVI spatial changes in the lower reaches of the Tarim River during different periods from 1990 to 2025

Year	Area percentage / %: Significant improvement	Area percentage / %: Slight improvement	Area percentage / %: Unchanged	Area percentage / %: Slight degradation	Area percentage / %: Significant degradation
1990–1995	14.48	83.00	0.01	2.50	0.01
1996–2000	0.50	32.47	0.24	64.85	1.94
2001–2005	11.63	75.86	0.07	11.82	0.62
2006–2010	4.35	88.38	0.01	7.06	0.20
2011–2015	1.23	80.23	0.09	17.90	0.55
2016–2020	1.25	53.28	0.40	43.90	1.17
2021–2025	0.75	44.12	0.31	53.90	0.92
1990–2025	86.99	5.60	0.15	3.63	3.63

[[sentence begins on previous page]] the interaction-enhancement effect among natural factors is the key driving force governing the evolution of the spatial pattern of NDVI, and the explanatory power of multifactor interactions is generally higher than that of single factors.

4 Discussion

4.1 Synergistic evolution of NDVI spatiotemporal changes and natural-anthropogenic driving factors

From 1990 to 2025, NDVI in the lower reaches of the Tarim River showed an overall increasing trend, and the growth pattern exhibited phased differences. Before 2000, it showed fluctuating growth; after 2000, it shifted to steady growth (Fig. 2). Areas with significant NDVI changes were mainly concentrated along the banks of the Tarim River, and both the intensity of change and the degree of clustering were markedly higher than in other regions (Fig. 4). This spatiotemporal pattern is associated with ecological management, water-resource allocation, land-use planning, and natural condi[[text continues on next page]]

Fig. 6 labels

(a) 1990–1995

(b) 1996–2000

(c) 2001–2005

(d) 2006–2010

(e) 2011–2015

(f) 2016–2020

(g) 2021–2025

(h) 1990–2025

Legend: significant improvement; slight improvement; unchanged; slight degradation; significant degradation.
Scale: 0–80 km.

Fig. 6 Spatial distribution of the significance of NDVI change in different periods in the lower reaches of the Tarim River from 1990 to 2025

Fig. 7 labels

Legend: precipitation; air temperature; radiation; land use; population density; nighttime lights.
Vertical axis: q value.
Horizontal axis: year.

Fig. 7 Explanatory power q value of the influencing factors of NDVI in the lower reaches of the Tarim River

…the result of the combined action of multiple factors such as changes in [[unclear: type of conditions]] [28–30]. Studies show that land-use type is the strongest driver influencing the spatial differentiation of regional vegetation (Fig. 8). This may be because ecological-management measures such as returning farmland to forest and grassland, establishing and restoring artificial shelterbelts, and ecological restoration along river channels are mostly preferentially arranged in areas near river channels with relatively high water accessibility and in the core areas of existing oases. The results of optimal-parameter geographical detector analysis (Fig. 8) also confirm that the spatial differentiation of land use is strongly consistent with the spatial layout of the corresponding management measures. Although this study did not set the ecological water conveyance project as a direct variable, the spatial analysis results (Fig. 4) show that the areas where land use shifted toward types with high vegetation cover are highly consistent in spatial pattern with the areas affected by the ecological water conveyance project, such as areas near river channels and zones of rising groundwater. Therefore, land-use change can be regarded as one of the key surface manifestations of the response of regional ecosystems under the influence of ecological water conveyance projects [31]. In other words, ecological water conveyance may not act directly on plant growth; rather, by altering local moisture conditions, it drives favorable transitions in land-use types and further interacts with socioeconomic factors such as population concentration.

(a) 1990 **(b) 1995** **(c) 2000**
(d) 2005 **(e) 2010**
(f) 2015 **(g) 2020**

Color bar: q value

Note: X_1 denotes precipitation; X_2 air temperature; X_3 radiation; X_4 land use; X_5 population density; X_6 nighttime light.

Fig. 8 Interaction of the driving factors of NDVI in the lower reaches of the Tarim River

The factors interact with one another and ultimately jointly promote the overall restoration of vegetation cover. Therefore, this also indirectly confirms that ecological projects and related management measures centered on water-resource regulation are an important foundation for regional vegetation restoration.

4.2 Synergistic enhancement of vegetation patterns by multi-factor interactions

For most interaction combinations, the explanatory power is greater than the independent contribution of any single factor, and the strength of interactions increases markedly over time (Fig. 8). This indicates that the spatial differentiation of vegetation in the lower reaches of the Tarim River is the result of nonlinear coupling and synergistic effects among multiple natural and human factors; analysis from the perspective of a single factor alone would seriously underestimate their actual influence. Among all interaction combinations, two-factor interactions centered on land-use type are the most prominent. For example, the interaction q value between land-use type and population density approached 0.8 in 2020 (Fig. 8g), meaning that their joint effect can explain approximately 80% of the spatial differentiation of vegetation. This suggests that the spatial pattern of vegetation cover does not form spontaneously under conditions unrelated to human activities, but is closely associated with the geographical distribution of human activities. Densely populated areas usually correspond to more intensive agricultural management, maintenance of ecological projects, and resource inputs, further amplifying the influence of land-use categories.

···the positive effect of land-use type on vegetation restoration[32]. Likewise, the strong interaction between land-use type and the intensity of economic activity represented by nighttime-light data indicates that regional economic development or urbanization processes, through pathways such as changing land-use modes and regulating management intensity, form spatial associations with changes in vegetation cover.

In addition, interactions between natural factors and human-activity factors also generally strengthened (Fig. 8). For example, the explanatory power of the interaction between precipitation and land-use type increased from 0.3068 to 0.7809. This phenomenon reflects clear spatial regulatory characteristics: in areas with relatively sufficient water availability (such as regions with more precipitation), optimization of land-use structure is more likely to generate ecological benefits; meanwhile, reasonable human activities such as water-saving irrigation and planting of drought-tolerant vegetation can also, to a certain extent, buffer the effects of climatic fluctuations on vegetation[33]. This interaction pattern—"natural conditions provide the foundation, while human activities enhance the response" —indicates that, under the fragile ecological background of the lower Tarim River, vegetation restoration depends on positive spatial synergy between natural conditions and human intervention. Ecological restoration strategies should therefore emphasize interaction effects among factors, rather than focusing only on a single driving factor.

4.3 Implications for Ecological Restoration and Management

At the scale and with the set of factors considered in this study, land-use management is a direction that deserves priority attention in ecological restoration. Given that land-use type has a strong and continuously increasing explanatory power for changes in NDVI (Fig. 7), future ecological strategies can further optimize land-use regulation measures. Key priorities include strictly protecting native vegetation in ecologically fragile areas and preventing unreasonable land reclamation[34]; scientifically planning ecological land in the oasis–desert ecotone and optimizing vegetation structure to enhance its stability[35]; and, in areas along river channels and areas with higher water accessibility, prioritizing land-use types with high ecological benefits, such as ecological forests and shrub–grass composite systems, so as to improve the spatial utilization efficiency of water[36]. In addition, attention should be paid to the influence of synergistic enhancement among factors such as land use, population distribution, and economic activities on vegetation restoration. In future spatial planning, different elements of human activities should be coordinated and arranged in an integrated manner to promote positive spatial synergy in their ecological benefits. In areas with population outflow or insufficient economic vitality, even ecological water conveyance may yield limited benefits because of a lack of follow-up maintenance and management; whereas in areas where human activities are concentrated, appropriate water-resource allocation and land-use guidance can efficiently drive vegetation restoration. Finally, a long-term ecological monitoring and assessment system based on multisource data fusion should be established, integrating remote-sensing, meteorological, hydrological, and socioeconomic data to continuously track the implementation effectiveness of ecological projects, including ecological water conveyance, and the evolution of their driving mechanisms, thereby realizing closed-loop management from "project implementation" to "effectiveness feedback and optimization."

4.4 Assessment of the Influence of Noise on Spatial Analysis

This study used long-term time-series fused remote-sensing data to analyze NDVI change trends in the lower Tarim River. Owing to factors such as sensor performance, atmospheric conditions, and calibration differences, some images contain residual striping noise. These stripes mainly originate from inconsistencies in the quality of the original images across different periods; although standard preprocessing was performed, they still appear in the spatial trend analysis to some extent[37]. However, the locations of these striping noises are basically fixed and are mainly distributed in specific areas far from the river channel, appearing as systematic background noise. By contrast, the areas with the most drastic changes and the most significant trends remain stable and clearly concentrated around the river channel, where the strength of the real ecohydrological signal significantly exceeds the noise level. Therefore, the overall spatial pattern of "vegetation improvement along the river channel and localized degradation in peripheral areas" is not affected. Nevertheless, the stripes still introduce some uncertainty. First, fixed striping noise may have a certain influence on the accuracy of trend-slope estimation in non-key areas, such as far-bank desert areas. Second, it may produce systematic bias in the absolute values of the area proportions of various trend grades based on pixel statistics in the paper[37]. Therefore, when interpreting the area-statistical data, this paper focuses on the relative changes in the proportions of different grades across periods, while reducing the reference value of absolute numerical values. Future studies may further weaken noise interference and improve the accuracy of quantitative analysis results by introducing high-precision data-fusion algorithms and pixel-level quality-control methods, and by calibrating them with ground-observation data.

5 Conclusions

Based on remote-sensing data of vegetation in the lower Tarim River from 1990 to 2025, this study employed trend analysis, significance testing, and the optimal-parameter geographical detector model to systematically evaluate the spatiotemporal characteristics of NDVI change, and identified the influence intensity and interactions of various influencing factors, including air temperature, precipitation, solar radiation, land-use type, population density, and nighttime-light values. The main conclusions are as follows:

(1) Overall, NDVI in the lower Tarim River showed a sustained and significant upward trend. The year 2008 was a key abrupt-change point in vegetation evolution; 1990–2000 was a period of fluctuating growth, 2001–2010, including the abrupt-change point, was a period of accelerated improvement, and 2011–2025 shifted into a period of stable growth.

(2) Vegetation cover in the lower Tarim River improved significantly overall, with areas of significant vegetation improvement accounting for 86.99%.

The area proportion of high-vegetation-cover zones increased continuously from 0.02%-0.76% to 7.90%. These zones were mainly distributed along the river channel and in oasis core areas, and gradually expanded outward, forming a spatial pattern of “continuous vegetation enhancement in oasis core areas and localized degradation in peripheral deserts.”

(3) Land-use type is the factor with the greatest explanatory power for the spatial differentiation of NDVI, and its independent explanatory power has continued to increase; population density

The explanatory power of human-activity factors such as nighttime lighting also increased significantly. Interaction detection showed that the explanatory power of most interacting factor combinations was higher than that of any single factor, and interactions centered on land-use type were the most prominent. The synergistic enhancement effect among factors strengthened continuously over time. Overall, the explanatory pattern shifted from the relative dominance of natural factors toward the relative enhancement of human-activity factors, exhibiting the characteristics of multi-factor synergistic enhancement.

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Analysis of driving factors for spatiotemporal changes of NDVI in the lower reaches of the Tarim River over the past 30 years

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Abstract: As a key component of terrestrial ecosystems, vegetation is highly sensitive to global changes and human activities. The lower reaches of the Tarim River, located in a typical arid desert region of China, represent an important area for studying vegetation cover, and identifying the main driving factors for change is of great significance for ecological conservation and restoration. Based on long-term remote sensing vegetation data from 1990 to 2025 in the lower reaches of the Tarim River, this study used linear trend analysis and significance testing to reveal the spatiotemporal evolution patterns of the normalized difference vegetation index. The optimal parameter-based geographical detector model was then applied to systematically analyze the interactive effects and spatial impacts of multiple factors—including temperature, precipitation, solar radiation, land use type, population density, and nighttime light—on vegetation. The results indicate that: (1) From 1990 to 2025, the NDVI in the lower reaches of the Tarim River showed a significant phased increasing trend, with varying growth rates across periods: fluctuating rise before 2000, rapid increase from 2001 to 2010, and a steady rise thereafter. (2) Spatially, the NDVI exhibited a pattern of continuous enhancement in core areas and localized degradation in peripheral regions. Areas centered around river channels and oasis cores continued to strengthen and expand outward, while degradation occurred in outer peripheral zones. (3) Analysis of seven periods of data from 1990 to 2020 revealed that land use type was the dominant driving factor influencing the spatial differentiation of NDVI, with its explanatory power increasing steadily from 0.23 to 0.74. The explanatory power of human activity-related factors (population density and nighttime light) also showed a significant upward trend, and multi-factor interactions further enhanced their collective influence on vegetation patterns. By quantifying the interactive mechanisms of natural factors and human activities, this study provides a scientific basis for understanding the complex drivers of vegetation cover in arid regions and offers a methodological framework for evaluating the comprehensive benefits of ecological restoration projects.

Keywords: lower reaches of the Tarim River; NDVI; influencing factors; spatiotemporal variation; optimal parameter-based geographical detector