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Analysis of Changes and Potential Characteristics of Cultivated Land Productivity based on MODIS EVI: A Case Study of Jiangsu Province, China

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Abstract: Cultivated land productivity is a basic guarantee of food security. This study extracted the multiple cropping index (MCI) and most active days (MAD, i.e., days when the EVI exceeded a threshold) based on crop growth EVI curves to analyse the changes and potential characteristics of cultivated land productivity in Jiangsu Province during 2001–2017. The results are as follows: (1) The MCI of 83.8% of cultivated land remained unchanged in Jiangsu, the cultivated land with changed MCI (16.2%) was mainly concentrated in the southern and eastern coastal areas of Jiangsu, and the main cropping systems were single and double seasons. (2) The changes in cultivated land productivity were significant and had an obvious spatial distribution. The areas where the productivity of single cropping system changed occupied 67.8% of the total cultivated land of single cropping system, and the decreased areas (46.5%) were concentrated in southern Jiangsu. (3) For double cropping systems, the percentages of the changed productivity areas accounting for cultivated land were 82.7% and 73.3%. The decreased areas were distributed in central Jiangsu. In addition, the productivity of the first crop showed an overall (72%) increasing trend and increased areas (40.8%) of the second crop were found in northern Jiangsu. (4) During 2001–2017, cultivated land productivity greatly improved in Jiangsu. In the areas where productivity increased, the proportions of cultivated land with productivity potential space greater than 20% in single and double cropping systems were greater than 60% and 90%, respectively. In the areas where productivity decreased, greater than 25% and 75% of cultivated land had potential space in greater than 80% of the single and double cropping systems, respectively. This result shows that productivity still has much room for development in Jiangsu. This study provides new insight for studying cultivated land productivity and provides references for guiding agricultural production.

Keywords: cultivated land productivity; productivity potential; EVI; MAD; Jiangsu

1. Introduction

Cultivated land is a crucial resource and environmental factor for human survival and development. Cultivated land has multiple functions that include production, spatial bearing capacity, and environmental protection, and is a fundamental guarantee of national food security and social stability [1–4]. For a long time, with the rapid development of industrialization and urbanization and the impact of global climate change, the limited cultivated land resources have been under considerable pressure in China, which poses a great threat to food security and the ecological environment [5–10]. Food is the primarily need of people, and how to make use of limited cultivated land resources to guarantee food for nearly 1.4 billion people is a realistic problem in China. Food originates from cultivated land, and the core of food security is the safety of cultivated land resources. The National 13th five-year plan in China proposes adhering to the strictest systems for protecting cultivated land, adhering to the red line of cultivated land (i.e., the cultivated land minimum), implementing the strategy of rotation and fallow of cultivated land, improving the food production capacity, and ensuring basic grain self-sufficiency. Cultivated land is the basis of food and ensuring a certain area of cultivated land and steadily increasing the productivity of cultivated land is fundamental to ensure food security [11,12]. Therefore, the study of cultivated land productivity is of great significance for the rational use and protection of cultivated land and for ensuring national food security.

During recent years, progress has been made in the research of cultivated land productivity [13–16]. Internationally, research on cultivated land productivity has mainly focused on the potential of land productivity. During the 19th century, Liebig, a German scholar, put forward the law of the minimum factor, which began the study of the land productivity potential [17]. Since the beginning of the 20th century, research studies on the land productivity potential have gradually shifted to a deeper level, focusing more on the impact of crop physiological mechanisms on the potential [18]. From the 1960s to the 1970s, to establish a model between crop yield and ecological factors, the international biological program (IBP) conducted a large-scale measurement and survey of crop yield worldwide and developed an empirical and mechanistic mathematical model for estimating crop productivity based on the relationship between crop yield and environmental factors [19]. At the same time, they initiated an upsurge in the study of crop mechanistic models which gradually led to the basic concept of estimating the crop productivity potential by using mechanistic models. Currently, with the rapid development of science and technology, research methods for studying the land productivity potential are continually improving, from simple computer calculations to the combination of 3S technology (RS, GIS, GPS) and models [20]. Compared to international research, the research history of cultivated land productivity is relatively short and not sufficiently systematic in China. Research in China mainly centres on the macro and micro levels. Research at the microcosmic scale of cultivated land productivity is the same as that of international scholars and begins with the study of the land productivity potential [21]. In 1950, Ren's [22] research on crop productivity in Sichuan marked the beginning of Chinese research on crop productivity. Subsequently, many scholars began to construct crop yield prediction models based on the crop productivity potential and to analyse crop productivity under different natural conditions such as light, temperature, soil, air, and water [23,24]. At the macro level, with the extensive development of agricultural land classification, many scholars have studied regional cultivated land productivity based on the results of agricultural land classification.

At present, the methods for monitoring and estimating cultivated land productivity include productivity estimations based on a statistical model, remote sensing, crop growth modelling, and combination of a crop growth model and remote sensing [25–27]. With the rapid development of remote sensing technology, the spatial and temporal resolutions of remote sensing images have been greatly improved. Remote sensing images with high spatial and temporal resolutions can accurately and rapidly reflect a wide range of ground information and have been widely used in the estimation of crop productivity and growth monitoring [28,29]. The common practice of crop productivity estimation via remote sensing is to establish estimation models based on the relationship between the remote sensing vegetation index and productivity. Application of normalized difference vegetation index (NDVI) and enhanced vegetation index (EVI) in crop productivity estimation and monitoring is most extensive and practical; there is a significant correlation between NDVI and EVI, and agricultural productivity has been widely proven by scholars [30–32]. Maselli et al. [33] used MODIS NDVI data to estimate the wheat planting area and yield in Tuscany, Italy, and compared them with provincial statistics. The results showed that there was a high consistency between the estimated and reported values. Using MODIS NDVI and wheat yield data, BeckerReshef et al. [34] established an empirical model for wheat yield prediction. David [30] used MODIS NDVI data to monitor crop changes and estimate U.S. maize and soybean yields. The results showed that NDVI had a significant positive correlation with crop yields. Using EVI and wheat yield data, Wang et al. [32] established a yield prediction and growth monitoring model for winter wheat in the U.S. and then verified the prediction results and showed that the model achieved excellent results. Compared to NDVI, EVI improves the sensitivity of estimating the canopy biomass of dense vegetation, reducing the impact of atmospheric and soil reflection, and avoiding the saturation problem of vegetation indexes based on a ratio. Previous studies have shown that EVI is more effective in crop monitoring and productivity estimations [32,35].

From the above summary, it is clear that abundant achievements and apparent effects have been obtained in monitoring and estimating cultivated land productivity via remote sensing. However, current estimations of cultivated productivity with remote sensing are mostly based on a specific region, and different regions have different environmental characteristics, which makes the established estimation model lack applicability and generalizability. Most current studies regarding the estimation and changes of cultivated land productivity are aimed at the whole production process of cultivated land, without considering the changes in cultivated land productivity in different cropping systems and during different production stages. Therefore, this study selected Jiangsu Province, the main grain-producing area in China, as the study area. Using MODIS EVI data and land use data to reconstruct crop growth EVI curves, based on the generated EVI curves, this study extracted the multiple cropping index (MCI) and calculated the most active days (MAD) to characterize the cultivated land productivity and explored the changes and potential characteristics of cultivated land productivity under different cropping systems. The study results have practical application value for protecting cultivated land, guiding agricultural production, and ensuring national food security.

2. Material and Methods

2.1. Study Area

Jiangsu Province is in the eastern coastal center of China, along the lower reaches of the Yangtze River. The Yellow Sea is to the east, Zhejiang and Shanghai are to the southeast, Anhui is to the west, and Shandong is to the north (Figure 1). Jiangsu is also an important part of the Yangtze River Delta. Jiangsu lies between 30°45′N–35°20′N and 116°18′E–121°57′E and has an area of 10.72×10^4 km^2. There are 13 cities and 96 counties in Jiangsu and the total population was 80.29 million in 2017. The GDP was 8.59 trillion RMB in 2017, ranking second in China, with an average per capita GDP of 10.7×10^4 RMB, which is 81.35% higher than the national average. With 1.1% of the national land area, Jiangsu contains 5.78% of the total population and 10.3% of the total economic output. Jiangsu is the frontier of industrialization and urbanization in China.

The cultivated land area of Jiangsu Province is 4.58×10^4 km^2, accounting for 3.4% of the total cultivated land area in China. The per capita cultivated land occupies 0.057 hm^2, which is 60% of the national average. The proportion of high standard farmland reaches 59%. Jiangsu Province is in the east Asian monsoon region, in the transition zone between the subtropical and warm temperate zones, and has distinct seasons, concentrated precipitation, rain during the warm season, and photothermal abundance. The terrain of Jiangsu is dominated by plains, accounting for more than 70% of the total area, and is low and flat with numerous lakes, a dense water network, diverse ecological types, and unique agricultural production conditions. Jiangsu is known as the "land of fish and rice" in China. Jiangsu is among the most developed provinces agriculturally and is also the main grain-producing area in China. In 2017, the sown area of grain was 5.4×10^4 km^2 and the total grain output was 3.61×10^7 t, accounting for 5.5% of that of the country and ranking 5th in China. The per capita grain output was 451 kg, the total power of agricultural machinery was 49.91 million kilowatts, and the level of agrarian mechanization was 83%. In addition, the main crops in Jiangsu are rice, wheat, rape, maize, peanuts, and soybeans (The data in this section are from Jiangsu Provincial People's Government (http://www.jiangsu.gov.cn) and Jiangsu Statistical Yearbook 2018 and the land use types in Figure 1 are from the GlobeLand 30 dataset (http://ngcc.sbsm.gov.cn/).

Figure 1. Location of Jiangsu Province in China.

2.2. Framework of the Study

Cultivated land productivity refers to the cultivated land production capacity of a certain region, at a certain time, and under certain economic, social, and technological conditions. Cultivated land productivity can be divided into three types [36]: theoretical, realizable, and actual productivity. Theoretical productivity refers to the maximum productivity of a crop without the limitation of agricultural production conditions under the current level of technology, input, and utilization. Realizable productivity refers to the maximum productivity of crop that has been basically guaranteed by agricultural production conditions under current levels of technology, input, and utilization. Actual productivity refers to the production capacity that has been realized at present, that is, the productivity that the crop has reached during a certain year.

EVI can reflect crop growth states and relevant studies have shown that the growth of a crop during its critical growth period has a crucial impact on crop productivity [35,37]. Therefore, this study used the length of the crop during the critical growth period, i.e., the most active days (MAD), to characterize crop productivity. Then, the changes and potential characteristics of cultivated land productivity in the study area were explored by the changes in MAD. Extraction of MAD is based on crop growth EVI curves. However, different crops have different growth characteristics; therefore, the EVI curves vary for different crop types and the MAD extracted from the EVI curves is also different. In other words, the MAD of different crop types is not comparable. In addition, there is a lack of large-scale and high-precision crop type data at present. Therefore, this study hypothesized that during the study period, the main crop types remained unchanged in the study area. Thus, cultivated land areas with a changed MCI were not considered in this study. In summary, this study used crop MAD to explore the changes and potential characteristics of cultivated land productivity under different cropping systems with the unchanged area of the MCI in Jiangsu Province during the period 2001–2017.

The framework of this study is shown in Figure 2. First, MODIS reflectance and land use data were used to obtain EVI data from cultivated land. Second, smooth crop growth EVI curves were rebuilt using the Savitzky–Golay (S–G) techniques. Then, the daily EVI data were derived from the time series of EVI at an 8-day resolution using the linear interpolation. Third, considering the possible influences of climatic factors on crop productivity, the moving window method was used to process the EVI curves with an average of 7 years as the moving window (T_1: 2001–2007; T_2: 2002–2008; …; T_{11}: 2011–2017). Then, based on the EVI curves, the cultivated land MCI was obtained and the unchanged area of the MCI in the study area was determined. Finally, the crop MAD was extracted based on the EVI curves in the area with an unchanged MCI, and we further analyzed the changes and potential characteristics of cultivated land productivity in Jiangsu Province.

Figure 2. Study framework.

2.3. Data Source and Pre-Processing

The data used in this study mainly include remote sensing and land use data. The remote sensing data originate from MOD09A1 of the MODIS series product provided by the National Aeronautics and Space Administration (NASA, https://search.earthdata.nasa.gov). These series have a spatial resolution of 500 m, a temporal resolution of 8 days, and a temporal coverage of 2001–2017. The MODIS row and column numbers for the study area are h27v05 and h28v05, respectively. MOD09A1 data include four images per month, totalling 816 images, and the data format is EOS-HDF. The data were processed by cloud detection, radiometric correction, and atmospheric correction. Land use data (GlobeLand30) of 30 m × 30 m from 2000 and 2010 were provided by the National Geomatics Center of China (http://ngcc.sbsm.gov.cn/).

Data preprocessing was as follows: 1. On the basis of the MOD09A1 reflectance data and geographic coordinates, MATLAB software was used to calculate EVI, and EVI data from Jiangsu were obtained by clipping the EVI data with the vector file of the Jiangsu administrative boundary. 2. The two periods of GlobeLand30 in 2000 and 2010 were selected to extract the cultivated land from Jiangsu Province. The GlobeLand30 data were upscaled to 500 m × 500 m resolution based on MODIS EVI data, and the land cover type with the largest fraction of each 500 m grid cell was allocated to the aggregated grid cell. To ensure both a certain level of homogeneity in the land cover type and an adequate number of grid cells for a meaningful analysis, only the grid cells in which the fraction of the cultivated land type was greater than 75% were included in this study. Then, we extracted the intersection of two periods of cultivated land data for subsequent analysis. 3. The EVI data and cultivated land data were masked to obtain the EVI data for cultivated land in Jiangsu Province.

2.4. Analytical Methods

2.4.1. Extraction of the MCI and MAD based on EVI Curves

(1) Extraction of the MCI

EVI is disturbed by various factors during acquisition and processing, which results in a seasonal variation in EVI curves that is not obvious; thus, the data need to be denoised and reconstructed. There are many methods for EVI denoising and smoothing. Referring to existing research results [38–40], this study used S–G techniques to smoothly reconstruct the EVI curves. In addition, the moving window method was used to average the EVI curves and obtain smooth crop growth EVI curves. According to the relationship between the crop growth EVI curves and the MCI, it can be seen that the MCI is the peak frequency of the EVI curves. Referring to the research results of Zhu et al. [41] and Ding et al. [39], this study used a difference algorithm to extract the peak frequency. The EVI curves of each pixel can be regarded as a sequence of discrete points of several elements. The principle of the difference algorithm is as follows: First, by calculating the difference between the adjacent EVI using Equation (1), we obtain the sequence S_1; Second, judging the symbol of the data in S_1 using Equation (2), if the result is positive, it is marked as 1, and if negative, it is marked as −1, and then, sequence S_2 is obtained. Finally, by calculating the difference between the adjacent element in the sequence S_2 using Equation (3), the peak of the crop growth curves appears in the position of an element value of −2 in sequence S_3, and the element value before and after is 0. In the equation, i represents the i^{th} element in the sequence.

$$S_{1i} = EVI_i - EVI_{i-1} \quad (1)$$

$$S_{2i} = \begin{cases} -1, & S_{1i} < 0 \\ 1, & S_{1i} > 0 \end{cases} \quad (2)$$

$$S_{3i} = S_{2i+1} - S_{2i} \quad (3)$$

This method is susceptible to interference peaks when extracting the MCI, including peaks formed by the fluctuation of the EVI value, peaks outside the growing season, etc. To reduce the error in MCI extraction, we set the EVI value of the wave crest to be greater than 0.32 in this study [42]. With the maximum value of EVI as the main peak during the year, the time interval between the second peak and the main peak should be more than 40 days and the time to limit the peak should be between March and October.

(2) MAD Extraction

Based on the crop growth EVI curves, the threshold method was used to extract the MAD from pixels. The principle of the algorithm is as follows [41]: First, determine the number of growth cycles according to the MCI. For a growth cycle, all the EVI values on the growth curves of 11 periods (T_1–T_{11}) are expanded from small to large, and an EVI value of 80% for the whole data sequence is taken as the threshold Q value; second, compare all the EVI values on the crop growth curves in T_1 to the threshold Q one by one; if an EVI value is greater than Q, then the MAD accumulates 1, and by contrast, it does not increase until all the EVI values are compared in T_1, at which point the crop MAD of T_1 is obtained. This cycle lasts until T_{11}. The equation for this calculation is as follows:

$$MAD = \sum_{i=1}^{n} 1\{y(x,i) > Q\} \quad (4)$$

where y is the EVI value; x is the study period, namely T_1–T_{11}; i is the days; n is the days of a year, namely 365; and Q is the threshold.

2.4.2. Analysis of Productivity Changes and Potential Space based on the MAD

(1) Analysis of the changes in cultivated land productivity

Based on the crop MAD, the change process and trend of cultivated land productivity in Jiangsu Province from 2001 to 2017 were analysed using a simple difference method and simple linear regression method. The simple difference method was to subtract the MAD of a single pixel during different periods (P_1:T_2–T_1; P_2:T_3–T_2; …; P_{10}:T_{11}–T_{10}) and use the difference in the MAD to measure the productivity changes. This method can directly reflect the change process and characteristics of cultivated land productivity. The calculation equation is as follows:

$$D_{ij} = MAD_{ij}^{Tn+1} - MAD_{ij}^{Tn} \quad (5)$$

where D_{ij} is the MAD difference of the i^{th} row and j^{th} column; MAD_{ij}^{Tn+1} is the MAD value of the i^{th} row and j^{th} column during the T_{n+1} period; MAD_{ij}^{Tn} is the MAD value of the i^{th} row and j^{th} column during the T_n period, n=1, 2, 3, ..., 10.

In this study, the changed trend of cultivated land productivity was reflected by a simple linear regression method. Linear fitting of 11 MAD values on a single pixel was conducted, and the slope of the fitting equation was used to characterize the trend of productivity changes. A positive slope indicates a productivity increase, and a negative slope indicates a productivity decrease. The larger the absolute value of the slope, the more dramatic the productivity changes. The p value between the MAD sequence and time series is used to show the significance of the productivity change trend, that is, the degree of confidence of the change trend. In this paper, $p < 0.05$ indicates a significant change in productivity and $p > 0.05$ indicates a non significant change in productivity. Combining the slope of the linear fitting equation with the p value of significance, this study divides productivity changes into three types: significantly increased productivity (slope > 0, $p < 0.05$); stable productivity ($p > 0.05$); and significantly decreased productivity (slope < 0, $p < 0.05$).

(2) Estimation of the potential space of cultivated land productivity

As described in Section 2.2, cultivated land productivity mainly includes three types: theoretical, realizable, and actual productivity. Based on the concept and types of cultivated land productivity [21], the productivity potential can be divided into the following two types: theoretical potential and realizable potential. Theoretical potential refers to the difference between theoretical productivity and realizable productivity and realizable potential refers to the difference between realizable productivity and actual productivity. The potential explored in this study refers to the realizable potential; we analysed the potential in areas where the productivity increased and decreased. In this study, MAD was an indicator of cultivated land productivity; the productivity potential cannot be simply expressed by the difference in MAD. Therefore, we used ratios of MAD to characterize the productivity potential, i.e., potential space.

1. Estimation of potential space in areas where productivity increased

In this study, the average of the crop MAD during the T_1–T_{11} period was used to characterize the actual productivity of cultivated land, and the maximum of the crop MAD during the T_1–T_{11} period was used to describe the realizable productivity. The potential space in areas where productivity increased refers to the ratio of the difference of realizable productivity and actual productivity to actual productivity (Equation (6)).

$$\text{Potential space} = \frac{\left|MAD_{max} - MAD_{mean}\right|}{MAD_{mean}} \times 100\% \quad (6)$$

where MAD_{max} is the realizable productivity of cultivated land during the T_1–T_{11} period and MAD_{mean} is the actual productivity of cultivated land during the T_1–T_{11} period.

2. Estimation of potential space in areas where productivity decreased

The maximum of the crop MAD during the T_1–T_{11} period was used to characterize the realizable productivity of the cultivated land and the crop MAD during the T_{11} period was used to characterize the actual productivity. The potential space in areas where productivity decreased refers to the ratio of the difference of realizable productivity and actual productivity to realizable productivity (Equation (7)).

$$\text{Potential space} = \frac{\left|MAD_{max} - MAD_{T11}\right|}{MAD_{max}} \times 100\% \quad (7)$$

where MAD_{max} is the realizable productivity of the cultivated land during the T_1–T_{11} period and MAD_{T11} is the cultivated productivity during the T_{11} period.

3. Results

3.1. Changes in the MCI of Cultivated Land

Based on the aforementioned MCI extraction method, the MCI of cultivated land in Jiangsu Province during the period 2001–2017 (T_1–T_{11}) was obtained. To further obtain the invariant area of the MCI, the cropping systems of each period were separately extracted, and 11 images were captured of each cropping system. Then, the 11 images of each cropping system were intersected using ArcGIS 10.2 and the invariant area of each cropping system was obtained. Then, the invariant area of the MCI was obtained. Finally, the cropping systems under the invariant area of the MCI were determined. The results are shown in Figure 3.

Figure 3. Changes in the MCI (a) and main cropping systems (b) under the invariant area of the MCI in Jiangsu Province during the period 2001–2017.

As shown in Figure 3a, the MCI of most of the cultivated land in Jiangsu Province remained unchanged. The changed areas of the MCI were mainly concentrated in the southern and eastern coastal areas of Jiangsu Province. The invariant area of the MCI accounted for 83.8% of the total cultivated land and the changed areas of the MCI accounted for 16.2%. As seen from Figure 3b, as far as the invariant area of the MCI is concerned, the main cropping systems were single and double seasons; the double season composed the majority and the single season was mainly distributed in southern Jiangsu and northern Lianyungang City. The percentages of the single and double seasons occupying the total cultivated land were 15.1% and 68.7%, respectively, accounting for 18% and 82% of the cultivated land with an unchanged MCI.

3.2. Analysis of Productivity Changes and Potential Characteristics in Single Cropping System

After determining the invariant area of the MCI, the MAD of single cropping system was extracted based on the EVI growth curves and the spatial distribution of the MAD of single cropping system from T_1 to T_{11} was obtained (Figure 4). According to Figure 4, the productivity of single cropping system in southern Jiangsu was generally higher than that in northern Jiangsu.

Figure 4. Spatial distribution of the MAD of single cropping system. Partial results (T_1, T_3, T_5, T_7, T_9, and T_{11}) are shown. T_1: 2001–2007; T_2: 2002–2008; T_3: 2003–2009; ...; T_{11}: 2011–2017.

To further analyze the process of productivity changes of single cropping system in Jiangsu Province during the period 2001–2017, a simple difference method was used to subtract the MAD of a single cropping system. The results are shown in Figure 5. From the spatial distribution of the MAD changes, it can be seen that the areas where productivity decreased for a single cropping system were mainly distributed in southern Jiangsu. At the same time, the statistical analysis of the MAD changes showed changes in crop productivity (Figure 5).

It can be seen from Figure 5 that the productivity of most single cropping system in Jiangsu Province showed a decreasing trend from 2001 to 2017. The average proportion of the decreased areas of productivity accounted for more than one-half of the total cultivated land of single cropping system, which was 60%. The fluctuation in productivity changes was stable during P_7-P_{10}. Except for P_2, P_3, and P_6, the decreased areas during the remaining periods were more than one-half of the total cultivated land, of which P_9 was the largest (69.7%) and P_{10} was the second largest (69.2%).

Figure 5. Changes and statistical results of the MAD of single cropping system. Partial results (P_1, P_4, P_7, and P_{10}) are shown. The statistical chart shows that the proportion of cultivated land of the MAD changed from P_1 to P_{10}. P_1: T_2–T_1; P_2: T_3–T_2; …; P_{10}: T_{11}–T_{10}.

To explore the overall change in single cropping system productivity in Jiangsu Province from 2001 to 2017 under the invariant area of the MCI, this study identified changes in productivity using the simple linear regression method previously mentioned, combining the slope of the fitting equation and the p value of significance. The results are shown in Figure 6. A total of 34.1% of the cultivated land had a positive slope, and 65.9% of the cultivated land had a negative slope (Figure 6a). In terms of significance, the productivity of 67.8% of the cultivated land significantly changed (Figure 6b). The productivity changes in single cropping system are shown in Figure 6c. The areas where productivity decreased were mainly concentrated in southern Jiangsu, accounting for 46.5% of the total cultivated land of single cropping system, and the increased areas and stable areas accounted for 21.3% and 32.2%, respectively (as summarized in Table 1).

Table 1. Changes in cultivated land productivity in single cropping system.

Changes in productivity	Decreased Area	Increased Area	Stable Area
Proportion of cultivated land	46.5%	21.3%	32.2%

Figure 6. Slope, p, productivity changes, and potential space of single cropping system. (a) the slope of the linear regression equation; (b) the significance of the productivity changes ($p < 0.05$); (c) the productivity changes; (d,e) the productivity potential space of a single cropping system in an area with a significant change in productivity.

In view of the changed areas of crop productivity, the potential space of single cropping system productivity in the invariant areas of the MCI in Jiangsu Province from 2001 to 2017 was estimated using the method previously mentioned. Meanwhile, according to the natural breakpoint method, the potential space of the changed areas of productivity was divided into five categories and the distribution of potential space is shown in Figure 6d and 6e. At the same time, the potential space was statistically analyzed to obtain the proportion of cultivated land under different potential spaces (see Table 2). Table 2 shows that the proportion of cultivated land was 61% with a potential space greater than 20% and 4.2% of the cultivated land with a potential space greater than 80% was in areas where productivity increased.

In areas where productivity decreased, cultivated land with a productivity potential space greater than 20% accounted for 95.5% of the total cultivated land of single cropping system. The largest proportion of cultivated land with potential space was 27.1%, which was between 40% and 60%, followed by a potential space greater than 80% accounting for 26.3% of cultivated land. The results suggest that the productivity of single cropping system in Jiangsu Province had a larger space to improve.

Table 2. Statistics of the potential space of single cropping system in productivity changed areas.

Potential Space	<20%	20% - 40%	40% - 60%	60% - 80%	>80%
Proportion of cultivated land in areas where productivity increased	39%	38.2%	14.2%	4.4%	4.2%
Proportion of cultivated land in areas where productivity decreased	4.5%	22.6%	27.1%	19.5%	26.3%

3.3. Analysis of Productivity Changes and Potential Characteristics in the First Crop of a Double Season

The MAD of the first crop in a double season in Jiangsu Province during the period 2001–2017 was extracted from the EVI growth curves (see Figure 7). It can be seen from Figure 7 that the productivity of the first crop increased on the whole.

Figure 7. Spatial distribution of the first crop MAD during a double season. Partial results (T1, T3, T5, T7, T9, and T11) are shown. T1: 2001–2007; T2: 2002–2008; T3: 2003–2009; ...; T11: 2011–2017.

Using the simple difference method, the MAD of the first crop was subtracted to further clarify the change of crop productivity in Jiangsu Province from 2001 to 2017 (Figure 8). Moreover, MAD changes were obtained to determine the changes in crop productivity. The average proportion of the areas where productivity decreased accounted for 43.4% of the total cultivated land of the double season; P_8 was the largest (53.9%), and P_{10} was the second largest (53.3%). The fluctuation in productivity changes was stable during P_8–P_{10}, but the decreased area was greater than one-half of the total cultivated land.

Figure 8. Changes and statistical results of the first crop MAD during a double season. Partial results (P_1, P_4, P_7, and P_{10}) are shown. The statistical chart shows that the proportion of cultivated land of the first crop MAD changed from P_1 to P_{10}. P_1: T_2-T_1; P_2: T_3-T_2; …; P_{10}: T_{11}–T_{10}.

Using the simple linear regression method previously mentioned, the general trend of crop productivity in the first crop was further explored. The results are shown in Figure 9. A total of 81.7% of the cultivated land had a positive slope, and 18.2% of the cultivated land had a negative slope (Figure 9a). Figure 9b shows that 82.7% of the cultivated land productivity significantly changed. The changes in productivity are shown in Figure 9c. The areas where productivity decreased were mainly concentrated in central Jiangsu, and the percentages of the decreased areas, the stable areas, and the increased areas occupying the total cultivated land of the double season were 10.7, 17.3, and 72%, respectively (see Table 3).

Table 3. Changes in cultivated land productivity in the first crop of a double season.

Changes in Productivity	Decreased Area	Increased Area	Stable Area
Proportion of cultivated land	10.7%	72%	17.3%

Figure 9. Slope, p, productivity changes, and potential space of the first crop during a double season. (a) the slope of the linear regression equation; (b) the significance of the productivity changes ($p < 0.05$); (c) the productivity changes of the first crop; (d,e) the productivity potential space of the first crop in the areas where productivity changed.

The distribution of the productivity potential space is shown in Figure 9d and 9e. It can be seen from the figure that the crop productivity of the first crop in Jiangsu Province had great potential space during the period 2001–2017. Through statistical analysis, Table 4 shows that 88% of the cultivated land had more than 40% of potential space in areas where productivity increased, and cultivated land with a potential space more than 80% was 34.4%. The results showed the productivity of the first crop in Jiangsu Province significantly improved.

In areas where productivity decreased, cultivated land with a productivity potential space greater than 20% accounted for 99.5% of the cultivated land of the first crop. Furthermore, 78.1% of the cultivated land had greater than 80% of potential space. Therefore, the results indicated that the productivity of the first crop in Jiangsu Province had great potential for enhancement.

Table 4. Statistics of the potential space of the first crop in productivity changed areas.

Potential space	<20%	20%–40%	40%–60%	60%–80%	>80%
Proportion of cultivated land in	1.5%	10.5%	24.8%	28.8%	34.4%

areas where productivity increased					
Proportion of cultivated land in areas where productivity decreased	0.5%	4.6%	8.80%	8.0%	78.1%

3.4. Analysis of Productivity Changes and Potential Characteristics in the Second Crop of a Double Season

The MAD of the second crop in Jiangsu Province during the period 2001–2017 was extracted based on the EVI curves (Figure 10). It can be seen from Figure 10 that the spatial distribution of the MAD had a clear spatial transition. During the early stage, the low-value areas of the MAD were mainly concentrated in northern Jiangsu, and then, the low-value areas moved southward to middle and southern Jiangsu.

Figure 10. Spatial distribution of the second crop MAD during a double season. Partial results (T_1, T_3, T_5, T_7, T_9, and T_{11}) are shown. T_1: 2001–2007; T_2: 2002–2008; T_3: 2003–2009; ...; T_{11}: 2011–2017.

Based on the simple difference method, the MAD of the second crop was subtracted to further analyze the process of crop productivity change in Jiangsu Province from 2001 to 2017 (Figure 11). In terms of the spatial distribution, the areas where productivity decreased were mainly concentrated in central Jiangsu. The changes in the MAD were obtained by statistical analysis; the average proportion of the decreased areas of productivity accounted for more than one-half of the total cultivated land, which was 55.6%, and P_9 was the largest (70.3%), followed by P_1 (66.7%).

Figure 11. Changes and statistical results of the second crop MAD during a double season. Partial results (P_1, P_4, P_7 and P_{10}) are shown. The statistical chart shows that the proportion of cultivated land of the second crop MAD changed from P_1 to P_{10}. P_1: T_2–T_1; P_2: T_3–T_2; …; P_{10}: T_{11}–T_{10}.

Based on a simple linear regression method, combining the slope of the fitting equation and the p value of significance, the overall change in productivity of the second crop was analyzed (Figure 12). A total of 53.6% of cultivated land with a positive slope was mainly distributed in northern Jiangsu, and cultivated land with a negative slope accounted for 46.4% and was mainly distributed in central Jiangsu. Figure 12b shows that most of the crop productivity in the second crop had significantly changed, and that the changed areas accounted for 73.4% of the total cultivated land. Figure 12c suggests that the productivity changes had a clear spatial distribution pattern. The areas where productivity increased were mainly concentrated in northern Jiangsu, and the decreased areas were mainly concentrated in central Jiangsu. The percentages of the decreased areas, the stable areas, and increased areas occupying the total cultivated land during the double season were 32.5%, 26.7%, and 40.8%, respectively (Table 5).

Table 5. Changes in cultivated land productivity in the second crop of a double season.

Changes in productivity	Decreased Area	Increased Area	Stable Area
Proportion of cultivated land	32.5%	40.8%	26.7%

Figure 12. Slope, p, productivity changes, and potential space of the second crop MAD during a double season. (a) the slope of the linear regression equation; (b) the significance of the

productivity changes ($p < 0.05$); (c) the productivity changes in the second crop; (d,e) the potential space of the second crop in the area with significant changes in productivity.

The potential space of productivity in the second crop was estimated using the method previously mentioned. The results are shown in Figure 12d and 12e. It can be seen that the productivity of the second crop in Jiangsu Province had great potential space during the period 2001–2017. Statistical analysis of potential space was conducted. The results are shown in Table 6. In areas where productivity increased, 80% of cultivated land had more than 40% of potential space and 19.2% of cultivated land had greater than 80% of potential space. The results showed that the crop productivity of the second crop significantly increased in Jiangsu Province during the period 2001–2017.

It can be seen from Table 6 that 99.5% of cultivated land had more than 20% of productivity potential space in the areas where productivity decreased. A total of 75.1% of cultivated land had greater than 80% of productivity potential space. The results suggest that there was still considerable space to improve crop productivity in the second crop of the double season in Jiangsu Province.

Table 6. Statistics of the potential space of the second crop in productivity changed areas.

Potential space	<20%	20%–40%	40%–60%	60%–80%	>80%
Proportion of cultivated land in areas where productivity increased	1.5%	18.5%	33.1%	27.7%	19.2%
Proportion of cultivated land in areas where productivity decreased	0.5%	5.0%	9.6%	9.8%	75.1%

4. Discussions

Cultivated land productivity refers to the productivity of crops under certain conditions. The relevant research indicates that cultivated land productivity is subject to the dual constraints of natural conditions and socioeconomic conditions [43,44]. Natural factors mainly include the quantity and quality of cultivated land, climate, water, topography, land degradation, etc., whose changes directly affect cultivated land productivity. Compared to other natural factors, climate and land degradation are considered to be important factors that affect changes in agricultural productivity [45,46]. Regarding climate, its influence on agricultural production can be divided into two categories: the effect of inter-annual climate variation on agriculture and the impact of extreme weather events (drought, floods, typhoons, etc.) on agricultural production. Notably, the impact of inter-annual climate change on agricultural production is uncertain and different regions have different responses to climate change. For example, research has indicated that a higher temperature can significantly increase the productivity of cultivated land in Northeast China, but reduces productivity in South China [47,48]. However, the negative impact of extreme climate conditions on cultivated land productivity has been unanimously recognized and agricultural disasters significantly reduce food production [49].

In addition, land degradation is a global phenomenon causing a decrease in the productive capacity of the land. Approximately 25% of the world's land surface is considered to be degraded; every year, 12 million hectares are added to the total area of degraded land [50]. Land degradation results from unreasonable exploitation of natural resources, which causes the destruction of vegetation, a decrease in soil erosion resistance, and thinning of soil layers and the bedrock exposure in many areas, resulting in a reduction in cultivated land, a decrease in productivity, and a threat to food security [46]. Land degradation is common in areas of intensive crops and would diminish potential increases in production in affected areas.

In addition to natural factors, cultivated land productivity is also affected by socioeconomic development. There developments affect productivity according the level of agricultural production inputs, such as land, labor, capital, and technology inputs [51]. As previously mentioned, cultivated land productivity is affected by many factors, and the influences are comprehensive and complex. In this study, it is undeniable that the factors that influence cultivated land productivity, as previously mentioned, have a certain impact on the research results. However, because of the limitations of the data sources and research methods, the aforementioned factors are not included in the scope of this paper. Moreover, the purpose of our work was to provide new insight into studying cultivated land productivity and detecting potential productivity. Therefore, the causes of the changes in productivity are not an objective of this study and need to be explored in a follow-up study.

In addition to the issues previously mentioned, there are still some deficiencies in this study. First, the MAD of different crops cannot be simply compared; at the same time, there is a lack of large-scale and high-precision crop classification data. Therefore, the preconditions of this study are that the crop types remain unchanged during the study period and that only the crop productivity changes and potential characteristics in the invariant areas of MCI were explored, not all cultivated land. Second, only the MODIS grid cells which the cultivated areas accounted for over 75% of the entire areas were maintained for further analysis in this study. Hence, given the level of homogeneity in the valid grid cells, we supposed that MODIS had sufficient resolution. Third, MODIS EVI with a spatial resolution of 500 m was used as the basic data. Mixed pixels are unavoidable in medium resolution satellite remote sensing images. As a result, EVI extracted by pixel may be a mixture of multiple crops in multiple plots which will interfere with the reconstructed EVI growth curves and lead to errors in the extraction of the MCI and MAD. The aforementioned shortcomings are subject to further improvements and modification in subsequent research.

5. Conclusions

In this paper, the changes and potential characteristics of cultivated land productivity in Jiangsu Province during the period 2001–2017 were explored based on the multiple cropping index (MCI) and most active days (MAD), which were extracted using a difference algorithm and threshold method based on MODIS EVI.

This study suggested that the cropping systems were dominated by single and double cropping systems in Jiangsu and that the changes in cultivated land productivity were obvious and had distinct spatial distribution features during the study period. The areas where productivity changed for single cropping system occupied 67.8% of the total cultivated land of single cropping system. The areas where productivity decreased accounted for 46.5% and were primarily concentrated in southern Jiangsu. The percentages of the areas where productivity increased and stable were 21.3% and 32.2% of cultivated land, respectively. For double cropping systems, the productivity of most cultivated land (82.7% and 73.3%) changed, and the decreased areas (10.7% and 32.5%) were distributed in central Jiangsu. In addition, the first crop was dominated by a productivity increase, and the areas where productivity increased (40.8%) for the second crop were largely in northern Jiangsu. Through estimation of the productivity potential space, we found that the cultivated land productivity had great potential space in Jiangsu. In areas where productivity increased, greater than 60% and 90% of cultivated land had potential space in more than 20% of the single and double cropping systems, respectively. Notably, the percentages of cultivated land with a productivity potential space more than 80% in the single and double cropping systems were greater than 25% and 75%, respectively, in areas where productivity decreased. This indicated that the cultivated land productivity still had a greater potential for improvement.

Based on a remote sensing vegetation index combined with the growing process of crops, this study used the MAD as an indicator of cultivated land productivity to study the changes and potential characteristics of productivity. Our work provides new insight into the study of cultivated land productivity and is significant for improving cultivated land productivity and agricultural production. Also, our work can serve as a reference to study cultivated land potential for food security. More importantly, as a large agricultural province with an economically developed area in eastern China, Jiangsu Province serves as a good example of regional development for other areas in China and developing countries throughout the world. Particularly, our work presents a typical case study for assessing cultivated land productivity and potential based on agricultural production and economic development. Therefore, we envision our work will be used to explore cultivated land productivity in broader areas and supply references for the study of cultivated land productivity in other areas.

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