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Spatial Analysis of Chinese Grain Production for Sustainable Land Management in Plain, Hill, and Mountain Counties

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Academic Editors: Hualin Xie and Yanni Yu
Received: 24 December 2016; Accepted: 22 February 2017; Published: 27 February 2017

Abstract: In the context of China's food security, spatially explicit information on grain production is an important asset to achieve the sustainable management of cultivated land. Previous studies have shown that spatial mismatches exist between grain production and water and cultivated land resources. In this paper, county-level data are used to investigate the degree of spatial (mis)match between grain output and the geographical distribution patterns of plain, hill, and mountain counties. We estimate the difference in grain output between these different types of counties with a Spatial Autoregression Model. The results indicate that plain counties have the highest grain output, followed by hill counties and mountain counties subsequently. The reasons for the higher production in plain counties lie in the presence of more cultivated land, as well as a higher degree of irrigation and agricultural mechanization. The current pattern of Chinese total grain production follows the law of substituting labor with mechanization. Improving efficiency in the use of water resources and chemical fertilizer is both urgent and crucial. In this paper, we propose that the future roles for total grain production in relation to landforms should be: increased production and competitiveness in plain counties, a stabilization of capacity in hill counties, and a decrease in grain production in mountain counties.

Keywords: food security; agricultural labor cost; landform; Spatial Autoregression Model; China

1. Introduction

Grain self-sufficiency is one of the most important agricultural policy goals in China. Along with a dramatic growth in grain output, the spatial pattern of grain production has strongly changed since the 1990s. The geographical center of grain production has been moving northwards and westwards [1,2]. Grain circulation patterns have shifted from the traditional pattern of 'grain in the south being transported to the north' to the present pattern of 'grain in the north being transported to the south' [3,4]. Given the highly diverse natural and socio-economic conditions in China, the scale of this spatial pattern is, however, still very crude. Verburg et al. [5] explored Chinese grain production in a spatially explicit way. Since then, spatial analysis, i.e., identifying the spatial relationship of geographic data and visualizing the results on a map, has been widely adopted in many studies [6–8], which present more detailed knowledge about the spatial pattern of Chinese grain production.

Today, the simultaneous increase in grain output, grain import volume, and grain stocks in China attracts more and more attention. Increased grain output has led to increased soil degradation [9], agricultural non-point source pollution [10], and water scarcity [11]. Thus, increased attention needs to be directed towards new sustainable strategies for grain production with reduced environmental impacts [12]. The Chinese Central Government has enacted and promulgated more practical policies, such as the Plan for National Cropping Structure Adjustment (2016–2020) and the Plan for National

Agricultural Modernization (2016–2020). These policies aim at harmonizing grain production and environmental protection in order to achieve the sustainable use of natural resources as a whole. The success of Chinese grain production in the past, to some extent, depended on the natural resources present [6]. However, some researchers have shown that spatial mismatches exist between grain production and water and cultivated land resources in China [13,14]. Despite the consensus that Chinese grain production will be impacted significantly by climate change, the relative importance of these impacts is still under debate [15]. The impacts of climate change on Chinese grain yields in different regions are very complicated, and it is hard to generate a general conclusion [16].

We hypothesize that the spatial pattern of Chinese grain production follows the geographical distribution of certain specific natural factor(s). The availability of land is the basic premise for grain production. The production potential of land resources, however, is different for plain, hill, and mountainous regions. Differences will be more emphasized as external conditions change. The Chinese Central Government issued the Grain for Green Project (GGP) in 1999. Under the GGP, sloping cultivated land (particularly that with a slope of more than 25°) is converted to forest and grassland, with profound impacts on grain production [17–19]. Grain production is also affected by the abandonment of cultivated land, which has emerged as a prevalent phenomenon in the mountain regions in China [20]. Cultivated land abandonment is often due to a lack of agricultural laborers or the rise of agricultural labor costs [21,22]. The off-farm income and per capita net income of rural residents has dramatically increased, which has lead to fast-rising agricultural labor cost in China [23]. As a consequence, the geographical focus of grain production might have shifted towards plain regions, as these are more suited for mechanical agricultural practices. In other words, cultivated land in mountainous (and/or hill) regions is more likely to be converted to ecological land [24]. Knowing the information on the conversion between cultivated land and ecological land is helpful for achieving sustainable land management [25].

As such, there is an urgent need to conduct research on the spatial pattern of Chinese total grain production from the perspective of landforms (plain, hill, and mountain). To do so, we first identified spatial clusters of grain output, given that grain output quantities are always the primary focus for policymakers. Subsequently, we investigated the degree of spatial match between clusters of grain output and landforms and studied the impacts of different landforms. Based on our results, we made some suggestions to spatially coordinate total grain production and environmental protection in plain, hill, and mountain counties.

2. Data and Methods

2.1. Data

In the China County Statistical Yearbook, all counties are classified as plain counties, hill counties, or mountain counties, based on the dominant landforms present in their territory (Figure 1). The county-level data on grain output (tons) in 1992, 1995, 2000, 2005, 2010, and 2014 and the total power of agricultural machinery (10^4 kW) in 1992, 2000, and 2014 were extracted from the China County Statistical Yearbook [26–31]. County-level data on cultivated land area (hm^2), irrigated area (hm^2), labor (person), and chemical fertilizer (tons) in 1990 and 2008 were provided by the Ministry of Agriculture of the People's Republic of China.

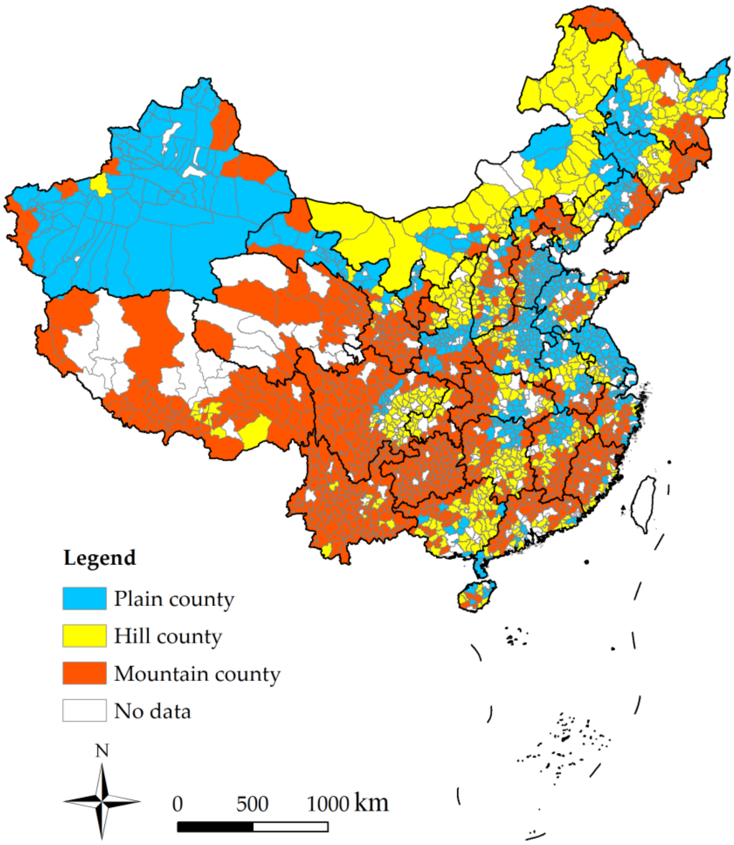

Figure 1. County-level dominant landform classification into plain counties, hill counties, or mountain counties based on the China County Statistical Yearbook [30].

2.2. Optimized Hot Spot Analysis

The tools of Cluster and Outlier Analysis (Anselin Local Moran's I [32]) and Hot Spot Analysis (Getis-Ord Gi* [33]) are primarily used to perform cluster analysis in the geographical information system (GIS). Optimized Hot Spot Analysis (OHSA) executes the Hot Spot Analysis tool using parameters derived from the input data characteristics. That is, it automatically aggregates incident data, identifies an appropriate scale of analysis, and corrects for both multiple testing and spatial dependence. The detailed instructions can be found in the ArcGIS Help [34]. We used the OHSA to identify statistically significant spatial clusters of both high and low values of grain output in China.

2.3. Spatial Autoregression with Panel Data

As a generalization of the linear regression model, the spatial autoregression model (SAR) can yield better classification and prediction accuracy for many spatial datasets exhibiting strong spatial autocorrelation [35]. Given that Chinese grain output is spatially dependent, we used a SAR model with panel data to estimate the difference in grain output in the plain, hill, and mountain counties. A SAR model was developed as follows:

$$\ln Y_{it} = \alpha_0 + \delta \sum_{j=1}^{n} W_{ij} \ln Y_{ij} + \varphi_1 Geo_1 + \varphi_2 Geo_2 + \mu_i + \varepsilon_{it} \tag{1}$$

where Y is the grain output, δ is the spatial auto-regressive parameter (*rho*), W is the spatial weights matrix, Geo_1 and Geo_2 are the dummy variables, and u_i and ε_{it} represent the individual effect and error term, respectively.

W was calculated based on the inverse of the Euclidean distance between counties i and j using the *spmat* command in Stata. Where no data was available on the required variables for a certain county, it was removed from the analysis, resulting in some counties being 'no neighbors'. As a consequence, W was not created by the definition for the 'contiguity' relationships between counties i and j.

*Geo*s indicating the dominant landforms are considered to be qualitative factors. The relevant information can be captured by defining a dummy variable or a binary variable in empirical work. The ranking for the slope of the surface has an order of plain < hill < mountain. Thus, Geo_1 and Geo_2 were defined as follows: let Geo_1 = 1 if plain county and Geo_1 = 0 otherwise; let Geo_2 = 1 if mountain county and Geo_2 = 0, otherwise; hill county is the base. The benefit of capturing qualitative information using the values zero and one is that it leads to regression models in which the coefficients have very natural interpretations. In Equation (1), φ_1 is the difference in Y between a plain county and a hill county and φ_2 is the difference in Y between a mountain county and a hill county, keeping other factors constant.

The endowments of land resources, including the quantity and condition for development, are different in plain, hill, and mountain counties. More specifically, the impacts of the amount of cultivated land, irrigation, and agricultural mechanization were considered. The amount of cultivated land has captured extensive concern in the light of its impact on food security in China. Drought is a powerful natural force with a significant impact on food security in China [36]. Irrigation plays a crucial role in Chinese grain production [11]. With increasing agricultural labor costs [23], mechanization is being used increasingly to limit the costs of grain production. In China, most cultivated land can be found in the plain regions, followed by the hill and mountainous regions [37]. Due to the absence of a slope of the surface, the conditions for irrigation and agricultural mechanization are more advantageous in plain regions, compared to hill and mountainous regions. To assess the impact of cultivated land quantity, irrigation, and agricultural mechanization on grain output, we used the following model:

$$\ln Y_{it} = \beta_0 + \lambda \sum_{j=1}^{n} W_{ij} \ln Y_{ij} + \beta_1 \ln Land_{it} + \beta_2 \ln Irri_{it} + \beta_3 \ln Power_{it} + \varphi_i + v_{it} \tag{2}$$

where λ is the spatial auto-regressive parameter (*rho*), *Land* is the amount of cultivated land, *Irri* is the irrigated area, *Power* is the total power of agricultural machinery, and φ_i and ν_{it} represent the individual effect and error term, respectively.

In agricultural production, chemical fertilizer and labor are two essential factors. The two control variables were added in Equations (1) and (2). Equations (1) and (2) were thus modified to Equations (3) and (4), respectively, as follows:

$$\begin{aligned} \ln Y_{it} = \alpha_0' + \delta' \sum_{j=1}^{n} W_{ij} \ln Y_{ij} + \varphi_1' Geo_1 + \varphi_2' Geo_2 \\ + \alpha_1 \ln Fert_{it} + \alpha_2 \ln Labor_{it} + \mu_i' + \varepsilon_{it}' \end{aligned} \tag{3}$$

$$\begin{aligned} \ln Y_{it} &= \beta_0' + \lambda' \sum_{j=1}^{n} W_{ij} \ln Y_{ij} + \beta_1' \ln Land_{it} + \beta'_2 \ln Irri_{it} + \beta'_3 \ln Power_{it} \\ &\quad + \beta_4 \ln Fert_{it} + \beta_5 \ln Labor_{it} + \varphi_i' + v_{it}' \end{aligned} \tag{4}$$

where *Fert* is the input of chemical fertilizer and *Labor* is the amount of labor.

It should be noted that the values of Y and *Power* in 1992 are equivalent to those of *Land*, *Irri*, *Labor*, and *Fert* in 1990. The mean values of Y and *Power* in 2000 and 2014 are also equivalent to the values of *Land*, *Irri*, *Labor*, and *Fert* in 2008.

We used random effects estimators (RE) of Equations (1)–(4) for two reasons. First of all, the key explanatory variables Geo_1 and Geo_2 are constant over time. RE avoids the problem that the coefficients of time-invariant variables cannot be estimated. Second, the quantity of counties is much larger than the number of years (the minimum proportion of the former to the latter is 2015: 3). The random effects model can avoid the loss of degrees of freedom incurred in the fixed effects model associated with large N and relatively small T, yet we also presented the fixed effects estimators (FE) of Equations (2) and (4) and used the Hausman test.

3. Results

3.1. Spatial Clusters of Grain Outputs

Maps of statistically significant high values (hot spots) and low values (cold spots) of Chinese grain output in 1992, 1995, 2000, 2005, 2010 and 2014 were created using the OHSA (Figure 2). Figure 2 shows that the distribution of high and low values expanded during 1992–2000 and then shrank. An apparent feature is the increased low values of grain output found in Zhejiang, Fujian, Guangdong, and Hainan.

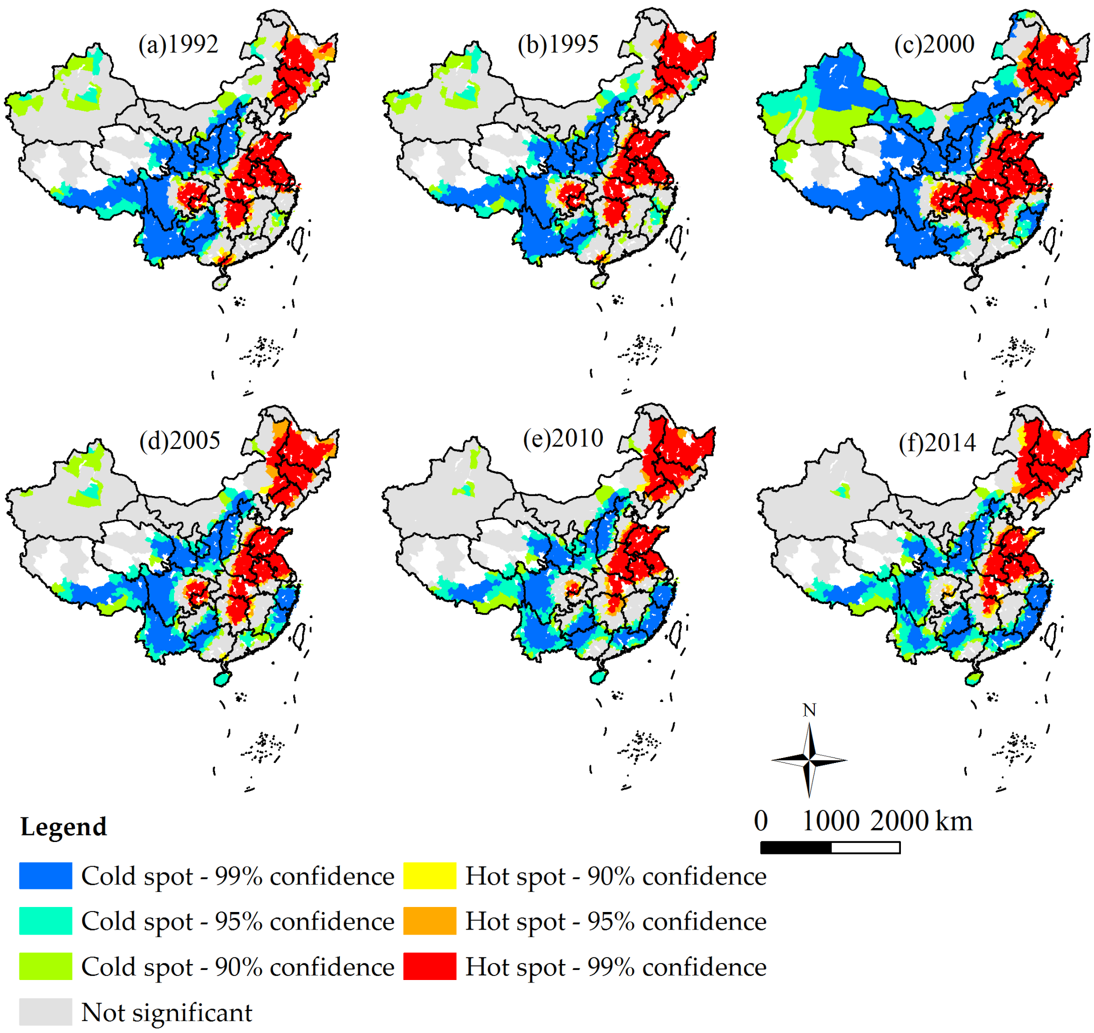

Figure 2. Spatial clusters of Chinese grain output. (**a**) 1992; (**b**) 1995; (**c**) 2000; (**d**) 2005; (**e**) 2010; (**f**) 2014.

In 1992, high values of grain output were mainly found; (1) in northeast China, (2) south of the Yellow River and north of the Huai River, (3) in the Jianghan-Dongting Plain, (4) in the Sichuan Basin, and (5) south of Guangdong and Guangxi. Low values of grain output were mainly found in Southwest China and the Loess Plateau region. Compared to 1992, more counties in northeast China showed a high grain output in 2000. Counties across the east of the Sichuan Basin, south of the Yellow River, and north of the Yangtze River were also hot spots of grain output. Most of the counties in western China were the cold spots of grain output, as well as the counties in Fujian and south of Zhejiang. In 2014, high values of grain output were concentrated in northeast China (including eastern

Inner Mongolia), Shandong province, Huanghuai, and Jianghan-Dongting Plains. Low grain output values were concentrated in the coastal provinces in the south of Jiangsu, southwest China, and the Loess Plateau.

To investigate the degree of spatial match between grain production and landforms, we reclassified the maps of Figure 2, using the following rules: (1) hot spots in plain counties and cold spots in mountain counties are determined a 'match'; (2) hot spots in mountain counties and cold spots in plain counties are determined a 'mismatch'; and (3) hill counties are defined as grey zones, i.e., we did not consider hot or cold spots there. These rules meet the fundamental assumption that plain counties have the highest grain output, followed by hill counties and mountain counties, because of the difference in the endowments of land resources. As an intermediate level, hill counties with hot or cold spots are not the keynotes compared to plain and mountain counties as a whole.

Figure 3 presents the results of the reclassification to match-mismatch. The mountain counties with hot spots in grain output are mainly located in northeast China, Shandong province, and central China. Plain counties with cold spots in grain output first increased, from 1992 to 2000, and then decreased, from 2000 to 2014, in northwest China. In southeast China, plain counties with cold spots showed a continuous increase from 1992 to 2014.

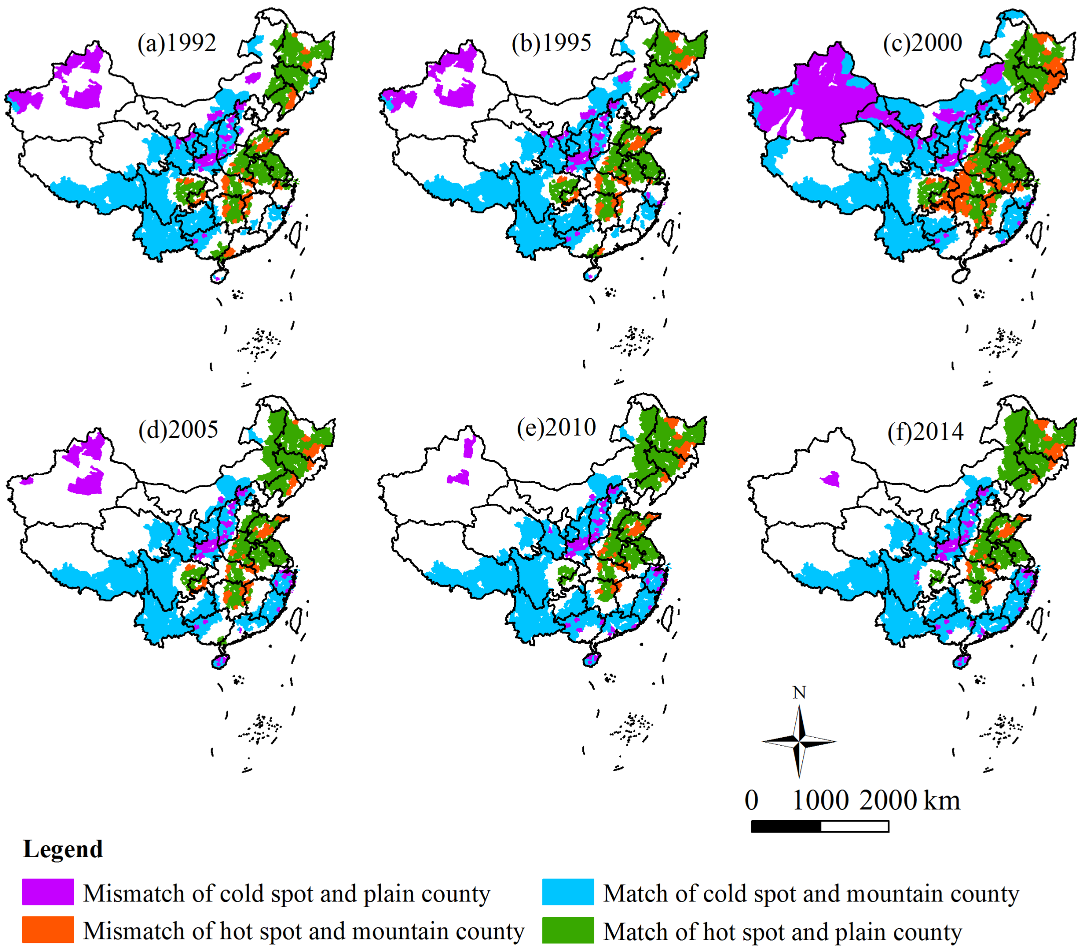

Figure 3. Match or mismatch between grain output and landforms. (**a**) 1992; (**b**) 1995; (**c**) 2000; (**d**) 2005; (**e**) 2010; (**f**) 2014

Most grain output hot spots are located in plain counties, while most cold spots are located in mountain counties (Table 1). As such, generally speaking, a spatial match exists between grain production and landforms. The year 2010 represents a turning point in terms of the match degree between grain production and landforms, changing from a decreasing to an increasing degree of match. A likely explanation is the Grain for Green Project, which brought cultivated land into forest and grassland [17–19]. Additionally, migration from rural to urban areas has been higher since about 2002 [38]. Agricultural labor loss causes the abandonment of cultivated land and a subsequent reduction of grain output in mountain regions, as the labor loss cannot be counteracted by increased mechanization due to the restrictions presented by the terrain [20–22].

Table 1. Distribution of hot spots and cold spots of grain output in plain, hill, and mountain counties.

Type of County	**Hot Spotss**											
	1992		**1995**		**2000**		**2005**		**2010**		**2014**	
	No.	**%**	**No.**	**%**	**No.**	**%**	**No.**	**%**	**No.**	**%**	**No.**	**%**
Plain counties	273	48	326	54	356	46	304	52	304	57	292	57
Mountain counties	89	16	82	14	201	26	81	14	63	12	62	12
Type of County	**Cold Spotss**											
	1992		**1995**		**2000**		**2005**		**2010**		**2014**	
	No.	**%**	**No.**	**%**	**No.**	**%**	**No.**	**%**	**No.**	**%**	**No.**	**%**
Plain counties	128	18	124	17	178	23	119	15	120	14	122	14
Mountain counties	462	64	447	61	464	59	504	65	541	64	555	65

3.2. Estimates of the SAR

Equation (1) was estimated using the Maximum Likelihood Estimate (MLE) method. The estimates are reported in column 2 of Table 2. The Ordinary Least Squares (OLS) regression results of Y on Geo are shown in column 1 of Table 2. The *rho* is statistically significant at the level of 1%, which means the SAR model is acceptable. The estimated coefficient of Geo_1 is positive and significant at the level of 1%, and the coefficient of Geo_2 is negative and significant at the level of 1%. This indicates that grain output in plain counties is higher than in hill counties, and grain output in mountain counties is lower than in hill counties.

Table 2. Results of regressing grain output (Y)on the dummy variables (Geo).

Independent Variables	**OLS**	**SAR(RE)**
	(1)	**(2)**
Geo_1	0.354 *** (0.040)	0.304 *** (0.059)
Geo_2	−0.756 *** (0.037)	−0.621 *** (0.056)
Number of obs.	6045	6045
rho		0.995 *** (0.003)
R^2	0.152	0.173

Note: (1) Numbers in parentheses are standard errors; (2) *** denotes statistical significance at the level of 1%.

The dominating landform (Geo) can have an impact on the grain production via the amount of cultivated land, irrigation, and agricultural mechanization. To test this, ln($Land$), ln($Irri$), and ln($Power$) were regressed on Geo using OLS (Table 3). Geo_1 had positive significant effects on ln($Land$), ln($Irri$), and ln($Power$), and Geo_2 had negative significant effects on ln($Land$), ln($Irri$), and ln($Power$). These results imply that plain counties have the largest amount of cultivated land and the highest degree of irrigation and agricultural mechanization, followed by hill counties and mountain counties.

Table 3. Results of regressing ln(*Land*), ln(*Irri*), and ln(*Power*) on *Geo*.

Independent Variables	**ln(*Land*)**	**ln(*Irri*)**	**ln(*Power*)**
	(1)	**(2)**	**(3)**
Geo_1	0.165 *** (0.045)	0.602 *** (0.049)	0.476 *** (0.034)
Geo_2	−0.652 *** (0.045)	−0.870 *** (0.050)	−0.724 *** (0.034)
Number of obs.	3902	3426	5871
R^2	0.110	0.241	0.202

Note: (1) Numbers in parentheses are standard errors; (2) *** denotes statistical significance at the level of 1%.

Next, Equation (2) was estimated using the MLE method to investigate the impact of the amount of cultivated land, irrigation, and agricultural mechanization on grain output. The estimates are reported in columns 2 and 3 of Table 4. The results with OLS regression of *Y* on ln(*Land*), ln(*Irri*), and ln(*Power*) are presented in column 1 of Table 4. Using a SAR model is acceptable, given that *rho* is statistically significant at the level of 1%. We preferred the RE according to the Hausman test; because chi2 = −1629.51 < 0, we do not reject the null hypothesis that RE provides consistent estimates. Column 2 of Table 4 shows that the estimated coefficients of ln(*Land*), ln(*Irri*), and ln(*Power*) are positive and significant at the 1% level. Furthermore, ln(*Land*) has the greatest impact on grain output, followed by ln(*Irri*) and ln(*Power*).

Table 4. Results of regressing *Y* on ln(*Land*), ln(*Irri*) and ln(*Power*).

Independent Variables	**OLS**	**SAR(RE)**	**SAR(FE)**
	(1)	**(2)**	**(3)**
ln(*Land*)	0.506 *** (0.014)	0.393 *** (0.017)	−0.001 (0.012)
ln(*Irri*)	0.192 *** (0.011)	0.148 *** (0.011)	0.013 * (0.007)
ln(*Power*)	0.295 *** (0.013)	0.141 *** (0.015)	0.007 *** (0.010)
Number of obs.	3364	3364	3364
rho		0.792 *** (0.063)	0.904 *** (0.047)
Hausman test		chi2= −1629.51	
R^2	0.716	0.748	0.581

Note: (1) Numbers in parentheses are standard errors; (2) *** and * denote statistical significance at the levels of 1% and 10%, respectively.

To test the robustness of these results, Equations (3) and (4) were estimated (Tables 5 and 6). Compared to column 2 of Table 2 and column 2 of Table 4, column 2 of Table 5 and column 2 of Table 6 have much larger values of R^2, respectively. The estimated coefficients of the key explanatory variables are statistically significant, and the signs of these coefficients are constant. Additionally, the estimated coefficients of the two control variables are within expectations, i.e., both ln(*Fert*) and ln(*Labor*) have a statistically significant impact on grain output. The empirical evidence hence is robust.

Table 5. Results of regressing grain output on *Geo* and the control variables.

Independent Variables	**OLS**	**SAR**
	(1)	**(2)**
Geo_1	0.058 ** (0.024)	0.108 *** (0.031)
Geo_2	−0.234 *** (0.023)	−0.317 *** (0.030)
ln(*Fert*)	0.447 *** (0.009)	0.310 *** (0.011)
ln(*Labor*)	0.292 *** (0.011)	0.264 *** (0.011)
Number of obs.	3900	3900
rho		0.390 *** (0.052)
R^2	0.763	0.781

Note: (1) Numbers in parentheses are standard errors; (2) *** and ** denote statistical significance at the levels of 1% and 5% levels.

Table 6. Results of regressing grain yield on ln(*Land*), ln(*Irri*), ln(*Power*) and control variables.

Independent Variables	OLS	SAR(RE)	SAR(FE)
	(1)	**(2)**	**(3)**
ln(*Land*)	0.331 *** (0.013)	0.309 *** (0.014)	−0.003 (0.012)
ln(*Irri*)	0.064 *** (0.010)	0.059 *** (0.014)	0.005 (0.008)
ln(*Power*)	0.064 *** (0.013)	0.014 * (0.008)	0.054 *** (0.012)
ln(*Fert*)	0.299 *** (0.011	0.263 *** (0.011)	0.048 *** (0.009)
ln(*Labor*)	0.188 *** (0.011)	0.178 *** (0.012)	0.018 * (0.010)
Number of obs.	3336	3336	3336
rho		0.378 *** (0.060)	0.810 *** (0.063)
Hausman test		chi2= −526.13	
R^2	0.799	0.858	0.757

Note: (1) Numbers in parentheses are standard errors; (2) *** and * denote statistical significance at the 1% and 10% levels, respectively.

4. Discussion

4.1. Interpretation

The quantity of land resources and conditions for their development vary in plain, hill, and mountain counties. This is the major reason that the spatial pattern of Chinese total grain production agrees with the geographical distribution of landforms, in keeping with the findings from Xu and Zhu [39]. The results also support previous studies [17–21] on the impacts of the GGP and cultivated land abandonment on grain production and vice versa.

In this paper, we did not consider the impacts of climate change on Chinese total grain production in the regression models. Increasing evidence shows that the impacts of socio-economic factors on grain production are much stronger than those of climate change [15,40–42]. With adaptation (e.g., irrigation and increased use of fertilizers and machines), the impacts of climate change could be reversed in China [42]. In addition, county-level data on climate (e.g., temperature and precipitation) during 1992–2014 are unavailable. However, the conclusions of this study are supported by the convincing results.

4.2. Implication

It is vital for sustainable land management to improve the green use efficiency of cultivated land in plain, hill, and mountain counties. The 13th Five-Year Plan has listed 'green development', or environmentally friendly growth, as a key path for economic progress. Improving land use efficiency is a central issue in the realization of sustainable development in China today [43]. Grain production in different types of counties is different. Any attempt to implement a one-policy-fits-all design should be resisted. Targeted policies on sustainable land management in plain, hill, and mountain counties will be more effective.

The amount of cultivated land area is clearly a base factor impacting the amount of grain production. Today, cultivated land area has however reached a maximum in China. In the 13th Five-Year Plan, the Chinese government proposed to instead improve cultivated land quality in order to guarantee food security. An important proposed measure is the improvement in cultivated land use by engineering projects, such as land reclamation and water conservation projects. These actions are more likely to occur in plain counties than in hill or mountain counties.

Greater consideration should be put into mechanization in grain production, especially in rice and maize production, to further increase grain output in plain counties. To be able to fully operate machinery, it is necessary to level land as well as to transfer land to reduce the degree of fragmentation. Plain counties are mainly concentrated in northern China where a water resource shortage exists. Chinese grain production currently is not in accord with the distribution of water resources [39]. With the current scenario of global climate change, plain counties should improve access to water in grain production by developing proper irrigation and drainage systems. The implementation of the South-to-North Water Diversion Project would, at least to a certain extent, relieve the pressure caused by the water resource shortage in the North [13]. However, insufficient water supply is a long-term problem for economic and social development. Moreover, groundwater has become the dominant source of water supply for irrigation in the North China Plain [11]. Extensive exploitation of groundwater is unsustainable. Therefore, plain counties (especially in northern China) must develop water-saving irrigation to increase water use efficiency in grain production.

Having the highest concentration of grain production in China, plain counties consume the most chemical fertilizer. Agricultural non-point source pollution caused by overuse of chemical fertilizers should be controlled in plain counties. The implementation of the Action Plan for Zero Growth in Chemical Fertilizer Input by 2020 is an opportunity for plain counties to reduce the overuse of chemical fertilizer and improve efficiency in the use of chemical fertilizer in grain production.

As a cold spot of grain output, mountain counties should weaken the role of grain production compared to the other counties in order to strengthen ecological improvement and environmental protection. It is important for mountain counties to restore cultivated land to forest and pasture following free market principles, e.g. abandonment due to increased agricultural labor cost [17–19]. Hill counties should stabilize grain production capacity. It is important to prevent soil erosion in hill counties, especially in northeast China and Shandong province since they are the hill regions with the highest grain output.

5. Conclusions

Spatial analysis was applied to investigate the pattern of total grain production in China in relation to the dominant landforms. Plain counties produce more grain as they contain more cultivated land and have a higher degree of irrigation and agricultural mechanization. The spatial pattern of Chinese grain production follows the law of substitution of labor for mechanization.

The future roles of total grain production in the counties of each landform should be as follows: increased competitiveness in plain counties, a stabilized capacity in hill counties, and a further reduction in grain production in mountain counties. In grain production, plain counties should improve efficiency in the use of water resources and chemical fertilizer, hill counties should prevent soil erosion, and mountain counties should restore cultivated land to forest and pasture.

Acknowledgments: The authors acknowledge the financial support of the National Natural Science Foundation of China, No. 71233004; the Scientific Research Innovation Project for Graduate Students of the Higher Education Institutions of Jiangsu Province, No. KYZZ16_0372; and the Doctoral Dissertation Scholarship Foundation of the China Institute for Rural Studies, Tsinghua University, No. 201615.

Author Contributions: Jinlang Zou and Qun Wu had the original idea for the study. Jinlang Zou was responsible for data collecting. Jinlang Zou and Qun Wu carried out the analyses. All the authors drafted the manuscript and approved the final one.

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

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