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Spatial-Temporal Pattern of Vegetation Net Primary Productivity and Its Natural Driving Factors in Ordos Section of the Yellow River Basin

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Abstract: Weather change has a great impact on vegetation growth restoration and ecosystem service function, resulting in significant changes in vegetation net primary productivity (NPP). Therefore, based on MOD17A3 NPP data and meteorological data, this study used the slope of a one-dimensional linear regression equation, Spearman correlation analysis method, and geographical detector model to reveal the spatial and temporal evolution characteristics of NPP in the Ordos section of the Yellow River Basin from 2000 to 2021 and the impact of weather change on NPP. Results: (1) NPP increased from 25.4 gC/m^2 in 2000 to 60.3 gC/m^2 in 2021. The NPP of vegetation in the northeastern and southern parts of the study area showed a significant increasing trend. (2) From 2000 to 2021, the evaporation showed a fluctuating downward trend, and the relative humidity, temperature, wind speed, surface temperature, and precipitation showed a fluctuating upward trend. (3) Evaporation is the most important factor hindering the growth of NPP. Precipitation, wind speed, and temperature played an important role in promoting NPP, and the average correlation coefficients were 0.62, 0.33, and 0.15, respectively. Relative humidity and surface temperature can promote NPP, but the effect is not significant. (4) The interaction results showed that the combination of temperature and precipitation, wind speed and precipitation, wind speed and temperature, precipitation and evaporation, and precipitation and relative humidity could effectively improve NPP. The interaction of climatic factors has a significant effect on the change of NPP in the Ordos section of the Yellow River Basin. The results provide a strong reference for ecological protection and restoration, the realization of dual carbon goals, and sustainable development in the Yellow River Basin.

Keywords: yellow river basin; vegetation net primary productivity; spatio-temporal pattern; climatic change; interaction

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1. Introduction

NPP is the total amount of organic matter produced by green plants through photosynthesis in a given time and area, and when subtracted from their autotrophic respiratory depletion, the mass of dry matter remains [1–3]. This concept not only reflects the productive capacity of vegetation in the natural environment, but is also a key parameter of terrestrial ecosystems and the surface carbon cycle [4,5]. NPP can directly characterize the productive capacity of vegetation communities under natural environmental conditions and estimate carbon sources and sinks in terrestrial ecosystems, describing the carbon cycle and energy flow [6–8]. Therefore, the NPP is not only the basis for studying the response of global terrestrial ecosystems to weather change [9], but also an important indicator for assessing vegetation growth and ecosystem quality. Determining the dominance of various weather factors and quantifying the effects of weather factor NPP are essential to exploring whether changes in NPP will feedback on regional weather through processes such as the carbon cycle [10,11]. Although relevant research results are available, there are few studies on the combined effects of multiple weather factors on NPP. Therefore, it is important to clarify the impact of weather change on NPP to accurately assess the future trend of the regional carbon cycle, as well as regional ecological protection and sustainable development [12,13].

In previous studies, the research methods of NPP include field surveys, biomass measurement [14], CASA model [15], Century model [16], and so on. The biomass measurement method is destructive to vegetation and there are great differences in biomass estimated. The Century model is complex and requires a large number of input parameters, and the uncertainty of the model is high. The CASA model is the Carnegie-Ames-Stanford Approach model, which is an ecosystem model. It is mainly used to estimate the NPP of terrestrial ecosystems. The model combines the two key factors of light energy utilization and photosynthetically active radiation absorbed by vegetation, and comprehensively considers the physiological and ecological characteristics of plants (such as photosynthetic capacity) and environmental factors (such as temperature and water conditions), in order to simulate the temporal and spatial dynamic changes of vegetation productivity. It is widely used in many fields such as global or regional ecosystem research. For example, Bao et al. [17] modeled the NPP of terrestrial ecosystems in the semi-arid weather of the Mongolian Plateau using the Land Surface Water Index (LSWI)-based CASA ecosystem model. Liu et al. [18] The above LSWI is a vegetation index based on remote sensing data, which can reflect the water content of the vegetation canopy by calculating the reflectivity of the near-infrared band and short-wave infrared band. Estimated NPP of forests by modified CASA models and remotely sensed data, with promising results. Therefore, this study combines field sampling and the CASA model to improve the accuracy of data. In recent years, with the continuous development of remote sensing technology, the wide application of NPP remote sensing data provides a key tool for scientific research and practical production [19,20], and significantly improves the efficiency of the study of large-scale interannual changes. For example, Liu et al. [21] estimated NPP using a modified MOD17A3 model in the three-river headwaters region. The data are reliable and the results are good. MOD17A3 is a medium-resolution imaging spectrometer (MODIS) carried by the Terra satellite of the National Aeronautics and Space Administration (NASA) to provide annual NPP information on a global scale with a spatial resolution of 250 m. The MODIS satellite has been running since the early 2000s, and MOD17A3 data usually cover the period from 2000 to the present. The research on the influencing factors of NPP mainly lies in the influence of temperature and precipitation on NPP [22–24]. In view of this, the data of NPP estimated based on field investigation and the CASA model are reliable and accurate.

Ordos is located in the arms of the Yellow River. Geographically, it is located in the Yellow River Basin. Moreover, the Yellow River provides water resources for agricultural irrigation in the Ordos region, and it is also interrelated in the ecosystem. The changes in its ecological environment will have a corresponding impact on the ecology of the Yellow River Basin. The weather in the Ordos section of the Yellow River Basin changes rapidly, and the vegetation has difficulty adapting in a short period of time, and the growth is cyclical and stable. However, the uncertainty of weather changes may disrupt the balance, resulting in a disorder of growth rhythm and instability of NPP [25]. At present, research on the impact of weather change on NPP pays more attention to the impact of precipitation and temperature on NPP, but it is not possible to consider other climatic factors or whether the interaction between climatic factors has an impact on NPP. Therefore, based on the CASA model, this study calculated the regional-scale NPP of the Ordos section of the Yellow River Basin from 2000 to 2021. In order to ensure the accuracy of the model simulation, the existing data of MOD17A3 were collected and compared with the calculation results of this study, and the fitting results were better. On this basis, the effects of the interaction of six climatic factors, such as evaporation, relative humidity, temperature, wind speed, surface temperature, and precipitation, on vegetation NPP were quantitatively evaluated. The purpose of this study is to evaluate the health and stability of the ecosystem in the Yellow River Basin, detect the degree to which NPP is affected by weather change in real-time, provide a basis for regional ecological protection and restoration measures, and support the sustainable development planning of the Yellow River Basin.

Although the research time for detecting climate change from 2000 to 2021 is short, it still has very important research significance. First of all, in recent decades, the speed of climate change has accelerated significantly. During the period from 2000 to 2021, the climate system has produced more significant signals of change. For example, the global average temperature continues to rise during this period, and the frequency and intensity of extreme weather events such as rainstorms, high-temperature heat waves, and strong typhoons have changed significantly. These significant changes are enough to be detected in a relatively short period of time and provide strong evidence for the study of climate change. Secondly, with the rapid development of science and technology, meteorological observation technology and data collection methods have been greatly improved in the 21st century. Advanced data analysis methods and models can more effectively extract the characteristics and laws of climate change from limited-time data. Even if the research time span is relatively short, valuable conclusions can be obtained. Finally, 2000–2021 is a period of rapid urbanization, industrialization, or other major human activities, which may lead to more dramatic and unique changes in climate change and meteorological elements in the region. In this case, the study of this time period can more accurately capture the characteristics and driving factors of regional climate change and provide targeted recommendations for regional sustainable development and environmental governance.

2. Materials and Methods

2.1. Overview of the Study Area

The Ordos section of the Yellow River Basin is located in the semi-arid area of Northwest China, the average temperature of the coldest month in this area is lower than -3 °C or below 0 °C, and the annual precipitation distribution is relatively uniform, and the precipitation in the driest month in summer is less than 1/3 of the precipitation in the wettest month in winter. It belongs to the typical north temperate continental weather, which belongs to the typical northern temperate continental weather. With a total area of 87,000 km^2, the Ordos section of the Yellow River Basin is a city with seven banners and two districts. This is neighboring Shaanxi, Ningxia Hui Autonomous Region, and Shaanxi in the east, west, and south, and Bayannur and Baotou in the north across the Yellow River (Figure 1). Drought is a common climate problem in the Yellow River Basin. The average annual precipitation is between 190 mm and 300 mm. The lack of precipitation leads to a lack of soil moisture, which limits the growth metabolism and photosynthesis of vegetation, and then reduces the NPP [26,27]. The average annual temperature is between 6 °C and 8 °C, and the extreme temperature ranges from -35 °C to 40 °C, with the lowest temperature in January and the highest temperature in July. Persistent high temperatures may lead to extreme weather events such as drought, aggravate the negative impact on vegetation NPP, accelerate soil moisture evaporation, and restrict vegetation growth. The frequency and intensity of extreme climate events caused by climate change are increasing, which brings greater survival pressure to vegetation [28–30] and puts vegetation NPP at greater risk [29,31,32] (Figure 2).

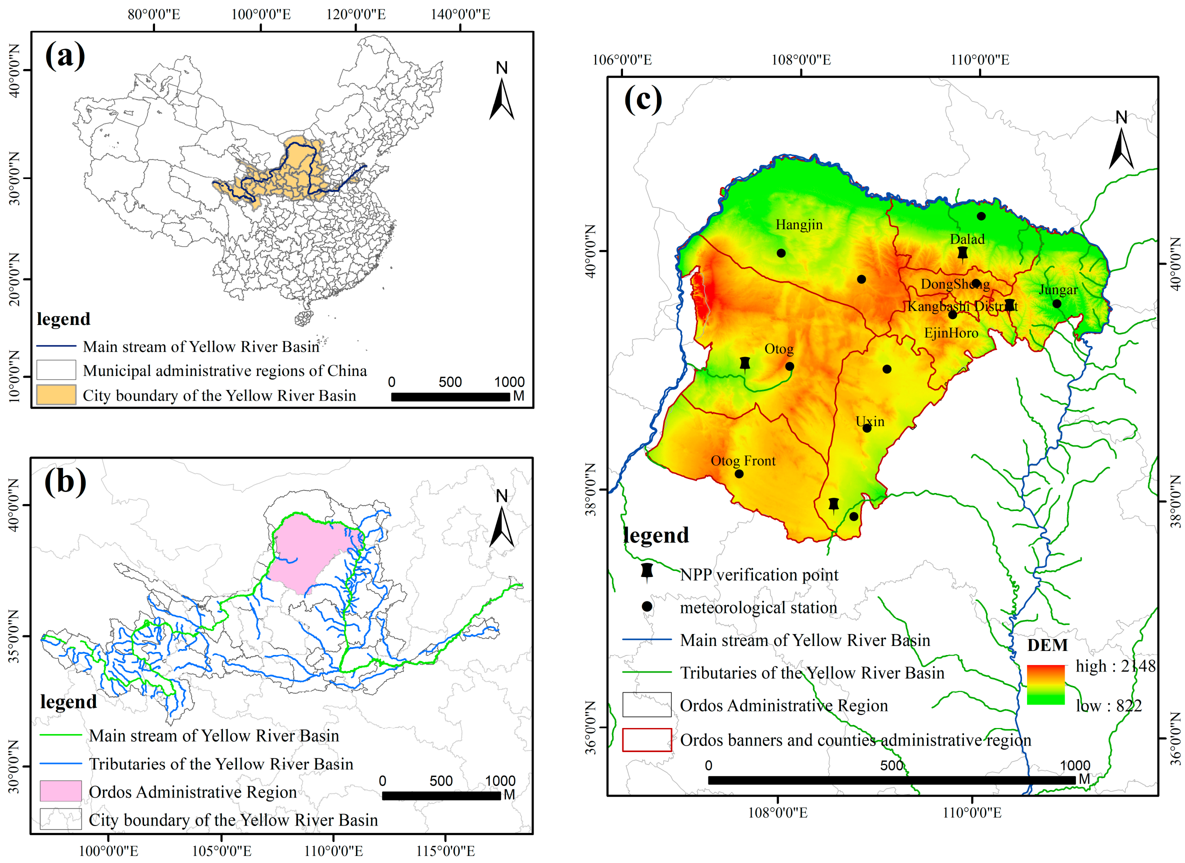


Figure 1. Overview of the study area: (**a**) map of China; (**b**) the indicator map of the Yellow River Basin; (**c**) the Ordos section of the Yellow River Basin, meteorological stations, and field monitoring points.

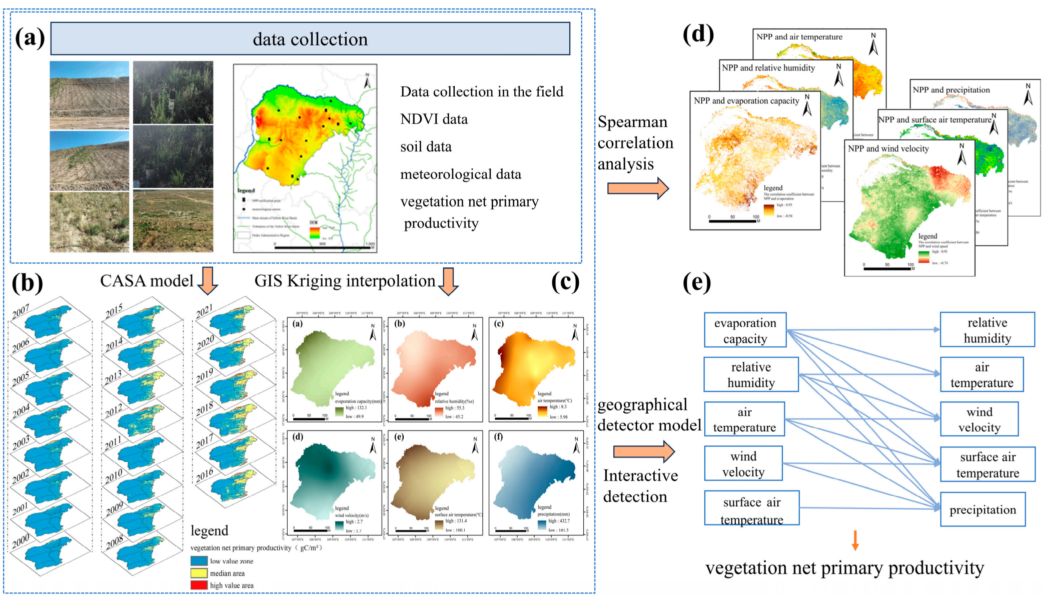


Figure 2. Studies the technical process. (**a**) Data collection; (**b**) temporal and spatial distribution of NPP; (**c**) multi-year average of various meteorological factors from 2000 to 2021; (**d**) correlation coefficient between various meteorological factors and NPP; (**e**) the interaction of various meteorological factors on NPP.

2.2. Data Sources

Based on the annual average meteorological data (evaporation, relative humidity, temperature, wind speed, surface temperature, and precipitation) of 11 meteorological stations in Ordos from 2000 to 2021, the Kriging interpolation method in ArcGIS10.8 was used to interpolate and analyze the station data, and obtain a long time series data set. NDVI data are obtained from quadrats. In order to improve the reliability and availability of data, the field monitoring data are compared with the NDVI data downloaded from the National Aeronautics and Space Administration (NASA) data center from 2000 to 2021, and the comparison results are good. The soil water content data were sampled at a depth of 0–20 cm at the sampling point in June 2019, July 2020, and August 2021, and the sampling was completed twice a year. The collected soil samples were placed in an aluminum box with a known weight, and the total weight of the aluminum box and the wet soil was recorded. After drying at 105–110 °C to constant weight, the dried soil sample was taken out and weighed after cooling in the dryer. The weight of the aluminum box and the dry soil was recorded, and the soil water content was calculated. The quadrat of vegetation coverage is 1 m × 1 m, and the time resolution is 3 months. The NPP data were downloaded from the NASA data center with a data accuracy of 250 m. The spatial resolution of the data was adjusted to 250 m by the resampling tool in GIS for data with different spatial resolutions (Table 1).

Table 1. Data source.

Data Type	Spatial Resolution	Format
NDVI data	250 m	Tif
meteorological data	monitoring stations (11 different)	Txt
Vegetation coverage quadrat data	sample points	shpfile
Soil water content data	sample points	shpfile
DEM data	30 m	Tif
NPP	250 m	Tif

2.3. NPP Estimate Method

The CASA model is widely used in the study of large-scale NPP and the global carbon cycle. The CASA model estimates the NPP by calculating the photosynthetically active radiation (APAR) and light energy utilization rate (ε) absorbed by vegetation. APAR represents the uptake of photosynthetically active fraction of solar radiation by vegetation, and ε is mainly affected by temperature and humidity. In a certain range, the increase in temperature can accelerate the activity of enzymes in photosynthesis, so that the dark reaction of photosynthesis can be carried out more efficiently, which is helpful to improve the utilization rate of light energy. Humidity mainly affects the utilization of light energy by affecting the opening and closing of pores. The model combines remote sensing data, meteorological data, and vegetation-type information to realize the spatial and temporal dynamic simulation of NPP, which provides an important tool for global change research. The specific formula is as follows:

$$\mathrm{NPP}\ (x, t) = \mathrm{APAR}\ (x, t) \times \varepsilon\ (x, t) \tag{1}$$

$$\mathrm{APAR}\ (x, t) = \mathrm{SOL}\ (x, t) \times \mathrm{FPAR}\ (x, t) \times 0.5 \tag{2}$$

$$\varepsilon(x, t) = T_1 \times T_2 \times W \times \varepsilon_{max} \tag{3}$$

In the formula: SOL (x, t) represents the total solar radiation in month t at pixel x [MJ/(m^2·month)]; FPAR (x, t) is the ratio of effective photosynthetic radiation absorbed by vegetation at pixel x in t month; 0.5 is the photosynthetically active radiation (PARE) that accounts for about half of the total solar radiation; APAR (x, t) is expressed as the amount of photosynthetically active radiation absorbed by the vegetation at location x in month t [MJ/(m^2·month)]; ε (x, t) is light utilization efficiency; T_1 and T_2 are the influence coefficients of low-temperature and high-temperature stress, respectively; W denotes the influence coefficient of water stress; and ε_{max} is the maximum light energy utilization rate (%) in the ideal state.

2.4. Slope Trend Analysis

The interannual significant change trend of vegetation NPP was evaluated by the slope of the linear regression equation (Slope). The trend of change is determined by the slope of the data sequence. If the slope is greater than 0, it indicates an increasing trend of NPP during the study period; otherwise, it decreases. This paper adopts the natural break method to divide the slope into three levels: significantly decreased (slope ≤ -5), no significant change (-5 < slope < 5), and significantly increased (slope ≥ 5). The specific formula is as follows:

$$NPP_{slope} = \frac{\mathrm{n}\sum_{i=1}^{n}\ (i \cdot NPP_i) - \sum_{i=1}^{n} NPP_i \sum_{i=1}^{n} i}{n \cdot \sum_{i=1}^{n} i^2 - \left(\sum_{i=1}^{n} i\right)^2} \quad (4)$$

In the formula: n represents the number of research years; *NPP_i* represents the NPP value in the i-th year; and slope represents the interannual change trend of NPP.

2.5. Spearman Correlation Analysis Method

The relationship between meteorological factors and NPP can be explored through correlation analysis. This paper selects evaporation, relative humidity, air temperature, wind speed, surface air temperature, and precipitation as six meteorological factors to calculate their Spearman correlation coefficient with NPP.

$$R_{xy} = \frac{\sum_{i=1}^{n}\ (x_i - \overline{x})\ (y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}\ (x_i - \overline{x})^2}\sqrt{\sum_{i=1}^{n}\ (y_i - \overline{y})^2}} \quad (5)$$

In the formula: *R_xy* is the correlation coefficient between NPP and various climatic factors; *x_i* is the annual NPP value of vegetation in the i-th year; *y_i* is the value of the climatic factor in the i-th year; $\overline{x}$ and $\overline{y}$ represent the mean values of the factors, respectively; and n is the number of samples.

2.6. Geographical Detector

Geodetector is a statistical method used to detect spatial heterogeneity and reveal the driving force behind it. It includes a variety of detectors. Among them, the factor detector can detect the spatial variability of the variable Y and the explanatory power of the independent variable X; the interaction detector is used to evaluate the degree of interaction between two or more independent variables on the dependent variable and to determine whether the relationship is enhanced, weakened, or independent. The model is widely used in many fields such as geography and ecology, and can effectively analyze the complex causal relationship behind geographical phenomena. The spatial differentiation is measured by the Geographical Detector q-value, which ranges from [0, 1]. The higher the q-value, the stronger the explanatory power of the factor on NPP, and vice versa. The interaction detector of the geographical explorer not only quantifies the interaction between influencing factors but also effectively avoids the problem of collinearity between factors. This paper adopts the interaction detector to explore the impact of various factors on the NPP of the Ordos section of the Yellow River Basin.

2.7. Koppen's Weather Classification Method

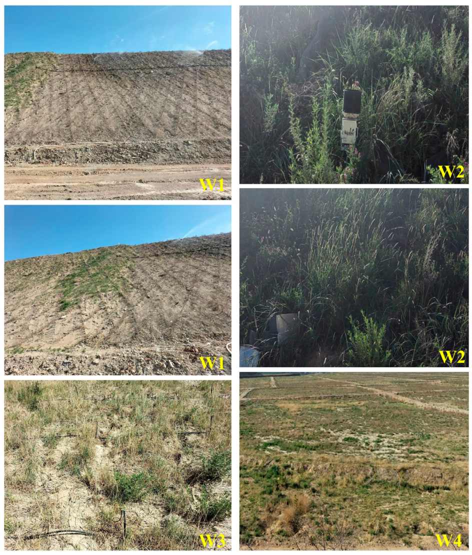
Köppen weather classification is a weather classification system founded by German climatologist Vladimir Peter Köppen. It takes temperature and precipitation as the main reference indexes, and divides the global weather into five categories: tropical weather, dry weather, temperate weather, continental weather, and polar weather. Each category can also be subdivided into different subcategories, such as tropical weather, tropical rainforest weather, tropical grassland weather, and so on. This classification method can intuitively reflect the climatic characteristics of different regions, and is widely used in many fields such as weather research and geography teaching.

3. Results and Analysis

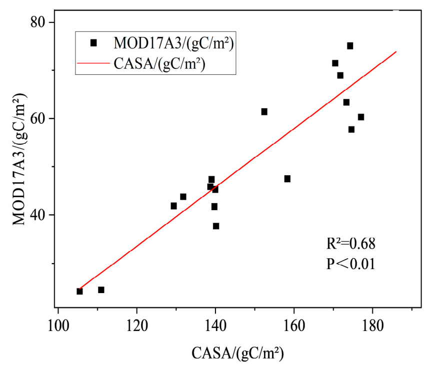
3.1. CASA Accuracy Verification

The NPP calculated based on the CASA model was compared with the collected MOD17A3 data. The results of the study showed that the calculated data were in good agreement with the data monitored in the field (R^2 = 0.68 p < 0.01). However, in the process of applying this model for research, continuous experiments, and monitoring are required based on a variety of different natural geographic environments and land use coverage. By continuously adjusting and correcting the model parameters based on the field experimental data, the aim is to improve the accuracy of the CASA model (Figure 3).

(a)



(b)



(c)

Sampling point code	Longitude (°)	Latitude(°)	Photo
W1	110.35	39.63	Sample plots of vegetation coverage
W2	109.83	40.06	Sample plots of vegetation coverage
W3	108.49	37.92	borrow point
W4	107.50	39.08	Close-to-nature restoration grassland

Figure 3. (**a**) Photos of field detection points; (**b**) linear fitting between the NPP data calculated by the CASA model and the downloaded MOD17A3 NPP data; (**c**) caption.

3.2. Vegetation NPP Spatio-Temporal Evolution Characteristics

Figure 4 shows that the NPP shows an overall fluctuating upward trend over time. Specifically, the average NPP in the whole area reached the lowest value of 24.13 gC/m^2 in 2001, and by 2018, this value had significantly increased to 82.44 gC/m^2. During the period from 2000 to 2011, the fluctuations in the average NPP were relatively small, but overall, there was still an increasing trend, with an increase of 13.74 gC/m^2. However, during the period from 2012 to 2021, the fluctuation of the average NPP in the whole region significantly increased, showing an "M-shaped" trend, that is, rising first, then falling, and then rising again. In this stage, the average NPP in the whole region decreased from 71.45 gC/m^2 in 2012 to 60.32 gC/m^2 in 2021. Overall, from 2000 to 2021, the average NPP in the whole region increased from 24.43 gC/m^2 to 60.32 gC/m^2, with a total increase of 35.89 gC/m^2.

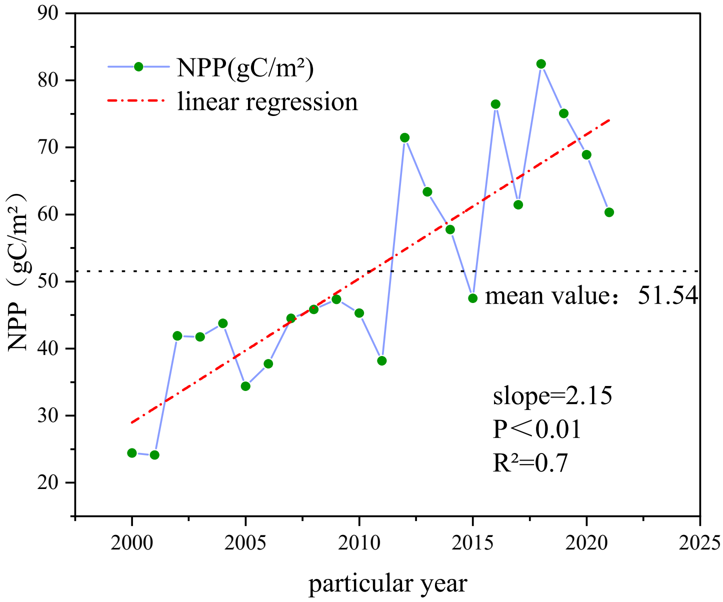


Figure 4. Temporal variation of NPP in the study area from 2000 to 2021.

Using the equal spacing method in ArcGIS10.8 software, the NPP is divided into three levels: low-value area (<100 gC/m^2), medium-value area (100–200 gC/m^2), and high-value area (>200 gC/m^2). Based on Figure 5, the distribution of NPP in the study area shows a trend where the low-value areas are greater than the median areas, and the median areas are greater than the high-value areas in terms of spatial scale. From 2000 to 2021, the area of the median and high-value zones significantly increased. Specifically, the area of the median zone increased from 1119.1 km^2 in 2000 to 14,412.6 km^2 in 2021, with the main areas of increase concentrated in Jungar, Ejin Horo, Uxin, Otog, and Otog Front; the area of the high-value zone also increased from 30.5 km^2 in 2000 to 1550.5 km^2 in 2021, with the main areas of increase in northern Dalad and southern Uxin. During the period from 2000 to 2001, except for northern Dalad, the other areas were all low-value zones. From 2002 to 2011, the low-value areas were upgraded to medium-value areas, mainly in Ejin Horo; from 2012 to 2021, the low-value areas in Jungar, Dongsheng, the southern part of Uxin, and the southeastern part of Otog were upgraded to medium-value areas. In addition, the low-value areas in the northern part of Dalad were upgraded to medium-value areas from 2000 to 2021, and the medium-value areas were further upgraded to high-value areas. The NPP in Ordos along the Yellow River increased gradually from west to east, with the areas of increase mainly concentrated in the internal part of Ordos along the Yellow River. The land use types are mainly cultivated land and grassland, including Jungar, Dalad, Uxin, and Otog. This indicates that during the study period, Ordos implemented effective ecological protection and restoration measures for the Yellow River Basin.

The changing trend of NPP is very important for ecosystem stability and the carbon cycle. If NPP shows a downward trend, it may indicate that the stability of the ecosystem is becoming worse. For example, in grassland ecosystems, a continuous decrease in NPP means poor vegetation growth and may lead to increased soil erosion. Because of the reduction of vegetation, the fixation of soil is weakened, which in turn affects the structure and function of the whole ecosystem. On the contrary, the increase in NPP may indicate the restoration or positive succession of the ecosystem. For instance, in a forest after a fire, the gradual increase in NPP means that the vegetation is growing again, and the service function of the ecosystem is gradually restored. Changes in NPP play a key role in the global carbon cycle. When NPP increases, vegetation absorbs more carbon dioxide, which helps mitigate global warming. For example, the NPP of tropical rainforests is very high, and its large absorption of carbon dioxide is of great significance for regulating the global climate. The decrease in NPP may mean that the ecosystem's ability to absorb carbon dioxide is reduced, which will have a negative impact on the global climate.

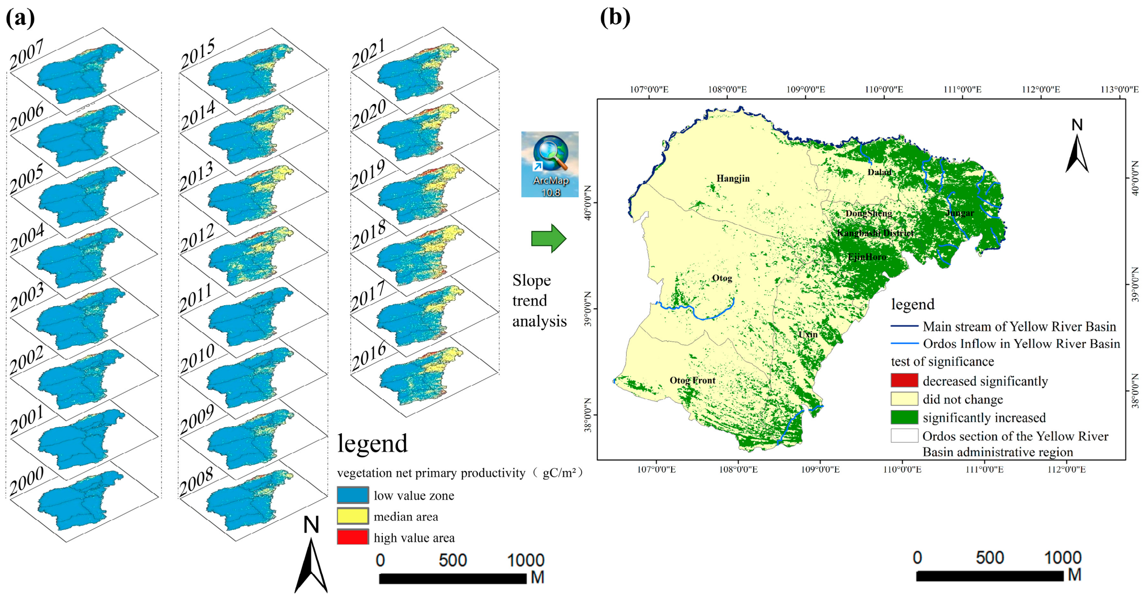


Figure 5. (**a**) The spatial and temporal distribution of NPP from 2000 to 2021; (**b**) the change trend of NPP from 2000 to 2021 obtained by slope trend analysis method.

The NPP in Ordos generally shows an upward trend. The areas with no change are mainly concentrated in Hangjin, Otog, Dalad South, and the western part of Otog Front, accounting for 76% of the total area of the study region. The climate in this region is relatively stable, and the precipitation has been maintained at a level that can only maintain the growth of existing vegetation, and there is no excess water to support the growth of vegetation. In addition, the west may not implement large-scale ecological restoration projects as the east, and the soil texture and nutrient content are still relatively poor. In addition, unreasonable land use methods such as overgrazing are still continuing, and vegetation is constantly destroyed. The growth and growth are in a dynamic balance, which limits the growth of vegetation and the improvement of productivity. Significant increases are mainly distributed across the entire regions of Jungar, Dalad, Ejin Horo, as well as some areas in front of Uxin and Otog, accounting for 23.99% of the total area of the study region. The increase in precipitation in this area is conducive to the growth of vegetation, and more precipitation can ensure that vegetation has a sufficient water supply during the growing season. In addition, a series of ecological protection projects have been implemented, such as afforestation, grass planting, and other vegetation restoration measures, which have increased the vegetation coverage area. In addition, in recent years, the control of land desertification and soil erosion has been strengthened, and the soil conditions have been improved, which provides a better environment for vegetation growth. The areas where the NPP in the study area has decreased can be ignored, which means that although there are some minor declines in some local areas, the overall impact on the ecosystem is relatively small, and these changes are within the natural fluctuation range.

3.3. Spatial and Temporal Variations in Weather Factors

According to the data in Figure 6, 2000–2021, the average temperature in Ordos increased from 6.3 °C in 2000 to 8.9 °C in 2021. The average precipitation generally increased, and the lowest value appeared in 2005, only 162.2 mm, and then showed a wave-like increase and large fluctuation. The lowest precipitation in 2005 may be due to the complex terrain of Ordos City. The western and northern parts are mostly plateaus and mountains. When water vapor is transported, the terrain such as mountains blocks and changes the direction of airflow, making it difficult for water vapor to effectively gather over Ordos City to form precipitation. The total evaporation decreased from 71.6 mm in 2000 to 109.9 mm in 2021. In 2003, the rapid decline of evaporation in Ordos City was due to the frequent dust weather in that year. When a dust storm occurs, a large number of dust particles are suspended in the air, and the dust particles will adsorb the water vapor in the air to a certain extent, which makes the air humidity increase relatively in the local range and is not conducive to the further evaporation of water. The average ground temperature is generally 'rise-fall-rise'; the highest and lowest values appeared in 2006 and 2012, respectively, at 114 °C and 101.7 °C. The lowest average temperature in 2006 was affected by the Mongolian cyclone on the ground, the eastward movement of the high-altitude deep trough, and the southward movement of the strong cold air on the north road. There were rare gales, dust storms, snowfall, and cold wave weather in the Ordos area. The daily average temperature of 11 stations was >20 °C. In addition, the Inner Mongolia section of the Yellow River began to flow with ice on November 30, and the river was closed for the first time on December 4, which was significantly affected by cold air activities. The average wind speed generally decreases first and then increases, and the highest value appears in 2021, which is 2.6 m/s. The decrease in wind speed from 2000 to 2010 was due to the vigorous implementation of ecological projects such as returning farmland to forest and returning grazing to grassland in Ordos City, and the vegetation coverage rate increased year by year. Vegetation can reduce the near-surface wind speed and play a role in wind prevention and sand fixation. With the increase in vegetation coverage, the blocking and friction effects on the wind are enhanced, resulting in a decrease in wind speed. The increase in wind speed in 2011–2021 may be due to economic development, and the land use pattern in some areas of Ordos City has changed. For example, some original grassland or forest land may be developed into construction land or other land use types, which reduces the surface roughness and leads to an increase in wind speed. The average relative humidity is generally 'up-down-up', with the highest value of 56.7% in 2020. In 2013, Ordos City may have been controlled by the continental high pressure for a long time, and the downdraft was prevalent. The weather was sunny and less cloudy, which is not conducive to the accumulation and condensation of water vapor, and the downdraft will also increase the temperature and reduce the humidity of the air, resulting in a decrease in relative humidity.

From a spatial scale perspective, the evaporation amount gradually decreases from northwest to southeast; the relative humidity gradually decreases from south to northwest; the temperature gradually rises from south to north; the wind speed gradually increases from northwest to the central region and gradually decreases from the central region to the south; the surface temperature gradually rises from the central region to the northwest and southwest directions; and the precipitation gradually decreases from east to west (Figure 7).

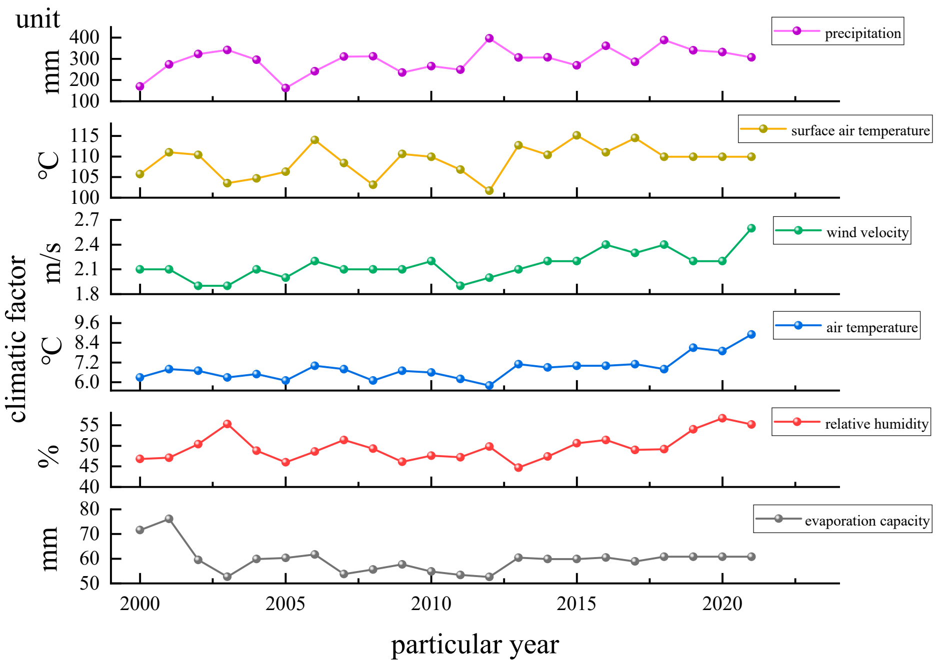


Figure 6. Temporal variation of meteorological factors from 2000 to 2021.

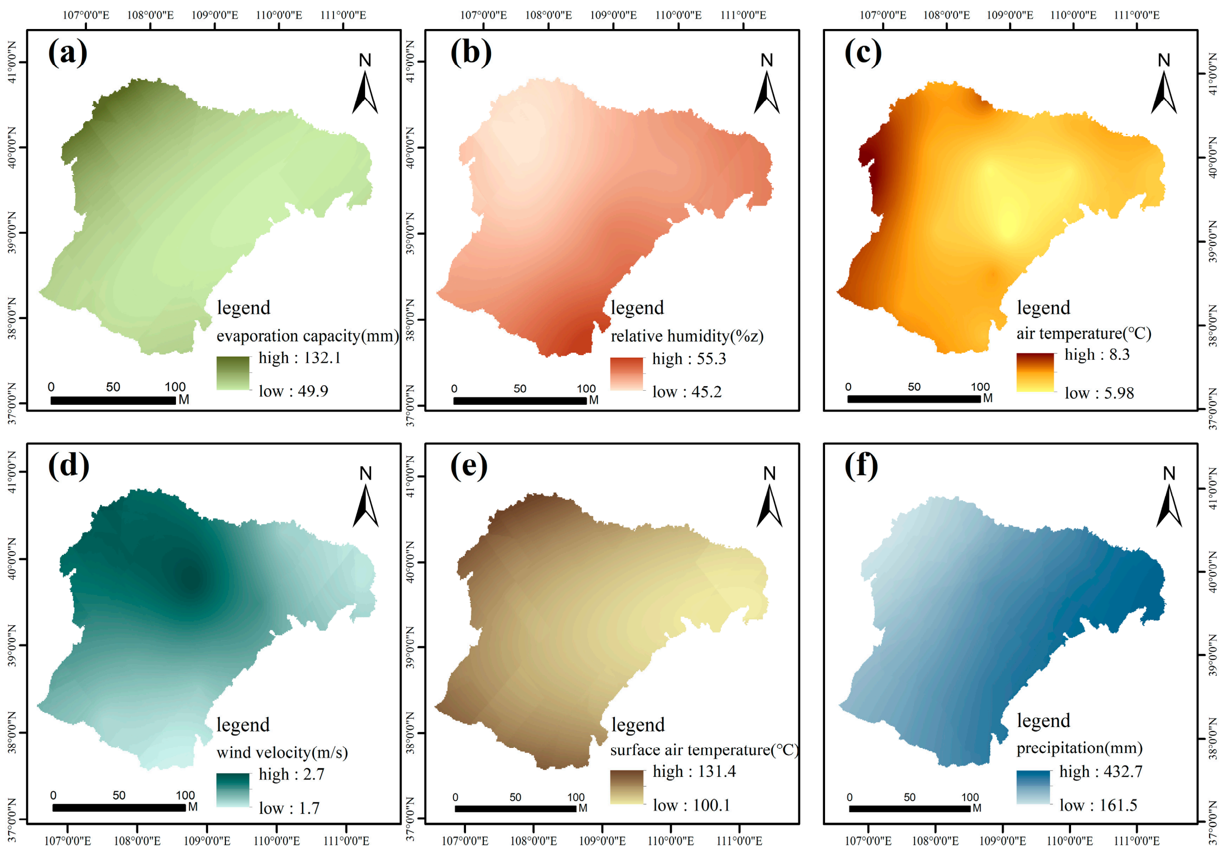


Figure 7. The multi-year average of meteorological factors from 2000 to 2021: (**a**) average evaporation for many years; (**b**) multi-year average relative humidity; (**c**) multi-year average temperature; (**d**) multi-year average wind speed; (**e**) multi-year average surface temperature; (**f**) average annual precipitation.

3.4. Influence of Climatic Factors on Vegetation NPP

In this study, six meteorological factors, such as evaporation, relative humidity, temperature, wind speed, surface temperature, and precipitation, were selected to evaluate their effects on the NPP in the Ordos section of the Yellow River Basin. Figures 8 and 9 show the effects of various climatic factors on NPP. The results showed that NPP was negatively correlated with evaporation, with a correlation coefficient of −0.31, and positively correlated with other meteorological factors, among which precipitation was the most significant, with a correlation coefficient of 0.76. From a spatial point of view, NPP, and evaporation were negatively correlated in 98.05% of the regional area; relative humidity was positively correlated with NPP in 59.37% of the western part of the study area, while it was not significantly negatively correlated in 40.63% of the eastern part of the study area. There was a positive correlation between air temperature and NPP in 72.01% of the northern and eastern parts of the study area. Wind speed was positively correlated with NPP in 91.9% of the area. The surface air temperature was positively correlated with NPP in 67.49% of the area, which was basically consistent with the distribution of air temperature. There was a significant positive correlation between precipitation and NPP in 99.31% of the area.

The above results indicate that there are significant differences in the effects of different meteorological factors on NPP, with precipitation and air temperature being the main positive drivers and evapotranspiration being a major negative influence. These findings are important for understanding regional ecosystem functions and developing corresponding ecological protection measures.

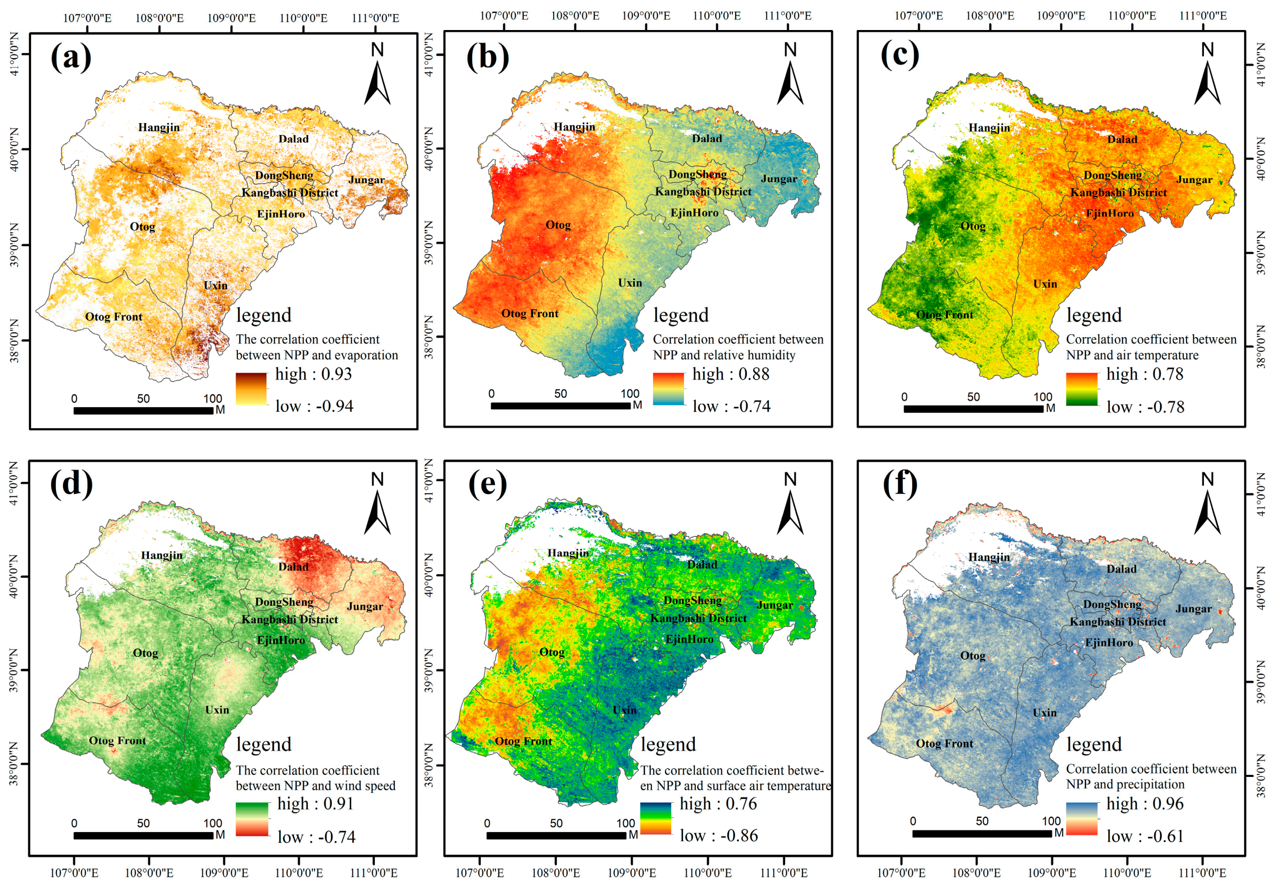


Figure 8. (**a**) The correlation coefficient between NPP and evaporation; (**b**) the correlation coefficient between NPP and relative humidity; (**c**) the correlation coefficient between NPP and temperature; (**d**) the correlation coefficient between NPP and wind speed; (**e**) the correlation coefficient between NPP and surface air temperature; (**f**) the correlation coefficient between NPP and precipitation.

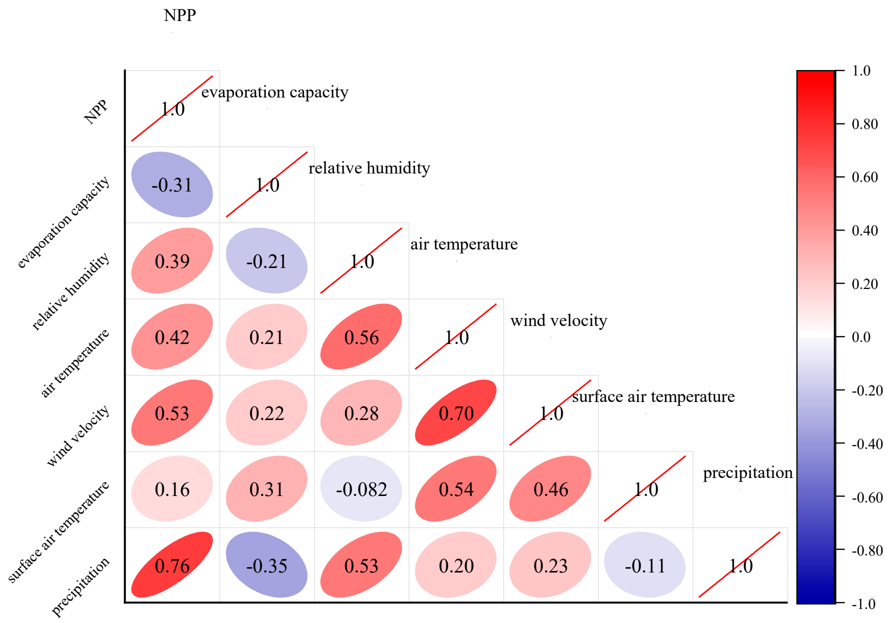


Figure 9. Correlation heat map between meteorological factors and NPP.

3.5. Two-Factor Influence Detection

The correlation between NPP and evaporation, relative humidity, air temperature, wind speed, surface air temperature, and precipitation was analyzed in the previous section. In order to further explore the driving factors of NPP, evaporation, relative humidity, air temperature, wind speed, surface air temperature, and precipitation were used as influencing factors for two-factor interactive detection by using the geographical detector model, and the driving factors of regional NPP were further analyzed.

Factor interaction detection shows that the explanatory power of the two-factor interaction on NPP is significant, and the main interaction types of various factors are mainly double-factor enhancement and nonlinear enhancement. Two-factor enhancement indicates that when two factors interact, the explanatory power of the dependent variable is stronger than the sum of the explanatory power of a single factor alone. Nonlinear enhancement means that after the interaction of two factors, the explanatory power of the dependent variable is not a simple additive or linear change relationship, but presents a complex and nonlinear enhancement effect. This nonlinear relationship may be exponential, logarithmic, or other complex functional relationships. The difference between the two is that the two-factor enhancement focuses on the combination of the two factors, and the explanatory power is stronger than the sum of the two factors alone; nonlinear enhancement emphasizes that the relationship between the two factors after interaction is a complex nonlinear form, not a simple linear combination.

Among them, the interaction between temperature and precipitation is the strongest, reaching 92%, indicating that the combination of temperature and precipitation plays a leading role in the increase in NPP. The influence of precipitation and wind speed, evaporation, relative humidity and surface temperature on NPP was second, and the explanatory power was more than 82% (Table 2). The influence of strong temperature on NPP is reduced when it interacts with relative humidity and evaporation. When the single factor with weak influence interacts with other factors, the influence on NPP increases significantly. For example, the influence of surface temperature on precipitation, wind speed, and other factors is much greater than that of a single factor.

In order to improve the pertinence and accuracy when studying the influence of meteorological factors on NPP, this study used partial correlation analysis to eliminate the influence of human disturbance on NPP. It can analyze the correlation between meteorological factors and NPP separately under the condition of controlling other variables (such as population density, land use change, and other human factor-related variables). For example, when calculating the partial correlation coefficient between vegetation net primary productivity and temperature, the related variables of human activity intensity are used as control variables, so as to eliminate the interference of human factors on the relationship between temperature and productivity.

Table 2. Influence factor interaction q-value.

Impact Factors	Evaporation Capacity	Relative Humidity	Air Temperature	Wind Velocity	Surface Air Temperature	Precipitation
evaporation capacity	0.35					
relative humidity	0.54 *	0.28				
air temperature	0.66 *	0.71 *	0.48			
wind velocity	0.80 *	0.92 #	0.84 *	0.49		
surface air temperature	0.60 *	0.67 #	0.58 *	0.82 *	0.29	
precipitation	0.83 *	0.83 *	0.92 *	0.87 *	0.82 *	0.67

Annotation: * is a two-factor enhancement, # is nonlinear enhancement.

4. Discussion

4.1. The Impact of Weather Change on NPP

From 2000 to 2021, the NPP in the Ordos section of the Yellow River Basin showed an overall upward trend, which was consistent with the results of Chen et al. [33]. Changes in NPP and Factor Detection in China's Yellow River Basin from 2000 to 2019. The area of NPP improvement is mainly in the eastern and southern parts of the study area, and the improvement area accounts for 23.99% of the total area. The results showed that the continuous improvement of the regional ecological environment, the significant effect of ecological protection measures, and the low evaporation and high precipitation had a positive impact on NPP. This is of great significance for future ecological protection and governance programs and sustainable development strategies.

The weather change has an important impact on NPP. In the past, the study of NPP in the Yellow River Basin focused on the influence of a single factor, and this study comprehensively considered the influence of weather factor interaction on NPP. It was found that evapotranspiration was significantly negatively correlated with NPP, and there was a significant positive relationship between precipitation and air temperature. This is consistent with the findings of Chen et al. [34] on the effect of weather change on NPP. Wind speed, surface air temperature, and relative humidity drive NPP, and the reasons for this result may be due to the following. Firstly, an appropriate wind speed is conducive to air circulation and the supplement of carbon dioxide, thereby providing sufficient raw materials for the photosynthesis of vegetation, and promoting the growth of vegetation. Secondly, higher surface air temperatures will raise soil temperatures, accelerate the activity of microorganisms in the soil, promote the decomposition of organic matter in the soil [35], release more nutrients for vegetation to absorb and utilize [36], and thus improve the NPP. Thirdly, when relative humidity is high, the water vapor content in the air is abundant, which can reduce the water dissipation of the vegetation and reduce the stress of the vegetation due to drought, allowing the vegetation to maintain a better moisture status [37].

The results of the study indicate that the weather factors together affect NPP more than the effect of single factors on NPP, a finding that highlights that the combined effect of temperature and precipitation, wind speed and precipitation, wind speed and temperature, precipitation and evapotranspiration, and precipitation and relative humidity has a significant effect on NPP. The reason for this finding may be due to the following. First, moderate wind speeds in conjunction with moderate precipitation promote gas exchange and nutrient uptake by vegetation in the northeastern portion of the study area, which indirectly affects the soil environment, reduces soil erosion [38], and promotes nutrient cycling and effectiveness in the soil [39], thereby increasing the NPP of regional vegetation. Secondly, Ordos has great temperature variation, and appropriate wind speed can reduce leaf temperature at high temperatures, prevent high-temperature damage, and facilitate photosynthesis to continue; at low temperatures, wind energy accelerates airflow, reduces cold air accumulation, and mitigates freezing damage, thus increasing the NPP. In addition, Ordos has a wide area, and the wind speed is favorable for the spreading and diffusion of plant pollen, seeds, and other propagules, expanding the distribution range and population size of plants, which has an important effect on the succession and productivity of vegetation communities [40]. At the same time, the temperature affects the plant growth rhythm and phenological period [41], and both of them work together to determine the timing and efficiency of plant reproduction and growth, which in turn affects the NPP. Thirdly, the annual precipitation in most parts of Ordos is low and evaporation is high, and the balance between the two directly determines the amount of effective water available for vegetation. The eastern part of Ordos is relatively rich in precipitation and is mainly dominated by grassland vegetation [42], while the western part is mostly desert vegetation due to low precipitation and high evaporation. The interaction between precipitation and evaporation affects the composition and structure of vegetation communities [43], which in turn has an important effect on the NPP. Fourth, Ordos precipitation is mostly concentrated in July, August, and September, while high relative humidity makes it easier for water vapor in the atmosphere to condense into water droplets and land on the ground to replenish soil moisture, enabling vegetation to more fully utilize precipitation, which together ensures adequate water supply to vegetation, promotes photosynthesis, and improves NPP. Fifthly, Ordos sometimes faces harsh environments such as wind and sand. In windy and sandy weather, suitable temperatures can avoid vegetation damage due to low or high temperatures, while wind speed can help vegetation shake off sand and dust, reduce the burial and damage of sand and dust to the photosynthetic organs of vegetation [44], and maintain the normal growth and productivity of vegetation.

4.2. Limitations and Prospects

Meteorological data in this study were obtained through weather station data using Kriging interpolation analysis. The interpolation analysis method may be biased, and it is hoped that a large amount of additional meteorological data will reduce the bias in future studies. In this study, only the effects of climatic factors on NPP were considered, and the effects of socio-economic factors and human activities on NPP were not taken into account. It is hoped that the effects of human activities on NPP will be quantitatively analyzed in future studies for a more comprehensive understanding of the potential processes affecting NPP.

In order to eliminate human interference factors when studying the influence of meteorological factors on NPP, SPSS Statistics statistical software (SPSS) was used to select the partial correlation analysis function. The human factor variables were selected in the 'control variable' column, and the meteorological factors and vegetation productivity variables were selected in the analysis column. The correlation coefficient after eliminating the influence of human factors was obtained by running the analysis. However, such an analysis method may have certain limitations in selecting human factor indicators, so it is hoped that this method will be improved in future research.

5. Conclusions

1. NPP on the time scale showed a fluctuating upward trend from 2000 to 2021, from 25.4 gC/m^2 in 2000 to 60.3 gC/m^2 in 2021. This conclusion is consistent with the research results of Xu et al. [45]. On the spatial scale, the high-value areas of NPP are mainly distributed in the north of Dalad and the south of Uxin. The median value areas are mainly distributed in Jungar and Ejin Horo, and the rest areas are low-value areas. From 2000 to 2021, the NPP showed a significant increasing trend in the northern part of Dalad, Jungar, Yijinhuoluo Banner, most of Uxin, and the eastern part of Otog Front, and there was no significant change in other regions.
2. Climatic factors on the time scale indicated that the evaporation from 2000 to 2021 showed a fluctuating downward trend, from 71.6 mm in 2000 to 71.8 mm in 2021. The relative humidity, temperature, wind speed, surface temperature, and precipitation showed a fluctuating upward trend, from 46.8%, 6.3 °C, 2.1 m/s, 105.7 °C, and 169.9 mm in 2000 to 55.2%, 8.9 °C, 2.6 m/s, 109.9 °C, and 307 mm in 2021. On the spatial scale, evaporation gradually decreased from northwest to southeast, relative humidity and precipitation gradually increased from northwest to southeast, temperature and surface temperature gradually increased from northeast to southwest, and wind speed gradually decreased from central to northeast and southwest.
3. The impact of weather change on NPP, evaporation, and NPP has a significant negative correlation. The average correlation coefficient is −0.42; there was a significant positive correlation between precipitation and NPP, and the average correlation coefficient was 0.62. Relative humidity, wind speed, temperature, surface temperature, and NPP have a positive correlation but are not significant, and the average correlation coefficients are 0.12, 0.33, 0.5, and 0.1, respectively. The negative correlation areas between each factor and NPP are mainly in the central and western parts of Otog Front, the western part of Otog, the southern part of Hangjin, and the northern part of Dalad, and the rest are positive correlation areas. This conclusion is consistent with the research results of Zhang et al. [46]. However, it is different from Jiang et al. [47]'s research on NPP in Xinjiang. Their research results show that precipitation and temperature are the main factors that increase NPP.
4. The two-factor interaction results of the geodetector are mainly manifested as two-factor enhancement and nonlinear enhancement. Among them, the interaction of temperature, wind speed, and precipitation has the strongest explanatory power, reaching 92% and 87%, respectively; the second is the interaction between wind speed and temperature, precipitation and evaporation, and precipitation and relative humidity, and the explanatory power is 84% and 83%, respectively. The explanatory power of the interaction between wind speed, precipitation, and surface temperature was 82%. The interaction between relative humidity and evaporation, surface air temperature, and air temperature was the weakest, and the explanatory power was 54% and 58%, respectively.

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