land

Article

Spatial Characteristics of the Non-Grain Production Rate of Cropland and Its Driving Factors in Major Grain-Producing Area: Evidence from Shandong Province, China

Liye Wang [1,2], Jiwei Xu [3], Yaolin Liu [3,4] and Siyu Zhang [1,2,*]

[1] School of Public Administration and Policy, Shandong University of Finance and Economics, Jinan 250014, China; lywang@whu.edu.cn
[2] Institute of Land Science and Policy, Shandong University of Finance and Economics, Jinan 250014, China
[3] School of Resource and Environmental Sciences, Wuhan University, 129 Luoyu Road, Wuhan 430079, China; jiwe_xu@whu.edu.cn (J.X.); 2012301120015@whu.edu.cn (Y.L.)
[4] Collaborative Innovation Center of Geospatial Information Technology, Wuhan University, 129 Luoyu Road, Wuhan 430079, China
* Correspondence: zhangsy@webmail.hzau.edu.cn

Abstract: The non-grain production rate (NGPR) of cropland is a grave threat to global grain and food supply, and has been a hot issue across the world. However, few scholars explored the impacts of the NGPRs of different cropland types, such as those of paddy land and irrigated land in the same region. Thus, according to the third land survey data, this research first estimated the NGPRs of cropland, paddy land, irrigated land, and dry land at different scales in Shandong Province, China in 2019. Then, their spatial characteristics at a county scale were identified by combining the standard deviation ellipse model and spatial autocorrelation analysis. Finally, the potential driving factors of the NGPR of cropland were explored with the geographical weight regression model. Results are as follows: (1) The NGPR of cropland is at relatively lower level in Shandong Province and is dominated by that of irrigated land, and the NGPR of dry land is higher than those of other cropland types; (2) Significant regional differences exist in the NGPR of cropland, with profound severity in the southeast and much lower in the northwest; (3) At the provincial scale, the total power of agricultural machinery per capita and utilization degree of cropland factors can relieve the NGPR of cropland in nearly the entire research area. The proportion of GDP of the primary industry in GDP, urban population rate, and DEM are the main obstacles for NGPR decrease. At the county scale, the influences of driving factors varied across regions. This research can provide targeted and regional differentiated references for policy improvement and NGPR management.

Keywords: non-grain production rate; grain supply; grain production base; spatial characteristics; driving factors

check for updates

Citation: Wang, L.; Xu, J.; Liu, Y.; Zhang, S. Spatial Characteristics of the Non-Grain Production Rate of Cropland and Its Driving Factors in Major Grain-Producing Area: Evidence from Shandong Province, China. *Land* **2024**, *13*, 22. https://doi.org/10.3390/land13010022

Academic Editor: Hossein Azadi

Received: 13 November 2023
Revised: 19 December 2023
Accepted: 20 December 2023
Published: 22 December 2023

Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

Grain production is closely connected to the social stability and sustainable development across the word [1,2]. The rapid urbanization and socioeconomic development lead to the population growth across the world, and consequently, the demand for grain production keeps increasing, consequently worsening the food security situation [3,4]. Furthermore, as the living standards improve, people are persistently seeking the high level of diet structure, thereby further increasing the need for food [5,6]. As the key element to maintain grain production, cropland is an essential foundation to achieve food supply and ensure the long-term development of the international community [7,8]. To protect the cropland and maintain grain production, the international community has promulgated a series of cropland protection policies (CPPs). For instance, in 1938, the United Kingdom issued a "Green Belt Policy" to avoid the cropland decrease around cities [9]. The US produced several approaches to protect cropland at the state scale due to the vacuum of policies across the country, for instance land use control and land tax benefit. China has implemented a range of CPPs since the 1970s, such as the Basic Cropland Protection Policy and Cropland Balance Policy [10,11]. However, the policies mentioned above have protected the area and quality rather than the planting type of cropland. Thus, the phenomenon of non-grain production (NGP) of cropland requires attention.

The fundamental connotation of the NGP of cropland is currently divided into two types: narrow and broad. The former refers to the behavior or progress of planting fruits, vegetables, flowers or other cash crops on cropland; the latter means all non-grain planting activities on cropland, including cash crops, flowers and seedlings, digging ponds for fish, leisure sightseeing and farmland abandonment [12,13]. We focus on the broad connotation of the NGP of cropland. Previous research has employed numerous methods to calculate the NGP of cropland. For example, at the early stage, researchers mostly used the statistical yearbook data or household survey data in calculating the different indicators to represents the NGP of cropland [14], such as the ratio of grain crop area to total cropland area [15], the proportion of grain crop sown area to the overall sown area of crops [12], and the percentage of NGP area to the total cropland area [16]. In addition, some researchers used the machine learning algorithm and remote sensing data to identify the planting type in each cropland patch and consequently calculated the NGP of cropland [17]. The existing methods for calculating of the NGP of cropland have these two problems: (1) using the statistical yearbook data or household survey data can enable large-scale research but it cannot reflect the detailed information for the cropland; (2) the machine learning algorithm can collect the NGP information at the patch scale; however, assessing its accuracy is difficult [15,17]. Moreover, several studies explored the driving factors of the NGP of cropland with various methods, for instance, the logistic regression model [18], the spatial Durbin model [12], the multiple regression model [19], and the geographical detector model [20]. These studies persistently have a research gap in exploring the spatial heterogeneity of the potential driving factors on the NGP of cropland based on the detailed survey data of the land patch. Therefore, determining a solution for calculating of NGP of cropland is important while considering the accuracy and research scale. The national land survey data of China has provided a perfect resolution because it records the detailed information for each patch of cropland: cropland type and planting type.

Considering China is one of the most populous countries, the food security problem in the country is more severe than that in other countries. The central government of China has promulgated numerous policies to relieve cropland loss and highly prioritize the grain production in their administrative politics [10,21]. Meanwhile, in China, the total grain production has been doubled in the past half century, which profoundly contributes to the global food supply and socioeconomic development [22]. Additionally, the implementation of CPPs in China has somewhat achieved effectiveness: the cropland area loss has been moderated [23,24]. However, in rural China, the grain yield is facing the problem of the NGP of cropland due to the agricultural labor loss and agricultural structure transformation [18,25]. In addition, owing to the increasing urbanization rate and further urban–rural migration expansion, this phenomenon will frequently occur in the near future [12,17]. For a long time, the CPPs promulgated in China primarily focused on the cropland area, quality and ecology [24,26]. Only a few policies begin to restrict the cropland non-grain use. Therefore, clarifying the spatial patterns of NGP of cropland and its potential driving factors is important for future policy making and conducting administrative practice.

Thus, this research considered Shandong Province, an important major grain producing area in China, as case study, choosing multiple potential driving factors to investigate the non-grain production rate (NGPR) of different cropland types. Specifically, based on the land survey data, cropland was further classified into paddy land, irrigated land, and dry land. The paddy land is used to plant aquatic crops, such as rice and the lotus root. The irrigated land refers to the land with water source and irrigation facilities and plant drought crops, for example wheat and corn. The dry land represents the land without irrigation facilities, mainly relying on natural precipitation to cultivate drought crops. This analysis leveraged high-precision land survey data at a regional scale and aimed to achieve the following objectives: (1) elucidate the spatial information of NGPR across diverse cropland types in 2019 at various scales; (2) detect the spatial NGPR heterogeneity of different types of cropland; (3) explore the potential driving factors influencing cropland NGPR from economic development, technology, population, land suitability, and utilization degree of cropland. This paper can offer a precise reference for understanding cropland NGPR while setting the future purpose for CPPs. This research also highlighted the necessity of using high-precision land survey data when investigating cropland NGPR.

2. Materials and Methods

2.1. Study Area and Data

Shandong Province is located between 114°47.5′–122°42.3′ E and 34°22.9′–38°24′ N on the eastern periphery of the North China Plain and adjacent to the lower reaches of the Yellow River (Figure 1). Encompassing a vast expanse over 151,100 km^2, the region comprises distinct percentage of land forms, with a mountainous area, a hilly area, and plains taking up approximately 56.1%, 14.9%, and 13% of the gross area, respectively. Shandong Province is a famous grain production province in China given its location in the warm-temperature zone with the annual mean temperature from 11 to 15 °C and annual precipitation spanning 550 mm to 950 mm. On the basis of the third national land survey data, more than 6.5×10^4 km^2 of cropland spreads across Shandong Province, taking up more than 40% of the total area. In 2020, the GDP in the primary industry was up to 1019.06 billion RMB, marking it the first provincial administrative region in China with a total agricultural GDP of more than 1 trillion RMB. Additionally, the GDP in the agricultural sector of Shandong Province has been in the first places in China for many years, reflecting the particularly important role that cropland plays. Therefore, a comprehensive investigation of cropland NGPR in Shandong Province is essential owing to its decisive role in securing food supply and fostering sustainable development of the society.

The NGPR of cropland information data in 2019 is identified from the land use map of Shandong Province according to the third national land survey. It identifies three types of cropland (paddy land, irrigated land, and dry land) and the following five types of cropland planting type: planting grain crops, planting non-grain crops, grain/non-grain and timber/grain intercropping, uncultivated, and fallow. According to the data, no area of cropland is in the status of fallow. Thus, the following section discusses the NGPR of cropland based on statistical data of the former four planting types mentioned above.

The Digital Elevation Model (DEM) data are sourced from the shuttle radar topography mission (SRTM) [27]. The soil organic matter content data are acquired from SoilGrids (https://soilgrids.org/ (accessed on 18 August 2023)) at a spatial resolution of 1 km. Precipitation data are obtained from the National Meteorological Information Center (http://data.cma.cn/ (accessed on 5 June 2023)). The original data are station-based, and the "Kriging" tool is used to generate spatially distributed data.

Socioeconomic data integrate data such as population, GDP, GDP in the primary industry, total power of agricultural machinery, urban population, and cropland area. The majority of these data originate from the Statistic Yearbook of Shandong Province in 2020 and some of them are from the Statistic Yearbook at the prefectural city level. Furthermore, the cropland area data are drawn from the third national land survey of Shandong Province.

2.2. Research Framework

We analyzed the spatial features of the NGPR of cropland and explored the spatial effects of driving factors in this research. Figure 2 displays the overall research framework, including the following steps: (1) Extracting the area of different types of cropland in 2019, including paddy land, dry land, and irrigated land, and their planting attributes of each patch; (2) Calculating the NGPRs of cropland, irrigated land, paddy land, and dry land, respectively, by calculating the ratio of planting grain crops, non-grain crops, grain/non-grain and timber/grain intercropping, and uncultivated patches on total area; (3) Exploring the spatial patters of NGPR across distinct cropland types utilizing the spatial autocorrelation analysis and standard deviation ellipse (SDE) model; (4) Selecting the independent variables considering economic development, technology, population, land suitability, and utilization degree of cropland through the previous studies and the research topic; (5) Using the GWR model to unravel the spatial disparities in the influences of the selected variables on the NGPR of cropland.

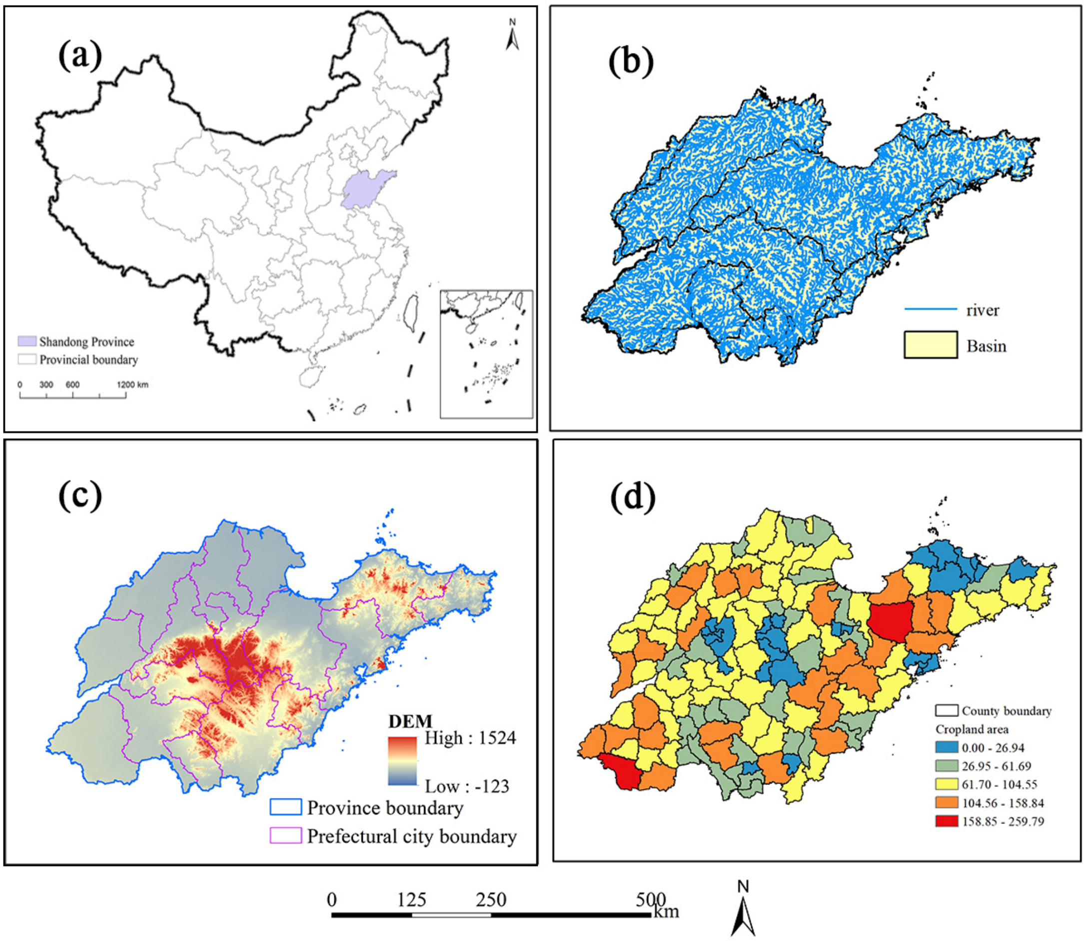

Figure 1. Location (**a**), river and basin (**b**), DEM (**c**), and the spatial distribution of cropland (**d**) of the study area.

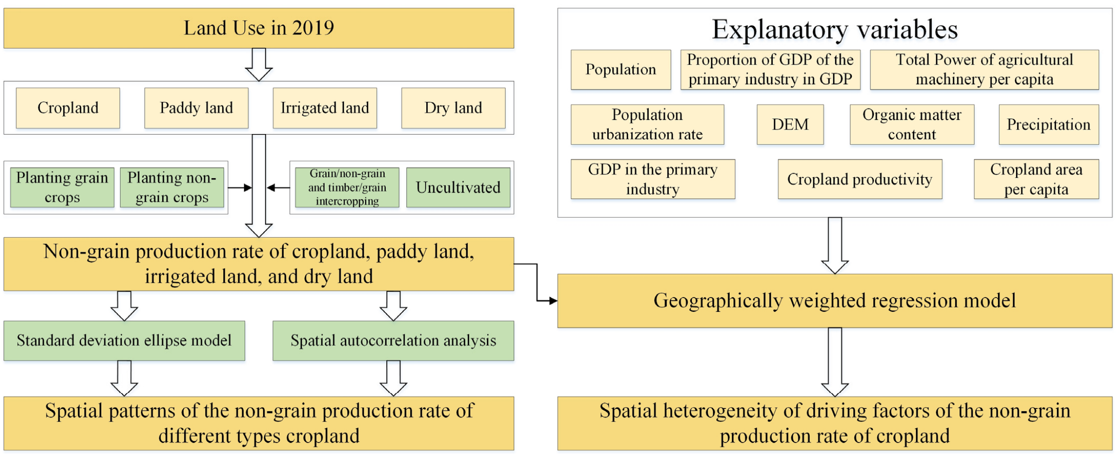

Figure 2. Overall framework of this study.

2.3. Methods

2.3.1. Calculating the NGPR of Cropland

The NGP of cropland means the adjustment of cropland use changing from grain crops to cash crops, for instance timber, fruit, and livestock [12,17]. At the bottom, it is the production structure adjustment of agricultural production subjects based on the internal comparative income of agriculture. Two types of the NGPR of cropland are explored, namely at the administrative district scale or at the patch scale [14,28]. For the administrative scale, calculating the NGPR of cropland is usually represented by the ratio of the cropland area of the NGP and the total cropland area. For the patch scale, different algorithms are carried out to identify the grain planting area, such as decision tree model [17] and human visual interpretation [18]. This research focuses on the NGPR of cropland at different administrative scales in 2019, which is calculated as follows:

$$\mathrm{NGPR}_{i,j} = \frac{\mathrm{PNGC}_{i,j} + \mathrm{UC}_{i,j} + \frac{\mathrm{GFI}_{i,j}}{2}}{\mathrm{A}_{i,j}}, \quad (1)$$

where i is the cropland type, including cropland, paddy land, irrigated land, and dry land; $\mathrm{NGPR}_{i,j}$ denotes the NGPR of cropland type i at research unit j; $\mathrm{PNGC}_{i,j}$ represents the planting area for non-grain crops; $\mathrm{UC}_{i,j}$ is the uncultivated area; and $\mathrm{GFI}_{i,j}$ denotes the cropland area for grain/non-grain crops and forest/grain intercropping. Given that the planting type is intercropping, a coefficient of 1/2 is used to adjust its area. $\mathrm{A}_{i,j}$ represents the total area of the ith cropland type.

2.3.2. SDE Model

The SDE model is a commonly used method for measuring the spatial distribution characteristics of geographic factors by calculating the standard deviation of the x and y coordinates to draw the ellipse axis [29,30]. It reflects the spatial distribution pattern mainly through rotation, semi-minor axis, semi-major axis, and oblateness. The rotation represents the direction of the ellipse. The semi-minor and semi-major axes indicate the directionality and changing number of a geographic factor, respectively. In addition, the oblateness reflects the distribution shape of the selected element in space or the degree of dispersion [31]. The formulas are listed as follows:

$$\bar{X} = \frac{\sum_m^n x_m E_m}{\sum_m^n E_m}, \ \bar{Y} = \frac{\sum_m^n y_m E_m}{\sum_m^n E_m}, \quad (2)$$

$$\tan\alpha = \frac{\left(\sum_{m=1}^n \tilde{x}_j^2 - \sum_{m=1}^n \tilde{y}_j^2\right) + \sqrt{\left(\sum_{m=1}^n \tilde{x}_j^2 - \sum_{m=1}^n \tilde{y}_j^2\right)^2 + 4\sum_{m=1}^n \tilde{x}_j^2 \tilde{y}_j^2}}{2\sum_{m=1}^n \tilde{x}_i \tilde{y}_i}, \quad (3)$$

where x_m and y_m denote the barycentric coordinates of research unit m, respectively; E_m is the research element value; $\bar{X}$ and $\bar{Y}$ denote the center coordinates of the ellipse; α indicates the ellipse rotation; and $\tilde{x}_j$ and $\tilde{y}_j$ represent the coordinate differences between the center of the research units and the ellipse.

2.3.3. Spatial Autocorrelation Analysis

Spatial autocorrelation analysis is extensively selected in revealing the distribution pattern of a geographical element owing to its advantages in presenting the spatial pattern by combining the value of geographic variables and its spatial location [32,33]. The spatial autocorrelation analysis model has two types: global and local Moran's I (LISA). The former is selected to calculate whether a spatial cluster pattern exists for the research subject and the latter performs well in detecting the exact location of an occurring spatial cluster pattern [34,35]. The following formula is established to estimate the global Moran's I:

$$\text{Moran's } I_i = \frac{n\sum_{j=1}^{n}\sum_{m=1}^{n} w_{jm}\left(NGPR_{ji} - \overline{NGPR_i}\right)\left(NGPR_{mi} - \overline{NGPR_i}\right)}{\sum_{j=1}^{n}\sum_{m=1}^{n} w_{jm}\sum_{j=1}^{n}\left(NGPR_{ji} - \overline{NGPR_i}\right)}, \tag{4}$$

where n denotes the amount of research units; w_{jm} denotes the matrix of spatial weight, determined according to Queen contiguity, and the contiguity is 1; j and m represents the research unit and its neighbors, respectively; $NGPR_{ji}$ and $NGPR_{mi}$ indicate the area of the NGPR of cropland type i in research unit j and m, respectively; and $\overline{NGPR_i}$ indicates the mean value of the NGPR of cropland. The global Moran's I score is within $[-1, 1]$ and a positive value denotes the existence of a spatial cluster pattern; the closer to 1, the stronger spatial cluster pattern, and vice versa.

The LISA is estimated as follows:

$$LISA_{ji} = z_{jm}\sum_{j=1, j\neq m}^{n-1} w_{jm} z_{mi}, \tag{5}$$

$$z_{ji} = \frac{NGPR_{ji} - \overline{NGPR_i}}{\alpha_i}, \tag{6}$$

where z_{jm} is the z-score value of the area of the NGPR of cropland; α_i is the standard deviation. According to a threshold of 0, four categories of LISA are determined, including High–High, Low–High, Low–Low, and High–Low. A pseudo p-value is used to detect the significance of LISA through a conditional permutation test [34]. This research included 999 permutations for the conditional permutation test to evaluate the significance of LISA.

2.3.4. Geographically Weighted Regression (GWR) Model

(1) Ordinary Least Squares (OLS) model

The OLS model is carried out as an accuracy reference of the GWR model [36,37]. This research first explored the driving factors of the NGPR of cropland in the OLS model and then detected their spatial effects by the GWR model. The equation of the OLS model is shown in Equation (7):

$$y = \beta_0 + \sum_{q=1}^{p} \beta_q x_q + \varepsilon, \tag{7}$$

where y represents the dependent variable, referring to the area of the NGPR of cropland in this research; β_0 denotes the intercept, representing all the variables that are equal to 0 and the value of the dependent variable; p represents the amount of the independent variables; β_q and x_q indicate the regression coefficient and the qth independent variable, respectively; and ε denotes the error, which represents the changes in the dependent variables which cannot be illustrated by the selected variables.

(2) GWR model

The OLS model is the normal used method to illustrate the potential driving factors of a geographic element [38]. However, one of the characteristics of the geographic element is the spatial location, which the traditional OLS model cannot handle. As an extension of the traditional linear regression model, the GWR model is developed by combining the OLS model and the spatial characteristics of a geographic element; consequently, it embodies the spatial heterogeneity by showing the changing regression coefficients according to space [39,40]. Thus, the GWR model is chosen to investigate the spatial heterogeneity of the potential driving factors on the NGPR of cropland. The formula is as follows:

$$y_j = \beta_0\left(\mu_j, \gamma_j\right) + \sum_{q=1}^{p} \beta_q\left(\mu_j, \gamma_j\right) x_{jq} + \varepsilon_j, \tag{8}$$

where y_j is the observed value of the NGPR of cropland in research unit j; $\left(\mu_j, \gamma_j\right)$ represents the spatial location, which means the combination of the x-coordinate and y-coordinate of its barycenter; p represents the amount of independent variables; $\beta_q\left(\mu_j, \gamma_j\right)$ shows the regression coefficient of x_q in the research unit j; and x_{jq} indicates the value of the qth variable.

In the GWR model, the spatial weight is determined by a Gaussian function and the bandwidth is decided according to the Akaike information criterion (AIC), which is estimated by the following equation:

$$AIC = 2p - 2\ln(SSR/m) \tag{9}$$

where SSR represents the sum of squared residuals and m represents the amount of research units. AIC can improve the goodness fit of data while avoiding the over-fitting phenomenon. Thus, the model with the smallest AIC is the preferred choice.

2.4. Explanatory Variables Determination

Societal development brought by urbanization has intensive connections with the behaviors of the NGPR of cropland in rural areas because of the cropland, capital, labor, and industrial interactions, consequently affecting the NGPR of cropland [12,41]. For a long time, driven by the rapid urbanization, the spatiotemporal transformation of cropland displays complex differentiation characteristics, directly influencing the stability of grain supply [42]. Taking the advantages of the increasing income, humans are more likely to transform cropland to non-food business activities with higher economic value, such as timber, fruits, tea, and aquaculture [43]. Meanwhile, the development of cities needs the transformation of rural labors to developed urban regions, resulting in the adjustment of famer's willingness to plant grain crops based on the number of family labors and cropland area [44,45]. Furthermore, the farmers balance their activities of planting grain or non-grain cropland by comparing the revenue of non-agricultural or non-grain employment [15,25]. Eventually, a farmer's decision on land use might be influenced by the status of cropland, such as whether it is suitable for grain production, and grain price, etc. [11,46]. Thus, informed by existing literature and considering the data accessibility, we grouped the potential driving factors of the NGPR of cropland into five aspects: economic development, technology, population, land suitability, and utilization degree of cropland. Afterwards, we selected representing variables (Table 1).

Table 1. Factors and independent variables of the driving factors of the NGPR of cropland.

Factor	Variable	Description	Unit
Economic development	GDP in the primary industry	The total GDP in the primary industry.	100 million CNY
	Proportion of GDP of the primary industry in GDP	The proportion of the GDP of primary industry in total GDP.	%
Technology	Total power of agricultural machinery per capita	The mean total power of agricultural machinery for a person living in the rural area.	kw
Population	Population	The total population in the research unit.	10,000 people
	Population urbanization rate	The proportion of the population in urban area of the total population.	%
Land suitability	DEM	The mean DEM in the research unit.	m
	Organic matter content	The mean soil organic matter content in the research unit.	t/km^2
	Precipitation	The total precipitation in a year.	m
Utilization degree of cropland	Cropland productivity	The GDP in the primary industry per unit of cropland area.	100 million CNY/km^2
	Cropland area per capita	The mean cropland area for a person in the research area.	$km^2/10{,}000$ people

The economic development factors represent the impacts of economic development on agricultural production behaviors [35,47]. Considering that our subject is the NGPR of cropland, GDP in the primary industry and the proportion of GDP of the primary industry to the total GDP were chosen.

The technology indicates the technological advances' influences on agricultural production. The agricultural machine can largely enhance the enthusiasm of farmers in agricultural production. Therefore, the total power of agricultural machinery per capita was adopted to provide technological support on agriculture and the agricultural mechanization levels.

The population factors are important elements that affect the NGPR of cropland because of their relationship with food demand and labor. This research takes both the variables in urban areas and agricultural sectors. Specifically, population and population urbanization rate were chosen to represent the total food demand in the research unit and the labors that are appealing in urban areas, respectively.

The land suitability factors are important elements to affect the NGPR of cropland because of its affection on the output and risk of agricultural planting [35,48]. DEM, organic matter content, and precipitation were chosen to reflect the land suitability of a region for grain production because these variables play key roles in grain plant selection and the difficulty of grain production.

The utilization degree of cropland denotes the level of the cropland being developed [49]; thus, cropland productivity and cropland area per capita were selected to represent this factor. The high cropland productivity indicates that a farmer can obtain additional profit in this cropland parcel when they input the same economic and labor costs. In addition, cropland area per capita represents whether the cropland in this region can satisfy the population's food requirement within this region.

3. Results

3.1. Characteristics of the NGPR of Cropland

Table 2 displays the NGPR of cropland at provincial and prefectural city scales at Shandong Province in 2019. The comprehensive NGPR of cropland in Shandong Province is 28.99% and varies from 14.67% to 46.55%, representing the ubiquitous phenomenon of the NGPR of cropland. The NGPRs of different types of cropland, paddy land, irrigated land, and dry land are 25.50%, 27.26%, and 33.96%, respectively, reflecting a small difference among them. The NGPR of irrigated land is particularly close to that of cropland, which has a difference of only 1.73%. This finding is due to the fact that in Shandong Province, the area of irrigated land takes up the unshakable leading position among different types of cropland with a total proportion of 72.33%; thus, the NGPR of irrigated land exerts a major part in the NGPR of cropland in the province. At prefectural city scale, except Weifang which has the highest NGPR of paddy land with a value of 100%, Linyi has the highest value of NGPR of cropland, irrigated land, and dry land, indicating the necessity to administer the NGPR of cropland in Linyi. Additionally, the NGPRs of paddy land of Weifang, Liaocheng, Heze, and Dezhou are extremely high with a value of over 80%. The latter is primarily due to the fact that most of the paddy lands in these regions are mostly selected for planting non-grain crops, such as lotus seed and water chestnuts.

On the basis of the calculations of the NGPRs of different types of cropland in 2019, this research classified the results into five levels to gain a clearer understanding as shown in Figure 3. The spatial characteristics of the NGPRs of different types of cropland have significant differences. Notably, most of the counties have the NGPRs of cropland lower than 40.00%. Additionally, several counties' NGPRs of cropland lies between 40–60% (Figure 3a). Only the following four counties have the NGPRs of cropland of over 60%: Chengyang, Lixia, Licang, and Laoshan districts. These districts all directly belong to Jinan and Qingdao cities, which are the most developed cites in Shandong Province. The spatial distribution pattern of the NGPR of irrigated land is similar to that of cropland, and only a few differences can be detected in the northeast and northwest between 40.00–60.00% and 60.00–80.00% (Figure 3c). As for the spatial characteristics of the NGPR of paddy land, they are much more different than those of the cropland and irrigated land (Figure 3b).

However, many counties in Shandong Province have no paddy land; counties with paddy lands display high levels of NGPR. Most of the counties have the NGPR of paddy land over 40% because of the following: in Shandong Province, farmers prefer to plant cash crop such as lotus root and water chestnuts rather than rice. The counties in the southeast coast and northwest regions have lower NGPR of paddy land. Figure 3d displays the spatial distribution trend of NGPR of dry land, which shows that the total distribution pattern is similar to those of cropland and irrigated land; additionally, only a few counties changed their position from lower to higher values. Specifically, a few counties in the southwest and northwest have the NGPR of dry land of over 80%, and those of a few counties in the central area are over 60%.

Table 2. NGPRs of cropland in Shandong Province and prefectural cities in 2019 (%).

Region	NGPRs of Cropland			
	Cropland	Paddy Land	Irrigated Land	Dry Land
Shandong	28.99	25.50	27.26	33.96
Jinan	25.48	47.38	24.44	28.63
Qingdao	33.11	5.12	32.32	34.04
Zibo	22.65	68.28	20.95	26.83
Zaozhuang	23.86	24.85	20.30	28.90
Dongying	36.79	17.18	37.65	45.42
Yantai	24.51	1.90	26.75	23.21
Weifang	32.01	100.00	36.23	24.00
Jining	23.17	20.79	24.16	19.49
Taian	25.62	53.55	24.11	28.52
Weihai	40.33	0.00	40.07	40.38
Rizhao	43.51	22.80	41.54	44.38
Linyi	46.55	39.31	45.18	48.17
Dezhou	14.67	81.48	14.65	24.93
Liaocheng	23.54	98.75	23.54	40.29
Binzhou	23.86	10.94	23.72	29.20
Heze	30.93	83.93	30.87	30.71

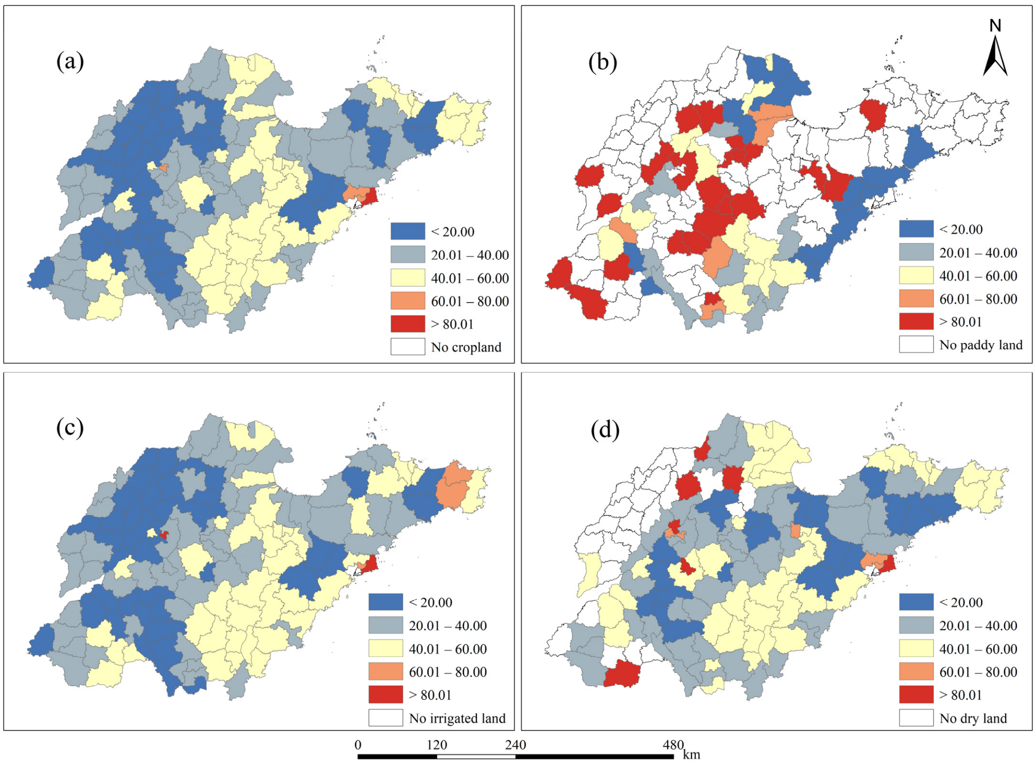

Figure 3. Spatial characteristics of the NGPRs of cropland (**a**), paddy land (**b**), irrigated land (**c**), and dry land (**d**) at county scale.

3.2. Spatial Patterns of the NGPR of Cropland

Figure 4 depicts the spatial characteristics of the SDE for the NGPRs of different types of cropland in 2019. Moreover, Table 3 shows the detailed key parameters for each SDE. The SDEs of the NGPRs of cropland, paddy land, irrigated land, and dry land are all roughly distributed in the southwest–northeast direction, which basically followed the shape of Shandong Province. The shapes of the standard ellipses of cropland, irrigated land, and dry land are nearly the same and in similar locations, whereas the paddy land shows a different shape and location, which is more likely to be a standard circle. In terms of the parameters of the ellipses, we summarized the rotation, semi-minor axis, semi-major axis, and oblateness in Table 3. The ellipse parameters of cropland and irrigated land are nearly equal, and the differences in their abovementioned parameters are −0.39°, −1.83 km, 1.47 km, and −0.01, respectively. The ellipse parameters of dry land are similar to those of cropland and irrigated land but with considerable differences among them, especially for rotation. From the perspective of the ellipse parameters of the paddy land, except for the semi-minor axis, all of the other parameters are quite different than those of the ellipse of cropland, with a difference value of 10.41°, 70.2 km, and 0.16, respectively. This phenomenon is primarily due to the dispersion of spatial distribution of counties with paddy land and the high values of the NGPR of paddy land in the majority of the counties.

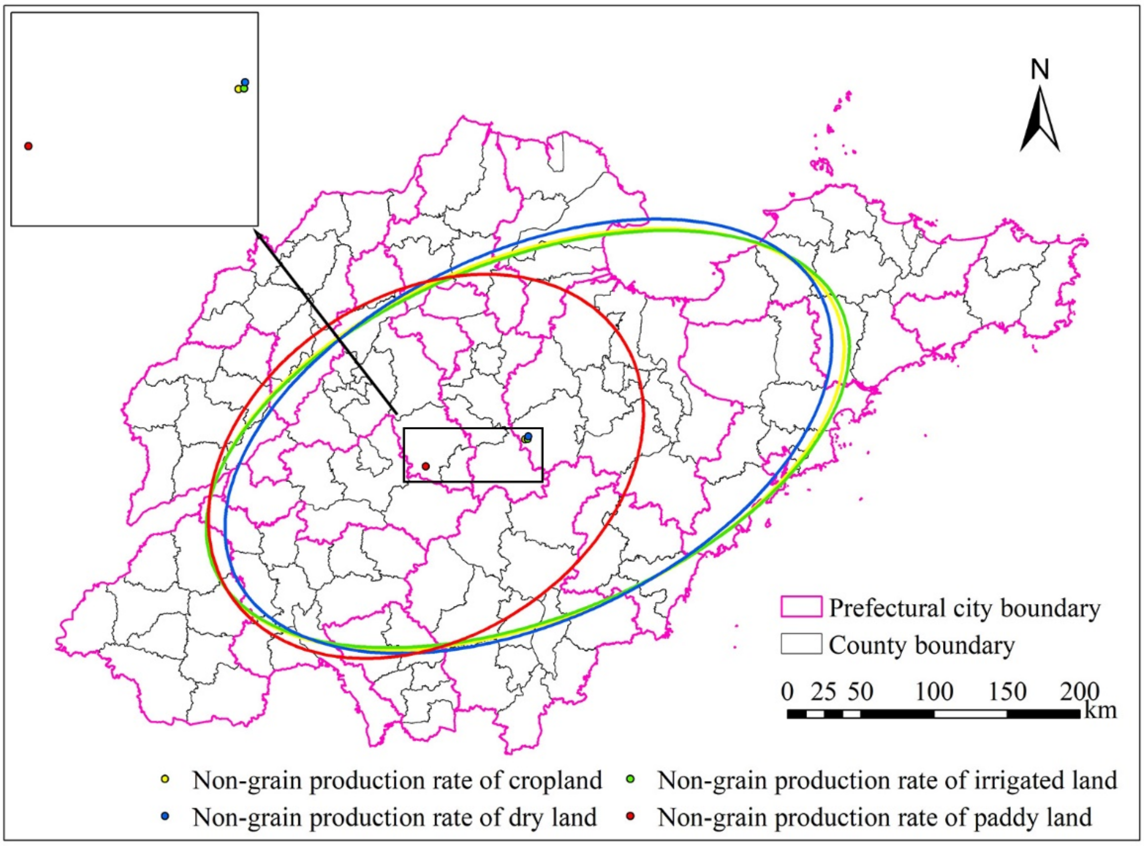

Figure 4. SDE of the NGPR of cropland.

Table 3. SDE parameters of the NGPR of cropland.

	Rotation (°)	Semi-Major Axis (km)	Semi-Minor Axis (km)	Oblateness
Cropland	67.59	230.19	123.37	0.84
Paddy land	57.18	159.99	117.29	0.68
Irrigated land	67.98	232.02	121.90	0.85
Dry land	64.42	221.97	125.71	0.82

The global Moran's I scores of the NGPRs of different cropland types and their corresponding P- and Z-values are displayed in Table 4. The global Moran's I score (0.443) of the NGPR of cropland among cropland, paddy land, irrigated land, and dry land indicates a significant spatial agglomeration trend in the distribution of the NGPR of cropland. The NGPR of irrigated land has the second highest global Moran's I score with a figure of 0.431, whereas the NGPR of dry land has the lowest score (0.113). The P-values and Z-values represent significance and effectiveness on all the spatial autocorrelation results; among them, those of paddy land and dry land are relatively higher, which may be due to the lack of samples.

Table 4. Scores of global Moran's I of the NGPRs of different types of cropland.

	Global Moran's I	*p*-Value	Z-Value
Cropland	0.443	0.001	5.0699
Paddy land	0.186	0.088	1.3822
Irrigated land	0.431	0.001	4.9771
Dry land	0.113	0.092	1.1998

Figures 5 and 6 display the scatter plots of local spatial analysis and the LISA detection results of the NGPRs of different types of cropland. The scatter plot of paddy land is relatively dispersed compared to those of other cropland types. Moreover, the scatter plots of cropland and irrigated land are relatively concentrated. Regarding the local spatial cluster pattern, those of the NGPRs of cropland and irrigated land have similar patterns: both the mostly distributed spatial cluster patterns are Low–Low and High–High clusters and largely located in the northwest and southeast areas, respectively, whereas the subtle differences can be noticed in the peninsula region, where the NGPR of irrigated land distributed a High–High cluster pattern. The High–High and Low–High clusters took up the leading position in the spatial cluster pattern of the NGPR of paddy land, and the High–High cluster was largely located in the center. For the spatial cluster pattern of the NGPR of dry land, the High–Low and Low–Low cluster patterns took up the leading position, and only one county reported the High–High cluster pattern. The High–Low cluster agglomerated in the middle, and the Low–Low cluster was distributed in the east.

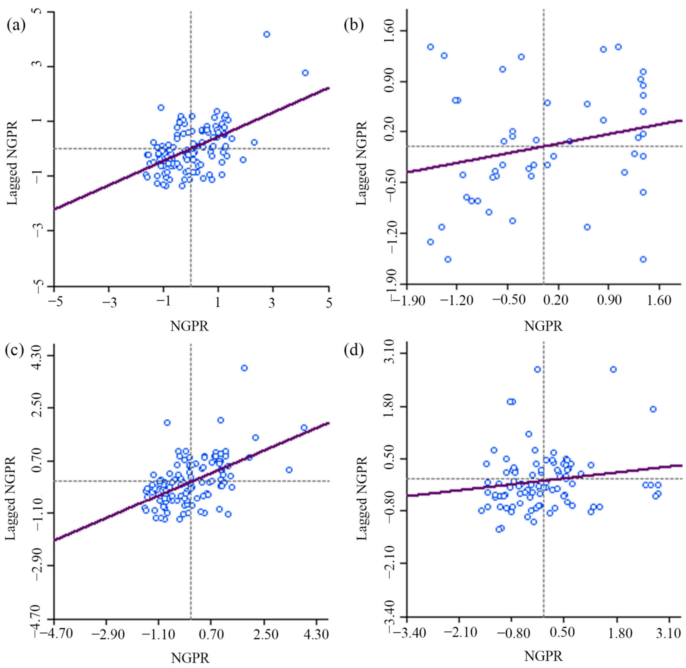

Figure 5. Scatter plot of LISA for the NGPRs of cropland (**a**), paddy land (**b**), irrigated land (**c**), and dry land (**d**) in 2019.

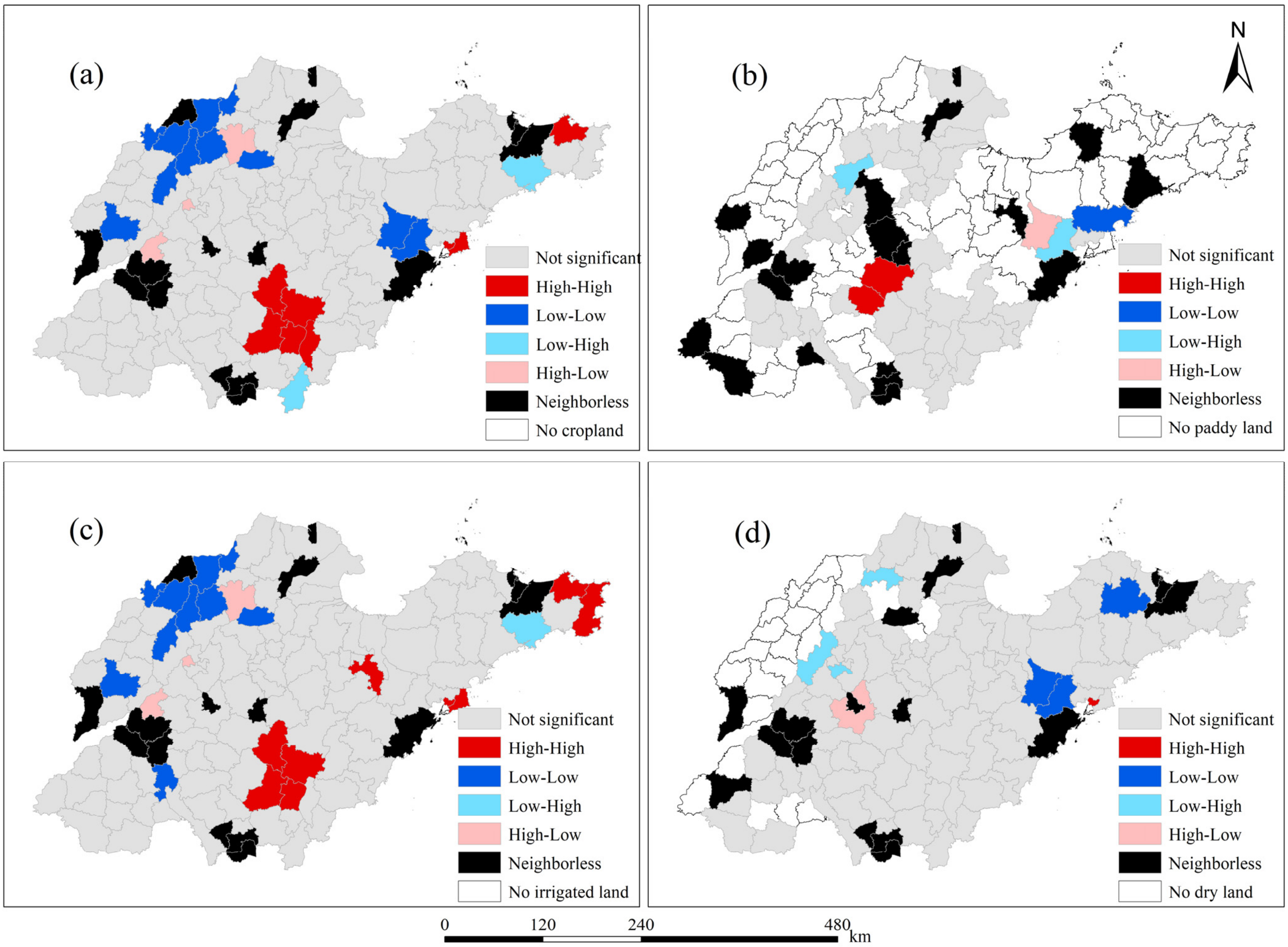

Figure 6. Spatial autocorrelation analysis of the NGPRs of cropland (**a**), paddy land (**b**), irrigated land (**c**), and dry land (**d**) at county scale.

3.3. Spatial Heterogeneity of Driving Factors

Taking the OLS and GWR models, this research explored the potential driving factors of the NGPR of cropland at a county scale. A comparison of the key parameters of the OLS and GWR models in AIC, R^2 and adjusted R^2 was carried out to detect the reliability of the GWR model (Table 5). The AIC of the GWR model reduced to 57.87, and the R^2 and adjusted R^2 increased to 0.251 and 0.271, respectively, reflecting a better fitting result. Thus, the GWR model is more suitable than the OLS model in analyzing the driving factors of the NGPR of cropland.

Table 5. Assessment of the GWR model.

	AIC	**R^2**	**Adjusted R^2**
OLS	1173.03	0.418	0.371
GWR	1115.16	0.669	0.642
Comparison	−57.87	0.251	0.271

3.3.1. Economic Development

The effects of GDP in the primary industry on the NGPR of cropland presented half of the positive influence and half of the negative influence: the negative effects were concentrated in the south of the central axis and the positive effects were distributed in the north area (Figure 7a). Shandong is a province with a large grain output, and its grain output increases steadily year by year owing to its stable climatic conditions. The increase in the GDP of the primary industry is somewhat due to enlarging the planting of the cash crops, such as vegetables and fruits, thus increasing the proportion of cropland that intercrops grain/non-grain and timber/grain plants as well as the NGPR of cropland. However, in the north regions, the growth of GDP in the primary industry has in turn further encouraged the enthusiasm to work on grain production.

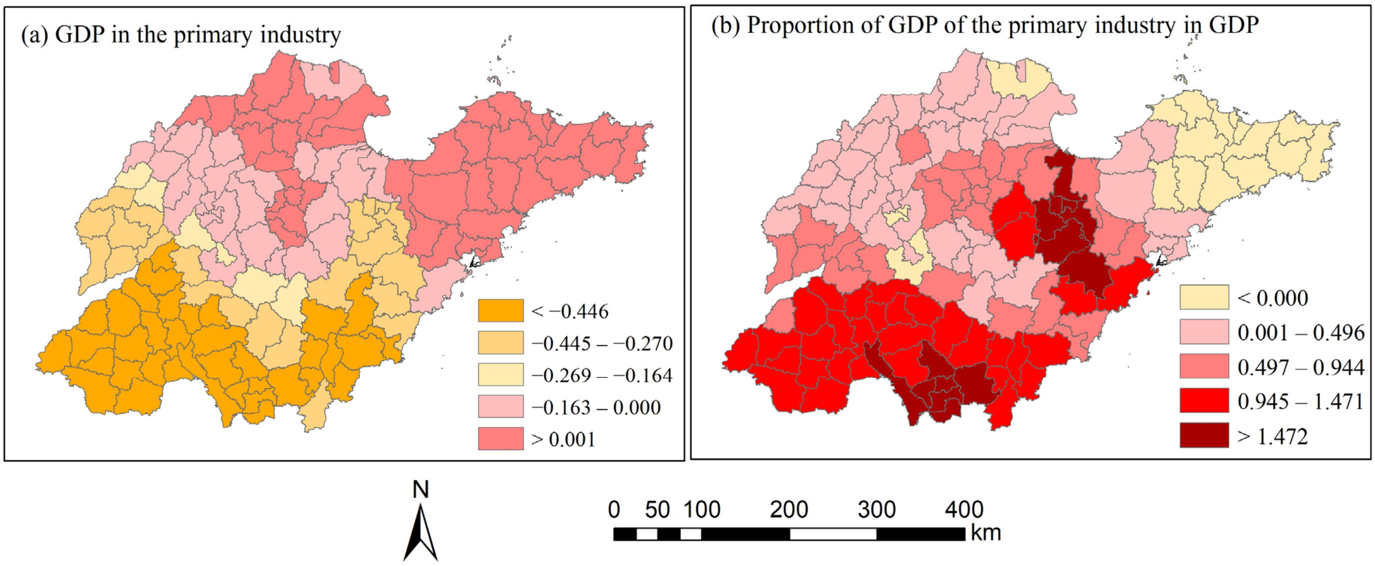

Figure 7. Spatial characteristics of the regression coefficients of economic development factors detected by the GWR model. Natural breaks method with adjustments by the authors is employed to classify the coefficient to distinguish the negative and positive values (figures below are the same).

Most of the counties displayed positive coefficients, indicating that the increase in the proportion of GDP of the primary industry in GDP can lead to the increase in the NGPR of cropland in most of the research units (Figure 7b). The increase in the proportion of GDP of the primary industry in GDP reflected the growth rate of the GDP of the primary industry which was higher than that of the GDP, implying that the proportion of cropland that planted grain crops was smaller than that of planting cash crops, consequently increasing the NGPR of cropland.

3.3.2. Technology

The negative effects of the total power of agricultural machinery per capita on the NGPR of cropland were distributed in nearly all of the research area and the positive coefficients can only be noticed in the southeast (Figure 8). The total power of agricultural machinery per capita reflected the agricultural machinery level. The increase in the agricultural machinery can release additional agricultural labors to work on the second or the third industry for extra income, and only a few labors can handle a large amount of cropland for grain production. Thus, it can alleviate the NGPR of cropland. Notably, the counties with relatively higher absolute value of regression coefficients are the counties with more mountains and higher DEM.

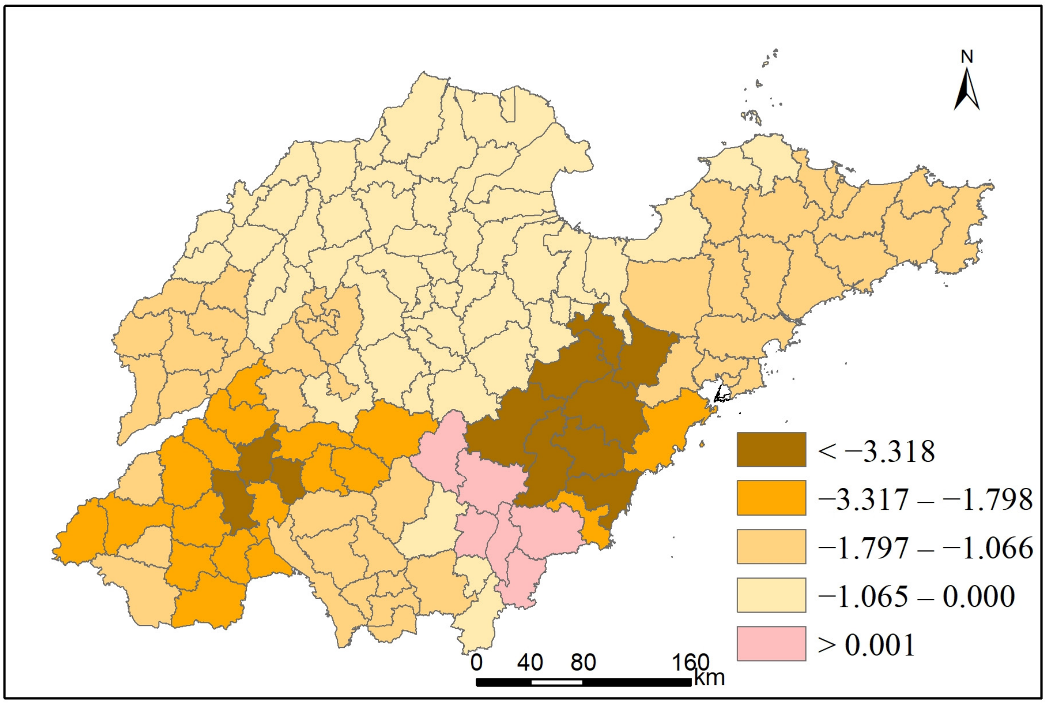

Figure 8. Spatial characteristics of the regression coefficients of the total power of agricultural machinery per capita detected by the GWR model.

3.3.3. Population

The regression coefficients of the population of the counties primarily displayed a distribution pattern of gradual reduction from the south to the north (Figure 9a). The counties with positive regression coefficients took up most of the research area, indicating that for most of the research units, population, and the NGPR of cropland change in the same direction. In the peninsula region and the Yellow River delta region, the regression coefficients were mainly negative, which meant that population increase can lead to the decrease in the NGPR of cropland. This finding is mainly due to the fact that these regions were developed regions with a large amount of population. Thus, the increase in population more easily awakens the human desire to protect grain planting.

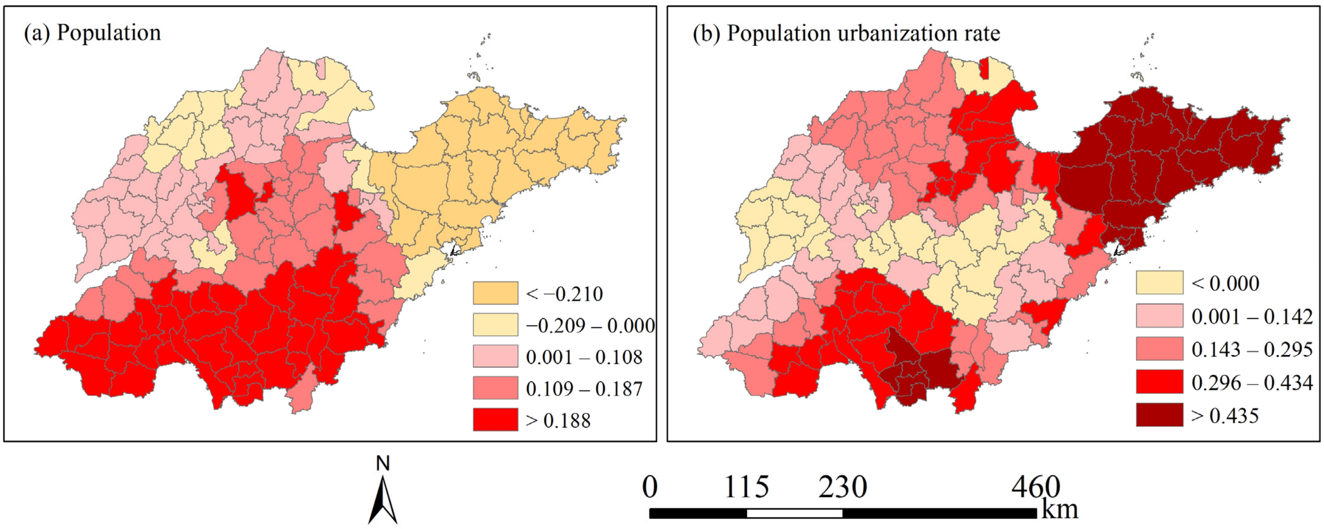

Figure 9. Spatial characteristics of the regression coefficients of technology detected by the GWR model.

The regression coefficients of the population urbanization rate for most of the counties were positive, and a small number of negative regression coefficients were noticed in the central and west areas, meaning that the increase in the population urbanization rate resulted in the growth of the NGPR of cropland in most of the research units (Figure 9b). This phenomenon is primarily due to the fact that the high level of population urbanization rate attracts a large number of agricultural labors to stay in urban areas, and then increases the urban requirement for fruit and vegetable. Consequently, the population urbanization rate increases the NGPR of cropland from the perspectives of both agricultural labor loss and planting structure adjustment.

3.3.4. Land Suitability

The spatial heterogeneity of the influences of DEM on the NGPR of cropland is shown in Figure 10a. In this figure, it can be seen the positive impacts were mostly distributed in the peninsula region and the southeast where mountains and hills are located, whereas the negative coefficients were fundamentally clustered in the central and west areas. Shandong Province is located in the North China plain and has flat land. Thus, the impacts of DEM are relatively small.

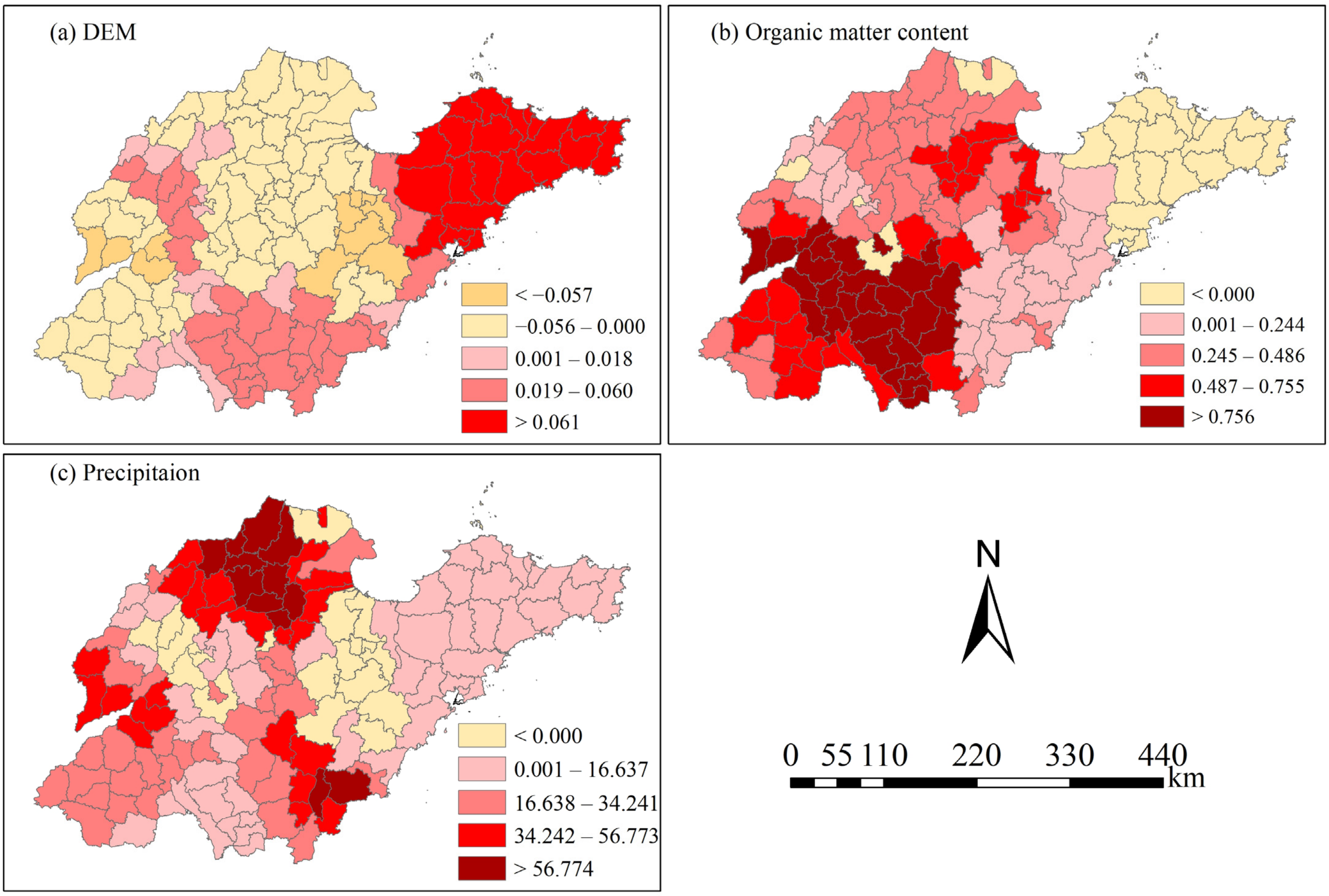

Figure 10. Spatial characteristics of the regression coefficients of land suitability factors detected by the GWR model.

The growth of organic matter content can lead to the increase in the NGPR of cropland in most areas of Shandong Province. This finding is due to the fact that most of the counties had positive regression coefficients of this variable, and only a few counties had negative coefficients; additionally, the negative coefficients' absolute values were quite small (Figure 10b). The cropland in Shandong Province is fertile; thus, the impacts of organic matter content on the NGPR of cropland are relatively slight. In addition, the increase in organic matter content may increase the output of the cash crops and promote farmers' willingness to intercrop or apply NGPR on cropland.

The impacts of precipitation on the NGPR of cropland are similar to those of the organic matter content: for most of the research units, it can significantly promote the NGPR of cropland (Figure 10c). Shandong Province has a temperate monsoon climate with simultaneously hot and rainy seasons; wheat and corn are the dominated grain crops which do not require excessive precipitation. For most of the season, the precipitation is enough for grain production but insufficient for fruit and vegetable production. Thus, the increase in precipitation can lead to an increase in the NGPR of cropland.

3.3.5. Utilization Degree of Cropland

The NGPR of cropland has close connections with the utilization degree of cropland. The characteristics of the regression coefficients of cropland productivity displayed a pattern of the positive influences distributed in the southwest, east, and peninsula region and the negative agglomerated in the other research units (Figure 11a). For the distribution pattern of the cropland area per capita, the positive regression coefficients were mostly clustered in the south, and the others were negative (Figure 11b). These phenomena indicated that the increases in cropland productivity and cropland area per capita can alleviate the NGPR of cropland. The output of cropland and the increase in cropland density can both reflect the income of grain farming. Thus, the increase in these two variables promotes farmer willingness to conduct grain production.

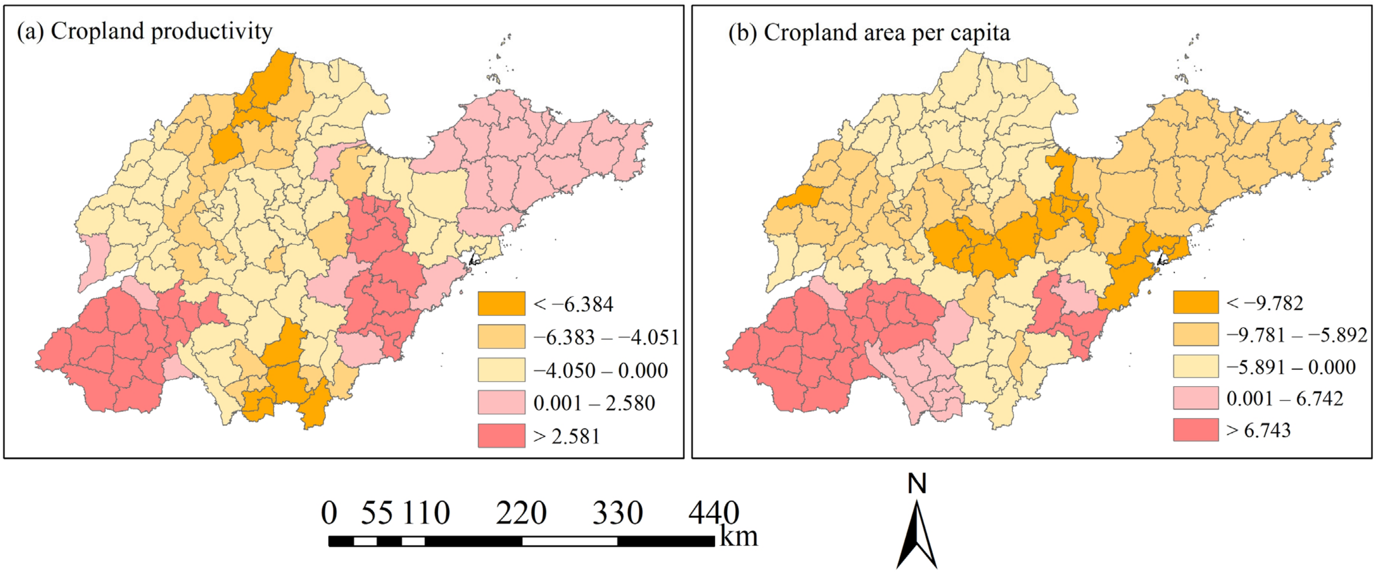

Figure 11. Spatial characteristics of the regression coefficients of the utilization degree of cropland factors explored by the GWR model.

4. Discussion

4.1. Understanding the Spatial Patterns of the NGPR of Cropland and Its Driving Factors

The level of the NGPR of cropland is closely correlated to global food security and the green development of society because it is one of the key parameters that can determine grain production [50]. The regional food security is under threat if a region has high level of the NGPR of cropland, regardless of the size of the existing area of cropland [51,52]. Existing studies have exerted a considerable amount of work to detect the NGPR of cropland in different regions and scales [12,14]. However, when detecting the NGPR of cropland, the existing literature usually considers the cropland as a whole and does not classify the cropland in detail [49]. In addition, most of the NGPR calculations in previous research were based on the statistical data or land use transfer data, which may lead to uncertainties [15,19]. Therefore, this research classified the cropland into paddy land, irrigated land, and dry land on account of the actual condition of the cropland use in the case region. Afterward, it calculated their NGPRs and the NGPR of cropland in 2019 based on the land survey data, which is the most accurate land use data in China. Distinct from previous research, this study showed that different types of cropland have different levels of NGPRs across regions, and the NGPRs of irrigated land and cropland are relatively similar because the area of irrigated land takes up 72.34% of the total cropland in Shandong Province. In 2019, the NGPR of cropland in Shandong Province is 28.99% (Table 2), which is lower than that in Sichuan Province and the mean level in China reported by Liang et al. [25] and Zhao et al. [19], showing the high efficiency in grain cultivation in Shandong Province. Interestingly, the NGPR of paddy land is the lowest, which may be due to its small area. As for the spatial characteristics of different types of cropland, the SDE model and the spatial autocorrelation analysis presented that the NGPR of cropland, irrigated land, and dry land shared a similar spatial pattern; by contrast, that of paddy land had its unique trend. Furthermore, a significant spatial cluster pattern exists in the spatial distribution of the NGRPs of all types of cropland, coinciding with the research conducted by Zhang et al. [20]. This phenomenon is due to the reasons listed as follows: (1) the NGPR of cropland is mostly decided by the NGPRs of irrigated land and paddy land because of their high proportion in cropland; (2) in Shandong Province, the paddy land is usually split up from the historical irrigated land where its irrigation water has disappeared; thus, paddy land and irrigated land typically share similar spatial distribution; (3) the paddy land is mainly distributed near the water source to ensure the water requirement, which has different location than the other types of cropland; (4) the paddy land in Shandong Province is mainly used to plant cash crops and thus has a high level of NGPR.

The driving factors analysis is a key process for understanding a typical phenomenon to better manage and promote its scientific development [53–55], which has been explored in many fields, for instance, land use change [56], ecosystem services [57,58], house price [59], carbon emission [60], etc. To obtain a clearer understanding of the NGPR, according to the previous studies, this research selected ten potential variables based on the aspects of economic development, technology, population, land suitability, and utilization degree of cropland at county scale and then explored the spatial effects of the driving factors on NGPR of cropland in 2019. The most effective way to manage the NGPR of cropland scientifically is on account of the spatial heterogeneity of driving factors at different administrative units [61,62]. Therefore, formulating targeted policies is the key for scientific management of the NGPRs of cropland across counties.

This research analyzed the specific influence of economic development, technology, population, land suitability, and utilization degree of cropland factors. The GDP in the primary industry, technology, and utilization degree of cropland factors was identified to have a predominantly negative effect on the NGPR of cropland, whereas other factors promoted the occurrence of the NGPR of cropland (Figures 7–11). These results are in line with the existing studies [18,25]. This research also found that the influence degree of different variables on the NGPR of cropland varied with their distributions. To be specific, the positive coefficients of population and proportion of GDP of the primary industry in GDP displayed both a spatial distribution of gradually deceasing from the south to the north and the negative coefficients mainly located in the peninsula region. These phenomena are mainly due to the relatively unstable geographical environment in hilly areas causing the small population and the relatively backward agricultural development in these regions [63,64]. The population urbanization rate affects the NGPR of cropland positively nearly in the entire research area. This finding can be explained by the following: on the one hand, the migration of population from rural to urban areas leads to labor loss in the agricultural sector and further leads to cropland abandonment; on the other hand, it increases the transformation from grain production to vegetable and flower production [36,65]. Precipitation as well as organic matter content also have a positive impact across the entire research area, which coincided with the study by Wang et al. [11]. By contrast, these two variables have negative coefficients only in the hilly regions. The factors that have a negative effect on the NGPR of cropland include total power of agricultural machinery per capita and the utilization degree of cropland factors, which are similar to the results of Hu et al. [49]. The former indicates the high input and scale production of cropland and the later represents the environment status of grain production [66]. Therefore, the increase in these factors brings out the reduction in the NGPR of cropland. In addition, every research unit should focus on the factor that can decline the NGPR of cropland in its own unit for good control efficiency.

4.2. Policy Implications

According to the analysis in this research, some policy references were suggested for the government, which require considerable attention to decrease the NGPR of cropland while protecting grain production.

(1) Strictly control the NGPR of irrigated land and improve grain utilization efficiency of paddy land and dry land. In Shandong Province, the irrigated land takes up the primary position; its proportion is more than 70%. The NGPR of irrigated land is closely related to the NGPR of cropland, regardless of its figure and its spatial distribution both at prefectural city and county scales. Therefore, controlling the NGPR of irrigated land is vital for decreasing the NGPR of cropland. Additionally, the proportion of paddy land and dry land is relatively low, but their NGPRs are relatively high, especially for paddy land (Table 2 and Figure 3). Thus, the targeted policies related to paddy land and dry land should be implemented by decision makers.

(2) Based on the spatial patterns of the NGPR of cropland, the focuses and proposals pay close attention to the cluster areas with high NGPR. Additionally, these regions need to draw inspirations from cluster regions with low NGPR. The spatial distribution of NGPR of cropland shows district characteristics, where the High–High cluster is located in the southeast and northeast and the Low–Low cluster is distributed in the northwest, regardless of the types of cropland (Figure 6). Consequently, to administer the NGPR of cropland in high-NGPR cluster regions, the government should consult the experiences of the regions with low NGPR. Moreover, the low-NGPR regions need to take precautions against the future increase in NGPR.

(3) By identifying the spatial heterogeneity of key factors at different counties, promulgate policies for regional differentiation to relieve the NGPR of cropland. This research identified that the total power of agricultural machinery per capita and the utilization degree of cropland factors affected the significant decrease in the NGPR of cropland, although impact degree varied across counties. Therefore, we suggest that nearly the entire research area can improve these abovementioned three factors to reduce the NGPR in Shandong Province. Meanwhile, we also found that a few factors can reduce the NGPR of cropland in specific regions; for instance, the population and proportion of GDP of the primary industry in GDP in the peninsula region and GDP in the primary industry in the south. Therefore, the regional differentiations should be reflected in policies.

4.3. Limitations

This research has estimated the NGPRs of cropland, paddy land, irrigated land, and dry land in 2019 and explored the driving factors of the NGPR of cropland in Shandong Province at county scale. Thus, this research has made contributions to future policy implementations. However, due to the data limitations, several limitations need to be ameliorated by further research. First, the NGPRs of different croplands at patch scale should be explored. This research only investigated the NGPRs of croplands at county scale and failed to identify which patch is under the progress of NGPR, which is the key element to manage and promote the NGPR of cropland to ensure grain production. Second, the effects of factors on NGPR are not constant. They varied with the value of factors. This research failed to investigate the non-linear effects of the factors on NGPR. Finally, the influences of labors in different sectors should be considered, because the loss of labors in the agricultural sector might result in cropland abandonment, which will exacerbate the phenomenon of NGPR.

5. Conclusions

Identifying the actuality of the NGPR of cropland and its driving factors is vital for maintaining grain supply and food security. However, a knowledge gap persists in the NGPRs of different types of cropland and their drivers. Thus, taking a grain production base, Shandong Province, China, as a case, this research explored the spatial features of the NGPRs of cropland, paddy land, irrigated land, and dry land in 2019, respectively, and identified the spatial heterogeneity of drivers of the NGPR of cropland from economic development, technology, population, land suitability, and utilization degree of cropland. The conclusions are as follows: (1) The NGPR of cropland is relatively lower in Shandong Province and dominated by that of irrigated land; (2) The phenomenon of NGPR of cropland is much more severe in the southeast of Shandong Province; (3) Spatial heterogeneity of driving factors exists in the impacts of the NGPR of cropland. The total power of agricultural machinery per capita and utilization degree of cropland factors can relieve the NGPR of cropland in nearly the entire research area. The proportion of GDP of the primary industry in GDP, urban population rate, DEM, and precipitation are the obstacles that influence the reduction in the NGPR of cropland. To control the NGRP of cropland, at a provincial scale, the government can improve the agricultural technology and increase the quality of cropland. At a regional scale, every county should make policies according to their exact driving factors. This research emphasized the importance of identification on the causes of NGPR of cropland and put forward targeted relieving the NGPR policies with regional differentiations.

Author Contributions: Conceptualization, L.W.; Data curation, J.X.; Formal analysis, L.W. and Y.L.; Funding acquisition, Y.L.; Methodology, L.W. and S.Z.; Resources, J.X.; Software, Y.L.; Visualization, S.Z.; Writing—original draft, L.W.; Writing—review and editing, S.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Key Program of National Natural Science Foundation of China (Grant No: 42230107).

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to data confidentiality.

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

References

1. Cottrell, R.S.; Fleming, A.; Fulton, E.A.; Nash, K.L.; Watson, R.A.; Blanchard, J.L. Considering Land–Sea Interactions and Trade-Offs for Food and Biodiversity. *Glob. Chang. Biol.* **2018**, *24*, 580–596. [CrossRef] [PubMed]
2. Zuo, C.; Wen, C.; Clarke, G.; Turner, A.; Ke, X.; You, L.; Tang, L. Cropland Displacement Contributed 60% of the Increase in Carbon Emissions of Grain Transport in China over 1990–2015. *Nat. Food* **2023**, *4*, 223–235. [CrossRef] [PubMed]
3. Cheng, P.; Tang, H.; Dong, Y.; Liu, K.; Jiang, P.; Liu, Y. Knowledge Mapping of Research on Land Use Change and Food Security: A Visual Analysis Using Citespace and Vosviewer. *Int. J. Environ. Res. Public Health* **2021**, *18*, 13065. [CrossRef] [PubMed]
4. Morales, C.; Pauw, K. Synergies and Trade-Offs between Agricultural Export Promotion and Food Security: Evidence from African Economies. *Word Dev.* **2023**, *172*, 106368.
5. Cheng, P.; Tang, H.; Lin, F.; Kong, X. Bibliometrics of the Nexus between Food Security and Carbon Emissions: Hotspots and Trends. *Environ. Sci. Pollut. Res.* **2023**, *30*, 25981–25998. [CrossRef]
6. Song, S.; Gao, Y.; Xia, T.; Zhou, Y.; Hooiveld, G.J.; Muller, M.; Li, C. Effects of High Dietary Chicken Protein on Obesity Development of Rats Fed High-Fat Diets. *J. Funct. Foods* **2023**, *108*, 105713. [CrossRef]
7. Foley, J.A.; Ramankutty, N.; Brauman, K.A.; Cassidy, E.S.; Gerber, J.S.; Johnston, M.; Mueller, N.D.; O'Connell, C.; Ray, D.K.; West, P.C.; et al. Solutions for a Cultivated Planet. *Nature* **2011**, *478*, 337–342. [CrossRef]
8. Oliveira, W.; Cruz-neto, O.; Tabarelli, M.; Galetto, L.; Peres, C.A.; Lopes, A.V. Markedly Declining Reproductive Functional Diversity of Food Plants in the World' s Largest Tropical Country despite Rapid Cropland Expansion. *Agric. Ecosyst. Environ.* **2023**, *357*, 108673. [CrossRef]
9. Cullingworth, B. *Town and Country Planning in the UK*; Routledge: Oxfordshire, UK, 2014.

10. Liu, X.; Zhao, C.; Song, W. Review of the Evolution of Cultivated Land Protection Policies in the Period Following China's Reform and Liberalization. *Land Use Policy* **2017**, *67*, 660–669. [CrossRef]
11. Wang, L.; Zhang, S.; Xiong, Q.; Liu, Y.; Liu, Y.; Liu, Y. Spatiotemporal Dynamics of Cropland Expansion and Its Driving Factors in the Yangtze River Economic Belt: A Nuanced Analysis at the County Scale. *Land Use Policy* **2022**, *119*, 106168. [CrossRef]
12. Ran, D.; Zhang, Z.; Jing, Y. A Study on the Spatial–Temporal Evolution and Driving Factors of Non-Grain Production in China's Major Grain-Producing Provinces. *Int. J. Environ. Res. Public Health* **2022**, *19*, 16630. [CrossRef] [PubMed]
13. Jarzebski, M.P.; Ahmed, A.; Boafo, Y.A.; Balde, B.S.; Chinangwa, L.; Saito, O.; von Maltitz, G.; Gasparatos, A. Food Security Impacts of Industrial Crop Production in Sub-Saharan Africa: A Systematic Review of the Impact Mechanisms. *Food Secur.* **2020**, *12*, 105–135. [CrossRef]
14. Su, Y.; Li, C.; Wang, K.; Deng, J.; Shahtahmassebi, A.R.; Zhang, L.; Ao, W.; Guan, T.; Pan, Y.; Gan, M. Quantifying the Spatiotemporal Dynamics and Multi-Aspect Performance of Non-Grain Production during 2000–2015 at a Fine Scale. *Ecol. Indic.* **2019**, *101*, 410–419. [CrossRef]
15. Zhu, Z.; Duan, J.; Li, S.; Dai, Z.; Feng, Y. Phenomenon of Non-Grain Production of Cultivated Land Has Become Increasingly Prominent over the Last 20 Years: Evidence from Guanzhong Plain, China. *Agriculture* **2022**, *12*, 1654. [CrossRef]
16. Li, Y.; Zhao, B.; Huang, A.; Xiong, B.; Song, C. Characteristics and Driving Forces of Non-Grain Production of Cultivated Land from the Perspective of Food Security. *Sustainability* **2021**, *13*, 14047. [CrossRef]
17. Zhang, D.; Yang, W.; Kang, D.; Zhang, H. Spatial-Temporal Characteristics and Policy Implication for Non-Grain Production of Cultivated Land in Guanzhong Region. *Land Use Policy* **2023**, *125*, 106466. [CrossRef]
18. Su, Y.; Qian, K.; Lin, L.; Wang, K.; Guan, T.; Gan, M. Identifying the Driving Forces of Non-Grain Production Expansion in Rural China and Its Implications for Policies on Cultivated Land Protection. *Land Use Policy* **2020**, *92*, 104435. [CrossRef]
19. Zhao, S.; Xiao, D.; Yin, M. Spatiotemporal Patterns and Driving Factors of Non-Grain Cultivated Land in China's Three Main Functional Grain Areas. *Sustainability* **2023**, *15*, 13720. [CrossRef]
20. Zhang, Z.; Zheng, L.; Yu, D. Non-Grain Production of Cultivated Land in Hilly and Mountainous Areas at the Village Scale: A Case Study in Le'an Country, China. *Land* **2023**, *12*, 1562. [CrossRef]
21. Guo, A.; Yue, W.; Yang, J.; Xue, B.; Xiao, W.; Li, M.; He, T.; Zhang, M.; Jin, X.; Zhou, Q. Cropland Abandonment in China: Patterns, Drivers, and Implications for Food Security. *J. Clean. Prod.* **2023**, *418*, 138154. [CrossRef]
22. van Wesenbeeck, C.F.A.; Keyzer, M.A.; van Veen, W.C.M.; Qiu, H. Can China's Overuse of Fertilizer Be Reduced without Threatening Food Security and Farm Incomes? *Agric. Syst.* **2021**, *190*, 103093. [CrossRef]
23. Liu, C.; Xu, Y.; Lu, X.; Han, J. Trade-Offs and Driving Forces of Land Use Functions in Ecologically Fragile Areas of Northern Hebei Province: Spatiotemporal Analysis. *Land Use Policy* **2021**, *104*, 105387. [CrossRef]
24. Zheng, W.; Li, S.; Ke, X.; Li, X.; Zhang, B. The Impacts of Cropland Balance Policy on Habitat Quality in China: A Multiscale Administrative Perspective. *J. Environ. Manag.* **2022**, *323*, 116182. [CrossRef] [PubMed]
25. Liang, X.; Jin, X.; Liu, J.; Yin, Y.; Gu, Z.; Zhang, J.; Zhou, Y. Formation Mechanism and Sustainable Productivity Impacts of Non-Grain Croplands: Evidence from Sichuan Province, China. *Land Degrad. Dev.* **2023**, *34*, 1120–1132. [CrossRef]
26. Tang, L.; Ke, X.; Zhou, T.; Zheng, W.; Wang, L. Impacts of Cropland Expansion on Carbon Storage: A Case Study in Hubei, China. *J. Environ. Manag.* **2020**, *265*, 110515. [CrossRef] [PubMed]
27. Berry, P.A.M.; Garlick, J.D.; Smith, R.G. Near-Global Validation of the SRTM DEM Using Satellite Radar Altimetry. *Remote Sens. Environ.* **2007**, *106*, 17–27. [CrossRef]
28. Yang, Q.; Zhang, D. The Influence of Agricultural Industrial Policy on Non-Grain Production of Cultivated Land: A Case Study of the "One Village, One Product" Strategy Implemented in Guanzhong Plain of China. *Land Use Policy* **2021**, *108*, 105579. [CrossRef]
29. Ahmed, G.; Zan, M.; Kasimu, A. Spatial–Temporal Changes and Influencing Factors of Surface Temperature in Urumqi City Based on Multi-Source Data. *Environ. Eng. Sci.* **2022**, *39*, 928–937. [CrossRef]
30. Gong, J. Clarifying the Standard Deviational Ellipse. *Geogr. Anal.* **2002**, *34*, 155–167. [CrossRef]
31. Xiong, Q.; Liu, Y.; Xing, L.; Xie, P.; Liu, Y. Exploring Temporal and Spatial Reliability of Individual Activity Space Measurements Using Massive Mobile Phone Data. *Trans. GIS* **2022**, *26*, 2669–2690. [CrossRef]
32. Anselin, L. Quantile Local Spatial Autocorrelation. *Lett. Spat. Resour. Sci.* **2019**, *12*, 155–166. [CrossRef]
33. Anselin, L. Local Indicators of Spatial Association—LISA. *Geogr. Anal.* **1995**, *27*, 93–115. [CrossRef]
34. Anselin, L.; Li, X. Operational Local Join Count Statistics for Cluster Detection. *J. Geogr. Syst.* **2019**, *21*, 189–210. [CrossRef] [PubMed]
35. Punzo, G.; Castellano, R.; Bruno, E. Using Geographically Weighted Regressions to Explore Spatial Heterogeneity of Land Use Influencing Factors in Campania (Southern Italy). *Land Use Policy* **2022**, *112*, 105853. [CrossRef]
36. Liu, G.; Zhao, L.; Chen, H.; Zhou, Y.; Lin, H.; Wang, C.; Huang, H.; Li, X.; Yuan, Z. Does Farmland Transfer Lead to Non-Grain Production in Agriculture?—An Empirical Analysis Based on the Differentiation of Farmland Renting-In Objects. *Sustainability* **2023**, *15*, 379. [CrossRef]
37. Sharma, P.; Sood, S.; Mishra, S.K. Development of Multiple Linear Regression Model for Biochemical Oxygen Demand (BOD) Removal Efficiency of Different Sewage Treatment Technologies in Delhi, India. Sustain. *Water Resour. Manag.* **2020**, *6*, 29. [CrossRef]

38. Laino-Guanes, R.; González-Espinosa, M.; Ramírez-Marcial, N.; Bello-Mendoza, R.; Jiménez, F.; Casanoves, F.; Musálem-Castillejos, K. Human Pressure on Water Quality and Water Yield in the Upper Grijalva River Basin in the Mexico-Guatemala Border. *Ecohydrol. Hydrobiol.* **2016**, *16*, 149–159. [CrossRef]
39. Wang, L.; Zhang, S.; Liu, Y.; Liu, Y. Interaction Between Construction Land Expansion and Cropland Expansion and Its Socioeconomic Determinants: Evidence from Urban Agglomeration in the Middle Reaches of the Yangtze River, China. *Front. Environ. Sci.* **2022**, *10*, 334. [CrossRef]
40. An, R.; Wu, Z.; Tong, Z.; Qin, S.; Zhu, Y.; Liu, Y. How the Built Environment Promotes Public Transportation in Wuhan: A Multiscale Geographically Weighted Regression Analysis. *Travel Behav. Soc.* **2022**, *29*, 186–199. [CrossRef]
41. Ariti, A.T.; van Vliet, J.; Verburg, P.H. The Role of Institutional Actors and Their Interactions in the Land Use Policy Making Process in Ethiopia. *J. Environ. Manag.* **2019**, *237*, 235–246. [CrossRef]
42. Ariti, A.T.; van Vliet, J.; Verburg, P.H. Farmers' Participation in the Development of Land Use Policies for the Central Rift Valley of Ethiopia. *Land Use Policy* **2018**, *71*, 129–137. [CrossRef]
43. Boudet, F.; Macdonald, G.K.; Robinson, B.E.; Samberg, L.H. Rural-Urban Connectivity and Agricultural Land Management across the Global. *Glob. Environ. Chang.* **2019**, *60*, 101982. [CrossRef]
44. Zhou, B.B.; Aggarwal, R.; Wu, J.; Lv, L. Urbanization-Associated Farmland Loss: A Macro-Micro Comparative Study in China. *Land Use Policy* **2021**, *101*, 105228. [CrossRef]
45. Foldvary, F.E.; Minola, L.A. The Taxation of Land Value as the Means towards Optimal Urban Development and the Extirpation of Excessive Economic Inequality. *Land Use Policy* **2017**, *69*, 331–337. [CrossRef]
46. He, X.; Yan, J.; Cheng, X. Household Perspective on Cropland Expansion on the Tibetan Plateau. *Reg. Environ. Change* **2021**, *21*, 21. [CrossRef]
47. Wang, J.; Wang, Z.; Li, K.; Li, C.; Wen, F.; Shi, Z. Factors Affecting Phase Change in Coupling Coordination between Population, Crop Yield, and Soil Erosion in China's 281 Cities. *Land Use Policy* **2023**, *132*, 106761. [CrossRef]
48. Volante, J.N.; Mosciaro, M.J.; Gavier-Pizarro, G.I.; Paruelo, J.M. Agricultural Expansion in the Semiarid Chaco: Poorly Selective Contagious Advance. *Land Use Policy* **2016**, *55*, 154–165. [CrossRef]
49. Hu, J.; Wang, H.; Song, Y. Spatio-Temporal Evolution and Driving Factors of "Non-Grain Production" in Hubei Province Based on a Non-Grain Index. *Sustainability* **2023**, *15*, 9042. [CrossRef]
50. Niu, Y.; Xie, G.; Xiao, Y.; Liu, J.; Wang, Y.; Luo, Q.; Zou, H.; Gan, S.; Qin, K.; Huang, M. Spatiotemporal Patterns and Determinants of Grain Self-Sufficiency in China. *Foods* **2021**, *10*, 747. [CrossRef]
51. Ge, D.; Long, H.; Zhang, Y.; Ma, L.; Li, T. Farmland Transition and Its Influences on Grain Production in China. *Land Use Policy* **2018**, *70*, 94–105. [CrossRef]
52. Su, D.; Cao, Y.; Wang, J.; Fang, X.; Wu, Q. Toward Constructing an Eco-Account of Cultivated Land by Quantifying the Resources Flow and Eco-Asset Transfer in China. *Land Use Policy* **2023**, *132*, 106822. [CrossRef]
53. Ariti, A.T.; van Vliet, J.; Verburg, P.H. Land-Use and Land-Cover Changes in the Central Rift Valley of Ethiopia: Assessment of Perception and Adaptation of Stakeholders. *Appl. Geogr.* **2015**, *65*, 28–37. [CrossRef]
54. Zhang, H.; Liao, X.; Zhai, T. Evaluation of Ecosystem Service Based on Scenario Simulation of Land Use in Yunnan Province. *Phys. Chem. Earth* **2018**, *104*, 58–65. [CrossRef]
55. Chai, C.; Zhang, B.; Li, Y.; Niu, W.; Zheng, W.; Kong, X.; Yu, Q.; Zhao, M.; Xia, X. A New Multi-Dimensional Framework to Assess Green Development Level of Cultivated Land Considering Environmental Impacts During 1990 to 2018 in China. *Environ. Impact Assess. Rev.* **2023**, *98*, 106927. [CrossRef]
56. Cheng, X.; Tao, Y.; Huang, C.; Yi, J.; Yi, D.; Wang, F.; Tao, Q.; Xi, H.; Ou, W. Unraveling the Causal Mechanisms for Non-Grain Production of Cultivated Land: An Analysis Framework Applied in Liyang, China. *Land* **2022**, *11*, 1888. [CrossRef]
57. Schild, J.E.M.; Vermaat, J.E.; de Groot, R.S.; Quatrini, S.; van Bodegom, P.M. A Global Meta-Analysis on the Monetary Valuation of Dryland Ecosystem Services: The Role of Socio-Economic, Environmental and Methodological Indicators. *Ecosyst. Serv.* **2018**, *32*, 78–89. [CrossRef]
58. Wang, S.; Liu, Z.; Chen, Y.; Fang, C. Factors Influencing Ecosystem Services in the Pearl River Delta, China: Spatiotemporal Differentiation and Varying Importance. *Resour. Conserv. Recycl.* **2021**, *168*, 105477. [CrossRef]
59. Wu, B.; Li, R.; Huang, B. A Geographically and Temporally Weighted Autoregressive Model with Application to Housing Prices. *Int. J. Geogr. Inf. Sci.* **2014**, *28*, 1186–1204. [CrossRef]
60. Mohmmed, A.; Li, Z.; Olushola Arowolo, A.; Su, H.; Deng, X.; Najmuddin, O.; Zhang, Y. Driving Factors of CO_2 Emissions and Nexus with Economic Growth, Development and Human Health in the Top Ten Emitting Countries. *Resour. Conserv. Recycl.* **2019**, *148*, 157–169. [CrossRef]
61. Gallego-salguero, A.; Calafat-marzal, C.; Mercedes, S.; Pi, V. Drivers of Winegrowers' Decision on Land Use Abandonment Based on Exploratory Spatial Data Analysis and Multilevel Models. *Land Use Policy* **2023**, *132*, 106807.
62. Rao, Y.; Yang, J.; Dai, D.; Wu, K.; He, Q. Urban Growth Pattern and Commuting Efficiency: Empirical Evidence from 100 Chinese Cities. *J. Clean. Prod.* **2021**, *302*, 126994. [CrossRef]
63. Zheng, H.; Zheng, H. Assessment and Prediction of Carbon Storage Based on Land Use/Land Cover Dynamics in the Coastal Area of Shandong Province. *Ecol. Indic.* **2023**, *153*, 110474. [CrossRef]
64. Deng, X.; Gibson, J.; Wang, P. Management of Trade-Offs between Cultivated Land Conversions and Land Productivity in Shandong Province. *J. Clean. Prod.* **2017**, *142*, 767–774. [CrossRef]

65. Han, Z.; Song, W. Abandoned Cropland: Patterns and Determinants within the Guangxi Karst Mountainous Area, China. *Appl. Geogr.* **2020**, *122*, 102245. [CrossRef]
66. Han, B.; Jin, X.; Yeting, F.; Chen, H.; Jin, J.; Xu, W.; Ren, J.; Zhou, Y. Trend and Spatial Pattern of Stable Cropland Productivity in China Based on Satellite Observations (2001–2020). *Environ. Impact Assess. Rev.* **2023**, *101*, 107136. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.