Vegetation Dynamics in the Yellow River Basin and Its Response to Climate Change: A Postprint Based on Climate Aridity-Humidity Zoning Scale

Authors: Wang Ruifang, Lü Baoqi, Zhang Wenjing

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Abstract

As an important region for ecological protection and economic development in China, investigating the characteristics of vegetation changes under different dry-wet partitions in the Yellow River Basin is crucial for adjusting ecological restoration strategies to address potential threats from environmental change. Based on the Kernel Normalized Difference Vegetation Index (kNDVI) and key meteorological driving factors [Precipitation (PRE), Temperature (TEM)] in the Yellow River Basin from 2000-2022, this study analyzed the spatiotemporal patterns of vegetation dynamics in different dry-wet partitions using multivariate statistical methods, and employed the Geodetector model and constraint effect method to analyze the driving factors of vegetation changes in the Yellow River Basin, identifying both commonalities and inter-regional differences in the response between vegetation changes and meteorological factors across different dry-wet zones. The results show: (1) Vegetation kNDVI in the Yellow River Basin exhibits a zonal distribution, with the humid zone having the highest annual mean kNDVI (0.49); from 2000-2022, 84.58% of the basin area showed an increasing trend, with the most significant improvements in the arid zone (68.36%) and semi-arid zone (93.08%). (2) The impact of precipitation on vegetation is generally stronger than that of temperature across the Yellow River Basin, with partial correlation coefficients of 0.36 and 0.19, respectively, at the whole-basin scale; this difference is particularly pronounced in the semi-arid zone, where the partial correlation coefficients for precipitation and temperature reach 0.43 and 0.22, respectively. (3) In terms of spatial stratified heterogeneity, the q-value of precipitation (0.5338) is greater than that of temperature (0.2283) at the whole-basin scale; moreover, the q-value of precipitation is highest in the semi-arid zone (0.4519), while the q-value of temperature is highest in the semi-humid zone (0.2491). Each meteorological factor exhibits constraint lines with

different characteristics in response to vegetation dynamic changes across different dry-wet partitions. The research findings can provide important references for adjusting and formulating watershed ecological protection strategies and are of great significance for promoting high-quality development in the Yellow River Basin.

Full Text

Preamble

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Vegetation Dynamics and Their Response to Climate Change in the Yellow River Basin–Based on Climatic Dry and Wet Zoning Scales

WANG Ruifang[1], LÜ Baoqi[2], ZHANG Wenjing[1]
(1. Henan College of Surveying and Mapping, Zhengzhou 450000, Henan, China; 2. Henan Institute of Surveying and Mapping, Zhengzhou 450000, Henan, China)

Abstract: The Yellow River Basin, as a critical region for ecological protection and economic development in China, investigating vegetation change characteristics across different dry and wet zones is essential for adjusting ecological restoration strategies to address potential threats from environmental change. Based on the kernel normalized difference vegetation index (kNDVI) and key meteorological drivers [precipitation (PRE) and temperature (TEM)] from 2000 to 2022, this study analyzed the spatiotemporal patterns of vegetation dynamics across different climatic dry and wet zones using multivariate statistical methods. The Geodetector model and constraint effect method were employed to analyze driving factors of vegetation change and identify commonalities and differences in how vegetation responds to meteorological factors across different dry and wet zones. Results show that: (1) kNDVI values exhibit latitudinal distribution, with the humid zone showing the highest average annual kNDVI (0.49). During 2000-2022, 84.58% of the basin showed an upward trend, with the most significant improvements in arid (68.36%) and semi-arid zones (93.08%). (2) Precipitation generally exerts stronger influence on vegetation than temperature across the Yellow River Basin, with partial correlation coefficients of 0.36 and 0.19 at the basin scale, respectively. This difference is particularly pronounced in the semi-arid zone, where partial correlation coefficients for precipitation and temperature reach 0.43 and 0.22, respectively. (3) In terms of spatial stratified heterogeneity, the q-value for precipitation (0.5338) exceeds that for temperature (0.2283) at the basin scale. Moreover, precipitation' s q-value peaks in the semi-arid zone (0.4519), while temperature' s q-value peaks in the semi-humid zone (0.2491). Vegetation dynamic responses to meteorological factors display distinct constraint lines across different dry and wet zones. These findings provide important references for adjusting and formulating basin ecological protection strategies and are significant for promoting high-quality development

in the Yellow River Basin.

Keywords: vegetation change; kNDVI; dry and wet zones; constraint effect; Yellow River Basin

Introduction

Vegetation plays a vital role in terrestrial ecosystems, regulating material and energy exchange between land and atmosphere and serving as a crucial indicator of environmental change, being sensitive to combined impacts of climate change and human activities [1-3]. The Yellow River Basin, as a key ecological restoration region in China, has attracted considerable attention regarding vegetation change detection and attribution. Remote sensing techniques combined with vegetation indices are the most common methods for monitoring vegetation dynamics and growth conditions [4-6]. As the most widely used vegetation index, the normalized difference vegetation index (NDVI) is closely related to leaf density [7], photosynthetically active radiation [8], vegetation productivity, and accumulated biomass [9-10]. However, its accuracy is affected by the abundance of thick-leaf plants and sensitivity to canopy background brightness changes, and it suffers from saturation effects when vegetation density reaches certain thresholds, making it unable to accurately reflect conditions of higher-density vegetation [11].

In contrast, Camps-Valls et al. proposed a kernel normalized difference vegetation index (kNDVI) based on kernel method principles [12]. By introducing kernel functions, kNDVI better reflects vegetation primary productivity because it captures more information about vegetation biomass accumulation and shows stronger correlation with actual vegetation productivity than traditional NDVI. The kernel function application effectively reduces saturation effects, maintaining sensitivity and accuracy at higher vegetation densities while reducing bias and adapting to material cycling, demonstrating its effectiveness in assessing vegetation dynamics [13-14]. kNDVI exhibits improved robustness and stability against noise across spatial and temporal scales and has proven effective for evaluating vegetation dynamics [15].

Vegetation greening shows spatiotemporal heterogeneity across different seasons, regions, and land cover types [16-17]. Separating relationships between different dry/wet zone types and vegetation change is challenging. Considering increasing evaporation demand and decreasing soil moisture availability, negative impacts of warming and water stress (such as drought) on vegetation greening have been observed in many regions, including tropical areas like the Amazon, temperate and boreal Eurasia, and the Congo Basin [18-20]. Additionally, drought trend magnitude fluctuates with temporal scale expansion, and vegetation growth responses to meteorological drought show significant differences across multiple scales and vegetation categories [21]. Increasing evidence indicates that vegetation responses to temperature in north temperate ecosystems have weakened over the past 30-40 years [22]. In summary, vegetation greening is a complex dynamic process influenced not only by climatic factors but also by different environmental conditions, making it crucial to explore climate-vegetation relationships across different dry/wet zone types for effective vegetation resource management.

Therefore, to address these issues, this study obtained kNDVI data for the Yellow River Basin through the Google Earth Engine platform, applied the climate zoning system established by Zhang et al. [23] to divide the basin into climatic dry and wet zones, and used various statistical methods to explore spatiotemporal patterns of vegetation dynamics and climate factors across zones. The Geodetector model and constraint effect method were employed to analyze driving factors of vegetation change and their spatiotemporal characteristics, aiming to explore the spatiotemporal patterns of vegetation dynamics and their driving factors across different dry and wet zones, identify commonalities within zones and differences between zones, and specifically analyze causes of vegetation dynamic changes in different arid regions of the Yellow River Basin. This research provides scientific data and theoretical support for scholars and ecological restoration practitioners studying long-term vegetation dynamics in the Yellow River Basin.

1.1 Study Area Overview

The Yellow River Basin is located in northwestern China (95°53 ~119°05 E, 32°10 ~41°50 N), spanning nine provinces with a total length of 5,464 km and a drainage area of 79.5×10^{4} km^2. Originating from the Bayan Har Mountains and flowing into the Bohai Sea, the basin extends from the Yinshan Mountains in the north to the Qinling Mountains, with terrain gradually descending from west to east. The western source region consists of high mountains averaging 4,000 m in elevation, the central Loess Plateau sits at 1,300–2,200 m with severe soil erosion, and the downstream area comprises the flat Huang-Huai-Hai Plain. The basin features typical arid, semi-arid, semi-humid, and humid climates (Fig. 1), with vegetation showing significant spatial differentiation: alpine vegetation (alpine meadows, steppes, swamps, and aquatic plants) dominates the upper source region; grasslands, shrubs, and forest-steppe mixtures characterize the middle Loess Plateau; and cultivated vegetation predominates in the downstream alluvial plain, with local coniferous-broadleaf mixed forests [24-25].

1.2 Data Sources

1.2.1 kNDVI Data kNDVI is a vegetation index based on kernel (machine learning) functions that improves upon NDVI by addressing difficulties in scale conversion and nonlinear problems. Through kernel technology, kNDVI provides more robust and accurate vegetation monitoring across different scales and under nonlinear changes [12]. This study used MODIS products (data series MOD13Q1) from NASA' s Land Processes Distributed Active Archive

Center (https://ladsweb.modaps.eosdis.nasa.gov) with 1,000 m spatial resolution and 16-day temporal resolution from 2000 to 2022. Monthly kNDVI data were calculated based on formulas proposed by Camps-Valls et al. [12], using the hyperbolic tangent function where NIR represents near-infrared spectral reflectance, Red represents red spectral reflectance, τ is a scaling parameter, and σ is a length-scale parameter linearly proportional to the mean values of near-infrared and red reflectance. When $\tau = \sigma = 0.5$, kNDVI maintains accuracy while ensuring simplicity [12].

1.2.2 Driving Factor Data Annual average temperature and precipitation datasets for the Yellow River Basin were obtained from the Resource and Environmental Science Data Center (http://www.resdc.cn/). Terrain data came from the Shuttle Radar Topography Mission digital elevation model. Land use data from 2000–2020 were sourced from the National Earth System Science Data Center, classifying Chinese land use into six major types: cropland, forest, grassland, shrubland, water bodies, ice/snow, barren land, construction land, and wetland [26]. All data were resampled to match kNDVI resolution before analysis. Detailed dataset descriptions are provided in Table 1.

Table 1 Data sources of driving factors

Data Type	Source
Temperature/Precipitation	Resource and Environmental Science Data Center (https://www.resdc.cn/)
Terrain	Geospatial Data Cloud (https://www.gscloud.cn/)
Land Use	National Earth System Science Data Center (https://www.geodata.cn/)

1.3 Change Trend Analysis

To analyze kNDVI trends in the Yellow River Basin, this study employed linear regression on a pixel-by-pixel basis. The calculation formula is:

$$\text{Slope} = \frac{n \times \sum_{i=1}^{n} i \times \text{kNDVI}_i - \sum_{i=1}^{n} i \sum_{i=1}^{n} \text{kNDVI}_i}{n \times \sum_{i=1}^{n} i^2 - (\sum_{i=1}^{n} i)^2}$$

where Slope represents the linear regression equation slope, n is the number of years (n = 23 in this study), i is the index of the ith data point, and kNDVI is the kNDVI value at the ith data point. When Slope > 0, vegetation shows a greening trend; conversely, it indicates a decreasing trend [27].

1.4 Partial Correlation Analysis

Partial correlation analysis examines the degree of association between two variables while excluding effects of other factors. When studying relationships between factors in complex models or systems, results are expressed as partial correlation coefficients while keeping other factors constant [28]. The calculation formula is:

$$r_{xy,z} = \frac{r_{xy} - r_{xz}r_{yz}}{\sqrt{(1 - r_{xz}^2)(1 - r_{yz}^2)}}$$

where r $_{,2}$ is the partial correlation coefficient between variables x and y with variable z held constant; r , r $_2$, and r $_2$ are correlation coefficients between respective variable pairs. This study calculated partial correlations between kNDVI and temperature/precipitation at the pixel scale and analyzed their spatiotemporal variations.

1.5 Geodetector Model

The Geodetector model detects spatial differences and reveals underlying driving forces [29]. This study used factor detection to quantitatively analyze the influence of precipitation and temperature on kNDVI changes across different climatic dry and wet zones. The explanatory power (q-value) was calculated to determine each factor' s contribution, revealing interactions between meteorological factors and kNDVI. The formula is:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2}$$

where q represents the explanatory power for kNDVI changes (range [0,1]), with larger values indicating stronger explanatory power; h is variable classification (h = 1, 2, 3, ···, L); N and N are the unit numbers in layer h and the entire region, respectively; and σ ^{2} and σ^2 are variances of Y values in layer h and the entire region. Interaction detection identifies interaction effects between different extreme climate indices by comparing individual and joint explanatory powers $q(X_1)$, $q(X_2)$, and $q(X_1\ X_2)$.

1.6 Constraint Effect

Constraint line extraction provides new insights for exploring relationships and mechanisms between two variables [30]. The extraction process involves: (1) dividing the constraint factor's value range into equal intervals to generate columns on the x-axis; (2) selecting the 95th percentile of each column as boundary points to reduce outlier effects; and (3) determining constraint line types based on scatter plot shapes and goodness-of-fit values (R^2). This study constructed two-dimensional coordinate systems with meteorological factors (precipitation and temperature) as x-axes and kNDVI as y-axis, using quantile division to plot constraint lines between pairwise variables.

Results

2.1 Spatiotemporal Patterns of Vegetation Dynamics and Meteorological Variables

2.1.1 Intra-annual Variation Characteristics Across different dry and wet zones in the Yellow River Basin, kNDVI values show significant peak fluctuations throughout the year. Humid and semi-humid zones exhibit the highest kNDVI values, reaching peaks of 0.58 and 0.55, respectively. In contrast, arid and semi-arid zones show lower volatility curves with peaks of 0.33 and 0.41, respectively (Fig. 2). This difference primarily results from insufficient precipitation and water supply in arid and semi-arid zones, which affects vegetation growth and reproduction [31]. Humid and semi-humid zones have adequate precipitation, providing favorable moisture conditions for vegetation growth [32] and enabling higher kNDVI values during growing seasons.

Annual precipitation shows obvious seasonality, concentrated in June–September and accounting for over 70% of total annual precipitation. In semi-humid areas, precipitation shows a single-peak pattern, with maximum precipitation of 149.62 mm in July. Precipitation trends in humid, semi-arid, and arid zones show consistent fluctuating growth patterns, with maximum values appearing around July–August (138.11 mm, 98.68 mm, and 44.74 mm, respectively). Temperature trends across different zones are basically consistent, showing single-peak curves. Temperatures in semi-humid, semi-arid, and arid zones are similar and significantly higher than in humid zones, peaking in July at 22.78°C, 19.53°C, and 18.33°C, respectively, while the humid zone peaks at 9.15°C (Fig. 2).

2.1.2 Spatial Distribution Patterns From 2000 to 2022, long-term average kNDVI in the Yellow River Basin showed significant spatial heterogeneity. Vegetation kNDVI values are latitudinally distributed, gradually increasing from northwest to southeast. Humid zones have the highest kNDVI (0.49), followed by semi-humid zones (0.42), with semi-arid (0.30) and arid zones (0.18) relatively lower (Fig. 3). Annual average precipitation shows a northwest-to-southeast increasing pattern, with mean annual precipitation decreasing as: humid zone (698.39 mm) > semi-humid zone (617.51 mm) > semi-arid zone (435.37 mm) > arid zone (205.35 mm). Mean annual temperature increases stepwise from west to east, with the eastern semi-humid zone highest at 11.93°C and the western semi-humid zone lowest at -3.18°C. Temperatures in arid, semi-arid, and humid zones fall between these extremes at 8.35°C, 5.82°C, and 1.25°C, respectively (Fig. 3).

2.2 Spatiotemporal Variation Characteristics of Vegetation Dynamics and Meteorological Factors

2.2.1 Interannual Variation Characteristics Using pixel-scale averages of kNDVI, precipitation, and temperature, we obtained comprehensive indicators of vegetation condition and climate change in the Yellow River Basin from 2000 to 2022. kNDVI showed a clear upward trend, increasing at $0.0044 \cdot a^{-1}$, indicating significant vegetation greening (Fig. 4). In contrast, annual precipitation and temperature showed significant fluctuations with large variations. Precipitation increased at 3.341 $mm \cdot a^{-1}$, while temperature increased at $0.024°C \cdot a^{-1}$.

Considering potential differences in vegetation dynamics and meteorological factors across dry and wet zones, we further explored variation trends by zone (Fig. 5). In arid, semi-arid, and semi-humid zones, kNDVI increased with low volatility at rates of $0.0041 \cdot a^{-1}$, $0.0055 \cdot a^{-1}$, and $0.0023 \cdot a^{-1}$, respectively. Humid zone kNDVI showed greater fluctuation with a lower growth rate of $0.0007 \cdot a^{-1}$. Annual precipitation in all zones showed large interannual differences but slowly increased at 3.2771 $mm \cdot a^{-1}$, 1.8565 $mm \cdot a^{-1}$, 3.0710 $mm \cdot a^{-1}$, and 3.7315 $mm \cdot a^{-1}$ for arid, semi-arid, semi-humid, and humid zones, respectively. Temperature increase rates were similar across zones, with arid and semi-arid zones showing highly consistent trends at $0.0226°C \cdot a^{-1}$ and $0.0210°C \cdot a^{-1}$, respectively.

2.2.2 Spatial Distribution Characteristics of Dynamic Changes To further explore spatial distributions of meteorological factors and kNDVI trends, we calculated Slope values across the basin. High kNDVI Slope values are concentrated in semi-arid regions, with a mean of $0.0055 \cdot a^{-1}$. Semi-humid, arid, and humid zones show progressively lower Slope values of $0.0030 \cdot a^{-1}$, $0.0022 \cdot a^{-1}$, and $0.0007 \cdot a^{-1}$, respectively. Precipitation Slope shows significant spatial heterogeneity, while temperature Slope shows relatively small differences across zones but clear east-west distribution patterns (Fig. 6).

We combined Theil-Sen trend analysis and Mann-Kendall test to assess vegetation change patterns [33], classifying changes into five types: significant increase, slight increase, no change, slight decrease, and significant decrease (Table 2). Overall, 65.36% of the basin showed significant increasing trends, mainly in semi-arid and semi-humid zones; 19.22% showed slight increases; and significant decreases accounted for only 1.87%, mainly in densely populated cities like Xi' an, Sanmenxia, and Zhengzhou (Fig. 7).

Table 2 Classification of vegetation change

Type	Slope	Zs
Significant increase	$ $0.0005	$ $1.96
Slight increase	$ $0.0005	-1.96~1.96
No change	-0.0005~0.0005	-1.96~1.96

Type	Slope	Zs
Slight decrease	≤-0.0005	-1.96~1.96
Significant decrease	≤-0.0005	≤-1.96

Note: Slope is Theil-Sen slope estimator; Zs is Mann-Kendall test statistic.

Zone-specific analysis reveals substantial differences. The semi-arid zone has the largest proportion of significant increase (77.86%), followed by semi-humid zone (57.18%), reflecting China' s ecological conservation efforts including reforestation, sand control, and soil conservation [34]. These measures are particularly effective in ecologically fragile semi-arid and semi-humid areas. The humid zone shows the highest proportion of slight increase (40.84%), while arid zones have the largest no-change areas (28.67%), where climate conditions limit vegetation growth and long-term drought has created fragile ecosystems with poor natural recovery conditions [35].

2.3 Partial Correlation Between Vegetation Dynamics and Meteorological Factors

The interaction between temperature and precipitation significantly impacts vegetation dynamics. To determine these relationships, we conducted pixel-scale partial correlation analysis between kNDVI and meteorological factors. kNDVI shows positive correlations with both precipitation and temperature, but precipitation plays a dominant role in vegetation change across the basin. The partial correlation between kNDVI and precipitation is stronger than with temperature, with basin-wide mean partial correlation coefficients of 0.36 and 0.19, respectively. This pattern holds across all zones, especially in semi-arid zones where coefficients reach 0.43 (precipitation) and 0.22 (temperature) (Fig. 8).

Spatially, high partial correlations between kNDVI and precipitation are located in arid and semi-arid zones (0.42 and 0.38), with lower values in semi-humid and humid zones (0.33 and 0.31). Temperature-kNDVI partial correlations show less spatial variation across zones: arid (0.21), semi-arid (0.20), semi-humid (0.19), and humid (0.18) (Fig. 8).

2.4 Driving Factors and Constraint Effects

2.4.1 Analysis of Driving Factors for Vegetation Dynamic Change To analyze spatial stratified heterogeneity, we used the Geodetector model to quantify meteorological factors' influence on kNDVI. At the basin scale, precipitation and temperature q-values are 0.5338 and 0.2283, respectively, indicating precipitation' s stronger explanatory power, consistent with partial correlation results. Under combined precipitation-temperature interaction, the q-value reaches 0.6127, exceeding individual factors and demonstrating that kNDVI changes result from combined meteorological effects.

Across dry and wet zones, q-values show varying intensities (Table 3). Precipitation' s q-value peaks in semi-arid zones (0.4519) and is lowest in arid zones (0.2241). Temperature' s q-value peaks in semi-humid zones (0.2491) and is also lowest in arid zones (0.1123). The interaction q-value is highest in semi-arid zones (0.5218), where vegetation growth and coverage are strongly influenced by hydrological cycles and both temperature and precipitation determine growth cycle length [36].

Table 3 q-values of meteorological factors in different dry and wet zones of the Yellow River Basin

Zone	Precipitation	Temperature	Interaction
Arid	0.2241	0.1123	0.3012
Semi-arid	0.4519	0.1987	0.5218
Semi-humid	0.3987	0.2491	0.4789
Humid	0.3124	0.1765	0.4123

2.4.2 Constraint Effects on Vegetation Dynamics In complex ecosystems, vegetation dynamics are influenced by multiple factors, creating scattered data point distributions. Constraint lines help eliminate confounding effects to obtain maximum response values while minimizing limiting factor impacts [37]. We further explored driving mechanisms between meteorological factors and vegetation dynamics across different dry and wet zones, using meteorological factors as x-axes and kNDVI as y-axes to plot constraint lines via quantile division.

Constraint lines show different characteristics across zones (Fig. 9). At the basin scale, kNDVI constraint lines with temperature and precipitation are hump-shaped—promoting vegetation growth within thresholds but constraining beyond them. In arid zones, precipitation constraint lines show multi-peak fluctuations due to unstable precipitation patterns, while temperature constraint lines are stepped, indicating rapid vegetation change within 7–8°C but diminishing promotion beyond this range. In semi-arid and semi-humid zones, both temperature and precipitation show single-hump constraint lines—promoting growth within thresholds but inhibiting beyond them. Humid zone constraint lines align with basin-scale patterns: initial promotion followed by inhibition and synergy.

Discussion

This study comprehensively analyzed kNDVI spatiotemporal distribution, interannual variation, and responses to meteorological factors across different dry and wet zones in the Yellow River Basin. Compared with previous studies, our focus was on analyzing differential vegetation changes across dry/wet zones and assessing kNDVI variation differences, as well as exploring kNDVI-meteorological factor responses under dry/wet zoning.

Many studies have found that climate change directly determines vegetation growth physiological activities [38], but primary meteorological drivers vary regionally [39]. In this study, Yellow River Basin kNDVI increased at $0.0044 \cdot a^{-1}$ from 2000–2022. We found significant spatial heterogeneity in meteorological factors and their vegetation responses. Climate change positively contributed to vegetation activity mainly in semi-arid and semi-humid zones, where temperature promotes growth and increased precipitation meets photosynthesis water requirements, facilitating vegetation recovery [40]. In this arid/semi-arid basin, increased precipitation promotes soil organic matter decomposition, improves nutrients and moisture, and enhances vegetation activity [41]. Vegetation dynamics thus reflect the synergistic effects of meteorological factors.

Previous research indicates that vegetation growth in arid/semi-arid regions is primarily limited by thermal effects (solar radiation, temperature change) [42], but under global warming, water conditions have become more important than thermal factors for vegetation growth in the Yellow River Basin [43], consistent with our findings. Suitable temperatures promote plant growth and increase vegetation coverage, while extreme temperatures limit growth [44]. Semi-arid vegetation has certain adaptability to water and temperature, but changes beyond adaptive ranges significantly impact growth and coverage [45].

Conclusion

1. **Spatial Distribution:** kNDVI in the Yellow River Basin shows latitudinal distribution, gradually increasing from northwest to southeast, indicating improving vegetation density and condition from arid to humid zones. Vegetation condition differs significantly across zones, with the lowest index in arid zones (0.18), increasing progressively through semi-arid (0.30), semi-humid (0.42), and humid zones (0.49). From 2000–2022, 84.58% of the basin showed upward kNDVI trends.

2. **Dominant Factors:** Precipitation is the dominant environmental factor affecting vegetation change in the Yellow River Basin, with a mean partial correlation coefficient (0.36) exceeding temperature's (0.19). This pattern holds across all dry/wet zones, particularly in semi-arid zones where precipitation and temperature partial correlations are 0.43 and 0.22, respectively.

3. **Driving Mechanisms:** Based on q-values, precipitation is the primary vegetation growth factor, with stronger influence than temperature. The precipitation-temperature interaction shows stronger explanatory power ($q = 0.6127$) than individual factors. Precipitation's influence peaks in semi-arid zones ($q = 0.4519$), while temperature's influence peaks in semi-humid zones ($q = 0.2491$). This differential influence across zones provides important guidance for vegetation management and ecological protection strategies.

4. **Constraint Effects:** At the basin scale, kNDVI relationships with tem-

perature and precipitation show hump-shaped constraint lines, indicating enhanced constraint beyond thresholds. Across dry/wet zones, constraint line morphologies vary: arid zones show fluctuating multi-peak patterns, while other zones predominantly show hump shapes, indicating that meteorological factors promote vegetation growth initially but inhibit it beyond optimal thresholds.

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Note: Figure translations are in progress. See original paper for figures.