

Article

Spatiotemporal Characteristics Prediction and Driving Factors Analysis of NPP in Shanxi Province Covering the Period 2001–2020

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Abstract: The advent of a range of high-precision NPP products, including MODIS NPP, MOD17 NPP, and GIMMS NPP, has sparked growing interest in the study of Earth's ecosystems. In order to enhance comprehension of ecosystem health, in order to facilitate the development of rational resource management and environmental conservation policies, this investigation employs the MOD17A3 dataset to analyze historical variations in Net Primary Productivity (NPP) within Shanxi Province from 2001 to 2020, while also exploring future trends. The Theil–Sen median trend analysis and Mann–Kendall test are commonly used methods for analyzing time series data, employed to study the spatiotemporal trends and variations in NPP. The Grey Wolf Optimization–Support Vector Machine (GWO–SVM) model combines optimization algorithms and machine learning methods, enhancing the predictive capacity of the model for future NPP time series changes. Conversely, the Hurst exponent utilizes historical NPP trends to assess the persistence characteristics of NPP and predict future spatial variations in NPP. This study additionally investigates the natural driving factors of NPP using the Geographic Detector approach. The key findings of this study are as follows. (1) Overall, NPP in Shanxi Province exhibits a fluctuating upward trend from 2001 to 2020, with an average value of 206.278 gCm⁻²a⁻¹. Spatially, NPP exhibits a northwest–low and southeast–high pattern, with significant spatial heterogeneity and considerable variability. (2) The average Hurst exponent is 0.86, indicating a characteristic of strong persistence in growth in future NPP. Regions with strong or higher persistent growth account for 95.54% of the total area. (3) According to the CMIP6 climate scenarios, NPP is projected to gradually increase from 2025 to 2030. (4) The interactive effects between natural factors contribute more to NPP variations than individual factors, with the rainfall–elevation interaction having the highest contribution percentage.

Keywords: Net Primary Productivity (NPP); spatial–temporal variations; future trend changes



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1. Introduction

Net Primary Productivity (NPP) refers to the quantity of organic matter generated by photosynthetic green vegetation per unit area and time, excluding the energy consumed during respiration. NPP is a crucial ecological indicator, reflecting the ecosystem's efficiency in utilizing solar energy, and its capacity for biomass production, reflecting the health of terrestrial ecosystems. In addition, NPP exerts a close influence on carbon cycling and the capacity of ecosystems to provide support. Firstly, NPP represents a significant carbon source within ecosystems, determining the accumulation of biomass and carbon storage. Through photosynthesis, vegetation converts carbon dioxide into organic matter and fixes carbon in vegetation and soil, thus impacting the carbon balance and carbon sequestration

functions of the ecosystem. Secondly, NPP plays a crucial role in supporting ecosystem capacity, directly influencing the construction of food chains and energy transfer. Higher NPP implies increased biomass and energy supply within the ecosystem, meaning it is capable of supporting greater biodiversity and more ecological processes. Therefore, investigating the historical dynamics and future changes of NPP is of significant importance for maintaining the health and stability of the ecosystem.

1.1. Research Background

To quantitatively estimate NPP in large-scale ecosystems and achieve monitoring and assessment of ecological environmental changes, early research on NPP primarily focused on establishing datasets and models through the collection of remote sensing data, meteorological data, and ground monitoring data. Most early NPP estimates were based on field measurements, which are relatively accurate but only applicable to small areas [1]. Subsequently, statistical models were widely used due to their simplicity and ability to be applied on a large scale, but these models primarily rely on existing observed data, making it challenging to comprehensively account for the complex dynamic processes of ecosystems and the spatial heterogeneity of ecological environments [2]. The current mainstream approach for estimating vegetation NPP using multi-source remote sensing data involves the use of models. This approach combines remote sensing technology with ecological models, enabling comprehensive capture of spatial distribution and temporal changes in vegetation growth. It exhibits high spatiotemporal resolution and coverage, thereby providing accurate and comprehensive vegetation productivity information. It can be classified into three categories: climate-related models, light use efficiency models, and ecosystem process models [3,4]. Climate-related models estimate NPP based on the relationship between climatic factors and NPP, and their advantage lies in their simplicity and directness, as they only require climatic data for estimation, making them suitable for regions with limited availability of complex ecological information. Ecological process models incorporate the dynamic processes of ecosystems, accounting for the interactions among vegetation growth, photosynthesis, and respiration, among other ecological processes. Consequently, ecological process models can more accurately simulate the variations in vegetation NPP under different environmental conditions. Light use efficiency models, on the other hand, primarily estimate NPP based on vegetation's efficiency in utilizing photosynthetically active radiation. Given that this model only requires vegetation photosynthetically active radiation data, it is particularly suitable for regions with abundant remote sensing data.

In recent years, with the release of a series of high-precision NPP products such as MODIS NPP, MOD17 NPP, and GIMMS NPP, both domestic and international research on NPP has shifted towards analyzing the spatiotemporal changes in NPP and exploring the mechanisms and interactions of various factors influencing NPP. The global land vegetation NPP dataset, MOD17A3, has been extensively validated and applied in various fields such as ecosystem monitoring, environmental monitoring, and global change studies worldwide [5,6]. Wenyan Ge et al. [7] identified climate change and human activities as the main influencing factors on vegetation dynamics, with climate change having a positive impact on vegetation productivity, while human activities have a negative impact. Zijian Li et al. [8] divided China into five climatic regions and analyzed the contributions of climate factors and human activities to NPP changes in each region. Xinru Zhang et al. [9] combined long-term time series data on vegetation fractional coverage (FVC), leaf area index (LAI), and NPP to elucidate the vegetation dynamics in the Yellow River Delta from 2000 to 2017, but they lacked a discussion on vegetation types. Jiangwei Wang et al. [10] studied the response of aboveground NPP in alpine grasslands on the Qinghai–Tibet Plateau to climate change and phenological variations, but their data only extended until 2013 and could not reflect the recent changes in NPP.

The MODIS product MOD17A3, based on MODIS remote sensing parameters, the reference BIOME-BGC model, and the light use efficiency model, provides simulated NPP

data [11]. Li et al. [12–14] conducted a series of studies using the annual average NPP data from the MOD17A3 dataset, with both temporal and spatial scales expanding. However, the analysis of influencing factors on vegetation productivity, such as climate change and human activities, remains limited in depth. Meng et al. [15] utilized the MOD17A3 dataset and the Geographic Detector method to comprehensively investigate the driving factors of NPP in the middle and lower reaches of the Minjiang River region. They identified temperature and elevation as the predominant factors influencing NPP in this area.

1.2. Research Content

The study analyzes the spatiotemporal characteristics of NPP in Shanxi Province from 2001 to 2020 using the MOD17A3 dataset. From a natural factors perspective, we analyze the relationships between precipitation, temperature, elevation, slope, and NPP to understand the influence of these factors on NPP changes. Furthermore, using an improved Grey Wolf Optimization (GWO) algorithm-optimized Support Vector Machine (SVM) and the CIMP6 China monthly climate scenario dataset, we predict the trends in NPP in 2025–2030 under three scenarios (SSP119, SSP245, and SSP585) to explore the future changes in NPP. The technical roadmap of this study is shown in Figure 1.

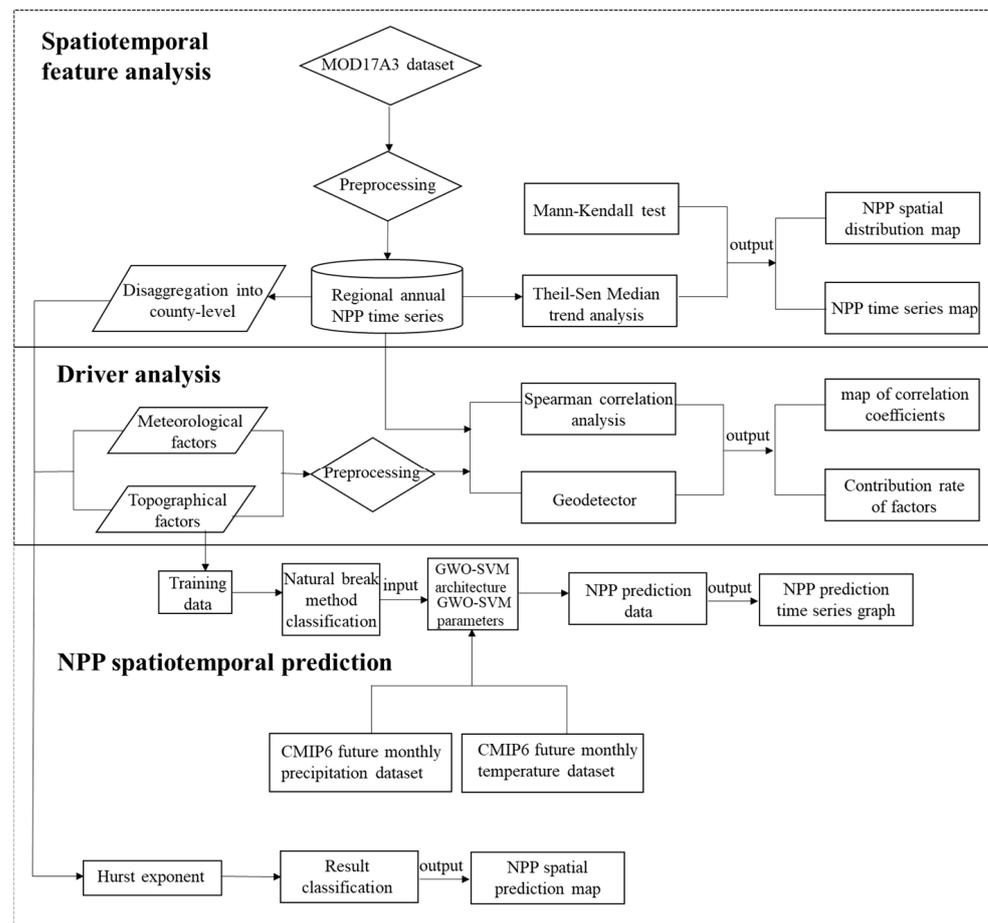


Figure 1. Technology roadmap.

2. Study Area Description and Data

2.1. Study Area Overview

Shanxi Province is located in central China, between longitudes $110^{\circ}15'$ to $114^{\circ}32'$ east and latitudes $34^{\circ}36'$ to $40^{\circ}44'$ north, with a total area of approximately 156,700 square kilometers. The geographical location of Shanxi Province is depicted in Figure 2. Situated amidst the middle stretches of the Yellow River's gorge and the Taihang Mountains, Shanxi Province lies at the heart of China's secondary topography.

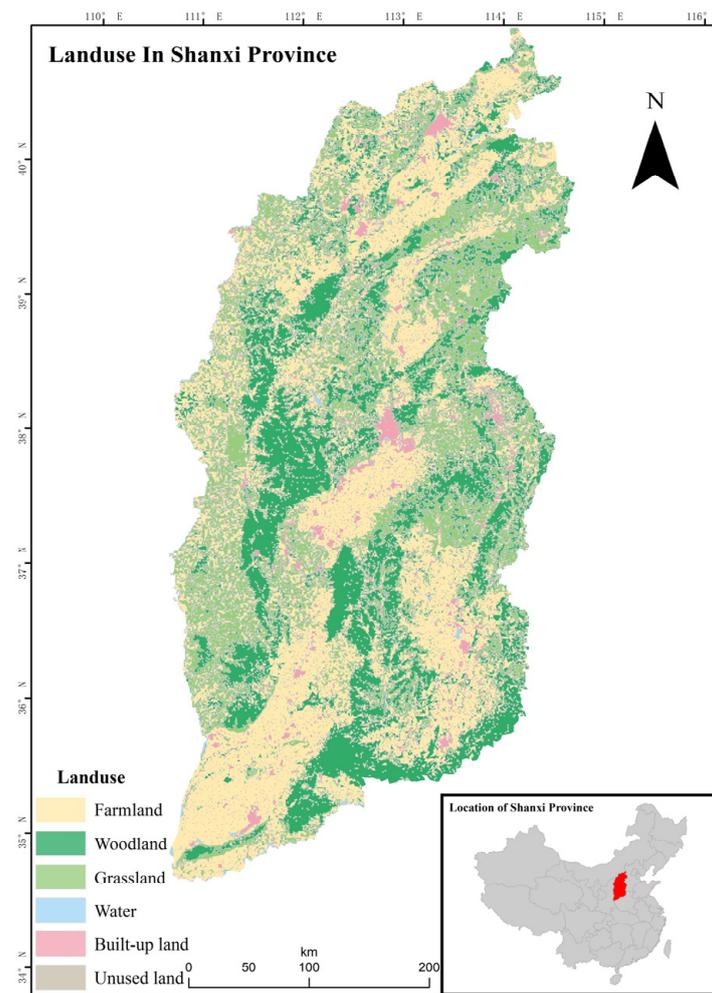


Figure 2. Geographical location map of Shanxi Province.

The province predominantly exhibits undulating and mountainous topography, covering over 80% of its total land area, thereby showcasing a predominantly rugged terrain. Shanxi Province experiences a climate that falls within the temperate continental monsoon category. Annual temperatures in the region typically fluctuate between 3 °C and 14 °C, accompanied by an annual precipitation range spanning from 400 mm to 650 mm. The bulk of the yearly rainfall, approximately 60%, occurs during the months spanning June to August. The main vegetation types in the region include temperate deciduous broadleaf forests, mixed coniferous and broadleaf forests, evergreen coniferous forests, shrubs, and meadows. Cultivated crops in the area encompass a variety of staples such as winter wheat, corn, sorghum, and cotton [16].

For this investigation, the study utilized the MOD17A3 dataset in conjunction with Theil–Sen Median trend analysis and the Mann–Kendall test to investigate the spatiotemporal changes in NPP in Shanxi Province from 2001 to 2020. In order to project the future NPP of Shanxi Province, the study utilized the SVM method, which was optimized using the GWO algorithm alongside the Hurst exponent. Moreover, the study employed the geodetector method to examine the underlying natural factors that drove variations in NPP.

2.2. Data Sources

The data used in this study include the MOD17A3 dataset, Shanxi Province DEM data, Shanxi Province boundary data, precipitation data, average temperature data, and CMIP6 future climate model dataset. All data came from official and up-to-date sources. The temporal coverage and spatial resolutions of the data are presented in Table 1.

Table 1. Summary of the collected datasets.

Data Name	Time Range	Spatial Resolution	Temporal Resolution
China net primary productivity annual synthetic product NPP(MOD17A3)	2001–2020	year	500 m
Elevation of Shanxi(SRTM)	-	-	90 m
Precipitation; Average Temperature	2001–2020	month	Weather Stations
CMIP6 Future climate dataset	2025–2030	month	50 km
Administrative divisions	2017	Year	1:1 million

2.2.1. MOD17A3 Data

The NPP data used in this study were derived from the MOD17A3 product of NASA EOS/MODIS (MOD17A3H.006), for the period 2001–2020. This dataset is based on remote sensing parameters from the MODIS/TERRA satellite and calculated using the BIOME-BGC model to estimate the interannual variation in global terrestrial vegetation NPP. The original data were processed using the Smoother algorithm to remove effects such as cloud cover and artifacts, resulting in a spatial resolution of 500 m. The standard NPP values were obtained by unit conversion in PIE Basic, and invalid values were removed using ArcGIS.

2.2.2. DEM Data

The elevation data used in this study were obtained from the Resource and Environmental Science Data Center of the Chinese Academy of Sciences. These are the ASTERG-DEM elevation data with a spatial resolution of 30 m × 30 m, resampled to 500 m to match the spatial resolution of the NPP data. This dataset, released in 2009, covers all land areas from 83° N to 83° S.

2.2.3. Average Temperature Data

The temperature data were obtained from the National Centers for Environmental Information (NCEI) under the National Oceanic and Atmospheric Administration (NOAA). These were based on daily average temperature records from meteorological stations, and a reverse distance weighting interpolation was used to generate daily average temperature data for the entire country. By combining administrative boundary data of prefecture-level cities, annual average temperature data for each prefecture-level city were calculated.

2.2.4. Precipitation Data

The precipitation data were sourced from the Geospatial Data Sharing Service Platform of the National Earth System Science Data Center. The data cover the period 2001–2020 with a spatial resolution of 1 km. They were resampled to 500 m to match the spatial resolution of the NPP data.

2.2.5. CMIP6 Data

The CMIP6 data used in this study were derived from the global climate model dataset, released under the Coupled Model Intercomparison Project Phase 6 (CMIP6) by the IPCC. Additionally, the World Climate dataset, which provides global high-resolution climate data, was used in conjunction with a Delta downscaling approach to downscale the data specifically for the China region. The GFDL-ESM4 model was selected for obtaining the climate data from the Global Climate Models (GCMs).

3. Methods

3.1. Theil–Sen Median Trend Analysis and Mann–Kendall Test

In this study, the Theil–Sen Median trend analysis method was employed to calculate the annual variation trend in NPP in Shanxi Province. Additionally, the Mann–Kendall test was used for significance testing. The Theil–Sen Median trend analysis combined with the Mann–Kendall test is an important approach for assessing long-term trends in time-series data. The Mann–Kendall test is a non-parametric method that does not require data to follow a specific distribution and can handle missing values, making it robust and flexible [17]. The calculation formula for trend analysis is as follows:

$$\beta = \text{median}\left(\frac{NPP_j - NPP_i}{j - i}\right), 2001 \leq i \leq j \leq 2020 \quad (1)$$

When $\beta > 0$, this indicates an increasing trend in vegetation NPP, while $\beta < 0$ indicates a decreasing trend.

The Mann–Kendall test was used to determine the significance of NPP trend. The calculation formula is as follows:

$$S = \sum_{j=1}^{n-1} \sum_{i=j+1}^n \text{sgn}(NPP_j - NPP_i) \quad (2)$$

$$\text{sgn}(NPP_j - NPP_i) = \begin{cases} 1, & NPP_j - NPP_i > 0 \\ 0, & NPP_j - NPP_i = 0 \\ -1, & NPP_j - NPP_i < 0 \end{cases} \quad (3)$$

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

$$\text{var}(S) = \frac{n(n-1)(2n+5)}{18} \quad (4)$$

In the above equation, sgn represents the sign function. The method for trend analysis is as follows. The null hypothesis H_0 is $\beta = 0$. When $|Z| > Z(1 - \alpha/2)$, the null hypothesis is rejected. A positive value of Z indicates an increasing trend, while a negative value of Z indicates a decreasing trend. α represents the significance level of the test. According to the critical values of the t -test, when $|Z| > 1.96$, this indicates a significant upward or downward trend at the 0.05 significance level. When $|Z| > 2.576$, the upward or downward trend is highly significant at the 0.01 significance level.

3.2. Spearman Correlation

Spearman correlation analysis is a non-parametric statistical method used to measure the monotonic relationship between two variables. In contrast to the Pearson correlation coefficient, the Spearman correlation is more suitable for detecting non-linear relationships or data with rank order. In this study, we employed the Spearman correlation analysis to calculate the correlation coefficients between NPP and climatic factors such as temperature and precipitation, as well as topographic factors such as elevation and slope, aiming to explore their univariate relationships.

3.3. Geodetector

Geodetector is a data mining tool used to study geographical phenomena and spatial relationships. In this study, we applied the geodetector method to explore the interaction relationship between NPP and climatic factors such as temperature and precipitation, as well as topographic factors such as elevation and slope.

The geodetector method is based on the principle of adaptive partitioning, where the study area is divided into several sub-regions for statistical analysis. First, we assessed the spatial variations in NPP, temperature, precipitation, elevation, and slope. Next, we calculated the correlation coefficients between these geographical factors and NPP to establish the univariate relationships. Subsequently, we investigated their interactive effects. By using the hierarchical analysis method, we decomposed the variance in NPP at different levels, identifying the main and interactive effects of each factor. Through the comparison of variances at different levels, we assessed the strength of interactions among various factors, thus determining the factors that exerted the most significant impact on NPP.

3.4. Hurst Exponent

The Hurst exponent reflects the autocorrelation within a time series, particularly the hidden long-term trends within the sequence. The basic principle is as follows. Consider an NPP time series $\{NPP(\tau)\}$. For any positive integer, define the mean sequence:

$$\overline{NPP} = \frac{1}{\tau} \sum_{t=1}^{\tau} NPP_{(t)} \quad (5)$$

$X(t)$ represents the cumulative deviation:

$$X(t, \tau) = \sum_{t=1}^t [NPP_{(t)} - \overline{NPP_{(\tau)}}] \quad 1 \leq t \leq \tau \quad (6)$$

The range $R(\tau)$ is defined as

$$R(\tau) = \max X(t, \tau) - \min X(t, \tau) \quad \tau = 1, 2, \dots \quad (7)$$

The standard deviation $S(\tau)$ is defined as

$$S(\tau) = \left[\frac{1}{\tau} \sum_{t=1}^{\tau} (NPP_{(t)} - \overline{NPP_{(\tau)}})^2 \right]^{\frac{1}{2}} \quad \tau = 1, 2, \dots \quad (8)$$

If the relation $R/S \propto \tau^H$ exists, this indicates the presence of the Hurst phenomenon in the NPP time series. H is referred to as the Hurst exponent, and its value is obtained through the least squares fitting method. The Hurst exponent H ranges from 0 to 1 and can be classified into three cases: when H is greater than 0.5, this indicates the time series exhibits persistence, and the closer H is to 1, the stronger the persistence; when H equals 0.5, this indicates the time series is random; when H is less than 0.5, this indicates the time series exhibits anti-persistence, and the closer H is to 0, the stronger the anti-persistence.

3.5. GWO-SVM

This study employed the GWO algorithm combined with the SVM to analyze the future trends in NPP. The GWO algorithm is an intelligent optimization algorithm that imitates the social behavior of grey wolves, simulating their hunting behavior to optimize problems. The algorithm starts by randomly generating a certain number of individuals within a wolf pack. Subsequently, the algorithm simulates their search behavior through iterative updates of individual positions, encompassing position and velocity updates, in order to locate the optimal solution.

The formula for searching the prey is as follows:

$$D = |C \cdot X_p(t) - X(t)| \quad (9)$$

$$X(t+1) = X_p(t) - A \cdot D \quad (10)$$

$$A = 2a \cdot r_1 - a, C = 2r_2 \quad (11)$$

In the above equations, t denotes the current iteration count; A and C are synergy coefficient vectors; X_p represents the position vector of prey, i.e., the global optimal solution; $X(t)$ denotes the current position vector of the grey wolf; during the entire iteration process, a linearly decreases from 2 to 0; and r_1 and r_2 are random vectors in the range $[0, 1]$.

The formula for identifying the optimal solution is as follows:

$$D_\alpha = |C_1 \times X_\alpha|, D_\beta = |C_2 \times X_\beta|, D_\delta = |C_3 \times X_\delta| \quad (12)$$

$$X_1 = X_\alpha - A_1 \cdot D_\alpha, X_2 = X_\beta - A_2 \cdot D_\beta, X_3 = X_\delta - A_3 \cdot D_\delta \quad (13)$$

$$X_{(t+1)} = \frac{X_1 + X_2 + X_3}{3} \quad (14)$$

In the above equations, X_α , X_β , and X_δ , respectively, represent the position vectors of α , β , δ in the current population; X denotes the position vector of the grey wolf; and D_α , D_β , and D_δ represent the distances between the current candidate grey wolves and the top three wolves. When $|A| > 1$, the grey wolves tend to disperse across various regions and search for prey, while, when $|A| < 1$, the grey wolves concentrate on searching for prey in certain areas. C is a vector composed of random values in the interval range $[0, 2]$, providing random weights for the prey.

For this study, the wolf pack size was set to 30, and 25 iterations were performed. Each wolf's fitness, which evaluates the quality of its position, was calculated based on the SVM model's fit to the training data and prediction accuracy.

For each iteration, we used SVM as the prediction model. SVM is a supervised learning algorithm that constructs a hyperplane to separate different classes of data samples. The regression function and objective function are as follows:

$$f(x) = \sum_{i=1}^n (\alpha_i - \alpha_i^*) (\rho(x_i), \rho(x)) + b \quad (15)$$

$$\min J = \frac{1}{2} \|\omega\| + C \sum_{i=1}^n (\xi_i^* + \xi_i) \quad (16)$$

$$s.t. \begin{cases} y_i - \omega \cdot \rho(x) - b \leq \varepsilon + \xi_i \\ \omega \cdot \rho(x) + b - y_i \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0, i = 0, 1, 2, \dots, n \end{cases}$$

In the equation, C is the penalty factor, ξ_i and ξ_i^* represent slack variables, $\|\omega\|$ is a term related to $f(x)$, and ε is the insensitive loss function.

We used the NPP data as training samples for the SVM model and optimized its parameters using the optimal position obtained from the GWO algorithm. This approach enabled the SVM model to better adapt to the training data and exhibit improved generalization capabilities. By combining the GWO algorithm and SVM, this method effectively enhanced prediction accuracy and improved the model's robustness.

4. Results and Analysis

4.1. Temporal Patterns in NPP Variation

Figure 3 shows a bar chart depicting the percentage of annual total NPP and a line graph illustrating the annual average NPP in Shanxi Province. From Figure 3, it can be observed that the annual average NPP in Shanxi Province exhibited an overall fluctuating

upward trend from 2001 to 2020. The average annual NPP value was $206.54 \text{ gCm}^{-2}\text{a}^{-1}$, with an average growth rate of 3.82%. From 2001 to 2004, there was a sharp increase in the annual average NPP, with a high growth rate of 21.13% from 2001 to 2002 and a decline of -13% from 2004 to 2005, indicating the largest decline. During the period from 2005 to 2010, Shanxi Province, due to its concentrated efforts to accelerate economic development, neglected environmental protection, resulting in fluctuating and slow growth of NPP values. During the period 2010–2020, although NPP showed significant fluctuations, it exhibited an overall increasing trend, with the mean NPP being significantly higher than that before 2010. The smallest annual average NPP occurred in 2001, with a value of $133.57 \text{ gCm}^{-2}\text{a}^{-1}$. After the enactment of the Shanxi Province Environmental Protection Regulation in 2017, the NPP value reached its peak in 2018, with an annual average NPP of $250.36 \text{ gCm}^{-2}\text{a}^{-1}$, and the percentage of total NPP exceeding $450 \text{ gCm}^{-2}\text{a}^{-1}$ accounted for 42.08%, which was the highest among all years. Overall, the NPP in Shanxi Province experienced a significant upward growth trend from 2001 to 2020.

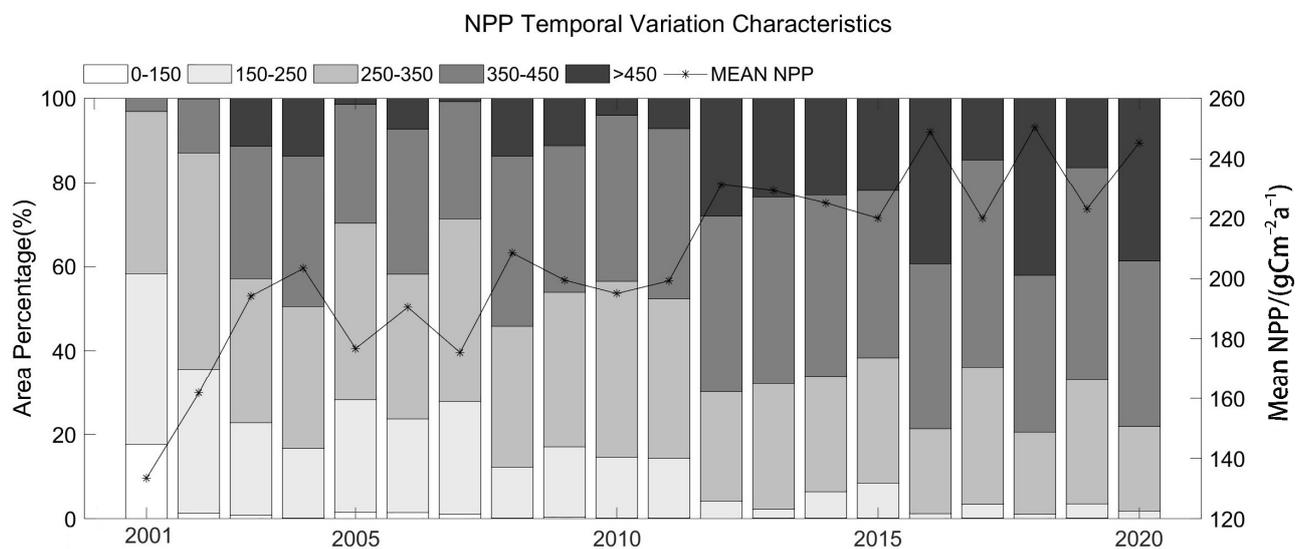


Figure 3. The temporal variation characteristics of NPP in Shanxi Province.

4.2. Spatial Characteristics of Vegetation NPP Variation

According to Figure 4A, the NPP total variations among different regions in Shanxi Province from 2001 to 2020 ranged from 0 to $591.38 \text{ gCm}^{-2}\text{a}^{-1}$, exhibiting significant spatial disparities. Due to the relatively lower terrain in the southeast region, the rainfall and temperature are more favorable, resulting in a spatial pattern of NPP in Shanxi Province that exhibited a northwest–low and southeast–high trend. Regions with NPP values exceeding $450 \text{ gCm}^{-2}\text{a}^{-1}$ were predominantly found in the western areas of Changzhi and Jincheng cities, the northeastern area of Yuncheng city, the central-eastern areas of Xinzhou and Lvliang cities, and the central areas of Linfen and Jinzhong cities. Areas characterized by NPP values below $250 \text{ gCm}^{-2}\text{a}^{-1}$ were predominantly found in the northwest region of Shanxi Province, including Xinzhou, Lvliang, and the western parts of Datong city, as well as the central areas of Taiyuan and Shuozhou cities. The peak NPP value of $591.38 \text{ gCm}^{-2}\text{a}^{-1}$ was recorded in Qingshui County, Jincheng city, at coordinates 112.007, 35.504, while the lowest NPP values were observed in the central-eastern region of Shanxi Province, including Lujiazhuang district in Changzhi city and the overlapping areas of Xiaodian, Yingze, Xinghualing, Jiancaoping, Wanbailin, and Jinyuan districts in Taiyuan city, Pingcheng and Yungang districts in Datong city, Zezhou County in Jincheng city, and the central areas of Yuncheng and Linfen cities.

Figure 4B shows that the NPP change rate in Shanxi Province was generally high, with the majority falling within the range of 40% to 80%. The western region of Lvliang city and the central areas of Linfen city exhibited higher change rates, with the highest

change rate reaching 253.74%. In contrast, the boundary areas between Lvliang, Taiyuan, and Jinzhong cities showed lower change rates. These results suggest that, due to the strict comprehensive ecological management implemented by the government, the vegetation growth status in the study area significantly improved and the ecological environment governance produced significant outcomes.

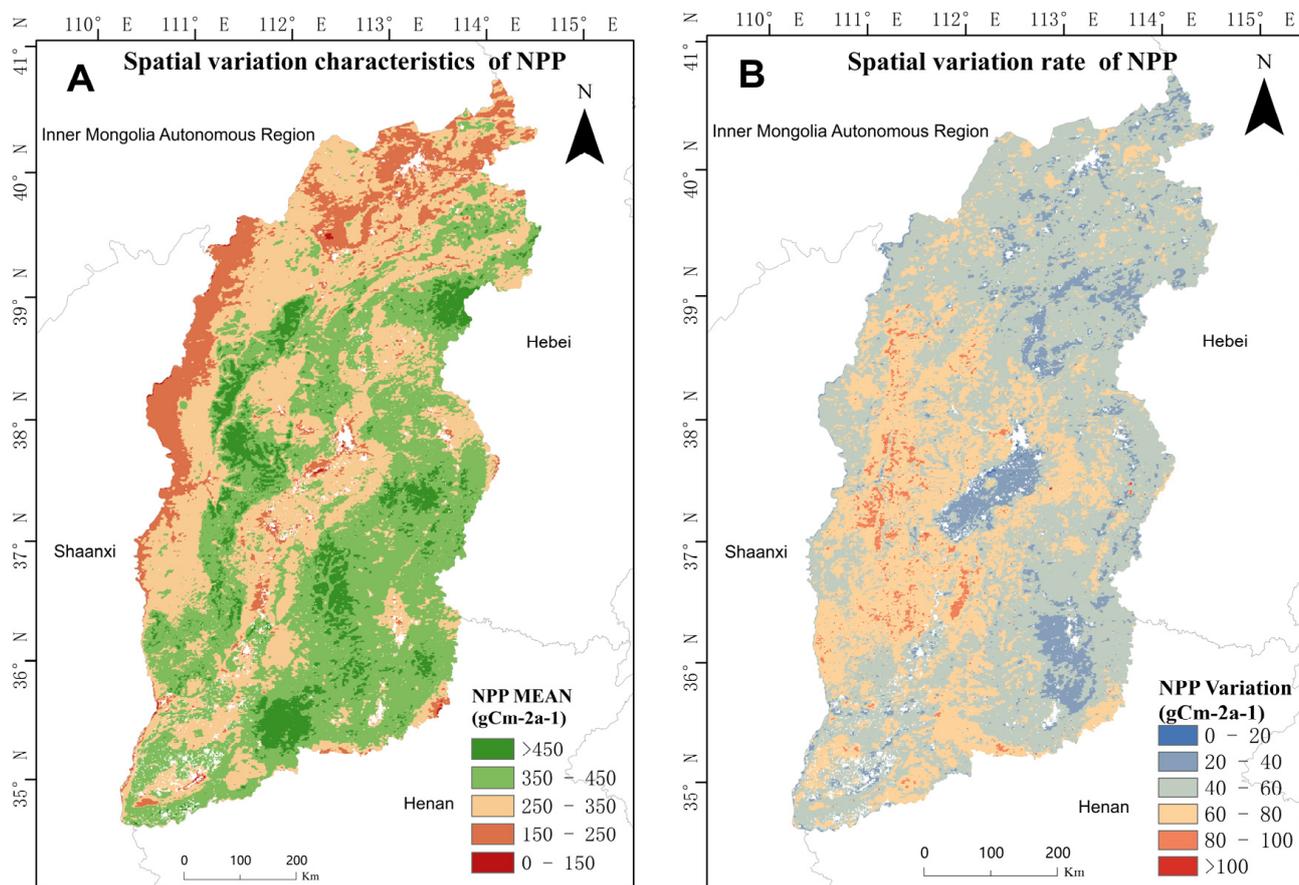


Figure 4. Spatial variation characteristics (A) and rate of NPP (B) in Shanxi Province.

4.3. Trend Analysis and Significance Testing

The β values obtained from the vegetation growth trend analysis in Shanxi Province ranged from -19.78 to 34.03 (Figure 5A). With the introduction of President Xi Jinping's environmental protection concept of 'Green mountains and clear waters are as valuable as mountains of gold and silver', Shanxi Province issued a series of environmental protection regulations. From 2001 to 2020, 96.68% of the areas in Shanxi Province showed an increasing trend in NPP. Figure 5 shows that there was a high level of overall variation in NPP in Shanxi Province, where 7.14% of the regions did not meet the significance threshold, while 92.86% of the regions met the significance threshold at a $p < 0.05$ level, and 86.65% of the regions met the significance threshold at a $p < 0.01$ level. Thus, the vegetation growth trend analysis in Shanxi Province based on the MK test is highly credible. There was a general upward trend in NPP, with regions with higher growth rates in the western region of Shanxi Province. The areas that did not pass the significance test were primarily located in the southeastern part of Shanxi Province, including certain regions in Jincheng, Yuncheng, Changzhi, and Linfen cities, suggesting relatively minor changes in these regions. Overall, the ecological environment in Shanxi Province has shown significant improvement. Efforts should be continued to strengthen ecological governance, consolidate conservation achievements, and implement a development strategy that prioritizes protection based on regional functional positioning and ecological suitability.

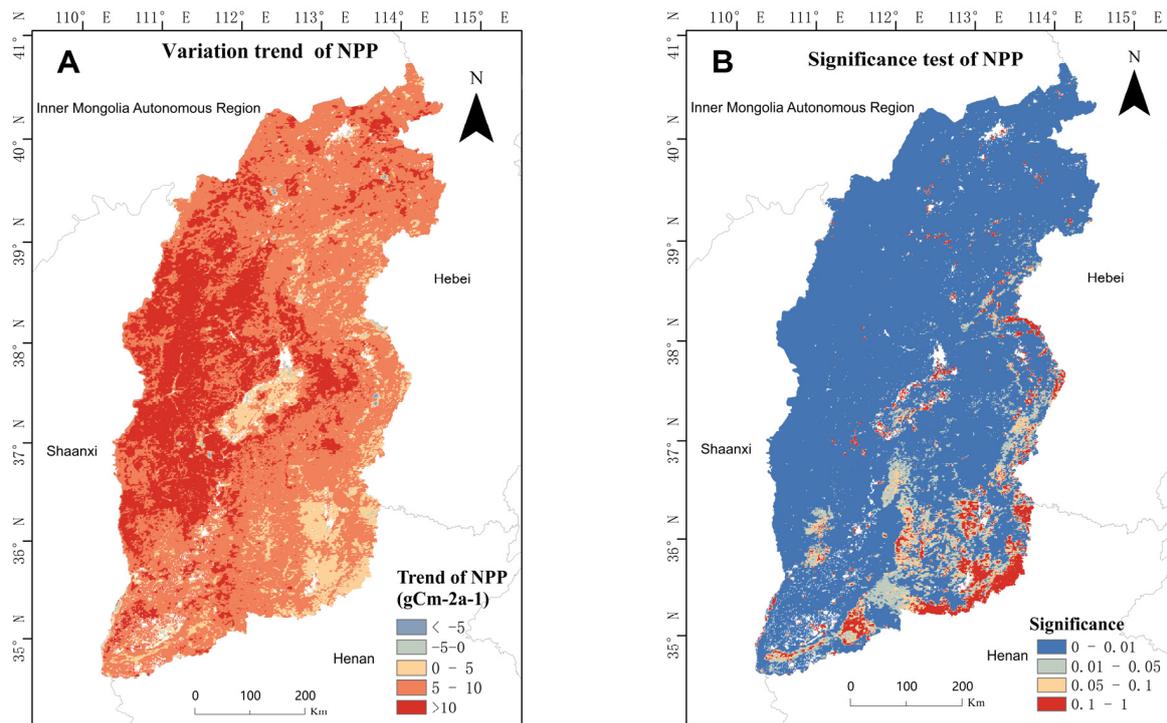


Figure 5. Variation trend (A) and significance test of NPP (B) in Shanxi Province.

4.4. Future Spatial Trend Characteristics of NPP

In order to enhance the prediction of future changes in NPP in Shanxi Province, the Hurst exponent of NPP variations from 2001 to 2020 was calculated in this study to assess the stability of NPP (Figure 6). Table 2 provides a categorization of the Hurst exponent into seven levels.

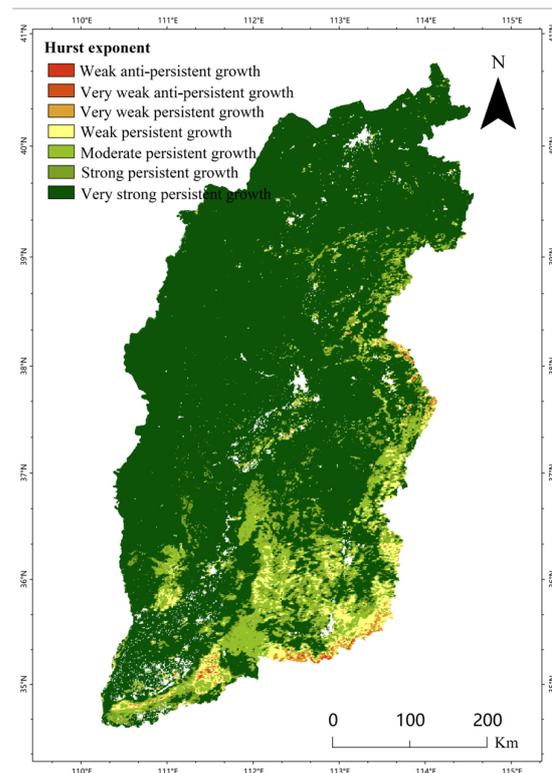


Figure 6. NPP Hurst exponent of Shanxi Province.

Table 2. Hurst exponent classification.

Level	Hurst Exponent	Intensity of Persistence
1	$0 \leq H \leq 0.45$	Very weak anti-persistent growth
2	$0.45 < H \leq 0.5$	Weak anti-persistent growth
3	$0.5 < H \leq 0.55$	Very weak persistent growth
4	$0.55 < H \leq 0.65$	Weak persistent growth
5	$0.65 < H \leq 0.75$	Moderate persistent growth
6	$0.75 < H \leq 0.8$	Strong persistent growth
7	$0.8 < H \leq 1$	Very strong persistent growth

Figure 6 illustrates that the future changes in NPP in Shanxi Province exhibit a strong persistent growth pattern, indicating consistency with past trends. Regions with a highly persistent characteristic comprise 80.26% of the total area, while those exhibiting strong persistent growth cover 7.16%, and regions displaying relatively strong persistent growth cover 8.14%. Regions exhibiting a reversed persistent pattern account for only 0.26% of the total area. The northwestern part of Shanxi Province displays a strong persistent growth trend in NPP, with the cities of Shuozhou, Lvliang, Linfen, Datong, Taiyuan, and Xinzhou exhibiting the strongest persistence. In the southeastern part of the province, the persistence of growth is slightly lower, primarily concentrated in the cities of Jincheng and Changzhi. With the implementation of ongoing governance policies, Shanxi Province's ecological environment is expected to continue improving, and future changes in NPP are projected to exhibit a strong persistent characteristic with an increasing trend.

The strong and sustained increase in NPP indicates significant improvements in the ecological health of Shanxi Province, leading to an increase in biomass, ecosystem capacity, and biodiversity. NPP represents the process by which plants absorb carbon dioxide through photosynthesis and convert it into organic matter, resulting in more carbon being sequestered within plants, leading to a reduction in atmospheric carbon dioxide concentration and contributing to climate change mitigation.

4.5. Future Temporal Trends of NPP

This study employed the GWO algorithm in combination with the SVM method to analyze the future temporal trends in NPP. Shanxi Province was divided into counties, and the temperature, precipitation, and NPP data from 2001 to 2020 were categorized into four levels using the natural breakpoint method. The first level had an NPP total between 68.2864 and 245.8615 $\text{gCm}^{-2}\text{a}^{-1}$, the second level had an NPP total between 245.8616 and 323.7666 $\text{gCm}^{-2}\text{a}^{-1}$, the third level had an NPP total between 323.7667 and 397.2088 $\text{gCm}^{-2}\text{a}^{-1}$, and the fourth level had an NPP total greater than 397.2088 $\text{gCm}^{-2}\text{a}^{-1}$. We used 2300 data points from 2001 to 2020 as training data for the model. We executed the GWO algorithm with a population size of 30 and 25 iterations. The optimal values for the penalty parameter C and the kernel parameter gamma were determined as 0.126 and 0.309, respectively.

To validate the accuracy of the model, the predicted values and actual values for the years 2005, 2010, 2015, and 2020 were compared. We present the comparison results in Figure 7 using a confusion matrix. From Figure 7, it can be observed that the number of correctly classified samples for each year exceeded 80% of the total samples, suggesting a strong performance of the model in fitting the data. Hence, the SVM model trained using the GWO algorithm successfully achieved accurate predictions of NPP values for different years in Shanxi Province.

Based on the trained model described above, this study used temperature and precipitation data from three scenarios of the CMIP6 project: SSP119 (Sustainable Development Pathway), SSP245 (Medium Development Pathway), and SSP585 (High Emission Pathway) to predict the NPP for the years 2025–2030. The results are shown in Figure 8.

From Figure 8, it can be observed that the highest number of NPP values fell within the third level across all three scenarios. Furthermore, NPP values in the third and fourth levels showed an increasing trend, while those in the second and first levels exhibited a decreasing trend. The growth rate followed the order $SSP119 > SSP245 > SSP585$, indicating that, under all three scenarios, the NPP in Shanxi Province will be in a phase of rapid growth.

Therefore, the results suggest that, under the SSP119, SSP245, and SSP585 scenarios, the NPP in Shanxi Province is projected to experience significant growth, with the highest growth rate expected in the SSP119 scenario, followed by SSP245 and SSP585 scenarios. The research findings underscore the significance of sustainable development strategies and environmental policies in managing the future growth of NPP. Therefore, striking a balance between economic development and environmental protection is of utmost importance for ensuring the long-term well-being of both the population and the natural ecosystems in Shanxi Province.

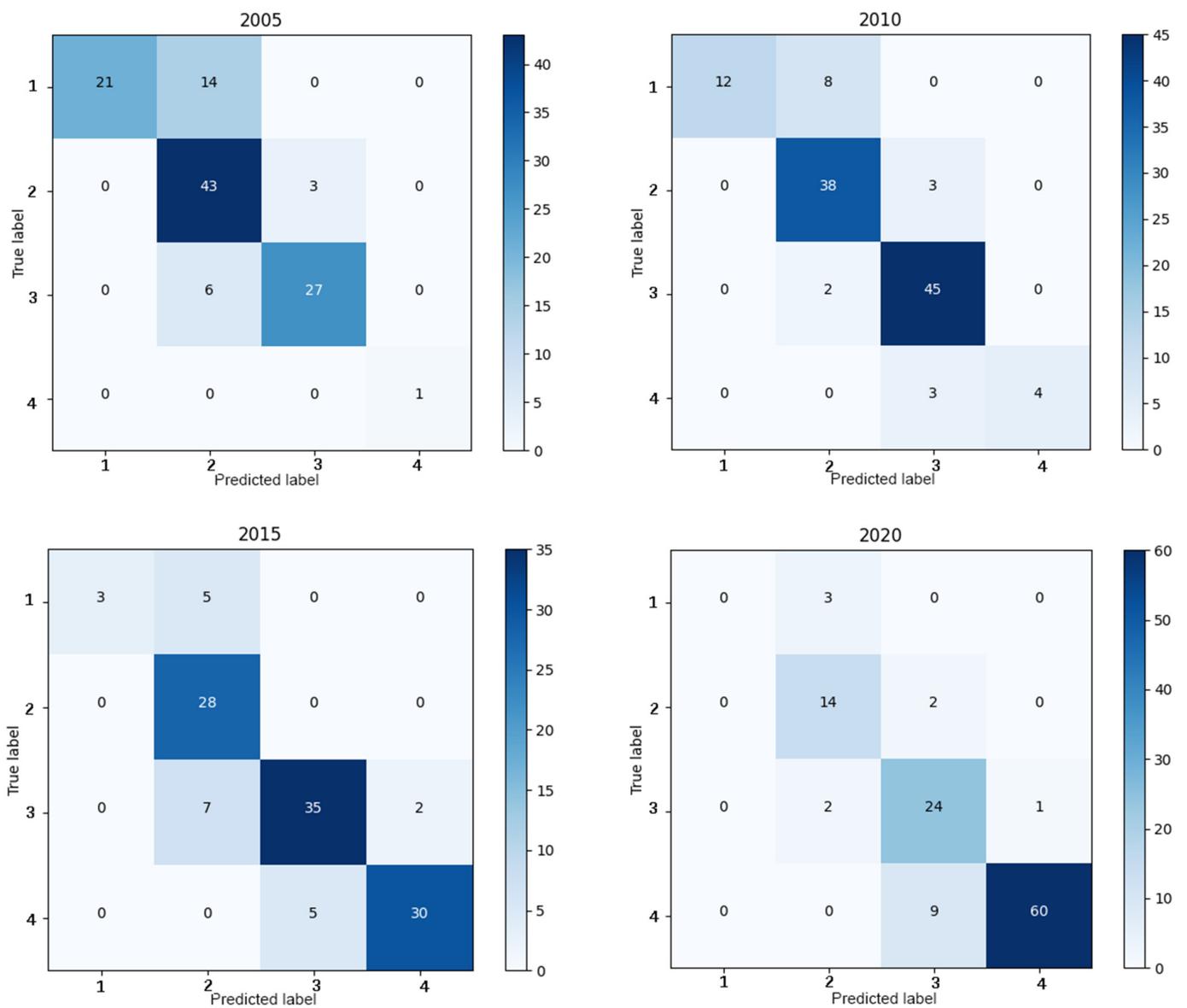


Figure 7. Confusion matrix for validation dataset.

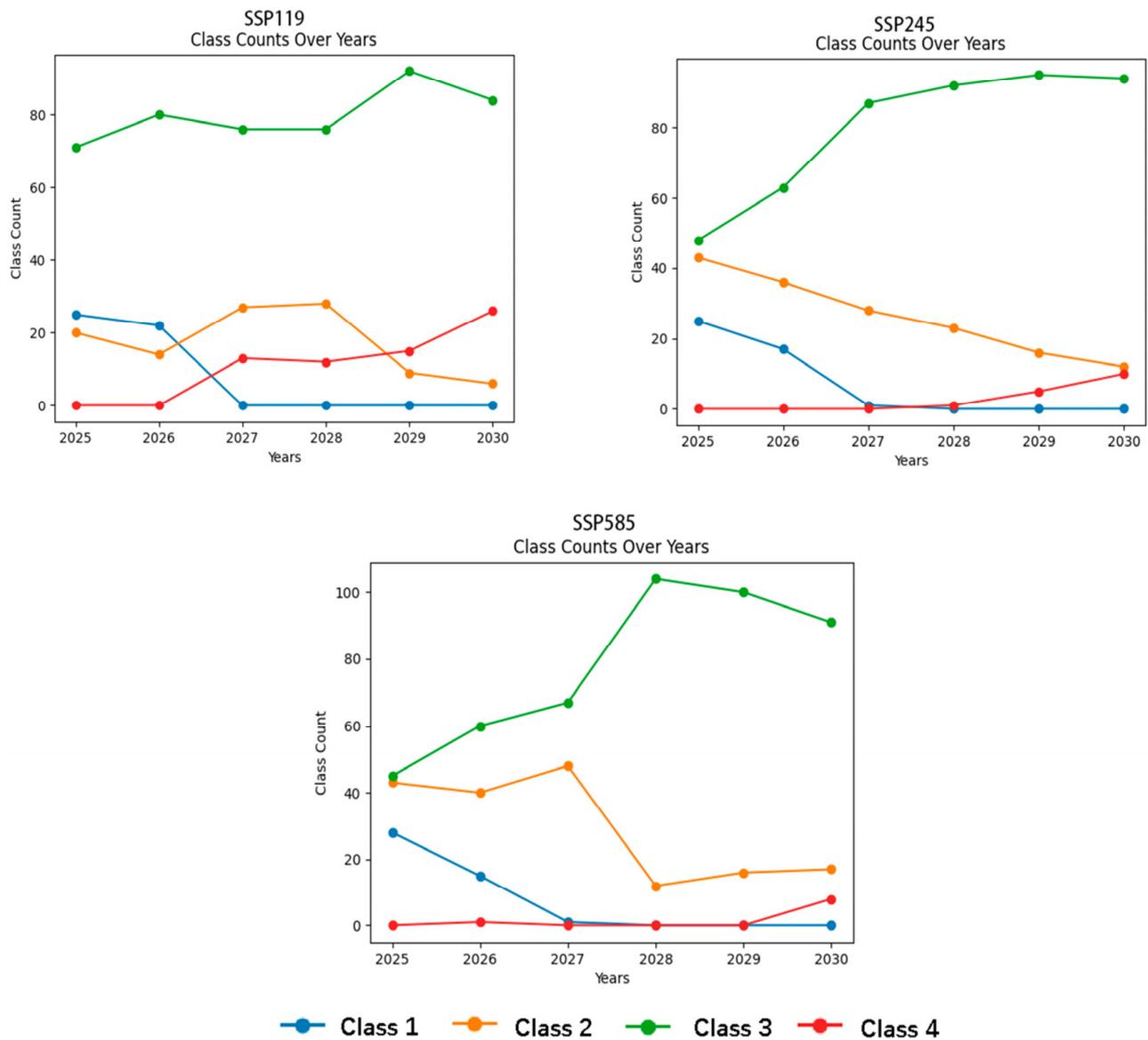


Figure 8. The temporal variation characteristics of NPP in Shanxi Province from 2025 to 2030.

5. Natural Factor Analysis

5.1. Correlation Analysis of Natural Factors

Previous studies [18–20] have shown that terrain factors such as elevation and slope, as well as climate factors such as temperature and precipitation, are closely related to vegetation growth. Apart from influencing temperature and precipitation patterns, elevation and slope also have an impact on soil properties, such as nutrient content and soil depth. Steeper slopes may cause more severe soil erosion, potentially affecting nutrient availability and limiting vegetation growth in high-slope areas, leading to variations in NPP. Moreover, terrain significantly influences the redistribution of precipitation in mountainous regions, resulting in spatially heterogeneous patterns of water availability for vegetation.

5.1.1. Impact of DEM and Slope

For this study, DEM data with a 50 m interval and slope data with a 2° interval were analyzed to investigate the performance of NPP under variations in elevation and slope, and the standard deviation was used to indicate the magnitude of these changes (Figure 9).

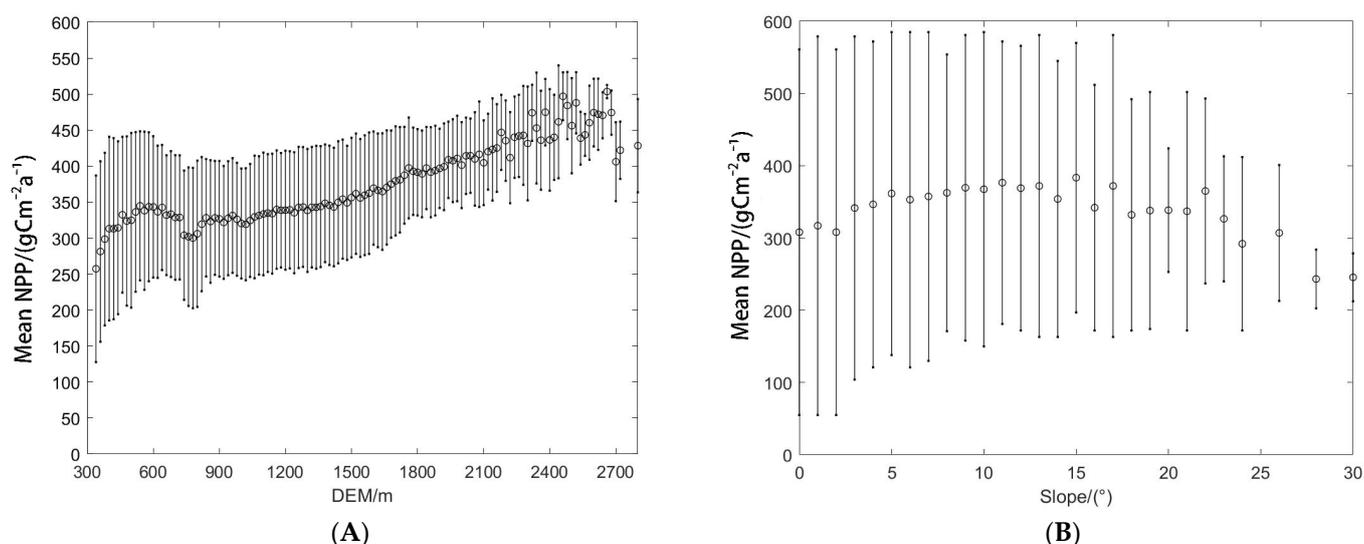


Figure 9. The relationship between NPP and both elevation (A) and slope (B).

As observed from Figure 9A, NPP shows an increasing trend within the elevation interval of 300–600 m, with a correlation coefficient of 0.906. For every 100 m increase in elevation, NPP increases by $316.72 \text{ gCm}^{-2}\text{a}^{-1}$. NPP exhibits a decreasing trend within the elevation interval of 600–780 m, with a correlation coefficient of 0.914. For every 100 m increase in elevation, NPP decreases by $321.52 \text{ gCm}^{-2}\text{a}^{-1}$. NPP shows a gradual increase within the elevation interval of 800–2160 m, with a correlation coefficient of 0.975. For every 100 m increase in elevation, NPP increases by $362.88 \text{ gCm}^{-2}\text{a}^{-1}$. Beyond 2160 m, elevation exhibits a fluctuating trend with a correlation coefficient of 0.062. It should be noted that, when the altitude exceeds 2000 m, terrain significantly influences precipitation redistribution [21], and, thus, it is not considered further. The standard deviation also follows a pattern of increase–decrease–slow increase with the variation in DEM.

Figure 9B shows that NPP initially increases and then decreases within the slope range of $0\text{--}2^\circ$, and the standard deviation follows a similar trend of initially increasing and then decreasing. In the slope interval $2\text{--}11^\circ$, NPP shows a gradual increase, and the standard deviation exhibits a pattern of increase–decrease–increase. There is a fluctuating decreasing trend in NPP within the slope interval of $11\text{--}30^\circ$, and the standard deviation also demonstrates a similar fluctuating decreasing trend.

5.1.2. Impact of Precipitation and Temperature

In Figure 10A, the partial correlation coefficient between vegetation NPP and annual precipitation in Shanxi Province during 2001–2020 ranges from -0.47 to 0.73 , with a mean of 0.06 . The proportion of NPP positively correlated with annual precipitation is 53.66% . Among them, the proportion of significantly positive correlation (correlation coefficient > 0.5) is 1.3% , primarily found in Tiantan County and Guangling County of Datong City, Lingchuan County and Yangcheng County of Jincheng City, Pingshun County of Changzhi City, etc. The proportion of negatively correlated NPP was 46.34% , suggesting an overall positive correlation between vegetation NPP and precipitation.

Figure 10B illustrates that the partial correlation coefficient between vegetation NPP and annual mean temperature in Shanxi Province during 2001–2020 varied between -0.86 and 0.84 having an average of 0.21 . The proportion of NPP positively correlated with annual mean temperature was 90.26% . Within this subset, the percentage of statistically significant positive correlation was 0.82% , predominantly in Pingshun County and Huguan County of Changzhi City, Jingle County of Xinzhou City, etc. The percentage of NPP that showed negative correlation was 9.74% , among which the proportion of significantly negative correlation was 0.38% . The proportion of NPP and annual mean temperature that

yielded statistically significant results ($p < 0.05$) was 6.79%. Hence, a positive correlation exists between NPP and annual mean temperature.

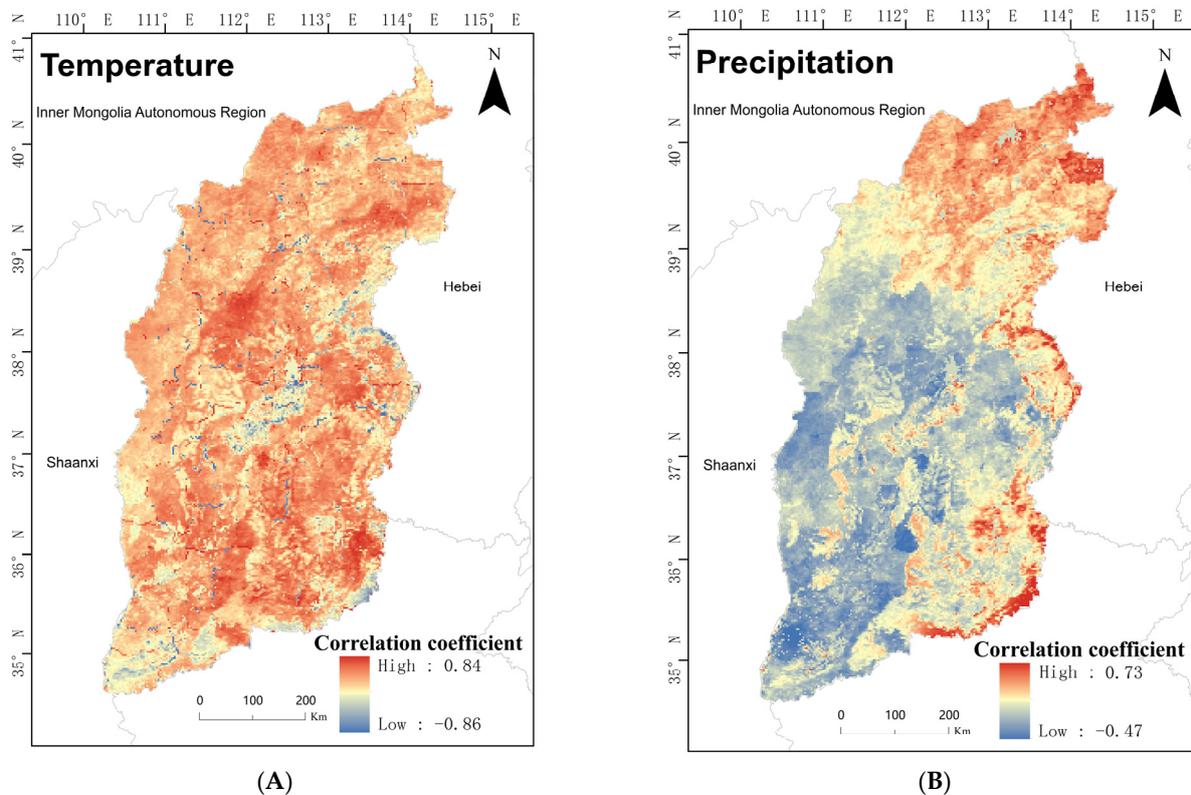


Figure 10. Correlation coefficient between NPP and annual precipitation (A) and temperature (B).

5.2. Geodetector Analysis

In order to further reveal the relationship between NPP and natural factors, as well as their impact on NPP, geodetector analysis was conducted in this study to analyze the factors of elevation, slope, precipitation, and annual mean temperature, as well as their interactions. Table 3 below presents the results of the geodetector analysis.

Table 3. Geographical detection results of NPP natural factors and interaction in Shanxi Province.

Factors	DEM/m	Slope/(°)	Rain/mm	Temperature/(°C)
DEM/m	0.0763	—	—	—
Slope/(°)	0.1296 *	0.0762	—	—
Rain/mm	0.4233 *	0.3312 #	0.2623	—
Temperature/(°C)	0.3394 *	0.2257 *	0.3892 *	0.1124

Note: “#” indicates a significant two-factor enhancement of interaction, “*” indicates a significant nonlinear enhancement of interaction, and “—” represents no data available.

Factor geographical detection results show that precipitation has the highest contribution rate (0.2623) to NPP in Shanxi Province, followed by temperature (0.1124), elevation (0.0763), and slope (0.0762). Therefore, climate factors, especially precipitation, are the main influencing factors on NPP, with precipitation contributing significantly more than temperature. The contribution rates of terrain factors are relatively smaller, with elevation and slope contributing approximately equally.

The interaction results reveal that the contribution rates of slope \cap elevation, precipitation \cap elevation, temperature \cap elevation, temperature \cap slope, and temperature \cap precipitation are higher than the maximum contribution rate of individual factors, indicating enhanced effects due to the interaction of two factors. The contribution rate of

precipitation \cap slope is greater than the sum of the individual factors, indicating non-linear enhancement.

Among the interactions, precipitation \cap elevation has the highest contribution rate, possibly due to the influence of terrain on the redistribution of climate factors. This is followed by precipitation \cap temperature and elevation \cap temperature. The interaction between rainfall and elevation suggests that lower-altitude areas may benefit from higher rainfall, promoting plant growth and increasing NPP. However, in higher-altitude regions, the influence of topography may result in localized rainfall variations and uneven distribution, leading to lower rainfall levels, which restrict plant growth and NPP levels. The interaction between rainfall and temperature is characterized by adequate rainfall providing the required water for plants, while temperature influences water evaporation and plant transpiration. Suitable levels of rainfall and temperature are favorable for plant growth and photosynthesis.

Overall, the results of the factor detection analysis demonstrate the importance of climate factors, particularly precipitation, in shaping NPP in Shanxi Province. The interactions between factors further enhance their impact on NPP, highlighting the complex and intertwined nature of the factors influencing vegetation growth.

6. Conclusions

The aim of this study is to comprehensively understand the historical changes and future development trends in NPP in Shanxi Province, and to reveal its associations with natural environmental factors, providing scientific support for ecosystem management, environmental protection, and sustainable development. Based on the MOD17A3 dataset, this study analyzes the spatiotemporal variations in NPP in Shanxi Province. We utilized the Theil–Sen median trend analysis and Mann–Kendall test. Additionally, the Hurst exponent and GWO–SVM model were used to estimate future NPP, and the geographic detector was applied to explore the correlation between NPP and natural factors. The resulting conclusions are as follows:

- I. In terms of temporal characteristics, NPP in Shanxi Province exhibited an overall fluctuating increasing trend from 2001 to 2020, with a mean value of $206.54 \text{ gCm}^{-2}\text{a}^{-1}$. The highest NPP value was recorded in 2018, reaching $250.36 \text{ gCm}^{-2}\text{a}^{-1}$. The overall trend indicated a rapid increase in NPP. Significant spatial heterogeneity was observed, with considerable fluctuations in NPP both spatially and interannually. The average variability rate of NPP in the region was 32.42%, with a maximum value of 253.74%. More than 57.54% of the area exhibited a variability rate exceeding 30%. In terms of spatial characteristics, NPP exhibited lower values in the northwest and higher values in the southeast of the province. Therefore, in future water resource management, particular attention should be given to water resource conservation and rational utilization in the southeastern region, to support its increasing NPP demand;
- II. Future changes in NPP are expected to exhibit a strong persistence of growth. The average Hurst exponent was 0.86, indicating a high degree of persistence. Regions characterized by strong persistent growth accounted for 80.25% of the total, with 7.15% displaying a significantly strong persistent growth and 8.14% exhibiting a moderately strong persistent growth. Regions with a reverse persistence accounted for only 0.26%. These findings suggest that the ecological environment in Shanxi Province will continue to improve, and the future changes in NPP will demonstrate a significant persistence and an increasing trend. Shanxi Province should focus on the protection of the ecological environment, especially in areas where NPP shows a sustained increasing trend, to ensure the health and stability of the ecosystem;
- III. Under the three future scenarios of CMIP6, the total NPP in Shanxi Province is projected to experience rapid growth, with the growth rate ranking as $\text{SSP119} > \text{SSP245} > \text{SSP585}$, in line with the assumptions of the scenario models. The number of regions classified as the fourth and fifth levels gradually increased, while the number of regions classified as the second and first levels decreased progressively;

IV. NPP in Shanxi Province showed a trend of increasing–decreasing–slowly increasing with changing elevation, while it exhibited a decreasing trend with changing slope. NPP demonstrated a positive correlation with both precipitation and temperature. According to the results of the geographic detector analysis, precipitation contributed the most to the variation in NPP in Shanxi Province, followed by temperature. Among the interactions, the interaction between precipitation and elevation had the highest contribution, followed by the interaction between precipitation and temperature. The contribution of any two-factor interactions exceeded that of single-factor contributions.

In conclusion, this study provides insights into the spatiotemporal dynamics of NPP in Shanxi Province. The results highlight the significant contribution of precipitation and temperature to NPP variations and emphasize the importance of considering the interactions between factors. The findings also suggest a positive outlook for the future ecological environment in Shanxi Province, characterized by strong persistent growth in NPP. These findings contribute to our understanding of the relationships between NPP and natural factors, laying a foundation for sustainable ecological management and decision-making in the region. However, there are some limitations in this study. Due to factors such as cloud cover, atmospheric disturbances, and sensor drift, the MOD17A3 dataset may have certain uncertainties and errors. In future research, we intend to incorporate more data sources to improve the accuracy and reliability of NPP estimation. Additionally, when predicting future NPP changes, we used three scenarios from the CMIP6 project, namely SSP119, SSP245, and SSP585. However, future climate change may be even more complex and uncertain. In future studies, it is important to consider more scenarios and uncertainties.

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