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Article

Spatiotemporal Variability of Vegetation NDVI in the Huaihe River Basin, China: Driving Force Analysis and Ecological Implications

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Abstract: This research seeks to advance the understanding of ecological management in the Huaihe River Basin, China. The spatiotemporal variability of the Normalized Difference Vegetation Index (NDVI) and its underlying driving forces are examined utilizing SPOT-NDVI data covering the period 2000-2019. Linear regression analysis is employed to quantify trends and assess the statistical significance of NDVI variations. A differencing approach is subsequently applied to discern the variability in NDVI. The distribution of its spatial pattern stability over 20 years is explored through the coefficient of variation. Lastly, the Geodetector method is utilized to elucidate the driving factors influencing NDVI dynamics. The results indicate that the overall NDVI is generally high, with an overall growth rate of 0.00148/year, and 2010 is identified as a significant inflection point in the trend. NDVI values are notably lower in urban areas, corresponding to urban expansion, except for regions near rivers and lakes. Land use type emerges as the strongest explanatory factor for NDVI among single factors, with climate factors exhibiting a relatively weaker degree of explanatory force. These findings suggest that the overall NDVI in the Huaihe River Basin is high, indicative of a vegetation condition that continues to improve.

Keywords: spatiotemporal variability; ecological drivers; NDVI; Geodetector; Huaihe River Basin

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1. Introduction

Vegetation indices are simple, valid, and empirical measures of the condition of land vegetation[1]. By analyzing the spectral characteristics of vegetation, the visible and near-infrared bands of remote sensing images can be combined to form various vegetation indices. There are more than 40 known vegetation indices. The Normalized Difference Vegetation Index (NDVI) can eliminate most of the variations in irradiance related to instrument calibration, solar altitude angle, topography, cloud shading, and atmospheric conditions so that it enhances the responsiveness to vegetation. It is the most widely used one of the vegetation indices currently available. Therefore, NDVI is an important indicator reflecting the vegetation cover and its growth condition, utilized in the dynamic monitoring of crop growth, the monitoring of phenology, and the monitoring of natural disasters, etc.[2,3].

NDVI is of great importance in various fields such as agriculture, forestry, animal husbandry, fishery, meteorology, and ecology. Researchers worldwide have utilized long-term NDVI time series data for their studies [4–6]. For instance, NDVI is used to evaluate vegetation growth and crop yield, as well as to analyze the spatial and temporal distribution of vegetation. It is also employed to assess grassland degradation, drought, and forest destruction [4,7]. There is an increasing amount of research that employs NDVI to examine the correlation between vegetation and climate [8,9], including the impact of human factors such as population and agricultural activities on greening patterns [7]. Furthermore, the effects of driving forces vary across different regions, emphasizing the need to examine the causal relationships of these factors to support strategic regional environmental management and scientific preservation.

The Huaihe River Basin, located in eastern China and serving as the primary agglomeration area of the Grand Canal Cultural Belt, encompasses multiple geographic divisions. Although there have been studies on the dynamic coverage[10,11] of vegetation or climate change[12], research focusing specifically on the driving forces and ecological implications behind such changes in this particular region is relatively scarce. This research focuses on the Huaihe River Basin as the research area and analyzes the spatial and temporal evolution characteristics of NDVI from 2000 to 2019. The research considers various driving factors, including topographic factors (slope, slope direction, elevation), climatic factors (annual mean temperature and annual precipitation, etc.), and anthropogenic factors (GDP, population density, etc.). We analyze the driving forces and interactions of factors that affect spatial differentiation, which aid in ecological management and environmental governance.

2. Materials and Methods

2.1. Study area

The Huaihe River is located in eastern China, between the Yangtze River and the Yellow River. Its latitude and longitude range is 31°-36°N and 112°-121°E. It is one of the seven major rivers in China that flow into the Pacific Ocean, covering a total basin area of about 270,000 km^2. The river runs through the mid-ridge portion of the Grand Canal, which is an important transportation route.

The Huaihe River has significant geographic research value as it serves as the demarcation line for various climatic and agricultural features. It marks the line between annual precipitation of 800 mm and below, the subtropical monsoon climate and temperate monsoon climate, rice and wheat production areas, and the cumulative temperature of 4500°C (daily mean temperature ≥ 10°C cumulative temperature).

In recent years, the provinces in the basin have proposed mandates for establishing a green ecological network.

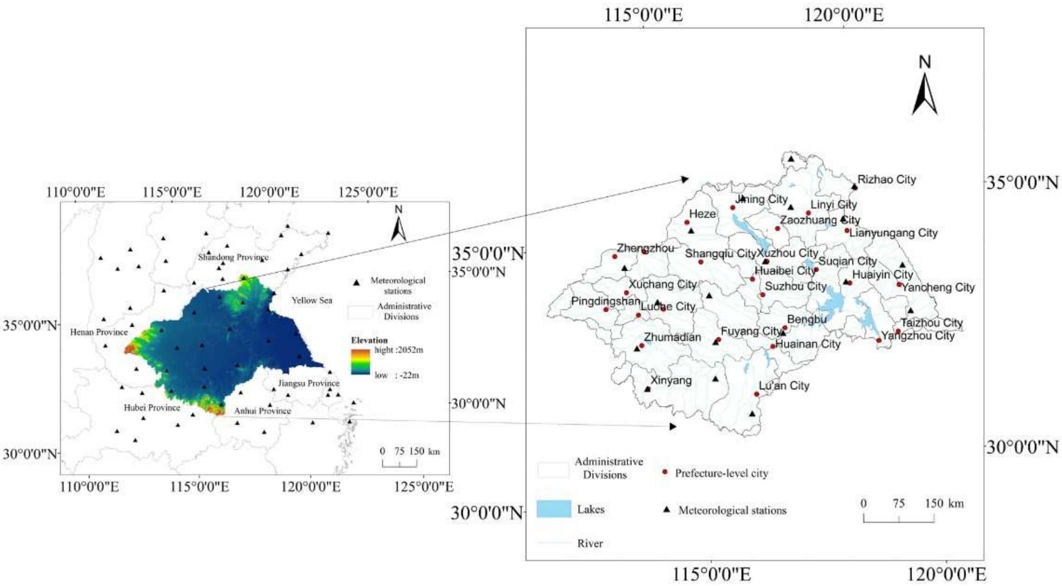

Figure 1. Extent of the Huaihe River Basin and corresponding administrative divisions.

2.2 Data sources and pre-processing

The research utilized various data sources including NDVI, land use, soil type, vegetation condition, DEM, population, GDP, and climatic background data (such as dryness, humidity index, and >10°C cumulative temperature). These data were obtained from the Resource and Environment Data Center of the Chinese Academy of Sciences (https://www.resdc.cn/data). Additionally, slope and direction data were generated from the DEM data (https://www.earthdata.nasa.gov/sensors/srtm). The meteorological station data were obtained from the National Climatic Data Center (NCDC), a part of the United States' National Oceanic and Atmospheric Administration (NOAA). The geographic base maps used in the research were prepared following the guidelines of the Ministry of Natural Resources of China (MNR) and were reviewed and approved as per the Review No. GS (2020) 4619.

The research utilized a method based on a thin disk spline function to interpolate weather station data [13]. It's challenging to establish a consistent classification standard when examining the driving forces behind various natural and human-induced factors [6,14,15] . Different regions may have different classifications depending on their specific situations. Consequently, this research selected 15 driving force factors (refer to Table 1) considering the natural conditions and human aspects of the Huaihe River Basin, while also prioritizing the timeliness and accuracy of data processing.

Table 1. Driving factors for the research area.

Factor	Indicator	Category	Factor	Indicator	Category
X1	Average annual temperature	10	X9	Slope	10
X2	Annual precipitation	10	X10	Slope direction	10
X3	Annual maximum temperature	10	X11	Soil type	12
X4	Annual minimum temperature	10	X12	Vegetation type	17
X5	Dryness	10	X13	Land Use Type	25
X6	Wetness index	10	X14	GDP	5
X7	＞10°C cumulative temperature	10	X15	Population	5
X8	Elevation	10			

After multiple experiments, climate factors (X1-X7) and topographic features (X8-X10) were consolidated into 10 categories. Soil data (X11) were organized into 12 categories based on soil outlines, vegetation types (X12) were categorized into 17 groups according to major vegetation categories, land use types (X13) were classified into 25 categories based on secondary classification, and Gross Domestic Product (X14) and population size (X15) were grouped into 5 categories.

2.3. Study methods

2.3.1. Linear Regression and Trend Analysis

The univariate linear regression equation, based on the least squares method, can analyze the trend of long time series data and can be assessed image by image. In this research, the overall trend of NDVI in the Huaihe River Basin from 2000 to 2019 was computed using the one-dimensional linear regression equation. The changes within the basin were examined image by image. The univariate linear regression equation is expressed as:

$$\theta_{slope}=\frac{n\times\sum_{i=1}^{n} i\times X_{NDVI,i}-\sum_{i=1}^{n} i\sum_{i=1}^{n} X_{NDVI,i}}{n\times\sum_{i=1}^{n} i^2-(\sum_{i=1}^{n} i)^2} \tag{1}$$

Where θ_{slope} represents the size of the slope of the trend change, its positive indicates an increasing trend in NDVI, its negative indicates a decreasing trend, and if it is 0, then it means no change; *n* represents the year of 2000-2019, taking the value of 1-20; and $X_{(NDVI,i)}$ represents the value of the NDVI of a certain region in a certain year.

In this research, we tested the significance of the trend analysis results using the F-statistic. The larger the F-statistic, the more significant the data. The F-statistic is calculated by the formula:

$$F=\frac{U\times(n-2)}{Q} \tag{2}$$

The sum of error squares (U) is calculated from the sample mean and the regression value, while the sum of regression squares (Q) is calculated from the sample value and the regression value. The variable n represents the number of years in the research. The F-statistic can be used to analyze the significance of the trend, by referring to the control table in conjunction with the results of the trend analysis.

2.3.2. COV-based Stability Analysis

The coefficient of variation represents another statistical measure of the variability of data observations, indicating the dispersion degree. It serves to neutralize the impact of varying units or different levels of data variability during comparisons, enabling an analysis of data stability across time and space. A higher coefficient of variation signifies greater data instability. In this investigation, the coefficient of variation was employed to scrutinize the NDVI of the Huaihe River Basin spanning from 2000 to 2019. The formula for the coefficient of variation is as follows:

$$COV=\frac{SD}{MN}\times 100\% \tag{3}$$

SD represents the standard deviation of the data, which was calculated for NDVI from 2000 to 2019; MN represents the mean of the data, which in this case is the average of the vegetation NDVI in the study area over the years.

2.3.3. Geodetector-based Methodology

Geodetector is a fascinating statistical method that helps in analyzing the spatial divergence of various factors to reveal their driving forces [16]. It is a powerful tool that quantifies the strength of independent variable factors and their explanatory power on the dependent variable factor. The research used Divergence and Factor Detector, as well as Interaction Detector, to achieve its objectives. Risk Zone Detector and Ecological Detector are other types of detectors included in Geodetector.

(1) The divergence and factor detector is a tool used to measure the strength of the explanatory power of a single factor on the dependent variable. This is expressed in terms of the q value, which ranges from 0 to 1. The larger the q value, the stronger the relationship between the single-factor independent variable and the dependent variable. Its principal formula is:

$$q=1-\frac{\sum_{h=1}^{l}\sigma_h^2\times N_h}{N\times\sigma^2}=1-\frac{SSW}{SST}$$
$$SSW=\sum_{h=1}^{L}N_h\times\sigma_h^2,\quad SST=N\times\sigma^2 \tag{4}$$

Where L represents the number of stratification or called categorization of the independent or dependent factors; N is the number of units in the whole area and N_h is the number of units in the layer; σ_h^2 and σ^2 refer to the intra-layer variance and the total variance, respectively, while SSW and SST represent the sum of intra-layer variance and the total variance in the entire area, respectively.

(2) The interaction detector is a tool that helps to determine the impact of various factors on a dependent variable. It analyzes the strength of the common effect of different influencing factors and tests the interaction between them. The detector uses q-values to compare single-factor effects with the resulting q-values and algebraic relationships. It can detect two-factor enhancement, nonlinear enhancement, one-factor nonlinear attenuation, and independence between factors.

3. Results

3.1. Spatial Distribution Characteristics

Figure 2 shows the spatial distribution of multi-year average NDVI in the Huaihe River basin. Based on the analysis of the figure, it can be observed that the NDVI is relatively higher in the central

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and western parts of the basin, including Luohe City, Shangqiu City, and Fuyang City. In contrast, the southeast and north-central parts of the basin have lower NDVI values, which can be attributed to the presence of several lakes such as Nansihu Lake, Hongze Lake, and Gaoyou Lake. Additionally, narrow areas with lower vegetation NDVI, as shown in the figure, are mostly due to rivers, railroads, and highways.

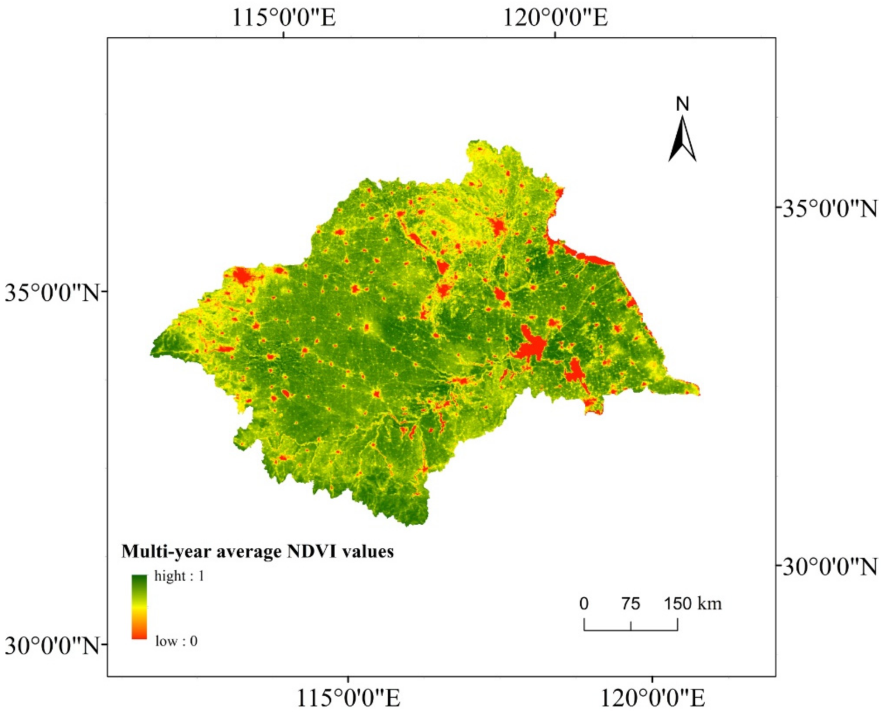

Figure 2. Spatial distribution of multi-year average NDVI in the Huaihe River Basin.

3.2. Characteristics of Spatial and Temporal Variations

3.2.1. Characteristics of Temporal Variations

The graph shows that NDVI in the Huaihe River Basin has been increasing overall, with a growth rate of 0.00148 per year, rising from about 0.74 to about 0.77. The correlation coefficient of the curve is about 0.49 ($P < 0.05$). The curve can be split into two sections. The first section has a high growth rate from 2000 to 2005, followed by a decline from 2005 to 2009, and then growth again until 2010, with a growth rate of 0.00559 per year for ten years and a correlation coefficient of about 0.87 ($P < 0.05$). The second section has a sharp decline in 2011, followed by a slow increase from 2011 to 2019, with a relatively low growth rate and weak linear correlation compared to the first half of the curve.

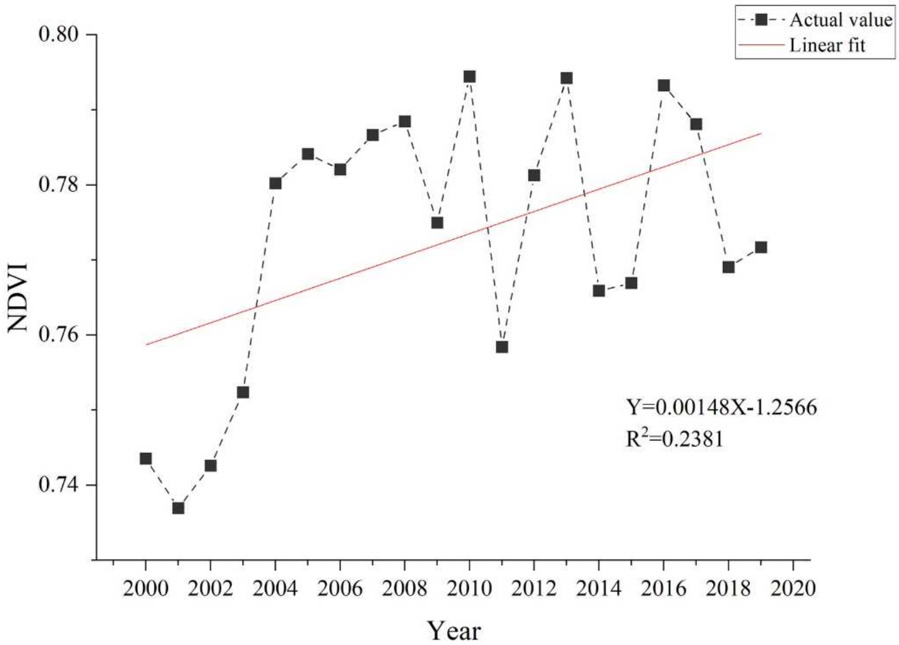

Figure 3. Characteristic curve of NDVI trend in the Huaihe River Basin.

3.2.2. Characteristics of Spatial Variation

The difference method was used to generate the spatial distribution map illustrating the changes in NDVI quantity from 2000 to 2019, as depicted in Figure 4. In the figure, the NDVI difference results are divided into three categories: increasing, unchanged, and decreasing. Upon analyzing the figure, a significant increase in NDVI is observed. The areas showing a decrease are primarily located in Zhengzhou City, Linyi City, Zaozhuang City, and between Yancheng and Yangzhou City. Meanwhile, the unchanged areas are more concentrated in Fuyang City, as well as around the lakes.

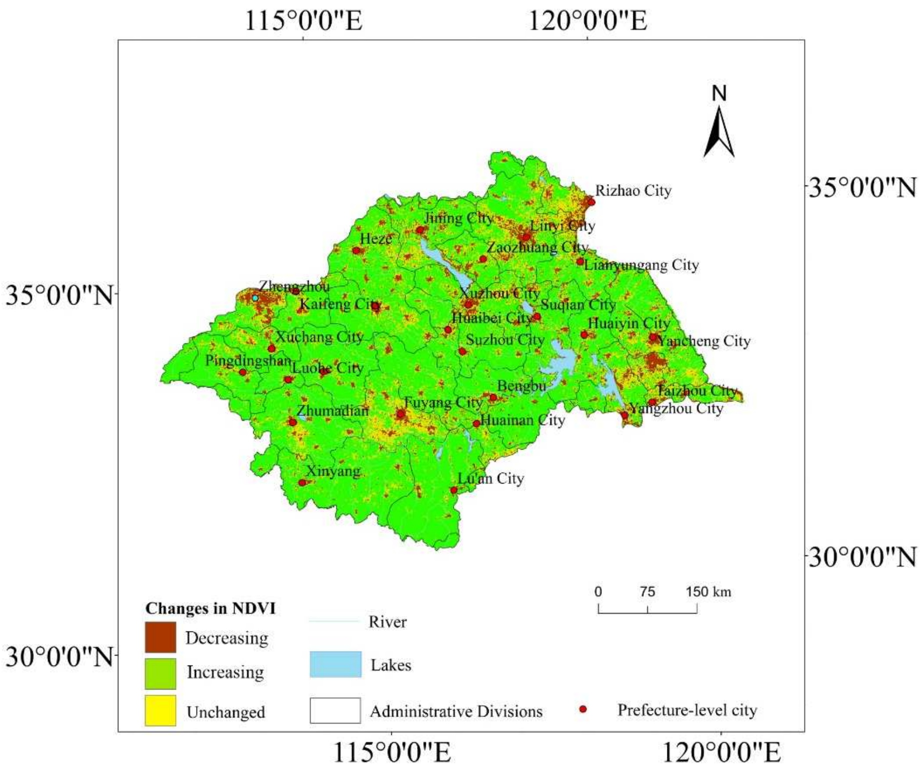

Figure 4. Spatial distribution of NDVI changes categories from 2000 to 2019.

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The spatial distribution of the coefficient of variation is depicted in Figure 5. Overall, the coefficients of variation in the Huaihe River Basin are small. The areas with higher coefficients of variation are primarily distributed around the lakes and their surrounding areas.

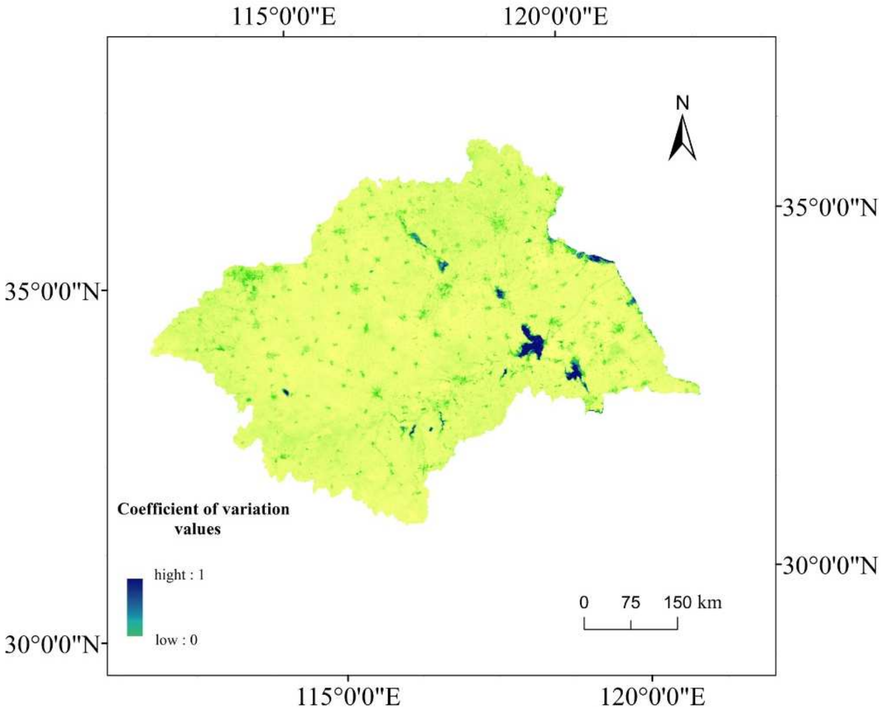
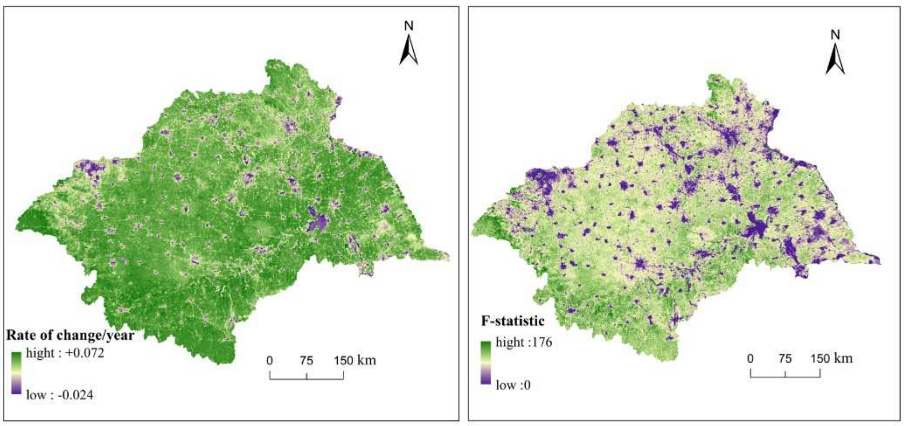


Figure 5. Spatial distribution of NDVI coefficients of variation over the years.

3.2.3. Trends in Spatial Variation

Using the unitary linear regression equation and F-statistic, the Huaihe River Basin was analyzed pixel by pixel. The research results are presented in Figure 6. Figure 6 (a) indicates that NDVI in the basin has experienced significant growth. However, there is a decreasing trend observed mainly near cities and towns, excluding rivers and lakes.



(a) The rate of NDVI changes over the years (b) Significance of NDVI changes

Figure 6. Spatial distribution of the rate of NDVI changes and the significance.

Figure 6 (b) illustrates the significance of NDVI changes in the Huaihe River Basin. From the figure, the F-statistic values are larger in areas other than those around urban areas, rivers, and lakes, which have lower significance. This is particularly evident in the southwestern and central parts of

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the basin, where the significance is stronger. Based on Figure 6 (a) and Figure 6 (b), a table of the significance area scale of the NDVI changes trend in the basin (Table 2) was produced.

Table 2. Significance of change trend and area proportion.

Changes in NDVI	Growth rate (slope) and P-value for significance	Area proportion
Very significant increase	slope＞0，P＜0.01	91.89%
Significant increase	slope＞0，0.01<P＜0.05	3.42%
No Significant Increase	slope＞0，P＞0.05	0.06%
Very significant decrease	slope＜0，P＜0.01	3.48%
Significant decrease	slope＜0，0.01<P＜0.05	0.12%
No significant decrease	slope＜0，P＞0.05	1.03%

Table 2 illustrates that the area with the significant increase in NDVI was the largest with 95.31%, a highly significant decrease was the next with 3.60%, and areas without significant change accounted for 1.09%.

3.3. NDVI Driving Force Analysis

3.3.1. Factor Detector Analysis

In the research, vegetation NDVI factor and 15 impact factors were analyzed for the years 2000, 2005, 2010, 2015, and 2019. Initially, NDVI and impact factors were sampled, with 7000 random point data selected for each year. The data results were then transformed into line graphs (Figure 7) after Factor Detection analysis for further research.

The line graph depicts the changes in the explanatory power of a single factor over the years. The q-value of the explanatory power of land use type on vegetation NDVI was consistently the highest, while slope orientation had the weakest explanatory power. The q-value of the explanatory power of climate factors on NDVI was relatively low. Precipitation had strong explanatory power in 2000. The q values of climatic factors are relatively larger only in the year 2010 compared to other years. The explanatory power q-value of the population factor generally increased over the years. The GDP factor showed fluctuations, with an overall increasing trend. The q-values of vegetation type and soil type fluctuated, but the overall explanatory power tended to decrease. The strength of the explanatory power of slope, slope direction, and elevation on NDVI remained relatively stable and tended to decrease overall.

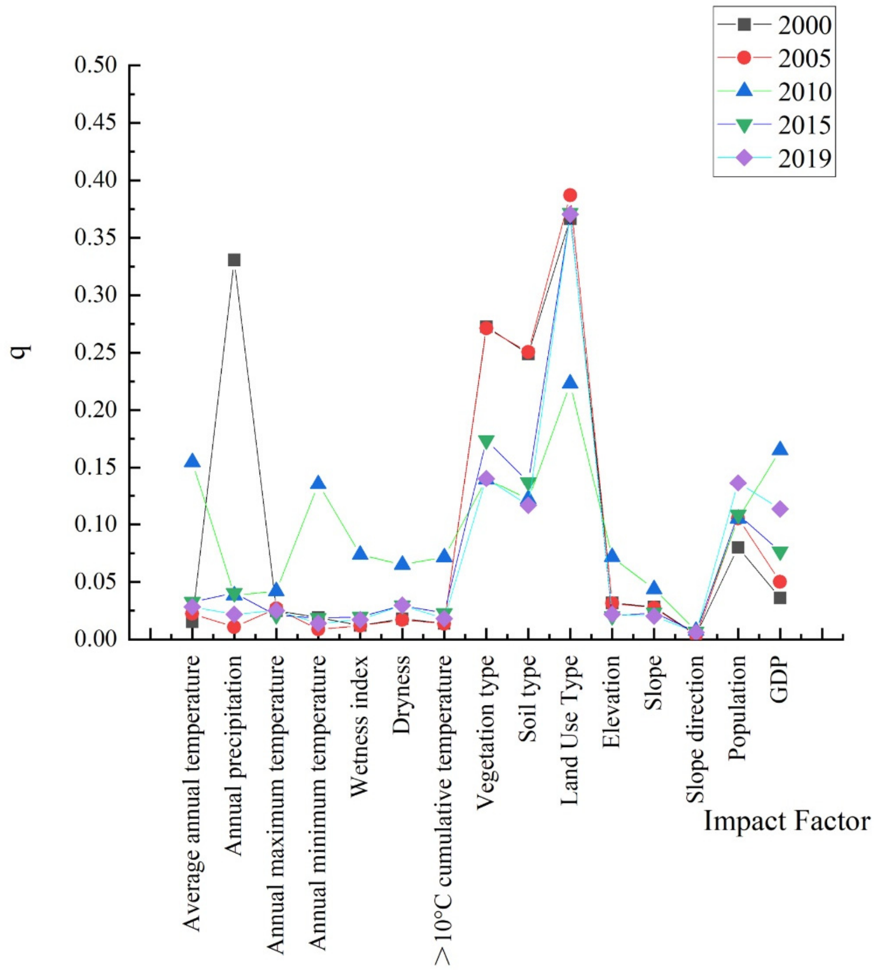

Figure 7. Variation curves of single-factor explanatory force strength.

3.3.2. Interaction Detector Analysis

The Interaction Detector was utilized to examine the impact of two-factor interaction on vegetation NDVI. The analysis revealed that most of the interaction q-values exhibited a non-linear increase, meaning that the magnitude of the interaction value was greater than the algebraic sums of the q-values of the two factors. This was demonstrated by the interactions of the land use and population factors, as well as the precipitation and vegetation factors. A slight amount of two-factor enhancement was observed, with the interaction q-value being larger than the largest q-value of the two factors, as represented by the interaction of vegetation and soil factors. To visually represent the strength of the interaction, a heat map was created using the interaction q-values generated by the detector (Figure 8 (a, b, c, d, e)), and the interaction relationship was illustrated using the precipitation factor as an example (Figure 8 (f)).

The heat map in Figure 8 shows the strength of the factor interactions for five periods. Among all the studied factors, the interaction between land use type and the factors stands out with the largest q-value. The interaction between land use type and annual mean temperature and annual precipitation is also significant. If we take precipitation as an example and examine its interaction, we can see that the q-value of the single factor of precipitation is smaller in all the years compared to the q-value of the two-factor effect. For instance, in 2019, the q-value of the single factor of precipitation is 0.022, while the q-value of the single factor of population is 0.13, and the q-value of their interaction is 0.18, which indicates a nonlinear enhancement. Similarly, the effects of precipitation on other factors also show nonlinear or two-factor enhancement. Moreover, similar characteristics are observed in the interaction analysis of other factors.

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4. Discussion

Besides the rivers and lakes, the regions with low NDVI in the basin are mainly around the prefecture-level city center. Query data has confirmed that the urban expansion of Zhengzhou City generally aligns with the trend of reduced NDVI in nearby vegetation [17]. The peripheral expansion of the central urban area of Linyi City is strongly linked to the reduced NDVI in nearby vegetation [18]. The spatial distribution of NDVI is closely connected to the physical geography and human conditions of the Huaihe River Basin.

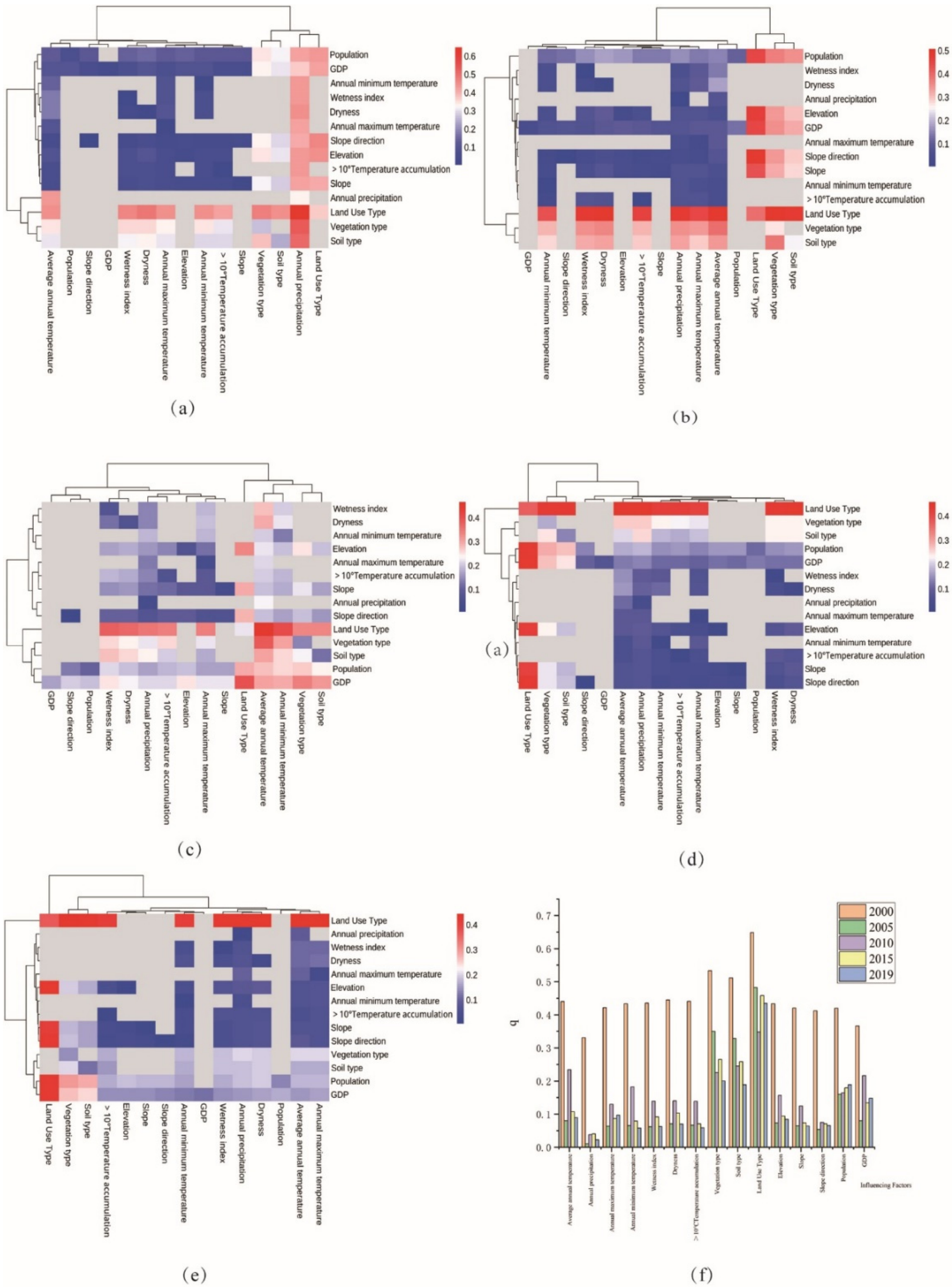

Figure 8. Factor interactions.

Studies have shown that Hongze Lake is currently facing water quality issues such as eutrophication and pollution[19]. These problems have been caused by both natural disasters and human activities, leading to an unstable environment. As a result, it is possible that sensors may identify certain water qualities with an NDVI greater than 0 or even increasing. Unfortunately, there

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will always be a conflict between the treatment of lake water quality and economic development. This is one of the main reasons why the corresponding region tends to have a high variation coefficient, meaning that the NDVI value of the region is unstable.

According to data, severe droughts occurred in the Huaihe River basin in 2000 and 2001[20]. During that time, precipitation in the basin decreased significantly, with only 95mm from January to May, which was 60% less than the same period in previous years. The agricultural department of Anhui province at that time reported direct economic losses of 7.7 billion yuan due to the drought, with 1.82 million tons of grain production lost in Bengbu and Huainan, and over 3 billion yuan in cash crops. It can be inferred that the lack of precipitation had a significant impact on the vegetation NDVI, resulting in a larger difference in NDVI compared to previous years. Additionally, the overall vegetation NDVI in the Huaihe River Basin showed a faster growth between 2001 and 2005 after a short decline in 2000-2001. This may explain the stronger explanatory power presented by the precipitation factor in the beginning of the figure. Different land use types also affect vegetation growth. Xerophilous crops such as wheat, corn, and cotton dominate the northern part of the basin, while crops such as rice and oilseed rape dominate the southern part. These differences in land use types result in different NDVI results obtained from remote sensing sensors.

Urban expansion in the Huaihe River Basin is currently the prevailing trend. This expansion, coupled with economic development, the growth of urban construction areas, and an increase in both migrant and birth populations, has led to a significant conflict between man and land, which has negatively impacted vegetation development in the region. Additionally, policy orientation plays a critical role in influencing the NDVI.

5. Conclusions

This research has comprehensively analyzed the spatiotemporal variability of vegetation NDVI in the Huaihe River Basin, China, over a 20-year period from 2000 to 2019. Utilizing linear regression equations, F-statistics, difference analysis, and the coefficient of variation, the research has examined the trends, stability, and spatial patterns of NDVI changes. Furthermore, the Geodetector analysis has further illuminated the explanatory power of various factors and their interactions on NDVI variability.

The key findings are as follows:

1.The research period revealed a notable increasing trend in NDVI, indicating a progressive greening of the basin at an average annual growth rate of 0.00148. This finding highlights the positive trajectory of ecological health in the region.

2.Spatially, approximately 95.31% of the basin’s area exhibited significant NDVI growth, with only a marginal 3.60% showing decline. This suggests an overwhelmingly positive shift in vegetation cover.

3.Land use type significantly influenced NDVI magnitude, with the q-value for this factor being particularly significant. The impact of precipitation became more pronounced during drought years. The evolving influence of economic (GDP) and demographic (population) factors underscored the need for holistic policy considerations.

These findings have important ecological implications, suggesting improved vegetation conditions in the Huaihe River Basin, which are crucial for maintaining ecosystem health and resilience. Consequently, policies that promote sustainable land management and support green and healthy development in the region should be prioritized. Given the basin’s vulnerability to droughts and floods, adaptive strategies to mitigate the impact of these extreme events on agricultural production and vegetation cover are essential. Policy recommendations could include the following: preserving and nurturing existing greenspaces, strategically developing barren lands as part of comprehensive land use policies, fostering the research and development of drought-resistant crops, and enhancing irrigation systems to ensure their efficacy during periods of drought.

Despite the research's contributions, we acknowledge its limitations, particularly in the selection of explanatory variables for the driving force analysis. For instance, the annual precipitation factor did not exhibit strong explanatory power during periods of lower NDVI values. This suggests that a seasonal analysis of the precipitation factor may yield a more nuanced understanding of its influence on NDVI dynamics, especially in the context of droughts and floods. Future research should explore this avenue to enhance the precision and applicability of ecological assessments and conservation strategies in the Huaihe River Basin.

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