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Spatiotemporal Distribution of Carbon Sink Indicators—NPP and Its Driving Analysis in Ordos City, China

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Abstract: Ordos City is an important energy supply city for Chinese provinces and cities, providing a secure energy supply for China while also generating corresponding environmental pollution. Examining the spatiotemporal patterns of net primary productivity (NPP) in Ordos City and its driving factors is relevant to the realization of the carbon emission policy in Inner Mongolia. This study was undertaken to analyze NPP and its driving factors in Ordos City from 2000 to 2019 using NPP data, CO_2 spatial grid data, meteorological data and statistical yearbook data accordingly. The NPP in Ordos City increased significantly from 2000 to 2019, mainly showing low values of NPP in the northwest and high values in the southeast. The usable grassland area and annual mean precipitation had a significant positive correlation with NPP, whereas the other factors had a more significant negative correlation. The usable grassland area had the largest influence on NPP, and fixed asset investment had the smallest influence on NPP. The total NPP–anthropogenic factor regression model and the mean NPP–natural factor regression model constructed allow for the prediction of NPP. Anthropogenic carbon emissions, population growth and usable grassland area were the main causes of NPP changes. Planting and protecting green plants and scientific and effective energy extraction plans are measures that enhance the degree of carbon sequestration in Ordos City.

Keywords: NPP in Ordos City; spatial and temporal patterns; factors influencing the trends; Google Earth Engine

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1. Introduction

The net primary productivity (NPP) of vegetation is defined as the gross quantity of green plant organic matter accumulated per unit time by photosynthesis, minus the remainder after autotrophic respiration [1,2]. NPP is a key indicator by which to judge the carbon balance of an ecosystem [3,4]. With the in-depth development of terrestrial ecosystem carbon cycle research, it is vital to investigate the spatiotemporal distribution of NPP and its driving factors for ecological protection [5,6].

The study of the spatiotemporal distribution of NPP and its driving factors is a topical issue for research and is influenced by a variety of factors. Among them, the influence of climate change and human activities on NPP is more obvious. Climate change affects vegetation growth, which in turn affects NPP. Human activities emit large amounts of carbon dioxide and produce changes in land cover, which in turn have an impact on vegetation growth [7,8]. Corresponding work has been carried out on different ecological regions of China. For example, Yang et al. (2020) examined the spatiotemporal patterns of NPP in Anhui Province and its contribution to climatic factors and human activities from 2001 to 2016 [9]. Chen et al. (2021) explored the spatiotemporal variation in NPP and its main drivers in the Hengduan Mountains from 2000 to 2015 [10]. Zhang et al. (2021) researched the NPP of the Tibetan Plateau from 2001 to 2017 using spatiotemporal analysis and explored the effects of climate, altitude and human activity NPP [11]. Li et al. (2022) explored the spatial and temporal variability and future trends of NPP in the Yangtze Delta region as well as the response mechanisms of NPP to various driving factors [12]. Shi et al. (2023) explored the spatial and temporal variability of NPP, the climate and anthropogenic interactions on NPP impacts and the optimal characteristics of the driving factors in China from 2000 to 2020 [13]. Ordos City, as an energy supply city for 18 provinces and cities in China, solved the problem of tight coal energy supply and demand in the country in 2021. Ordos City has made an important contribution to securing the country's energy supply, but this has also created a range of environmental problems, e.g., the illegal discharge of coal gangue from abandoned mining pits and road dust pollution, etc. In recent years, China has given prominence to overall ecological civilization development and established sustainable development as a national strategy. In this case, it is scientifically relevant to further illuminate the changes in the ecosystem of Ordos City and to understand the degree of response of anthropogenic and natural factors to promote the creation of a national sustainable development agenda innovation demonstration zone [14]. Therefore, it is crucial to investigate the spatiotemporal distribution of NPP in Ordos City and its driving factors to manage carbon emissions scientifically and effectively.

Therefore, this study explored the spatiotemporal distribution of NPP in Ordos City and its driving factors from 2000 to 2019. Firstly, a spatiotemporal analysis of NPP from 2000 to 2019 was conducted using NPP data to explore the trend in NPP in Ordos City. Secondly, a correlation analysis was conducted using CO_2 spatial grid data, statistical yearbook data and meteorological data to explore the factors affecting NPP. Finally, regression analysis was utilized to construct a regression model between the relevant factors and NPP to provide a possible NPP forecast.

The main contributions of this paper are as follows: (1) We exploring the spatiotemporal distribution of NPP in Ordos City and its changing trends from 2000 to 2019. (2) A driving factor analysis on the changes in NPP in Ordos City is conducted from the perspectives of anthropogenic factors and natural factors. (3) The results of the driver analysis are combined with the construction of NPP–anthropogenic factor regression models and NPP–natural factor regression models. This study has theoretical implications for achieving carbon balance and the sustainable development of the ecosystem in Ordos City.

2. Materials and Methods

2.1. Study Area

As shown in Figure 1, Ordos City is located in the southwest of the Inner Mongolia Autonomous Region, between 37°35′24′′ and 40°51′40′′ north latitude and 106°42′40′′ and 111°27′20′′ east longitude [15,16]. Ordos City has a complex topography, with high terrain in the northwest and low terrain in the southeast, surrounded by the Loess Plateau and Yellow River. Ordos City is rich in mineral resources, and the main mineral energy sources are coal, oil and natural gas [17]. Among them, coal has proven reserves of 167.6 billion tons, accounting for one-sixth of the country. Petroleum, with proven reserves of more than 800 billion cubic meters of natural gas, accounts for one-third of China.

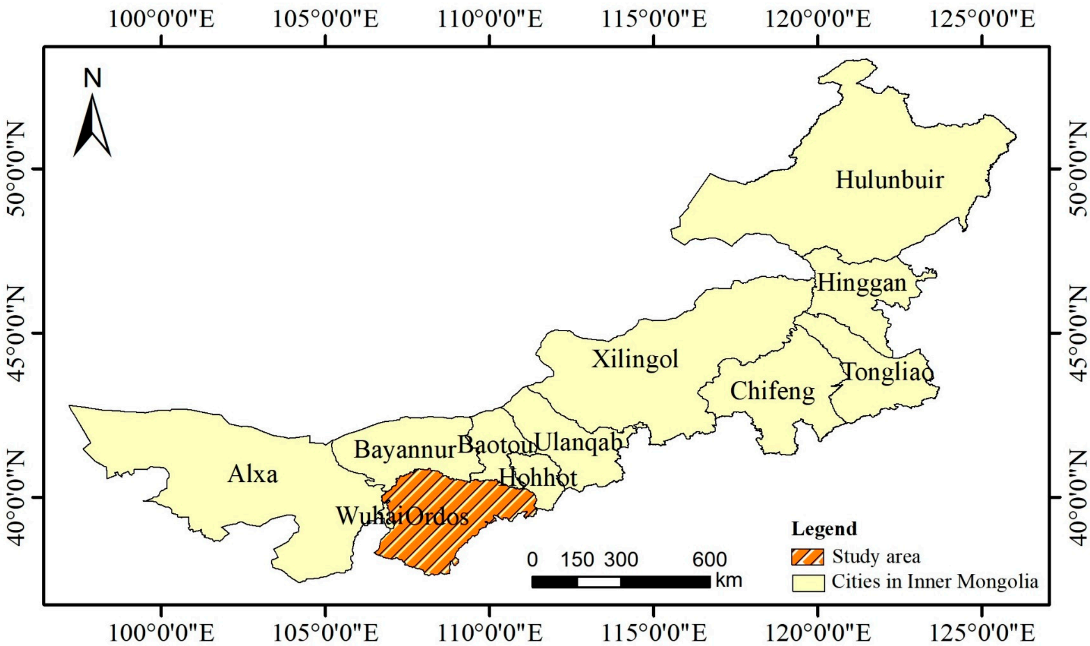


Figure 1. Location of Ordos City.

However, due to the development of these industries, the city of Ordos is also facing problems with environmental pollution. The quality of the atmospheric environment in Ordos City is poor, and the main pollutants include $PM_{2.5}$, PM_{10}, SO_2, etc. Among them, coal-fired emissions are one of the main causes of atmospheric pollution. In addition, water pollution is also a problem in Ordos City, mainly due to the direct discharge of sewage from coal mines and chemical companies, which leads to the pollution of local water resources. In order to improve the environmental quality, the government of Ordos City has taken several measures, and the air quality has improved, but further efforts are still needed to solve the problem of environmental pollution. Therefore, it is important to explore the spatiotemporal variation in NPP in Ordos City and its driving factors to achieve ecological conservation in the Inner Mongolia Autonomous Region.

2.2. Data

The adopted data were NPP data [18], CO_2 spatial grid data, meteorological data and data from statistical yearbooks. NPP data were acquired from MOD17A3H at a resolution of 500 m for the years 2000–2019 via the Google Earth Engine platform (https://code.earthengine.google.com/, accessed on 1 February 2023) [19–21]. These data are derived from the sum of the 45 8-day Net Photosynthesis (PSN) products (MOD17A2H) from the given year. The PSN value is the difference between the GPP and the Maintenance Respiration (MR) (GPP-MR). CO_2 spatial grid data were spatially gridded data for CO_2 emissions from fossil fuel combustion for 2000–2019 from the Open-Data Inventory for Anthropogenic Carbon dioxide (ODIAC) [22,23] (https://db.cger.nies.go.jp/dataset/ODIAC/DL_odiac2020b.html, accessed on 1 February 2023) at a resolution of 1000 m. CO_2 spatial grid data called ODIAC2020b differ from ODIAC2020 in their improved representation of point source emissions, which is based on the latest country fossil fuel CO_2 estimates (2000–2017) made by the new Carbon Dioxide Information Analysis Center (CDIAC) team at Appalachian State University. The spatial decomposition of emissions was performed using a variety of spatial proxy data, such as the geographic location of point sources, satellite observations of night light and aircraft and fleet trajectories. In ODIAC 2020b, the geographic location of power plants and emission estimates for the rest of the world (USA, China and Eastern European countries) were also improved. The seasonality of emissions is taken from the CDIAC monthly gridded data product. Meteorological data were derived from the annual mean precipitation data and annual mean temperature data from the Resource and Environmental Science and Data Center (https://www.resdc.cn/Default.aspx, accessed on 1 February 2023) for the years 2000–2015. The meteorological data are based on daily observations from over 2400 meteorological stations across the country and are generated by collating, calculating and spatially interpolating the data. Among the interpolations applied is the Australian ANUSPLIN interpolation software, with annual average temperature units of 0.1 °C and annual precipitation units of 0.1 mm. The relevant driver data were obtained from the Ordos City Statistical Yearbook for the years 2010–2019.

2.3. Methods

2.3.1. Trend Analysis

Trend analysis involves the use of various qualitative and quantitative analysis theories and methods that determine and speculate on the future trends and levels of developments of things based on known information [24]. Trend analysis was carried out using Origin2018 software for the NPP from 2000 to 2019 through simple linear regression. The specific formula is as follows:

$$Trend = \frac{n \times \sum_{i=1}^{n}(i \times Npp_i) - \sum_{i=1}^{n} i \sum_{i=1}^{n} Npp_i}{n \times \sum_{i=1}^{n} i^2 - \left(\sum_{i=1}^{n} i\right)^2} \tag{1}$$

where *Trend* is the trend line's slope; Npp_i is the *i*-th year's NPP value; and n is the total number of years.

2.3.2. Correlation Analysis

Correlation analysis involves the breakdown of the association among two or more variables, usually to analyze whether the trends in two or more sets of data are consistent [25–27]. SPSS25 software was used to explore which factors were associated with the NPP value. The specific formula is as follows:

$$r = \frac{\sum_{i=1}^{n}\left(sample1_i - \overline{sample1}\right)\left(sample2_i - \overline{sample2}\right)}{\sqrt{\sum_{i=1}^{n}\left(sample1_i - \overline{sample1}\right)^2}\sqrt{\sum_{i=1}^{n}\left(sample2_i - \overline{sample2}\right)^2}} \tag{2}$$

where $sample1$ and $sample2$ are comparison $sample1$ in the *i*-th year and comparison $sample2$ in the *i*-th year, respectively; $\overline{sample1}$ and $\overline{sample2}$ are the means of comparison for $sample1$ and $sample2$, respectively.

2.3.3. Regression Analysis

Regression analysis is defined as a statistical analysis method to determine the quantitative relationship between two or more interdependent variables [28–30]. SPSS25 software was utilized to obtain a quantitative model between the driving factors and the NPP.

3. Results

3.1. Spatiotemporal Distribution of NPP from 2000 to 2019

As shown in Figure 2, there were obvious spatial differences in the NPP in Ordos City from 2000 to 2019, basically showing a distribution of low values in the northwest and high values in the southeast. The years 2000, 2001, 2005 and 2011 presented more obvious low values of NPP in the northwest of Hanggin Banner, the west of Otog Banner and the west of Otog Front Banner in Ordos City. The NPP values of Ejin Horo Banner, Dongsheng District, Jungar Banner, Kangbashi District and Uxin Banner were generally high. The NPP values in the central part of Ordos City from 2000 to 2011 were mainly concentrated in the range of 1000 to 1500 kg C/m^2, and from 2011 to 2019, the NPP values in the central part of Ordos City were mainly concentrated in the range greater than 1500 kg C/m^2.

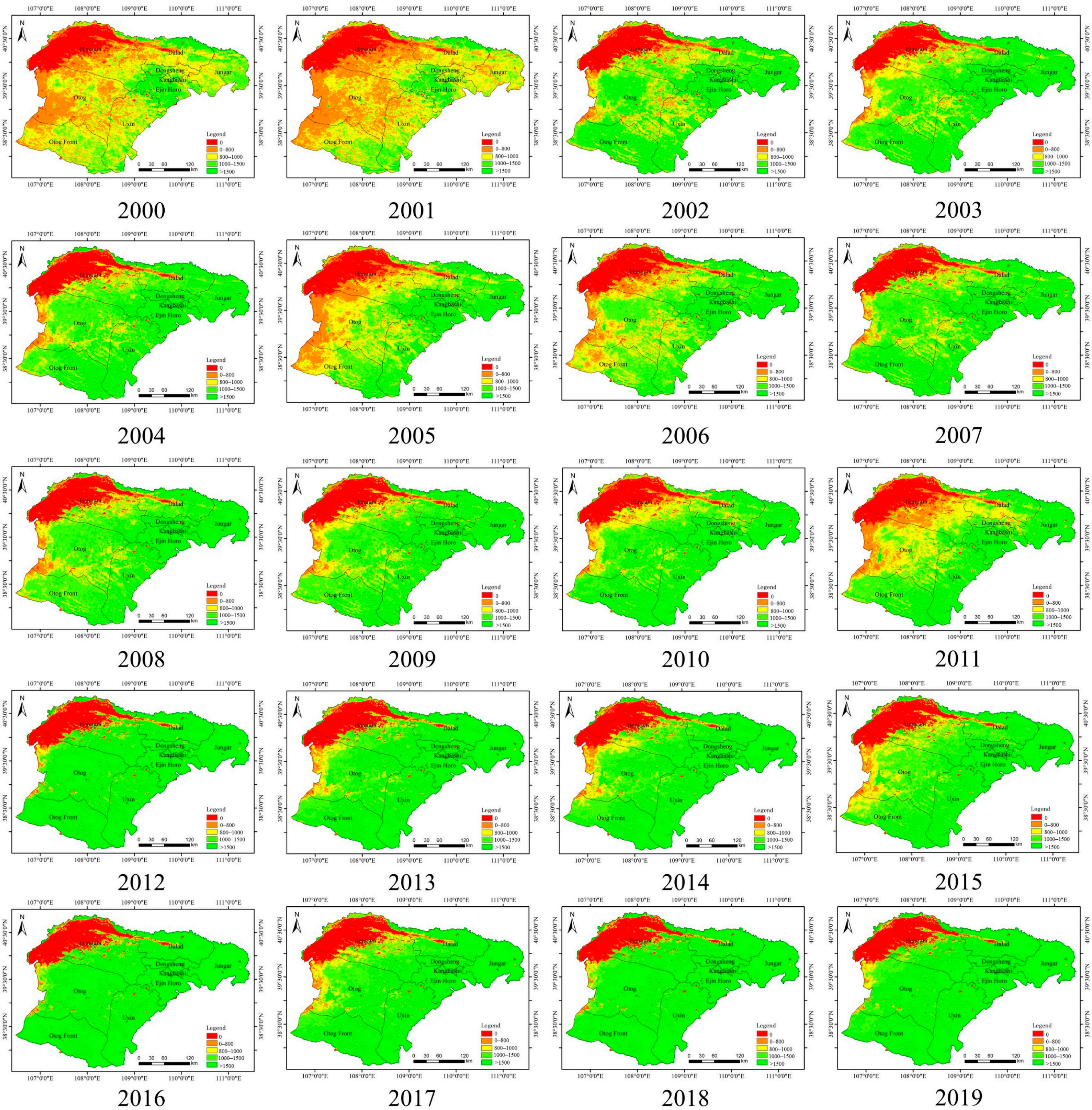


Figure 2. Spatial distribution of NPP over the years.

As shown in Figures 3 and 4, the total NPP in Ordos City exhibited a more obvious upward trend. The lowest total NPP value was 362,241,992 kg C/m^2 in 2001, and the highest total NPP value was 754,386,572 kg C/m^2 in 2016, followed by 753,298,833 kg C/m^2 in 2018. Comparing the NPP for 2000 and 2019, as shown in Figure 5, it is clear that the areas showing a large increase in NPP are mainly located in the eastern side of Ordos City, namely, Jungar Banner, Dongsheng District, Kangbaishi District and Ejin Horo Banner, whereas the areas showing a decrease in NPP are mainly concentrated in the northwestern part of Hanggin Banner, the northwestern part of Otog Banner and the central part of Dalad Banner.

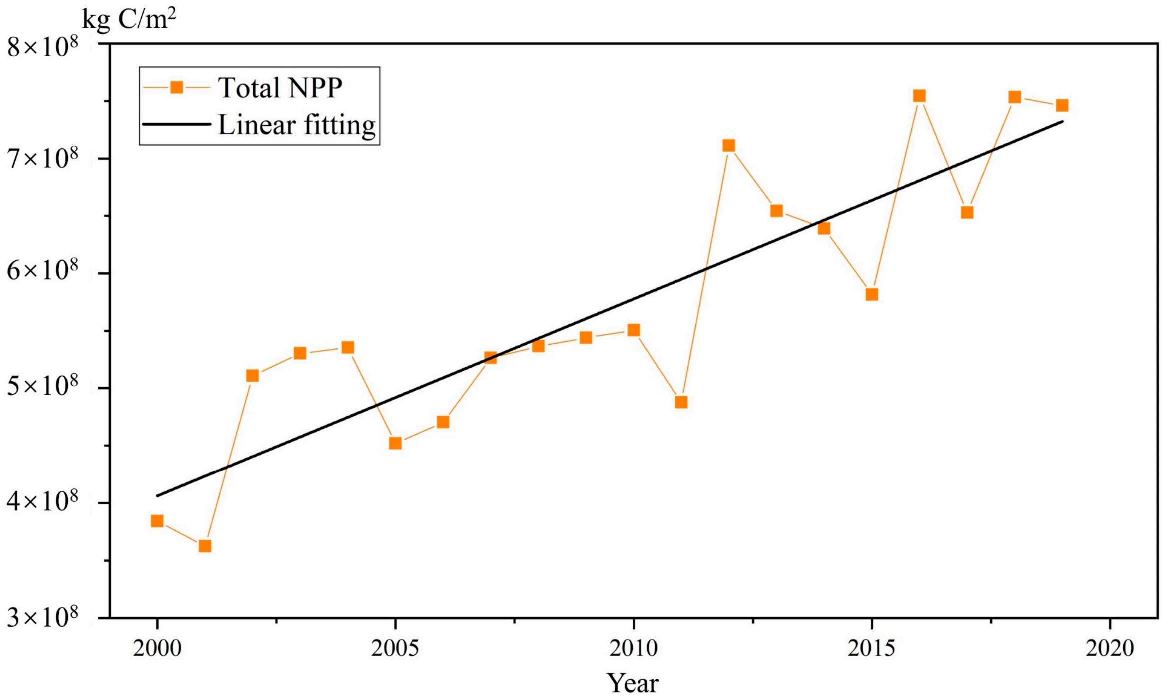


Figure 3. Inter-annual change in total NPP.

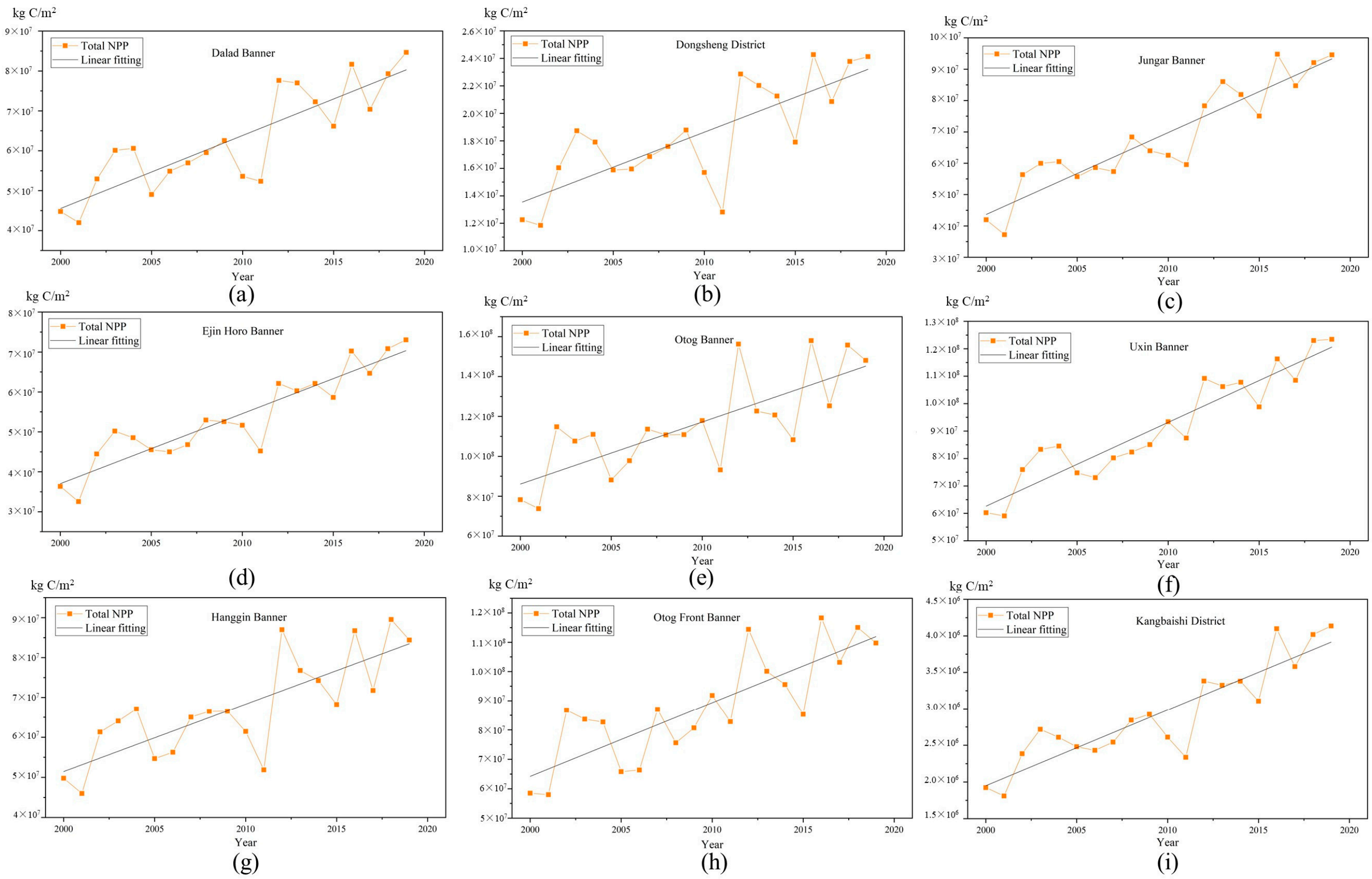


Figure 4. Inter-annual change in total NPP by district or banner. (**a**) Dalad Banner; (**b**) Dongsheng District; (**c**) Jungar Banner; (**d**) Ejin Horo Banner; (**e**) Otog Banner; (**f**) Uxin Banner; (**g**) Hanggin Banner; (**h**) Otog Front Banner; (**i**) Kangbashi District.

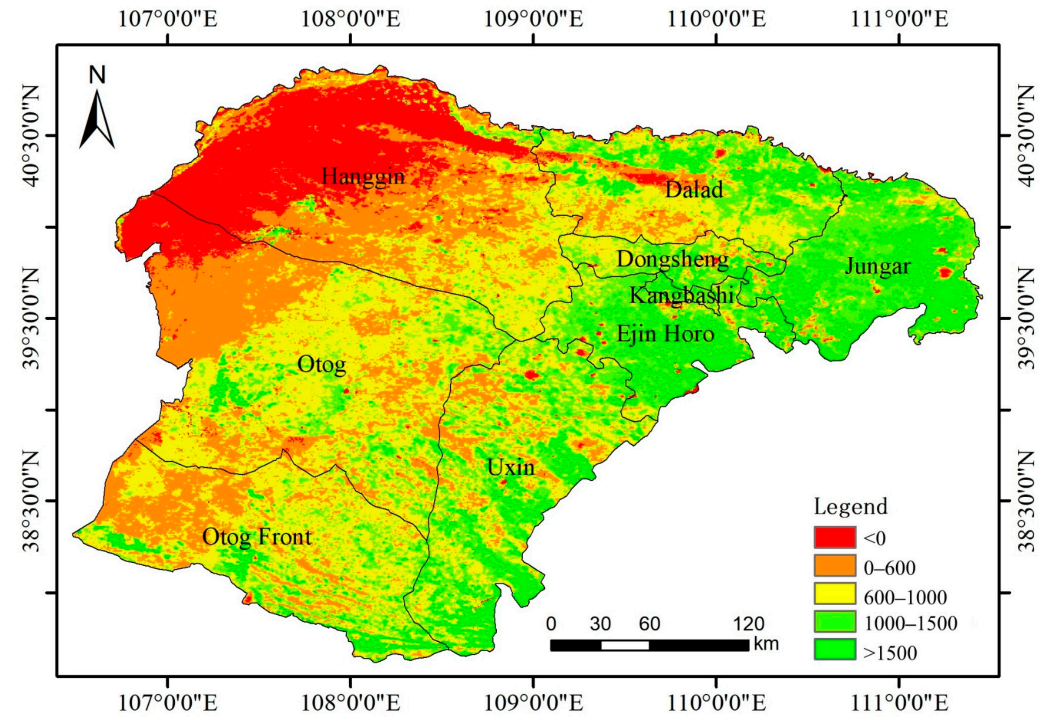


Figure 5. Spatial change in NPP between 2000 and 2019.

3.2. Correlation Analysis of NPP and Driving Factors

The total NPP reflects the increase or decrease in the mean NPP; therefore, the total NPP value and the mean NPP value were used for analysis with the driving factors. The CO_2 spatial grid data were monthly data, and the mean values were calculated for each district and banner of Ordos City separately to obtain the annual mean CO_2 data. Pearson correlation analysis was performed on the annual mean CO_2 data and the annual total NPP data to explore the link between them. The data for gross regional product, gross industrial product, gross construction product, total population, agricultural population, non-agricultural population, fixed asset investment, total crop area sown, total grain production, total number of end-of-year livestock, total output value of agriculture, forestry, animal husbandry and fishery, total power of agricultural machinery, usable grassland area and raw coal production were obtained from the Ordos City Statistical Yearbook for correlation analysis with the total NPP. Annual mean precipitation and annual mean temperature data were also correlated with mean NPP for the analysis.

As shown in Table 1, NPP is significantly correlated with CO_2 emissions from fossil fuel combustion, the total population, the non-agricultural population, fixed asset investment, usable grassland area, raw coal production and annual mean precipitation. Among them, the usable grassland area and annual mean precipitation show significant positive correlations with NPP, whereas other factors show more significant negative correlations. In descending order of influence: usable grassland area > non-agricultural population > emissions of CO_2 from fossil fuel combustion > annual mean precipitation > total population > raw coal production > fixed asset investment.

Table 1. Correlation analysis of NPP factors in Ordos City.

Driving Factors	Pearson Correlation Coefficient	p	Standard Error	Sig
Emissions of CO_2 from fossil fuel combustion	−0.618	$p < 0.05$	0.059	0.000
Gross regional product	−0.197	$p > 0.05$	0.121	0.107
Gross industrial product	0.093	$p > 0.05$	0.123	0.451
Gross construction product	−0.186	$p > 0.05$	0.121	0.128
Total population	−0.538	$p < 0.05$	0.095	0.000
Agricultural population	−0.132	$p > 0.05$	0.112	0.244
Non-agricultural population	−0.719	$p < 0.05$	0.079	0.000
Fixed asset investment	−0.302	$p < 0.05$	0.121	0.015
Total crop area sown	0.085	$p > 0.05$	0.113	0.453
Total grain production	0.019	$p > 0.05$	0.113	0.870
Total number of end-of-year livestock	0.069	$p > 0.05$	0.113	0.545
Total output value of agriculture, forestry, animal husbandry and fishery	0.182	$p > 0.05$	0.111	0.107
Total power of agricultural machinery	0.163	$p > 0.05$	0.112	0.149
Usable grassland area	0.731	$p < 0.05$	0.077	0.000
Raw coal production	−0.401	$p < 0.05$	0.124	0.002
Annual mean precipitation	0.546	$p < 0.05$	0.070	0.000
Annual mean temperature	−0.158	$p > 0.05$	0.083	0.058

3.3. Regression Analysis of NPP and Driving Factors

From the perspective of anthropogenic and natural factors, the factors with correlation were regressed with the NPP to construct the total NPP–anthropogenic factor regression model and the mean NPP–natural factor regression model. The independent variables of the total NPP–anthropogenic regression model are CO_2 emissions from fossil combustion, total population, non-agricultural population, fixed asset investment, usable grassland area and raw coal production, and the dependent variable is the total NPP value. The independent variables of the mean NPP–natural factor regression model are annual mean precipitation and annual mean temperature, respectively, and the dependent variable is the mean NPP value. As shown in Table 2, the total NPP–anthropogenic factor regression model was 0.955, indicating that the model may have a good fit, meaning that the independent variables have a strong explanatory power for the dependent variable. The model coefficients show that different independent variables have different degrees of influence on the dependent variable. The coefficients of CO_2 emissions from fossil combustion and usable grassland area are larger, indicating that they have a greater influence on the change in total NPP. The standard error of 11,423,367.71 indicates that the difference between the model prediction and the actual value of this model is large, which may be mainly due to the fact that raw coal production and usable grassland area are highly influenced by human fluctuations and are prone to outlier points. The mean NPP–natural factor regression model had a low R-value, indicating a mediocre fit. Combining the regression coefficients shows that annual mean temperature and annual mean precipitation have varying degrees of influence on mean NPP. The standard error of the model has a lower value compared to the total NPP–anthropogenic factor regression model, and the difference between the model predictions and the actual values is relatively small. This may be due to the fact that mean annual temperature and mean annual precipitation are less likely to produce outliers compared to anthropogenic factors. However, both models predict NPP values to some extent from different perspectives. Figures 6 and 7 show the regression models for the different factors. The total NPP–anthropogenic factor regression model produced better results than the mean NPP–natural factor regression model.

Table 2. Regression analysis of NPP factors in Ordos City.

	Regression Model	R	Standard Error
Total NPP–anthropogenic factor	$y = -826453.030 \times a + 28.258 \times b + 168.845 \times c + 4.792 \times d + 30174.469 \times e - 14.858 \times f + 50491864.150$	0.955	11,423,367.71
Mean NPP–natural factor	$y = 0.179 \times h - 3.255 \times i + 1023.737$	0.548	338.939

Where y is the NPP of the simulation; a is the emissions of CO_2 from fossil fuel combustion; b is the total population; c is the non-agricultural population; d is the fixed asset investment; e is the usable grassland area; f is the raw coal production; h is the annual mean precipitation; and i is the annual mean temperature.

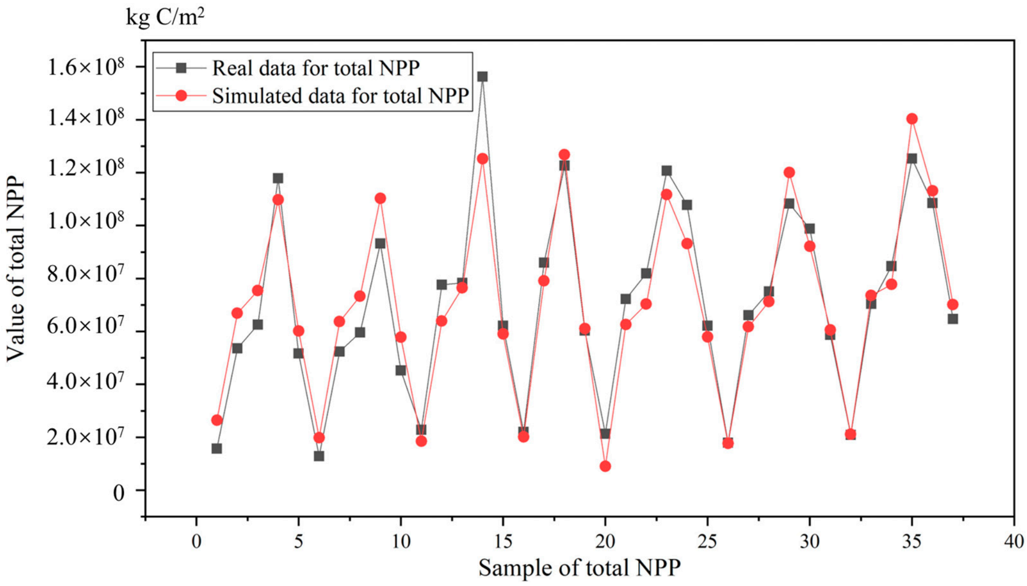


Figure 6. Comparison of simulated and real data from the total NPP–anthropogenic factor regression model.

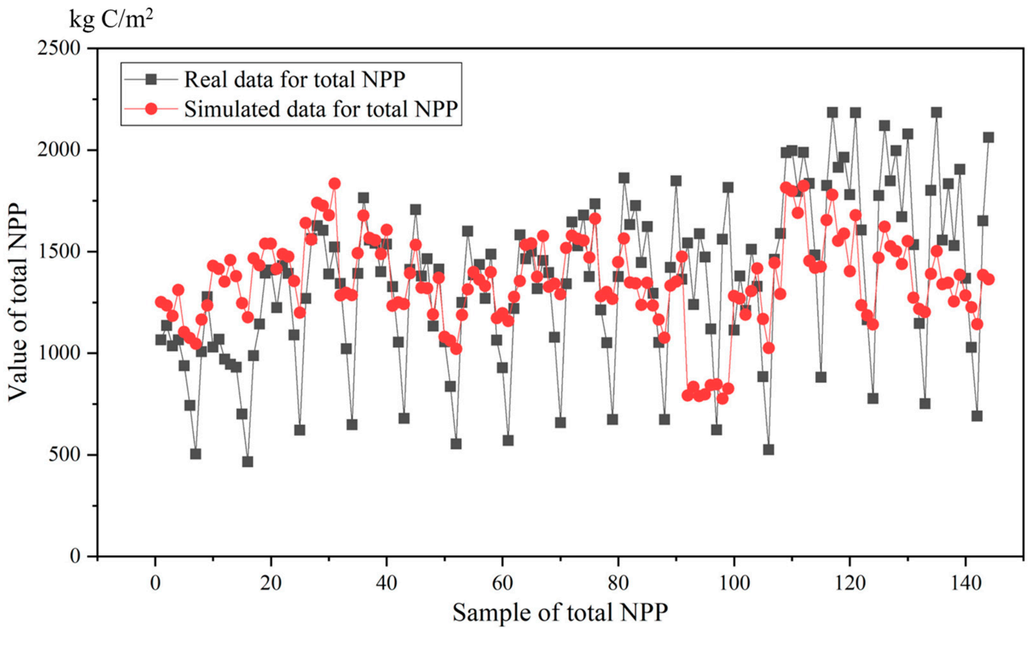


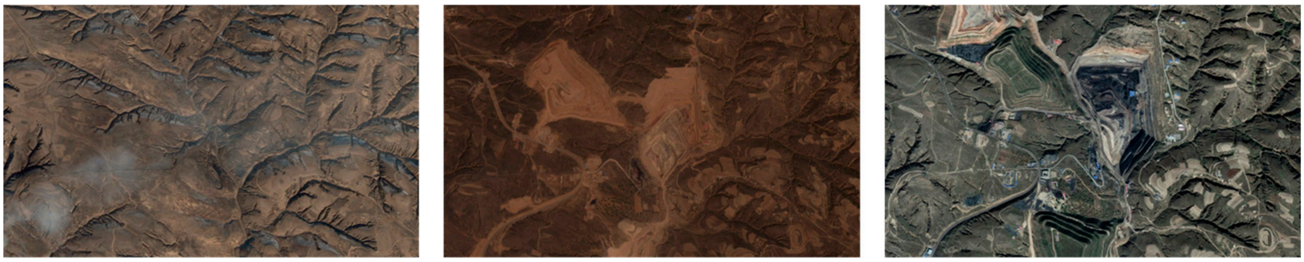
Figure 7. Comparison of simulated and real data from the mean NPP–natural factor regression model.

4. Discussion

4.1. Attribution Analysis and Recommendations for NPP Changes

The NPP in Ordos City shows an obvious increasing trend. Combined with the results of the analysis of the driving factors, the following reasons can be identified.

The coal industry in Ordos City started early, but development was relatively slow. Since 2000, it has entered an era of great development after the improvement of mining technology and equipment. According to the relevant data, the number of coal mines dropped from 5502 in 2000 to 306 in 2011, but the coal production capacity increased from 26,790,000 tons in 2000 to 588,000,000 tons in 2011. The year 2012 was influenced by the economic growth rate; the demand for coal dropped, the supply of domestic coal was over capacity, and there was a drop in the price of coal. According to incomplete statistics from relevant reports, the suspension of coal production in 2014 accounted for 23% of the total coal. With the enforcement of national eco-protection policies (e.g., returning farmland to forest), Ordos City has adopted a strategy of protecting large areas and treating small areas by implementing ecological construction projects, returning pasture to grass and small watershed management [31,32]. Figure 8 shows the temporal and spatial changes of a mining area in Ordos City, which was still mountainous in 2003 and had been mined in 2010, and in 2016, although the mine was still being mined, the area was ecologically restored accordingly and covered by green vegetation.



(a) 1 December, 2003 (b) 23 June, 2010 (c) 17 October, 2016

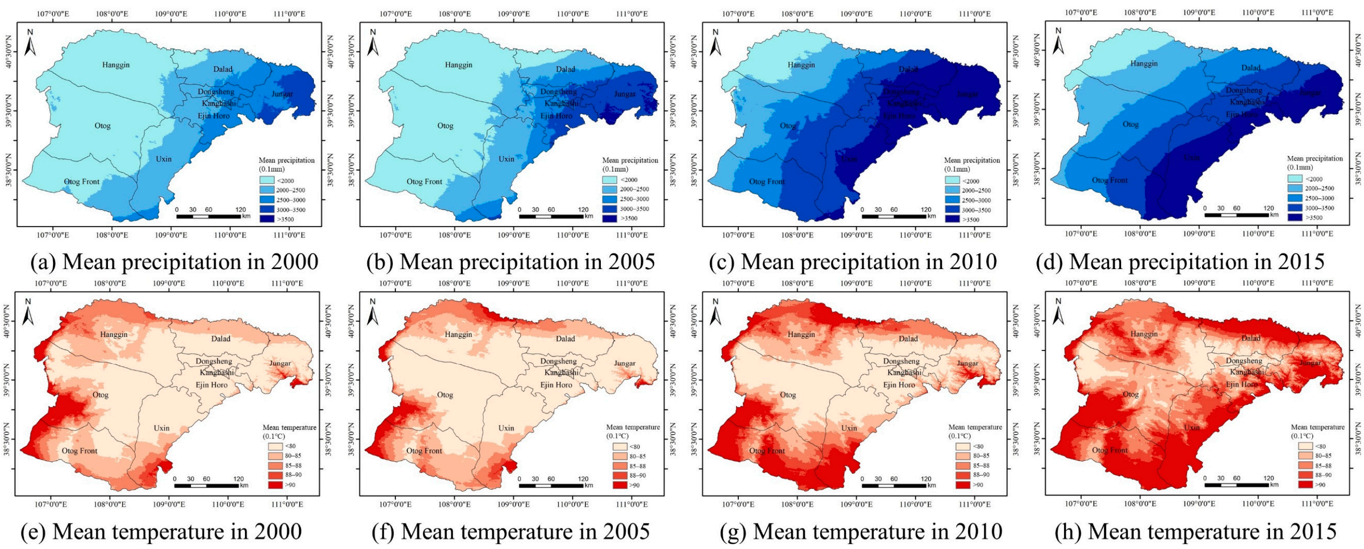
Figure 8. Spatiotemporal distribution in a mining area of Ordos City.

With the growth of the economy, the total population of Ordos City, especially the non-agricultural population, shows a growing trend, which also implies an increase in the level of urbanization. As shown in Figure 9, the urban areas in Ordos City show a clear trend of expansion. The expansion of urban areas will lead to a reduction in and the destruction of vegetation to a certain extent, which in turn will affect NPP. In addition, with the increase in human population, a large amount of human activities will be carried out (e.g., burning of fossil fuels, utilization of raw coal, production of electricity, investment in fixed assets, etc.), which will generate a large amount of carbon emissions. All of these factors have an impact on NPP.

(a) 8 October, 2006 (b) 5 October, 2010 (c) 19 March, 2020

Figure 9. Spatiotemporal distribution in urban areas of Ordos City.

Ordos City belongs to the northern temperate zone of the semi-arid continental climate zone, with large temperature variations in winter and summer. The ecological environment in Ordos City is fragile. As shown in Figure 10, the mean precipitation from 2000 to 2015 showed low spatial patterns in the northwest and high spatial patterns in the southeast, and the precipitation exhibited a more obvious area of increase. From 2000 to 2015, the mean temperature showed an upward trend, with a spatial distribution of a low center and high periphery. Precipitation and temperature affect the sowing and growth of plants, and the increase or decrease in plants directly affects the amount of organic carbon fixed through photosynthesis, which consequently has an impact on NPP.



(a) Mean precipitation in 2000 (b) Mean precipitation in 2005 (c) Mean precipitation in 2010 (d) Mean precipitation in 2015

(e) Mean temperature in 2000 (f) Mean temperature in 2005 (g) Mean temperature in 2010 (h) Mean temperature in 2015

Figure 10. Spatiotemporal distribution in mean precipitation and mean temperature of Ordos City.

From the positive correlation between the usable grassland area and NPP, it can be seen that the conservation and planting of green plants may raise Ordos City's carbon absorption capacity [33,34]. With the execution of the national Three-North Shelterbelt Project [35,36], Ordos City has been vigorously developing its forestry industry. It is worth noting that Ordos City is not suitable for large-scale forestry development implementation due to its location in the transition zone of semi-arid and arid areas [14]. In addition, the burning of fossil fuels, raw coal and other energy sources can produce large amounts of carbon emissions amid the development of scientific and effective energy extraction plans, as well as post-mining ecological restoration measures [37–39]. To promote the green energy development model, it is important to replace fuel-powered transport vehicles with renewable energy-powered transport vehicles and manage mining production and transportation in a green way [40].

4.2. Uncertainty Analysis in This Study

This study has some uncertainties. The NPP data, although a recognized dataset, have a resolution of 500 m, which is relatively low in terms of spatial resolution. Therefore, further research can start with increasing the spatial resolution of the NPP data to obtain more accurate raw data. In addition, this study is a relevant study for Ordos City, which is not too small in terms of the scale of the study area. Therefore, further research could start at a smaller scale (e.g., a mine site) to capture a more fine-grained relationship between the operational phase of each mine site and the NPP.

5. Conclusions

This study combines remote-sensing technology and model simulation methods to provide a comprehensive quantitative assessment of NPP. The spatial and temporal distribution of NPP and its driving factors are explored, and various factors are combined to analyze and predict NPP, providing an important reference basis for ecological environmental protection and sustainable development in Ordos City. Combining the needs of socioeconomic development and ecological protection, a series of ecological restoration and protection measures with high feasibility are proposed, which provide a reference for the ecological environmental management and sustainable development of Ordos City. The following conclusions can be drawn:

(1) The NPP in Ordos City mainly exhibited a distribution of low values in the northwest and high values in the southeast, with the low-value areas mainly concentrated in Hanggin Banner, the west of Otog Banner and the west of Otog Front Banner, and the high-value areas were in Ejin Horo Banner, Dongsheng District, Jungar Banner, Kangbashi District and Uxin Banner. The NPP showed an obvious upward trend.
(2) Usable grassland area and annual mean precipitation were significantly positively correlated with total NPP, whereas the other factors were more significantly negatively correlated.
(3) The degree of influence, in descending order, is: usable grassland area > non-agricultural population > emissions of CO_2 from fossil fuel combustion > annual mean precipitation > total population > raw coal production > fixed asset investment.
(4) A total NPP–anthropogenic factor regression model and a mean NPP–natural factor regression model were constructed, which can predict NPP to a degree. The R-value of the total NPP–anthropogenic factor regression model was higher.
(5) Human activities such as fossil and raw coal burning, electricity production, population growth and the area of available grassland were the main causes of change in NPP. Measures such as the planting and conservation of green plants and scientific and effective energy extraction plans can enhance the carbon sequestration level in Ordos City.

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Conflicts of Interest: The authors declare no conflict of interest.

Nomenclatures

Abbreviations	Full Name
NPP	Net primary productivity
CO_2	Carbon dioxide
ODIAC	Open-Data Inventory for Anthropogenic Carbon dioxide

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