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Spatiotemporal Vegetation Dynamics and Climatic Drivers in Qinshui Coalfield: MODIS-based Analysis

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Abstract: Based on MODIS remote sensing images and NDVI values, this research systematically investigates the temporal-spatial variations of vegetation coverage and their underlying drivers in the Qinshui coal mining area over a 20-year period (2001–2020).This study investigates vegetation dynamics in mining-affected ecosystems, with three primary objectives: to characterize vegetation cover evolution patterns under mineral resource extraction pressures;to quantify natural factors influencing vegetation changes; and to establish an empirical foundation for ecological rehabilitation strategies. The key findings reveal:(1) Spatial-temporal analysis demonstrates marked vegetation improvement across the Qinshui mining region (2000-2020), with distinct geographic variability - western and southern sectors exhibit superior vegetation conditions compared to central areas.(2) Statistical modeling identifies precipitation as the dominant climatic driver, showing strong positive correlation with NDVI, while temperature exhibits weaker association. Temperature generally has a positive correlation with vegetation index values, but its spatial influence varies significantly across regions. (3) Human activities have significantly influenced vegetation cover changes. The most intensive development of industrial, mining and residential zones is concentrated in northeastern and southeastern sectors, particularly near urban agglomerations. This urban expansion has directly reduced both grassland and farmland coverage. Grassland has largely been converted to cultivated land and forest, whereas forest loss is most evident in Qin County, Anze County, Qinshui County, and Fushan County.

Keywords: Qinshui Coalfield; Vegetation coverage; Driving factors; land-use type.

1. Introduction

Vegetation coverage reflects ecosystem conditions and indicates regional ecological quality. As an effective measure of plant growth, vegetation indices have become essential tools for ecological evaluation [1]. Since Jordan's Ratio Vegetation Index (RVI) proposal in 1969, various improved indices like NDVI and EVI have been developed [2].These indices are essential for monitoring vegetation cover [3], estimating biomass [4], and evaluating ecosystem health [5].

Climate change profoundly affects vegetation development worldwide and locally, causing observable changes in plant community structure and ecosystem functions.The growth status of surface vegetation will also have a positive feedback effect on corresponding climate change [6,7]. In recent years, vegetation changes under climatic variations have gained increasing attention in global change science. [8,9]. There are intricate connections between vegetation distribution and factors such as climate change, altitude, soil composition, and other related components, which require further exploration [10]. Researchers have made significant efforts to determine the individual impacts of each factor on local and global vegetation activity [11-13]. Climatic conditions, including rainfall amounts, thermal regimes and sunlight availability, serve as the principal determinants of spatiotemporal plant distribution patterns. [14,15]. The research linking vegetation with climate is limited, and the emergence of remote sensing technology has promoted extensive monitoring to understand vegetation dynamics. Satellite-derived vegetation indices, particularly NDVI, enable large-scale assessment of vegetation dynamics [16]. Human activities represent another key driver of terrestrial ecosystem changes, complementing climate effects [17]. Influenced by human activities, especially in urban areas, vegetation coverage has significantly decreased compared to before [18].

2. Overview of the Research Area

Qinshui Coalfield in Shanxi Province is a large Carboniferous Triassic coalfield with the largest coal production in China at present. The study area spans central and southern Shanxi Province, encompassing over 20 cities and counties within the mountain ranges of Taihang, Luliang, Wutai, and Zhongtiao, including Taiyuan, Shouyang, Yangquan, Xiyang, Heshun, Zuoquan, Wuxiang, Qinxian, Changzhi, Gaoping, Jincheng, Yangcheng, Qinshui, Anze, Qinyuan, with an area of nearly 30000 km^2. Large coal industry groups such as Yangquan, Lu'an, Jincheng, etc. have been built within the coalfield. There are more than hundreds of local coal mines. Coal development is extremely prosperous, forming nearly 2300km^2 .The goaf is the largest supply base of anthracite, chemical coal and coking coal in China. The research region spans latitudes 35°15′-38°10′N and longitudes 111°45′-113°45′E, with maximum dimensions of 220 km (N-S) and 120 km (E-W).The terrain exhibits a central highland pattern, with elevations averaging 1,077 m (range: 454-2,068 m) The specific geographical location is shown in Figure 1:

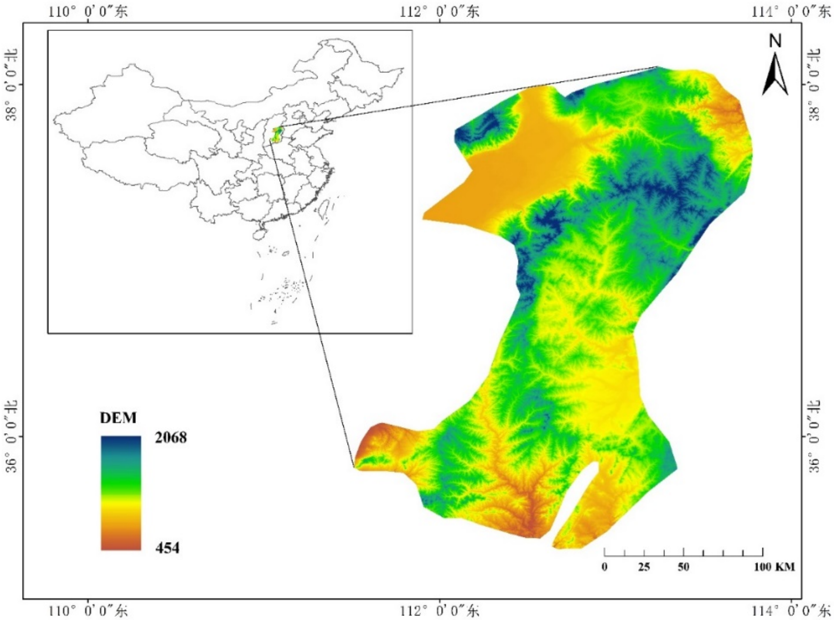

Figure 1. Geographical Location of Qinshui Coalfield

3. Data Source

3.1. Vegetation index data

The MODIS instrument, operating on both Terra and Aqua satellites, serves as a crucial earth observation tool. This dual-satellite system achieves near-complete daily global coverage through its 1-2 day revisit cycle.MODIS has three ground resolutions: 250m, 500m, and 1000m. This article uses 250m resolution data. The scanning width is 2330 kilometers, and 11 megabits of information from the atmosphere, ocean, and land surface can be obtained simultaneously per second. Global observation data can be obtained once a day or every two days, with high temporal resolution. Up to four transit orbit data can be obtained in a day, which is very beneficial for monitoring natural phenomena and processes of change.

The analysis primarily uses MOD13Q1 products from MODIS/Terra, which provide vegetation indices at 250m spatial resolution in a sinusoidal grid system. These 16-day composite data offer consistent global coverage for vegetation monitoring. These NASA-provided NDVI data offer consistent global coverage at medium spatial resolution.Remote sensing image data spanning 20 years from January 1, 2001 to December 31, 2020.

3.2. Climate Data

Precipitation data were obtained from CHIRPS (Climate Hazards Group InfraRed Precipitation with Station data), which combines satellite infrared data and in-situ measurements to produce high-resolution (0.05°) precipitation estimates. Temperature data were derived from the ERA5 MONTHLY reanalysis. The CHIRPS dataset provides global coverage with 5-day temporal resolution since 1981. For atmospheric analysis, this study employs ERA5, ECMWF's fifth-generation global reanalysis product. Reanalysis datasets are created by assimilating worldwide observational records with numerical model outputs, producing spatially and temporally consistent global climate data. ERA5 replaced its predecessor ERA Interim reanalysis. ERA5 MONTHLY aggregates seven key climate parameters from ERA5 reanalysis data, including 2m temperature, dew point temperature, precipitation totals, and atmospheric pressure measurements. For this study, we specifically utilize the 2m temperature data. Precipitation data were obtained through processing CHIRPS Daily datasets on the Google Earth Engine (GEE) platform, generating both spatial representations and tabular summaries of annual precipitation totals for the Qinshui Coalfield;Based on the GEE platform, call the ERA5 MONTHLY dataset, download the 2-meter air temperature, and obtain the annual average 2-meter air temperature image and table of Qinshui Coalfield. Using coordinate system transformation, we reprocessed the annual temperature and precipitation data to match the NDVI grid system, creating consistent raster datasets for Qinshui Coalfield (2001-2020). Following data processing, we calculated the spatial averages of these climate variables. This study focuses on analyzing how precipitation and temperature variations influence vegetation conditions in the study area.

3.3. Other vector data

In addition to the main data sources mentioned above, this article also requires vector boundary data of Qinshui coalfield and city county boundaries as the main auxiliary data to study the spatiotemporal changes of vegetation within the scope and analyze driving factors. The software used in this study mainly includes ArcGIS geographic information software, Matlelab data processing software, Origin mapping software, etc.

4. Research Method

4.1. Univariate linear regression analysis

Using univariate linear regression, we analyzed pixel-level vegetation index trends and performed significance testing to determine temporal patterns. The calculation follows Equation (1):

$$s = \frac{n\sum_{i=1}^{n}(i \times NDVI_i) - \sum_{i=1}^{n} i \sum_{i=1}^{n} NDVI_i}{n \times \sum_{i=1}^{n} i^2 - (\sum_{i=1}^{n} i)^2} \tag{1}$$

In Equation (1), S represents the slope, n denotes the sample size, and $NDVI_i$ indicates the NDVI value in year i. Positive S values denote increasing vegetation indices, while negative values reflect declining trends in vegetation coverage.

4.2. Theil Sen Median slope estimation and Mann Kendall significance test

Theil Sen Median slope estimation is a non parametric estimation method that is less affected by data outliers and is suitable for analyzing the spatiotemporal variation patterns of NDVI in long time series [16]. At the pixel scale, this method is used to analyze the trend of NDVI changes from 2000 to 2020, and the calculation formula is (2):

$$T_{slop} = median\left(\frac{x_j - x_i}{j - i}\right), \forall j > i \tag{2}$$

T_{slope} - slope; x_i and x_j - Annual average NDVI values for the i-th and j-th year. When T_{slope}>0, it indicates that NDVI shows an upward trend during the study period; conversely, it shows a downward trend. The magnitude of this value reflects the intensity of NDVI fluctuations, with larger absolute values corresponding to more pronounced vegetation changes.When T_{slope}=0, it indicates that NDVI remains basically unchanged during the study period.

Significance testing confirmed the reliability of the vegetation trends derived from Theil-Sen Median analysis. This method offers two key advantages: it requires no normal distribution assumption; it represents a widely-adopted trend analysis approach[17,18]. The calculation formula is as follows:

$$Z_{MK} = \begin{cases} \dfrac{S-1}{\sqrt{\dfrac{n(n-1)(2n+5)}{18}}}, S > 0 \\ 0 \qquad , S = 0 \\ \dfrac{S+1}{\sqrt{\dfrac{n(n-1)(2n+5)}{18}}}, S < 0 \end{cases} \tag{3}$$

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sgn(x_j - x_k) \tag{4}$$

$$sgn(x_j - x_k) = \begin{cases} 1, (x_j - x_k) > 0 \\ 0, (x_j - x_k) = 0 \\ -1, (x_j - x_k) < 0 \end{cases} \tag{5}$$

In the formula:

S-Mann Kendall's test statistic;

x_j, x_k - corresponding measurement values for years j and k;

n - length of data series;

sgn - Symbolic function. The threshold values for significance levels are ± 1.96 (95% significance test) and ± 2.58 (99% significance test), respectively. When the value range of Z_{MK} is between 1.96-2.58, it indicates that the growth trend has passed the 95% significance test; A Z_{MK} value ≥ 2.58 denotes statistically significant vegetation growth at the 99% confidence level, while values below this threshold indicate non-significant trends.

4.3. Correlation Analysis

To analyze temperature and precipitation effects on vegetation, we computed pixel-scale correlations between the vegetation index and both climate variables using Equation :

$$A_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{6}$$

In the formula:

Axy - the correlation between the changing trends of two variables;

y_i - NDVI value in the i-th year;

x_i - the numerical values of average temperature and precipitation for the corresponding year;

y and x- NDVI and average values of different variables during the study period. Statistical significance was assessed using t-tests, with NDVI-climate factor correlations categorized as: (1) highly significant (P<0.01), (2) moderately significant (P<0.05), and (3) non-significant (P≥0.05).

5. Result ad Analysis

5.1. Changes in NDVI spatial pattern

To visualize spatial vegetation variations across Qinshui Coalfield (2001-2020), a vegetation index spatial difference distribution with a boundary of every 5 years was used to represent it. That is, vegetation indices were calculated for the years 2001-2005, 2006-2010, 2010-2015, and 2016-2020, respectively. The study obtained vegetation index spatial distributions for Xishan Coalfield across four periods: 2001-2005, 2006-2010, 2011-2015, and 2016-2020 (Figure 2).

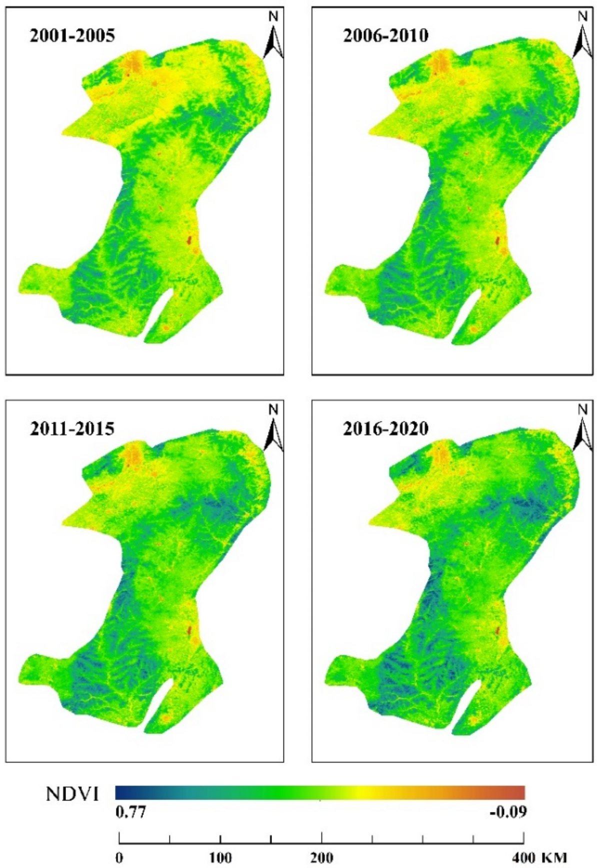

Figure 2. Vegetation index spatial patterns across Qinshui Coalfield

From Figure 2, it can be seen that the spatial distribution of vegetation indices for different time periods from 2001 to

2005, 2006 to 2010, 2011 to 2015, and 2016 to 2020 shows a significant improvement in the overall vegetation situation in the Qinshui coalfield, especially in the northwest and southern regions where there is a clear increasing trend.

To quantitatively assess vegetation cover dynamics, we calculated change rates and p-values to determine long-term trends and their statistical significance in Qinshui Coalfield. The results are shown in Figure 3:

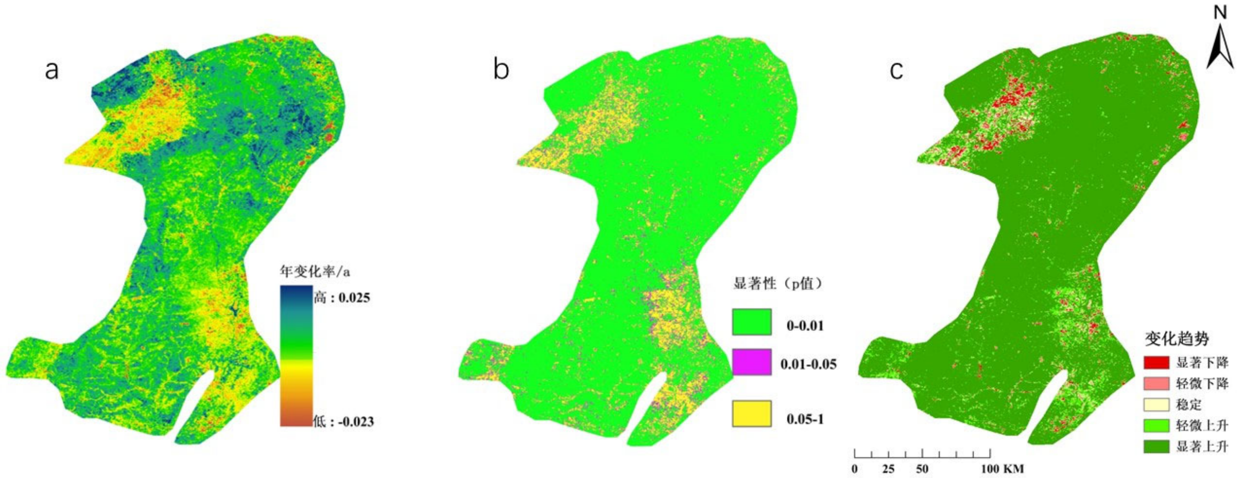

Figure 3. Spatial variation of vegetation NDVI in Qinshui coalfield over the past 20 years

Figure 3a shows NDVI annual change rates in Qinshui Coalfield ranging from -0.023 to 0.025/year, with increasing values from northwestern/southeastern margins toward central regions.According to Figure 3 (b), the significant growth rate of 0.01 is mainly distributed in areas other than Xiaodian District, Taigu District, and the northwest of Qi County, the south of Xiangyuan County, eastern Tunliu and northeastern Changzi areas. Figure 3(c) presents the classification results into five distinct trend categories: significant increase; slight increase; stable; slight decrease; significant decrease, with corresponding areal percentages calculated for each category.Vegetation improvement occurred in 92.54% of Qinshui Coalfield, with 85.55% showing statistically significant increases ($p<0.01$). These areas are concentrated in Shouyang County, Yushe County, Wuxiang County, and Qin County, and belong to forest and grassland land use areas. Among them, 1.74% showed a significant decrease ($p<0.01$). These areas are mainly distributed in Xiaodian District, Taigu District, and the northwest of Qixian County, belonging to urban and rural residential land areas. Overall, it can be seen that the vegetation in Qinshui Coalfield is mainly showing an improvement trend The slope of vegetation NDVI increase and the proportion of improved area show good consistency.

5.2. Annual variation of NDVI

Numerical statistics were conducted on the vegetation index of Qinshui Coalfield from 2001 to 2020. The average NDVI values over the years were compiled into a table and plotted using Origin software. The year was used as the X-axis and the vegetation index NDVI was used as the Y-axis. The specific data was plotted as a point line graph and linearly fitted to obtain the trend of vegetation index changes over the years. Finally, the interannual trend of vegetation index changes in Qinshui Coalfield from 2001 to 2020 is shown in Figure 4:

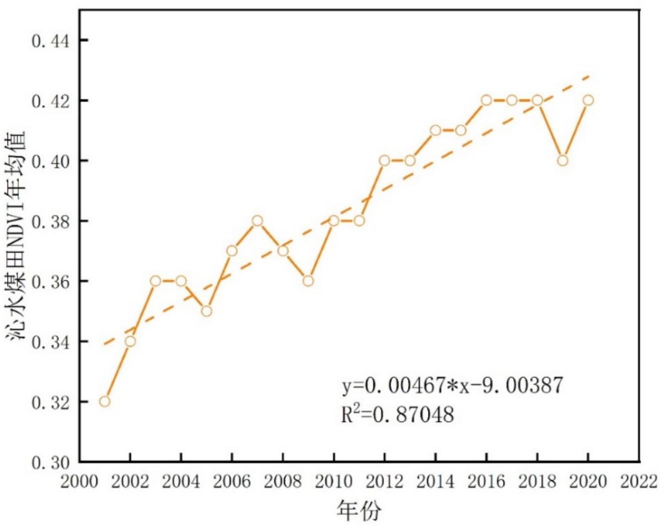

Figure 4. Temporal NDVI trends in Qinshui Coalfield

From Figure 4, it can be seen that the vegetation index of Qinshui Coalfield showed a significant increasing trend from

2001 to 2020, with an increase rate of NDVI of 0.005a -1. The overall annual average NDVI values from 2001 to 2020 did not change significantly, with specific values around 0.38. Nevertheless, specific value variations persist in the detailed analysis.From 2001 to 2012, the vegetation index fluctuated and increased from 0.32 to 0.40, showing a stable and slow increasing trend. From 2013 to 2020, it increased from 0.40 to 0.42.

5.3. The spatial correlation between climate factors and vegetation coverage

The spatiotemporal changes in vegetation cover not only have significant temporal dependencies, but also exhibit strong spatial heterogeneity. To investigate spatial-scale dependencies between climatic variables and vegetation dynamics, we conducted systematic correlation analyses using robust non-parametric methods (Theil-Sen/Mann-Kendall), with outcomes illustrated in Figure 5:

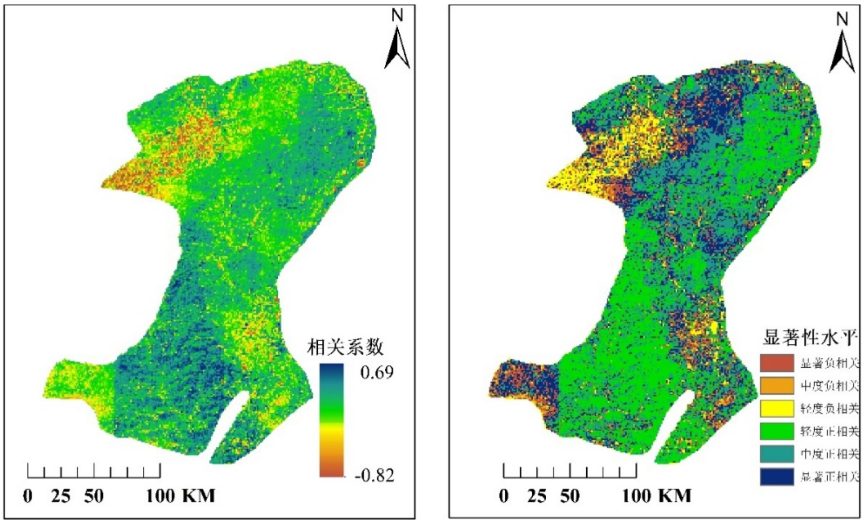

Figure 5. Significant correlation between NDVI and temperature

The spatial analysis reveals varying NDVI-temperature relationships across Qinshui Coalfield (Figure 5). Correlation coefficients range from -0.82 to 0.69, showing distinct regional patterns: predominantly positive correlations in southern sectors (77.26% of total area) versus negative correlations in northwestern portions (22.74%). Positive correlations include mild (36.42%), moderate (22.22%), and strong (18.62%) associations, while negative correlations consist of mild (4.79%), moderate (6.15%), and strong (11.80%) categories. Spatially, strong positive/negative correlations dominate northern and southwestern zones, while southeastern areas show significant negative correlations. Most regions exhibit mild positive correlations.

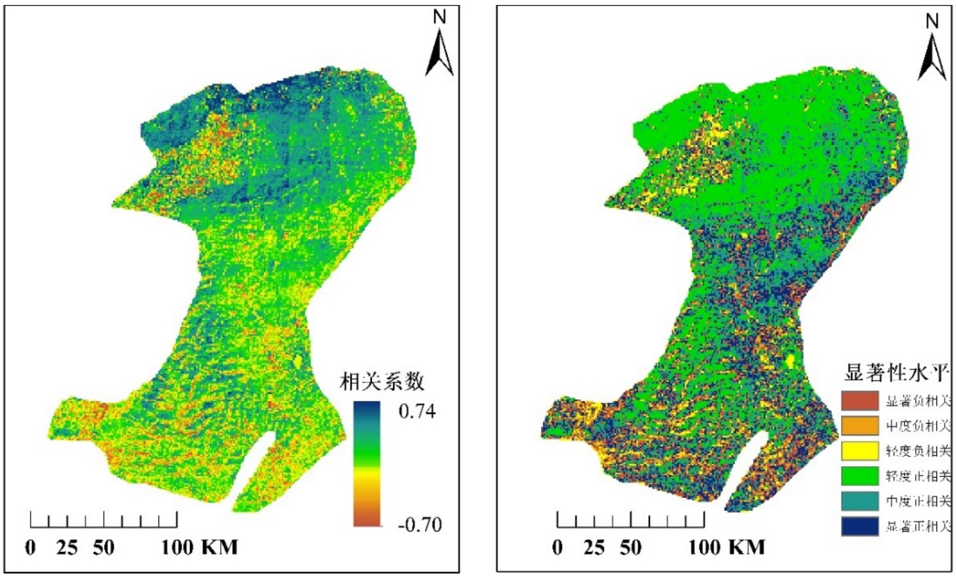

Figure 6. NDVI precipitation correlation significance

The spatial analysis demonstrates significant NDVI-precipitation relationships across Qinshui Coalfield (Figure 6). Correlation coefficients vary from -0.70 to 0.74, revealing clear geographical patterns: primarily positive correlations in northern and central zones (77.26% of total area) contrasting with negative correlations in southern sections (22.74%). Positive correlations exhibit three intensity levels: mild (36.42%), moderate (22.22%), and strong (18.62%) connections, whereas negative correlations display mild (4.79%), moderate (6.15%), and strong (11.80%) patterns.

6. Conclusion

(1) From 2001 to 2020, the overall vegetation coverage in the Qinshui coal field significantly improved, with particularly significant growth in the northwest and southern regions. The vegetation index displays an annual change rate ranging from -0.023 to 0.025/year, revealing a distinct spatial progression with increasing growth rates extending from peripheral northwestern/southeastern zones toward central areas.92.54% of the areas showed vegetation improvement, with 85.55% showing a significant increase, concentrated in forest and grassland areas such as Shouyang County and Yushe County; Significant NDVI decreases (1.74%) primarily occur in urban and rural residential areas, particularly Xiaodian and Taigu Districts.

(2) From 2001 to 2020, Qinshui Coalfield exhibited a significant upward trend in vegetation index values,with an increase rate of NDVI of 0.005a -1. The overall average NDVI values from 2001 to 2020 did not change significantly, with specific values around 0.38. However, there are still differences in the details of the specific values.

(3) Correlation analysis revealed strong relationships between vegetation indices (NDVI, kNDVI) and precipitation, identifying precipitation as the primary climatic driver of vegetation coverage. The overall effect of temperature on vegetation index is positive, but there are significant regional differences in spatial distribution.

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