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Research on Identification of Multiple Cropping Index of Farmland and Regional Optimization Scheme in China Based on NDVI Data

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Abstract: The multiple cropping index of farmland is a significant characterization of land use intensity. Based on the NDVI data, this paper calculated the multiple cropping index of farmland in China using the S-G filtering method, and proposed an optimized regionalization scheme for the farmland use. The findings reveal that from 2000 to 2018, the multiple cropping index of farmland in China underwent the fluctuation of rising first, then falling and rising continuously, which was closely associated with the agricultural support policies enforced in China. Counties whose multiple cropping indexes decreased from 2009 to 2018 were mainly located in areas primarily producing grain, which exerted a greater influence on food security. The gap between the multiple cropping index and potential multiple cropping index of farmland is increasingly widening from north to south in China. Accordingly, four types of grain producing zones were delineated: key development zone, potential growth zone, appropriate development zone, and restricted development zone. Some suggestions, such as rotation, fallow, determination of yield by water and offsetting the quantity balance of farmland by increasing the multiple cropping index, are put forward based on different zones.

Keywords: NDVI; land use transition; multiple cropping index; farmland; regional optimization scheme

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1. Introduction

With global climate change, continuous population growth, and rapid urbanization, food security issues and policies remain a subject of concern to the international community. China feeds about 18% of the global population using 8% of its farmland [1]. The fundamental reality of more people and less farmland in China demonstrates that food security is crucial to the lasting political stability in China. With the impact of the epidemic and rising uncertainty in the international trade environment, the issues of ensuring baseline of food security and grasping the initiative in food security have become more prominent. As an important factor affecting food security, the change of farmland area has received more attention. Over the past 40 years of the reform and opening up in China, irreversible non-agricultural changes in a large amount of farmland have taken place according to the progress of fast industrialization and urbanization, which has led to the decrease of farmland area, and a threat to food security [2]. Strict observation of the red line of 1.2 million km^2 of farmland has become a national political task to ensure food security. However, with the continuous increase of total population and urbanization, it is very difficult to increase the food supply by increasing farmland area. On the contrary, it is more feasible to ensure national food security by improving the level of intensive use of existing farmland [3]. Multiple cropping is an important aspect of the intensive use of farmland [4]. From 1986 to 1995, the increased grain yields attributed to the increasing multiple crop index (MCI) of farmland, accounted for one third of the average annual total grain yields (429 billion kg) in China [5]. About 12% of global farmland applied multiple cropping in 2000. In addition, 34%, 13%, and 10% of rice, wheat, and maize crops, respectively, utilize multiple cropping, demonstrating the importance of such cropping systems for cereal production [6]. Moreover, compared with reclaimed farmland, existing farmland possesses better production conditions. Multiple cropping is, therefore, an effective way to increase the grain yields and ensure food security [3,7,8].

With the expansion of the connotation of food security, the objectives of researches on multiple cropping of farmland in different countries have also shown differences. In European and North American countries with a high level of economic and social development, the researches mainly focus on the impact of multiple cropping on pest control and soil improvement. The conclusions based on field experiments prove that increasing the level of MCI of farmland can increase diversity, thereby contributing to pest control and reducing herbicide intensity [9]. Exploring different multiple cropping modes can effectively enhance organic matter and microbial activities in the soil, thereby developing organic agriculture and obtaining a higher income [10]. In South America, Africa, and Asia, where the level of economic and social development is relatively low, the goal of related researches is mainly to increase grain yields [11–13]. In recent years, however, it has begun to shift to the direction of balanced nutrition [14]. It is worth noting that in Asia, human-land contradiction is very serious. The production system characterized by smallholder determines the necessity of increasing MCI to increase the grain yields and incomes [15]. Therefore, Asia has become a region of focus for researches on MCI [16,17]. In India, the zoning map of rice MCI was drawn and used to estimate the irrigation demand of different zones to provide a scientific basis for policy evaluation [18]. From north to south in China, great differences in terms of crop types and cropping systems are exhibited among eight temperature zones [19,20]. Influenced by agricultural production conditions and socio-economic development, the MCI in the major grain producing areas [21,22] and the rice-growing areas, where "double cropping to single cropping" is common [23,24], has noticeably declined in recent years.

Reasons for this are summarized into the following four aspects. Firstly, marginal incomes earned via a multi-cropping system decrease significantly as a result of the increasing production cost. MCI was changed from multiple cropping to single cropping to maximize the economic benefits [25]. Secondly, the labor marginal incomes from non-agricultural employment are much higher than those of agricultural production for Chinese farmers. Farmers are more inclined to transfer more labor time and production resources to part-time or non-agricultural production activities [26], thus resulting in seasonal or year-round abandonment of farmland especially in labor-intensive cash crops and regions closer to urban areas [22]. Thirdly, more farmers may face a poor harvest after using the "double cropping to single cropping" method, since those that plant double-cropping rice may be exposed to the intensive damages of insects, birds, and animals [27]. Fourthly, the adjustment of food policies will also cause changes of MCI through incentives and constraints on the planting behaviors of farmers. In a word, decreasing multi-cropping level and even abandoning cultivation, is a rational choice of farmers under low planting efficiency [28].

Existing researches mainly concern the influence of MCI on food security, and use MCI as the input variable to calculate variations in farmland area and grain yields. These prove that multi-cropping system can indeed increase the outputs of corn and rice [29], while decreasing the multi-cropping level can inhibit, and even decrease the growth of food output. This makes maintaining the self-sufficiency of cereal a challenge. However, some researches pointed out that the improvement of the multi-cropping system might influence the resource ecological environment. The practices in Pakistan prove that around 51% and 13% of water inefficiency are present under multiple and sole cropping systems, respectively [30]. The expansion of the multi-cropping system increased agricultural greenhouse gas emissions in the North Plain and neighboring regions in China [31], and the growth of the annual mean temperature, in return, can influence the growth of crops [32,33]. Evidently, pursuing high MCI blindly, and ignoring the water and temperature conditions would work against the increasing of grain yields and the sustainable development of the ecological environment [34].

The cropping system of China is not only experiencing a decline of MCI, but also facing the risk of spatial mismatch between cropping system and natural production conditions (including water, soil, gas, etc.). Firstly, there are abundant water and heat resources in South China. Historically, the food supply pattern entailed "transport from south regions to north regions", but now has changed to "transport from north regions to south regions", thus increasing consumption of farmland resources [35]. Secondly, the location of large and medium cities often highly overlaps with that of high-quality farmland [36]. A considerable amount of farmland with high-quality water and heat resources is occupied by urban construction sprawl, while the reclaimed farmland with poor production conditions is used to compensate for the loss of high-quality farmland with fertile soil and high MCI. The imbalance of the quality and production capacity of farmland has threatened China's food security [37]. In this regard, some studies have measured the potential multiple cropping index (PMCI) of farmland in China based on water and temperature conditions, which is the theoretical highest MCI of farmland based on the natural environment conditions [3]. Based on PMCI, some researches inferred the most sown area [38] and grain yields [1] under the optimal cropping system.

Scientific analysis of the relationship between multi-cropping system and potential multi-cropping system is conducive to deepening our understanding of farmland use and the scientific exploration of the potential of farmland, as well as providing references and supports for the implementation of a strategy that "stores foods in farmland". Based on the normalized difference vegetation index (NDVI), this paper will analyze the spatio-temporal characteristics of the MCI of farmland in China from 2000 to 2018. The distortion of water-land resources will be judged by the gap of MCI and PMCI. Finally, suggestions will be put forward to give full play to the production potential of high-quality farmland so as to achieve a win-win situation for food security and ecological security. Compared with existing researches on MCI of farmland [16–24], one of the innovations of this study is the problem of increasingly serious farmland abandonment introduced into the study of multi-cropping system. We will further divide the decline of MCI into "seasonal" abandonment and year-round abandonment, so as to respond to attentions on abandonment of farmland in China's farmland protection system. Another innovation was the delineation of four types of grain producing zones, namely key development zone, potential growth zone, appropriate development zone, and restricted development zone, and the provision of references for optimization of food production layout and benefit compensation mechanism design.

2. Materials and Methods

2.1. Materials

NDVI, also called the standardized vegetation index, is a comprehensive reflection of vegetation type, coverage form, and growth conditions in unit pixel. The value of NDVI is determined by the vegetation coverage and leaf area index (LAI). The physical growth processes of crop sowing, seedling, heading, maturing, and harvest in a year reflect fluctuations of NDVI with time, and peaks correspond to the time phases when the biomass of crop populations is the largest. According to this principle, the MCI of farmland is gained by extracting the peaks number of NDVI in one year. NDVI ranges between minus 1 and 1. Specifically, a negative value represents that a surface is covered by cloud, water, or snow; 0 represents rocks or naked soils; a positive value indicates vegetation coverage, which increases with the increase coverage [39]. In this study, the monthly (January to December) NDVI sequence from 2000 to 2018 is generated by the maximum value combination based on continuous time series of SPOT/VEG satellite remote sensing data. The spatial resolution of NDVI was 1 km × 1 km.

The spatial distribution data of potential multi-cropping system in China is estimated by the Global Agro-Ecological Zones (GAEZ) model developed by the FAO and IIASA together based on data of DEM, soil, farmland, and meteorological. On this basis, the ideal cropping system can be realized for the farmland. The potential multi-cropping system data includes single cropping, double cropping, and triple cropping in a year, with a spatial resolution of 10 km × 10 km.

In this study, the farmland grid data in five phases (2000, 2005, 2010, 2015, and 2018) were used to restrict the identification range of cropping system in farmland and eliminate interferences of other land use types. The spatial resolution of it is 1 km × 1 km. The number of farmland grids has been decreasing continuously since 2000, and it experienced a sharp reduction from 2005 to 2010 and since 2015 (Figure 1).

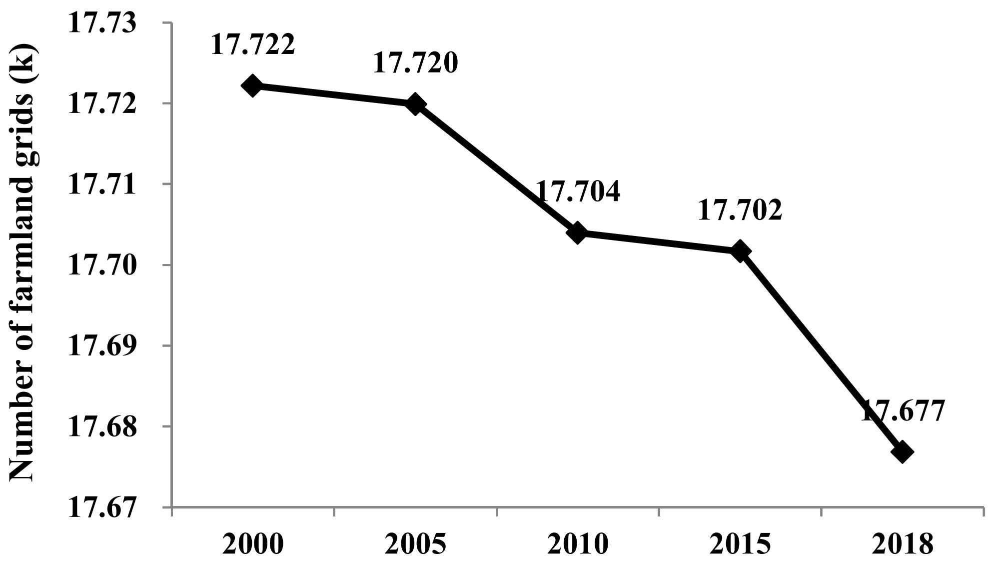

Figure 1. Variations of the number of farmland grids in China (2000–2018).

The above three types of data are provided by the Data Registration and Publishing System of Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (https://www.resdc.cn/data.aspx?DATAID=254, accessed on 12 October 2019). They cover 31 provinces in China, except Taiwan, Hong Kong, and Macau, as shown in Figure 2. In addition, it is necessary to introduce the locations of several important agricultural areas used in the paper. Huang-Huai-Hai Plain is composed of Hebei, Beijing, Tianjin, most of Henan, and northern Anhui and Jiangsu. It is the most important grain producing area in China due to its balanced rain and heat and flat terrain. The Loess Plateau includes Shanxi, Ningxia, north of the Qinling Mountains in Shaanxi, and southeastern Gansu. The terrain of this area is complex and diverse, and the ecological environment is fragile.

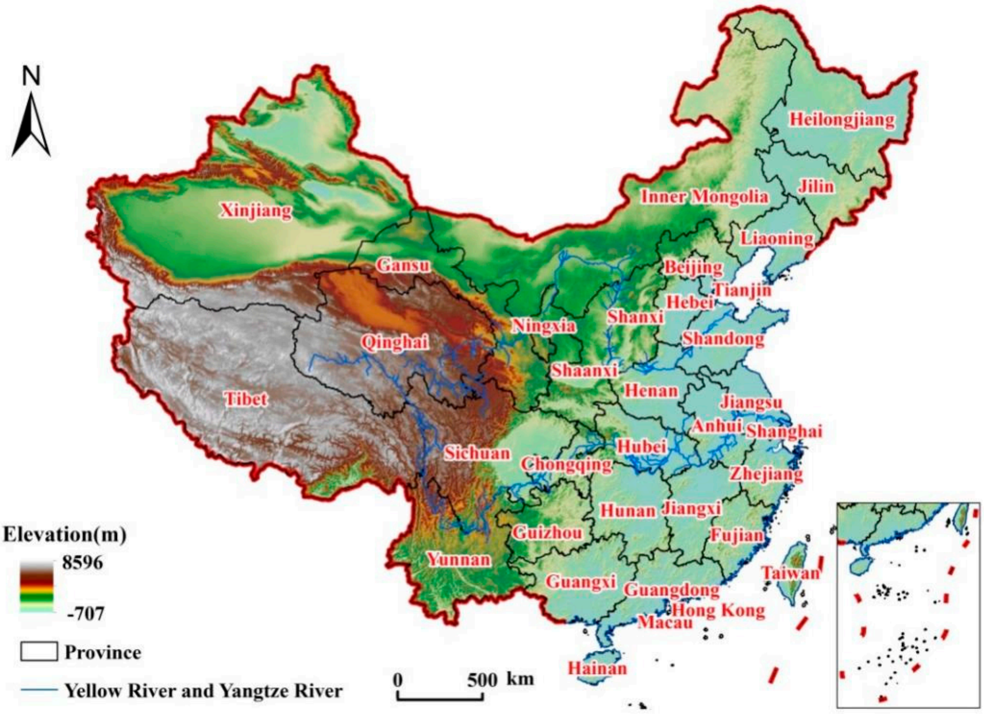

Figure 2. Location of the study area.

2.2. Methods

Step 1: Extract monthly NDVI sequence of farmland

This study concerns the MCI of farmland. Hence, the NDVI dataset of farmland was extracted only to eliminate interferences of other land use types. Firstly, the grids with farmland attribute in the dataset of national land use were clipped to build up a mask of farmland. Secondly, the mask of farmland was overlapped and spatial registration with NDVI data from January to December using ArcGIS software, thus extracting the NDVI sequences of farmland.

Step 2: Reconstruct NDVI sequence through the Savitzky-Golay (S-G) filter

The NDVI sequence of farmland had noise caused by atmospheric interferences or other reasons, thus making the NDVI value lower than the true value. Hence, the S-G filter was used for further smoothing and denoising of the NDVI sequence. As a result, high-quality NDVI sequence, which represented the growth trend of crops, was gained. The S-G filter is a convolutional smoothing approach based on the least square method [40], and it performs the polynomial least square fitting to the adjacent values in a local window. The S-G filter needs two parameters, which are the width of the smoothing window (m) and the degree of the polynomial (d). It requires that the m is shorter than the length of the NDVI sequence and is an odd number, and d is less than m. The larger the m and the smaller the d, the smoother the filtering result, but it also possibly eliminate more real details. Attributes of each farmland grid were the NDVI values from January to December and the sequence length was 12. According to the principle of parameter determination, three filtering windows of (m = 3, d = 2), (m = 5, d = 3) and (m = 5, d = 4) were chosen.

Step 3: Combine the original curve and fitting curve of NDVI

This step was used to maintain high values and decrease abnormal low values. When the original value of the NDVI was higher than the fitting value obtained in Step 2, the original NDVI value was retained. Otherwise, when the original NDVI value was smaller than the fitting value, it was replaced by the fitting value, and the NDVI curve was rebuilt.

Step 4: Calculate the fitting effect coefficient

This step was used to judge the fitting effect between the newly NDVI sequence obtained in Step 3 and the original NDVI sequences. The smaller coefficient indicates the better fitting effect. The calculation formula of the fitting effect coefficient is as follows:

$$fc = \sum_{i=1}^{n} \left(\left| N_i^1 - N_i^0 \right| \times W_i \right) \quad (1)$$

$$W_i = \begin{cases} 1, N_i^1 < N_i^0 \\ 1 - \frac{d_i}{d_{\max}}, N_i^1 > N_i^0 \end{cases} \quad (2)$$

where fc is the fitting effect coefficient of S-G filter; n is the length of NDVI sequence (which is 12); i is the serial number of elements in the NDVI sequence; N_i^1 and N_i^0 are the fitting value and original value of the NDVI of the element i, respectively; W_i is the weight of element i; d_i is the absolute residual error between the original value and fitting value of the NDVI of element i; and $d_{\max}$ is the maximum value in d_i. The fc of the three filtering windows in Step 2 was compared and that of the (m = 5, d = 4) was the smallest. The coefficient of (m = 5, d = 4) was 0.054, which was 0.014 and 0.013 lower than that of (m = 3, d = 2) and (m = 5, d = 3), respectively. The fitting accuracy of filtering windows of (m = 5, d = 4) increased by about 20% (Table 1). Therefore, the fitting values of the original NDVI data were performed by filtering windows (m = 5, d = 4).

Table 1. Fitting effect coefficient (fc) of different filtering windows.

Filtering Windows	(m = 5, d = 3)	(m = 3, d = 2)	(m = 5, d = 4)
fc	0.067	0.068	0.054

Step 5: Peak recognition

The first-order differential method was used to recognize the peaks and valleys of the NDVI sequence. In the NDVI sequence of three successive months that first rises and then falls, the middle value was recognized as peak. On the contrary, in the NDVI sequence of three successive months that first falls and then rises, the middle value was recognized as valley. Meanwhile, a statistical analysis on the peak number of each grid was carried out to represent the MCI in each farmland grid.

Step 6: Eliminate interference peaks

In order to reduce the error of the MCI, this paper set up some criteria to remove interference peaks : ① The NDVI value of each peak was higher than 0.4, which was the empirical value of relevant researches [41]; ② to remove interference peaks, the occurrence time of real peaks was limited from April to October; and ③ the NDVI difference between peak and its adjacent two valleys cannot be smaller than 20% of the difference between the maximum and minimum in the NDVI sequences of 12 months. When one peak could not meet the above three criteria at the same time, it was regarded as an interference peak and deleted.

3. Results

3.1. Changes in the Level of Multiple Cropping Index of Farmland in China

3.1.1. Stage Characteristics

The variation trend of the MCI of farmland gained from the NDVI was similar to that of MCI calculated by statistical data (national farmland area divided by total sowing area in the same year). From 2000 to 2018, the above two types of MCI of farmland in China underwent the fluctuation of rising first, then falling and rising continuously (Figure 3). In 2018, the MCI extracted by the NDVI was 124.9%, which is only slightly different when compared with the 126.2% calculated using statistical data. In summary, the identification method of MCI of farmland based on NDVI data is feasible and reliable.

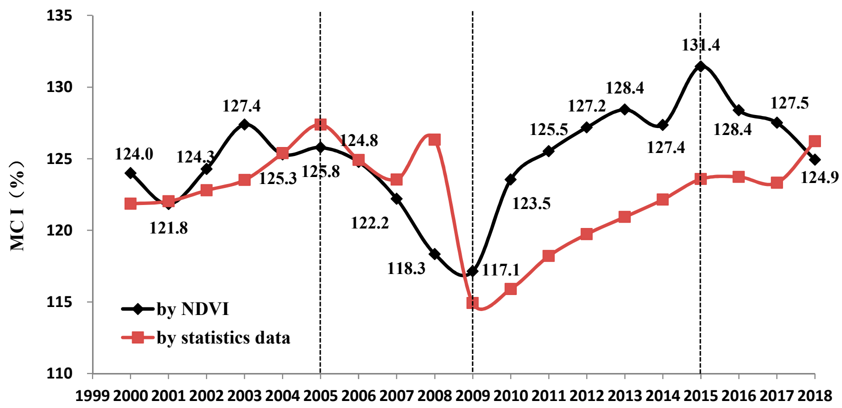

Figure 3. Stage characteristics of MCI of farmland in China (2000–2018).

Since the 21st century, the mean MCI of farmland in China was 125.4%, with a maximum and minimum of 131.4% and 117.1%, respectively (Figure 3). The fluctuation amplitude reached 14.3%, accounting for 11.4% of the mean. The MCI of farmland in China varies greatly from year to year, and it is necessary to analyze the characteristics of different stages. In general, it experienced four stages, which agree with the change in agricultural support policies enforced in China. From 2000 to 2005, the MCI of farmland remained stable and slowly grew from 124.0% to 125.8% (Figure 3). In the same period, the total grain yield in China in 2005 was 4.7% higher than that in 2000, which was due to the slight increase of MCI to a certain extent.

From 2005 to 2009, the MCI of farmland in China dropped sharply by 8.7% from 125.8% to 117.1% (Figure 3). During this stage, several food support policies, such as the lowest purchase price of rice and wheat and the temporary storage system of corn, were launched successively. Due to the low purchase price in the early stage of policy implementation and the hysteretic effect of incentive to farmers after the policy implementation, the MCI was not increased in this stage. Moreover, food support policies led to a rise in the prices of agricultural production materials and a rapid increase in production costs, thus further weakening the marginal benefits of agriculture. For farmers with more non-agricultural employment opportunities, seasonal or annual abandonment of farmland was the rational selection to achieve the maximum benefits. Hence, the MCI of farmland dropped dramatically.

From 2009 to 2015, the MCI of farmland increased continuously by 14.3% from 117.1% to 131.4% (Figure 3), which had something to do with the increasing supports for food production by the Chinese government in this period. With the annual growth of the lowest purchase price, farmers' enthusiasm in grain production was improved significantly, and they were able to gain more benefits by expanding the sowing area. In the same period, the grain yield in China in 2015 was higher by 18.2% compared with that in 2009. The increase of the MCI played an important role in the growth of grain yield.

From 2015 to 2018, the MCI of farmland began to decline again. With the inversion of domestic and foreign grain price, the problems of "high yield, high import and high inventory" became increasingly prominent. In 2016, China made a considerable adjustment to agricultural support policies, i.e., China canceled the temporary storage system of corn which had been implemented for eight years, and reduced the lowest purchase price of early indica rice. In 2017, the lowest purchase prices of all kinds of rice were declined as well. In 2018, the lowest purchase prices of both rice and wheat further decreased. In this context, the MCI of farmland decreased by 6.5% from 131.4% to 124.9% (Figure 3), which reflected the sharp reduction of farmer's enthusiasm for grain production.

3.1.2. Deconstruction of MCI Based on the Microscopic Perspective of Land Use Transition

Dynamic changes in the MCI of farmland are an important characterization of land use transition [42]. From the microscopic perspective, dynamic changes of the MCI reflect the production behavior response of farmers, who are independent "rational economists", to farmland use intensity under the principle of optimal allocation of production factors and maximum benefits. The proportion of farmland with double or triple cropping in total farmland area was calculated to determine the rate of multiple cropping. In general, the farmland in China was dominated by single cropping and the proportion had remained above 60% for a long period. The rate of multi-cropping (MCI > 1) of farmland in China experienced a sharp reduction in 2009 and a stable growth in 2015. In 2009, about 1/5 of farmland was engaged in a multi-cropping system, which increased to 1/3 in 2015. This also indicated that about 13% of farmland changed from a single cropping system into a multi-cropping system from 2009 to 2015. Due to the adjustment of agricultural support policies, the rate of multi-cropping of farmland decreased to 26.4% in 2018 (Figure 4).

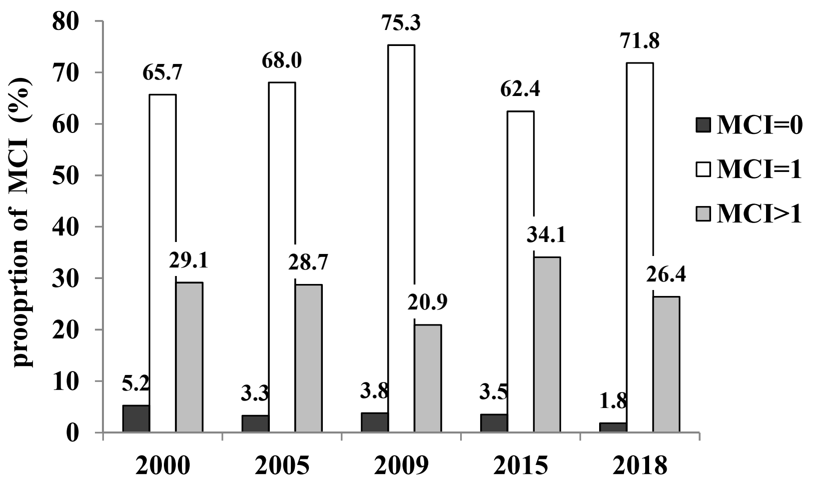

Figure 4. The proportion of different MCI of farmland in China.

To pursue maximum marginal benefits of agricultural production, farmers will adjust the production behaviors, i.e., choosing annual or seasonal abandonment of farmland or increasing the MCI. Variations in the planting behaviors of farmers can be further understood by analyzing the transfer matrix among different MCIs. From 2000 to 2018, production behaviors of farmers were mainly manifested via the following features (Table 2). Firstly, the seasonal abandonment of farmland by "transforming double cropping to single cropping" was the most universal. In the double cropping region in 2000, 52.0% of farmland changed from double cropping to single cropping, and only 46.4% continued to be double cropping. Secondly, the seasonal abandonment of farmland occurred widely among the triple cropping system. Only 1.6% of farmland was maintained as triple cropping system, while 59.4% and 37.4% of farmland changed to a single cropping system and double cropping system, respectively. On the contrary, 0.4% of farmland with single cropping and 0.3% of farmland with double cropping were adjusted to the triple cropping. This also indicated that the farmland with triple cropping experienced great spatial transfer. Thirdly, the "transformation from single cropping system to double cropping system" compensated for the decreased area of farmland with double cropping. About 17.8% of single cropping farmland was transformed into double cropping farmland. Moreover, since the proportion of single cropping farmland accounted for as high as 65.3% in 2000, the above transfer could compensate for the reduced double cropping farmland as much as possible. Fourthly, the massive reclamation of abandoned farmland was another important feature in this stage. Approximately 96.4% of abandoned farmland was all reclaimed. Due to the improvement of mechanization and the popularization of agricultural socialized services, the time cost of part-time farmers or migrant farmers to grow grain was reduced, which helped to slow down the occurrence of seasonal or year-round abandonment. During this period, the proportion of abandoned farmland fell by 3.5%.

Table 2. Transfer matrix among different MCIs (%) (2000–2018).

2000 \ 2018	Abandoned Farmland	Single Cropping	Double Cropping	Triple Cropping	Total in 2000
Abandoned farmland	3.6	74.8	21.6	0.0	5.3
Single cropping	1.9	79.9	17.8	0.4	65.3
Double cropping	1.3	52.0	46.4	0.3	29.4
Triple cropping	1.6	59.4	37.4	1.6	0.1
Total in 2018	1.8	71.8	26.0	0.4	100.0

3.1.3. Deconstruction of MCI Based on the Macroscopic Perspective of Land Use Transition

Influences on the production behaviors of farming households on the multi-cropping system of farmland have attracted considerable attention. However, variations of the MCI caused by land use transition based on macroscopic perspective are often ignored [43]. Since the 21st century, China's urbanization has been rapid. The urbanization rate increased from 36.22% to 59.58% from 2000 to 2018. The growth of the permanent population in urban areas led to continuous expansion of urban space, and a great deal of farmland was occupied by construction. Under the constraints of the farmland occupancy-compensation balance system, the contradiction between protecting farmland and guaranteeing construction land was alleviated by actively supplementing farmland through land consolidation and reclamation. However, quantity balance between occupation and supplementation of farmland was a hard requirement, and the attention paid to the improvement of quality was inadequate. Shoddy farmland for quality farmland was relatively universal, which generally influences the improvement of the MCI of farmland.

By comparing the average MCI of exited farmland, increased farmland, and unchanged farmland, it can be judged how the land use transition characterized by land use type change affects the multi-cropping system of farmland. It was found that there were three common laws in the four periods of 2000–2005, 2005–2009, 2009–2015, and 2015–2018 (Table 3). Firstly, the MCI of exited farmland was higher than that of unchanged farmland in the same period (1.26 > 1.24; 1.27 > 1.26; 1.32 > 1.30; and 1.34 > 1.31). This is because the exited farmland occupied by construction usually located in suburbs, and is high-level farmland with good irrigation, high soil fertility, flat terrain, and convenient traffic conditions, where farmers could increase the MCI of the farmland through intensive utilization. Secondly, the MCI of increased farmland was lower than that of unchanged farmland in the same period (1.04 < 1.26; 1.22 < 1.30; 1.06 < 1.32; and 1.25 < 1.26). In order to maintain the balance of farmland quantity, increased farmland is mainly reclaimed in areas with poor cultivated conditions. Due to the poor location and cultivated conditions, the increased farmland is prone to be non-agricultural, non-grain, and even abandoned directly. Thirdly, the MCI of exited farmland is higher than that of increased farmland (1.26 > 1.04; 1.27 > 1.22; 1.32 > 1.06; and 1.34 > 1.25). This again reflects the fact of the exiting of high-quality farmland and the compensation of low-quality farmland. It can be seen that the implementation of the policy of quantity balance between exited farmland and increased farmland was difficult to offset the degeneration of quality, and to achieve a balance of production capacity of farmland. Fourthly, the MCI of unchanged farmland showed a continuous upward trend over time. Evidently, stable expectations of farmers were conducive to the increase of the MCI.

Table 3. Comparative analysis of average MCI of exited, increased, and unchanged farmland.

Year	2000–2005		2005–2009		2009–2015		2015–2018	
	2000	2005	2005	2009	2009	2015	2015	2018
Decreased farmland	1.26	-	1.27	-	1.32	-	1.34	-
New increased farmland	-	1.04	-	1.22	-	1.06	-	1.25
Unchanged farmland	1.24	1.26	1.26	1.30	1.30	1.32	1.31	1.26

3.2. Spatial Variation Characteristics of MCI of Farmland in China

3.2.1. Grouping Structure of MCI of Farmland by County

The MCI of farmland in each county was obtained by summarizing and calculating the MCI of all grids within its range. As shown in Table 4, the MCIs of farmland of most counties in China were mainly distributed between 80–160%. Such counties accounted for 84.2% and 86.9% of all in 2000 and 2018, respectively. From 2000 to 2018, counties with decreasing MCI accounted for 33.5%, while counties with increasing MCI accounted for 62.8%. Based on the grouping structure of MCIs, the proportion of counties in group of 80–100% and 100–120% decreased from 2000 to 2018, while the proportion of counties in group of 120–140% and 140–160% rose. The phenomenon of the increase of counties with higher MCIs led to the overall upward trend of MCI of farmland in China. In addition, it was worth noting that the proportion of counties in group of >160% declined to some degree. These counties were generally the dominant production areas, where natural conditions such as water, soil, light, and heat were more suitable for food production. The decline of MCIs in these areas had prominently adverse effects on food production.

Table 4. Grouping structure of MCIs of farmland in all counties.

Proportion (%) / Group of MCI (%)	2000	2005	2009	2015	2018
0	2.4	2.3	3.3	2.5	2.7
0–80	0.6	0.4	6.4	0.4	0.1
80–100	19.5	19.5	32.5	19.0	18.8
100–120	28.4	20.7	31.1	7.3	11.6
120–140	23.9	29.8	8.3	17.9	39.4
140–160	12.4	13.3	4.7	37.2	17.1
>160	12.8	13.8	13.6	15.7	10.3

3.2.2. Spatio-Temporal Pattern of MCI of Farmland by County

The MCI of farmland is determined jointly by physical geographical environment and human economic activities. Overall, the MCI of farmland in China took on a general pattern of higher values in the south and lower values in the north (Figure 5). The areas where the MCI was lower than 100% were chiefly distributed in the northeast, northwest, and northern China. Restricted by the natural environment such as low temperature and less precipitation, the MCIs of farmland in these areas were dominated by single cropping. However, the spatial distribution of MCI does not entirely coincide with the spatial pattern of temperature and precipitation in China, which demonstrates that the MCI of farmland is also influenced by agricultural farming conditions and socio-economic conditions. In particular, the areas with MCI between 150% and 200% were not only distributed in the southern areas of Guangdong and Guangxi, but also extensively distributed in northern Jiangsu, Henan, northern Anhui, southern Shaanxi, and southern Gansu. These agricultural areas possessed the advantages of flat terrain and good farming conditions, which means it was easy to make use of large-scale machinery for farming and was favorable for saving labor input in agricultural production. In addition, the plains in the middle and lower reaches of the Yangtze River provide favorable light and heat conditions and have developed economy. So the MCI of farmland had maintained at around 140%. The hilly areas along the southeast coast, Sichuan Basin, Loess Plateau, Yunnan-Guizhou Plateau, and the hilly areas along the south of the Yangtze River are characterized by undulating terrain, limited farming conditions, and difficulty in using large-scale machinery. As a result, the MCIs of those areas were between 100% and 130%. From the perspective of administrative areas, the provinces and cities with the highest MCI of farmland in China were concentrated in Jiangsu, Guangdong, Henan, Guangxi and Anhui, while the provinces and cities with lowest MCI were concentrated in Liaoning, Xinjiang, Beijing, Jilin, Inner Mongolia, and other places.

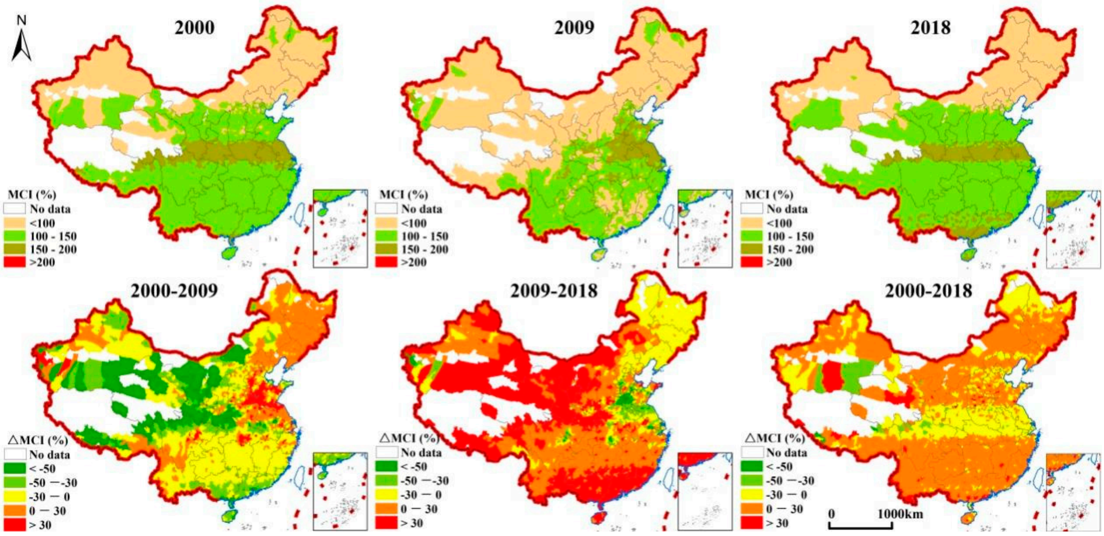

Figure 5. Characteristics of the MCI of farmland in Chinese counties from 2000 to 2018.

Comparing MCI in different periods, the counties with decreasing MCIs from 2000 to 2009 were chiefly concentrated in western China (such as Xinjiang, Gansu, Qinghai, and Sichuan) and in southern China (such as Guangdong, Jiangxi, Hunan, and Fujian). During this period, China enforced the national strategy of developing the western area, which launched large-scale construction of infrastructure and key industries in the western areas. The strategy expedited the course of transferring agricultural population to cities and towns, which resulted in the reduction of investment in agriculture and the decline of the MCI. From 2009 to 2018, the counties with declining MCIs were chiefly distributed in the Huang-Huai-Hai Plain and the lower reaches of the Yangtze River, which were the major grain producing areas. These areas are economically developed, which makes it easier for farmers to move to cities and decrease labor input in agricultural production. Although the enforcement of the policy of the lowest purchase price of grain aroused farmers' enthusiasm for growing grain and facilitated the growth of MCI of each province in the short term, while the MCI in developed areas declined first after the lowest purchase price lowered further. It was confirmed in relevant studies that there appear to be labor-saving planting methods, such as planting trees by shrinking the grain-planting area in Hebei Province, and changing two-season rice into one-season rice in Hubei Province, etc. Generally, there existed both counties with rising and falling MCI in China. But the principal areas with falling MCIs from 2009 to 2018 were concentrated in two major grain producing areas, which exert a more adverse influence on the food security of the country.

3.3. Gaps between MCI and PMCI of Farmland and Regional Optimization Scheme

Agricultural production is particularly dependent upon the endowment of natural resources. Theoretically, if the agricultural production entirely coincides with the resource endowment, it will help to boost the efficiency of agricultural production. Although agricultural technology can avoid some natural conditions to a certain extent, it is still hard to form structural changes. Thus, it is essential to carry out a comparative analysis of the MCI and PMCI to survey the degree to which the major grain production areas and the dominant production areas spatially match. To avoid the influence of inter-annual fluctuation, this paper made a comparative analysis of the average MCI from 2015 to 2018 and PMCI.

The findings reveal that farmland was overused in northern China and underutilized in southern China (Figure 6). From the north to the south in China, the gap between MCI and PMCI increasingly widened. In the northern China (such as Xinjiang, Inner Mongolia, Heilongjiang and Jilin), where single cropping system dominated, the gap between the MCI of farmland and the PMCI was kept within 10%, which means agricultural production was effectively matched with regional water and heat resources. It is worth noting that the ecotone between agriculture and animal husbandry in the north and south, which covers the water conservation areas of Beijing-Tianjin-Hebei, the soil erosion areas of Loess hills and gullies, and the fragile ecological environment areas of Qinghai-Tibet Plateau, exhibits the phenomenon of over-utilization of farmland. Some counties employ the agricultural production mode of triple cropping in two years or double cropping in one year, which is higher than the upper limit of single cropping in one year determined by local water and heat conditions and exceeds the carrying capacity of local resources and the environment. Meanwhile, there is a narrow strip along the Bohai Rim, the southern part of Huang-Huai-Hai region, the Qinling Mountains, Yunnan and South China, where the MCI of farmland increased by 10–100%. There are abundant water and heat conditions in the middle and lower reaches of the Yangtze River, south of the Yangtze River, and Sichuan-Guizhou area, and most areas are suitable for double cropping or even triple cropping in a year. However, the actual MCIs of farmland in those regions were not more than 150%, and even only single cropping per year.

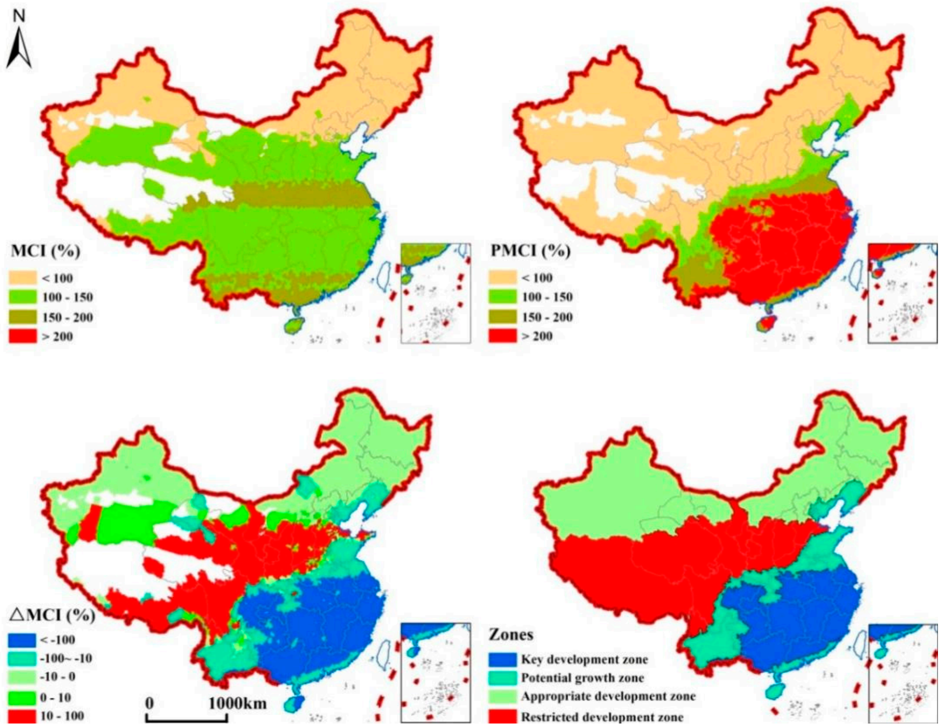

Figure 6. Gaps between MCI and PMCI of farmland in China and the division of types.

Based on the gap between the MCI and PMCI in counties, China was classified into four types of grain producing zones, such as key development zone, potential growth zone, appropriate development zone, and restricted development zone (Figure 6), which serve as a basis for the layout optimization of grain production and the design of the benefit compensation mechanism. The key development zone is intended to raise the MCI of farmland by 100% and make full use of abundant water and heat resources in southeast China. The potential growth zone aims to raise the MCI of farmland by 50%. The appropriate development zone continues to keep the current cropping system of farmland, and chiefly produces one-season crops. The restricted development zone is laid out to restrict the use of farmland appropriately, employs reasonable fallow and rotation measures to evade over-exploitation of groundwater resources and soil erosion, and protects the fragile local ecological environment.

4. Discussion and Conclusions

Based on the NDVI data, this paper calculated the MCI of farmland in China from 2000 to 2018, and explored the spatio-temporal characteristics of MCI. In addition, the spatial optimization scheme of farmland was put forward according to the gap between MCI and PMCI. The conclusions are drawn as below: from 2000 to 2018, China's MCI of farmland underwent the fluctuation of rising first, then falling, before rising continuously. These fluctuations were closely associated with the agricultural support policies enforced in different stages and farmers' reduction in the intensity and utilization of farmland, owing to the low income earned from growing grain. The areas with high MCIs in China were situated in the major grain producing areas, such as Huang-Huai-Hai plain and the southern areas including Guangdong and Guangxi provinces. The proportion of counties with declining MCIs from 2009 to 2018 was lower than that from 2000 to 2009, but the counties with declining MCIs in the later stage were chiefly situated in the major grain producing areas, which exert adverse influence on food security. Compared with the PMCI, the utilization intensity of farmland in northern China was high, while most areas in southern China boasted great potential to increase the MCI. Four different regions and relative optimizing countermeasures were proposed.

In consideration of China's basic national conditions, i.e., more people and less farmland, small-scale production restricts the increase of the income from agricultural production. Despite that, the overall MCI in China has shown a rising trend since 2000, with still more than 30% of the counties having experienced a downturn. Firstly, China's floating population was 376 million in 2020, and most of them were rural migrants. Along with the acceleration of China's industrialization and urbanization, a large number of laborers will still be transferred to cities and towns, and the input of agricultural labor will continue to be decreased. Farmland in Chinese agricultural areas takes the form of collective property rights, and some migrant farmers choose to make use of farmland in an extensive manner for fear of the loss of their rights and interests arising from land transfer. Secondly, government departments have not yet controlled the abandonment of farmland or the change of two seasons to one season according to legal instruments. Following the present development trend, the MCI of some counties will take a downturn trend in the future. It is necessary to attach enormous importance to the phenomenon of decreasing the MCI in principal grain producing areas to avoid food security problems as a result of a large-scale occurrence. Thirdly, non-agricultural farmland is inevitable due to rapid urbanization. In the pursuit of the balance of arable land, low quality "new" arable land reduces the multiple cropping of arable land, which leads to ecological problems.

There is an interactive relationship between the MCI of farmland and the natural environment. In the long term, the high level of climatic variability affects the MCI by affecting the PMCI. With the improvement of farmland irrigation facilities, the water supply limitations noticeably decreased under the irrigated scenario. The growth of the annual mean temperature was identified as the main reason underlying the increase of the PMCI. Furthermore, the area found to be suitable only for single cropping farming decreased, while the area suitable for triple cropping farming increased significantly from the 1960s to the 2000s. The magnitude of change of the PMCI showed a pattern of increase both from northern China to southern China and from western China to eastern China. However, the fluctuations of the MCI calculated in this paper are mainly related to agricultural policies and farmers' decision-making, and were not always increasing. Furthermore, the spatial pattern of the MCI does not change with longitude and latitude, and the proportion of single cropping farmland increased significantly. Clearly, the spatio-temporal characteristics of the MCI and PMCI variability are not consistent. It can be seen that from a short-term perspective, the MCI variability is mainly affected by farmers' planting behavior, whose goal is to maximize economic benefits, even at the expense of ecological resources and the environment. Among them, the impact on water has received widespread attention.

Thus far, there is no conclusive conclusion on whether increasing MCI can improve the efficiency of water utilization. Studies in Pakistan [30] and Brazil [44] proved that multi-cropping system improved water use efficiency. This situation is likely due to the fact that crop species selection is determined, in large part, based on farmers' financial interests, but not necessarily on which crop is the most suitable. However, the spatial mismatch between the MCI and PMCI in China is bound to increase the overall water consumption. Southern China possesses favorable water and heat conditions, but low efficiency in terms of the utilization of farmland, while northern China possesses high intensity utilization of farmland. In particular, groundwater has been over-exploited in the Huang-Huai-Hai plain for the development of irrigation agriculture. As a result, serious underground funnels appeared in this area.

Some suggestions were or will be put forward to solve the problem of increased water consumption. Firstly, the Chinese government has begun to enforce measures to close pumping wells in some areas of Hebei, and decrease over-exploitation of groundwater by way of cropping rotation. Secondly, following the concept of the green development of agriculture, China's agricultural production should optimize the pattern of utilization of farmland in the future, and reinforce the determination of yield by water in areas with high utilization intensity. Meanwhile, the government should increase the utilization intensity of farmland in key development zones. In southern China, it is necessary to issue agricultural support policies, such as comprehensive production subsidies, agricultural socialization services, and financial loans, etc., to encourage and support the adjustment of planting structure or land transfer, and promote the shift from single cropping to multiple cropping, or the rotation of food crops and cash crops. Thirdly, the distortion in the implementation of policy of "pothook of city construction land increase and rural residential land decrease" has caused a decline in quality and implicit decrease in quantity of farmland, respectively. To solve this problem, policies can be adjusted to establish a supplementary mechanism based on farmland productivity. The increase in the MCI of farmland can be used to offset the amount of farmland balance index.

In this paper, by comparing the MCI of farmland calculated based on NDVI data with statistics, we proved that the MCI of farmland, gained by ways of S-G filtering, peak extraction, and peak elimination, is credible and endowed with a reference and popularization value. Grain production in China is mainly carried out by smallholders, and the farmland vegetation is complex, diverse, and irregularly distributes on the surface, particularly in mountainous and hilly areas where there are few large-scale agricultural crops of the same type. Since remote sensing images are made up of regular grids of equal size and influenced by mixed pixels, there will inevitably be certain errors in our results. In future research, perfecting the selection of extraction methods and making use of higher resolution data, in order to raise the accuracy of the MCI of farmland, should be attempted.

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