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Tracking the spatio-temporal change of cropping intensity in China during 2000-2015

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Abstract: Improvement in the efficiency of farmland utilization and multiple cropping systems are of prime importance for achieving food security in China. Therefore, spatially-explicit analysis detecting trends of cropping intensity are important preconditions for sustainable agricultural development. However, knowledge about the spatiotemporal dynamics of cropping intensity in China remains limited. In this study, we generated annual cropping intensity maps in China during 2000-2015 using a rule-based algorithm and MOD09A1 time series imagery. We then analyzed the spatio-temporal changes of cropping intensity. The results showed single-cropping and double-cropping areas were about $1.28 \pm 0.027 \times 10^6 \text{ km}^2$ and $0.52 \pm 0.027 \times 10^6 \text{ km}^2$ in China in 2015 and their areas were relatively stable from 2000 to 2015. However, cropping intensity had substantial spatial changes during 2000-2015. About $0.164 \pm 0.026 \times 10^6 \text{ km}^2$ of single-cropping area was converted to double-cropping area, which mainly occurred in the Huang-Huai-Hai Region. About $0.193 \pm 0.028 \times 10^6 \text{ km}^2$ of double-cropping area was converted to single-cropping area, which mainly occurred in the southern part of China. About 85% of croplands with decreases in cropping intensity were located in southern part of China, and about 80% of croplands with increases in cropping intensity was distributed in the Huang-Huai-Hai Region and the northern part of the Middle and Lower Reaches of the Yangtze River region ($p < 0.05$). The landscapes of different cropping systems tended to be homogenized in major agricultural production regions.

Keywords: Cropland; food security; MODIS; remote sensing

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3 **1. Introduction**
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6 Increasing human population has made it difficult for agricultural systems to meet demand for crop
7 and livestock production, thereby making food security an especially serious challenge for China
8 (Foley et al., 2005). Increasing cropland area and yield have been the primary and direct solutions
9 for the rising agricultural production needs over the past decades (Godfray et al., 2010; Ray et al.,
10 2012). Cropland expansion is mainly converted from natural ecosystems and agricultural
11 intensification is mainly based on excessive fertilizer applications, which have resulted in
12 substantial threats to ecosystems (Lambin and Meyfroidt, 2011). Rising concerns are focusing on
13 exploring other means for achieving the balance between food security and environmental security
14 (Foley et al., 2011; Ray and Foley, 2013), and increasing cropping intensity is regarded as one of
15 critical and effective approaches (Ray and Foley, 2013; Stephan et al., 2016; Turner and Doolittle,
16 1978). Cropping intensity refers to the cropping frequency in a given cropland area per year, which
17 is often measured using multiple cropping indices (MCI). Mean cropping intensity of a region
18 represents the average intensity of areas cropped across the whole region during one year.
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36 Cropping systems in China are diverse due to complex, varied climate and socio-economic
37 conditions. Single-cropping rice, maize, or soybean systems dominate Northeast China (Zhang et
38 al., 2015). Wheat/maize and wheat/soybean rotations are the major cropping systems in most of
39 North China Plain (Liu et al., 2010). Rice-based cropping systems are prevalent in the Middle and
40 Lower Reaches of the Yangtze River Region (Leeming, 1979) with winter wheat/rice in the
41 northern Yangtze River region and rice/rice/green manure cropping rotation in the southern
42 Yangtze River region. Double season rice and rotations of rice, potato, and sugarcane are the major
43 cropping systems in South China.
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54 Several previous studies were carried out to identify cropping practices using various data
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sources. The National Agricultural Census datasets were used to calculate MCI for the administrative provinces (Xie and Liu, 2015), which reflects the general cropping intensity but does not capture detailed spatial information on cropping intensity (Yan et al., 2014). Satellite remote sensing can repeatedly observe the land surface, which makes it possible to monitor crop phenology and the spatial pattern and temporal changes of cropping intensity at large spatial scales. The spectral reflectance bands from optical satellites can be used to calculate vegetation indices (VIs), such as Landsat (Jain et al. 2013), SPOT Normalized Difference Vegetation Index (NDVI) (Ding et al. 2015), GIMMS-NDVI (Ding et al 2016), and MODIS (Yan et al. 2014). Although Landsat has a relatively high spatial resolution of 30 meters, it has a temporally coarse 16-day revisit cycle and observations are easily affected by frequent cloud contamination. MODIS provides daily observations at a spatial resolution of 500 meters but has a higher chance to capture cloud-free observations over the same time period, which are used to composite data products that are less affected by cloud cover and shadows. Considering the trade-off between spatial and temporal resolution, MODIS data is the better choice for identifying and tracking the spatio-temporal changes of cropping intensity across broad extents due to its higher frequency and higher number of cloud-free observations.

Additionally, different techniques and algorithms have been developed to quantify the cropping frequency (Jain et al. 2013). The MODIS peak value method has been widely used, which defines the number of peaks on MODIS time series vegetation indices as the number of cropping cycles (e.g. Biradar and Xiao, 2011). Correspondingly, various techniques have been used to extract the peak frequency, such as the wavelet transform method (Qiu et al. 2017) and the two-difference algorithm (Ding et al. 2016). However, using only these statistical methods to interpret the remote sensing data will likely introduce uncertainty because they do not consider *in situ*

knowledge about crop phenology and intensity.

Existing annual MCI products of China cover various spatial resolutions (500m, 1 km) and time spans (the latest year is 2013) (Ding et al., 2015; Qiu et al., 2017). Previous studies didn't achieve consensus on the overall trend of cropping intensity change in China since 2000. Ding et al. (2015) found that cropping intensity increased significantly during 1999-2013 in China based on 1 km SPOT NDVI imagery, while Qiu et al. (2017) found that the cropping intensity slightly declined during 2001-2013 based on 500m MODIS imagery. Therefore, knowledge about the spatio-temporal changes in cropping intensity in China remains limited and more accurate cropping intensity maps are needed.

The objectives of this study were two-fold: (1) to develop annual cropping intensity maps with high accuracy in China from 2000 to 2015 using a rule-based algorithm on time series MODIS enhanced vegetation index (EVI) and *in situ* crop phenology data from field observations; and (2) to assess the spatio-temporal changes of cropping intensity in China from 2000 to 2015. The results from this study can provide informational support for making cropland use policy, which is important for food security in China.

2. Materials and methods

2.1. Data

2.1.1. Cropland data

Cropland data was extracted from China's National Land-Use/Cover Change Dataset (NLCD-China) at a mapping scale of 1:100,000 by Chinese Academy of Sciences. The NLCD-China dataset was generated based on visual interpretation of the 30m Landsat TM/ETM+ images (Liu et al., 2014; Liu et al., 2005). The cropland layer used in our study had high accuracy (~95%) at the national scale based on substantial ground references. The interpreted NLCD-China was

converted to gridded raster datasets in the following steps (Liu et al., 2005). First, a fishnet of 1 km × 1 km grid was created. Second, the vector map was overlain with the fishnet and the area fraction for each land cover and land use type was calculated for each grid cell. Third, a series of raster layers for six land cover types and 25 five land use types were developed. Cropland area decreased about 0.7% of the total cropland in China from 2000 to 2010 (Liu et al. 2014). In this study, to reduce the influence from cropland change, we used the spatial distribution map of cropland in 2000 generated from those pixels where cropland was the largest area proportion. Then the cropland map was resampled to match the 500-m MODIS-derived cropping intensity data.

2.1.2. MOD09A1 land surface reflectance and EVI data

We downloaded the time series MOD09A1 (MODIS/Terra Surface Reflectance 8-Day L3 Global 500m SIN Grid) product during 2000 to 2015 from the Earth Resources Observation and Science (EROS) Center, United States of Geological Survey (USGS) (<https://eros.usgs.gov/>). For each pixel of MOD09A1, the highest good-quality value is selected from all the daily acquisitions within the 8-day composite period. Compared with the 30-m 16-day Landsat and 8-km 10-day AVHRR sensors, MOD09A1 has relatively good spatial and temporal resolution for identification and mapping of cropping intensity. Then the MOD09A1 land surface reflectance product was used to calculate time series EVI based on the following equation.

$$EVI = 2.5 \times \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + 6 \times \rho_{red} - 7.5 \times \rho_{blue} + 1} \quad (1)$$

where, ρ_{nir} , ρ_{red} and ρ_{blue} are the values of reflectance of near infrared (841–876 nm), red (620–670 nm), and blue (459–479 nm) bands, respectively.

2.1.3. Crop calendar data from agro-meteorological observations

Crop phenology information derived from agro-meteorological observations in 2002 was incorporated to guide decision rules in the cropping intensity mapping algorithm because of its data availability (Yan et al., 2014). A total of 394 in-situ observations from the national agro-meteorological stations (AMSs) across China were used (Figure S1), which is freely available from the China Meteorological Data Sharing Service System (<https://data.cma.cn/en>). The agro-meteorological observations included records of critical phenological phases (*i.e.*, planting date, emergence date, and maturity date) covering 11 major crop types (early rice, late rice, single rice, winter wheat, spring wheat, spring maize, summer maize, cotton, soybean, sorghum and rapeseed). The crop phenology information provided the ground references we used to build decision rules and thresholds for mapping cropping intensity.

2.1.4 Statistic data

We collected provincial agricultural and socio-economic datasets in China. We used these datasets to compare our MODIS-based cropping intensity product and analyze the potential factors influencing the spatio-temporal changes of cropping intensity. Table 1 is a brief summary for the provincial agricultural and socio-economic statistic datasets. Cost-profit ratio for major crops refers to the ratio of net profit to total cost for the agricultural production of major crops. The cost-profit ratio not only considered the farmer profit but also the total cost during the agricultural production including labor cost, land cost, and material cost such as fertilizer input. The major crop types in our study included Indica rice, Japonica rice, corn, and wheat.

Table 1 Provincial agricultural and socio-economic statistic datasets

Data	Years	Data source
Agricultural sown area	2000, 2005, 2010	National Bureau of Statistics of China
Prices for major crops	2000-2013	China Yearbook of Agricultural Price Survey
Labor cost for major crops	2000-2013	Cost and Profit for Agricultural Products
Cost-profit ratio for major	2000-2013	Cost and Profit for Agricultural Products

crops		
Migrant population data in every province	2000,2010	Tabulation on the 2000/2010 population census of the People's Republic of China

2.2. Methods

2.2.1. A rule-based algorithm for mapping cropping intensity

Annual time-series EVI data can clearly reflect crop phenological stages including planting, emergence, heading, maturity, and harvest (Sakamoto et al., 2005). Correspondingly, the dynamic process of “rise-peak-fall” in EVI time series represents the cropland growth cycle. EVI reached its peak on the heading date. We also showed the capacity of MODIS EVI time series to catch the crop growth cycle at three cropland ecosystem field stations with multiple cropping areas in China (Yan et al. 2014).

Based on the phenology data of *in situ* field observations, we developed a rule-based algorithm to identify and map the spatial distribution of cropping intensity in China in 2002 (Yan et al. (2014). The algorithm consisted of three following procedures: (1) smoothing the EVI time series using the Harmonic Analysis of Time Series (HANTS) method to remove noise and construct gapless images; (2) detecting the potential cropping cycles by determining the number of peaks of the smoothed EVI time series profile using a moving window method; and (3) determining the reasonable peak values as the number of cropping cycles. Decision rules and thresholds were further set to determine reasonable peak in the EVI profiles based on crop calendar information from agro-meteorological observations. First, the reasonable peak value of EVI should be higher than 0.35, which represents the peak value of semi-arid grasslands. Second, the temporal interval between two probable peak dates of crop growth should be larger than 80 days. Third, the possible earliest and latest dates that reasonable peaks occur should be earlier than the 320th day

of the year and later than the 56th day of the year. Figure 1 showed the smoothed EVI with the crop calendar information from Yugan station, which is in a typical double cropping region. For more detailed information about the rule-based algorithm of cropping intensity mapping, please refer to our previous study (Yan *et al* 2014). In this study, we applied this rule-based algorithm and generated annual cropping intensity maps in China from 2000 to 2015.

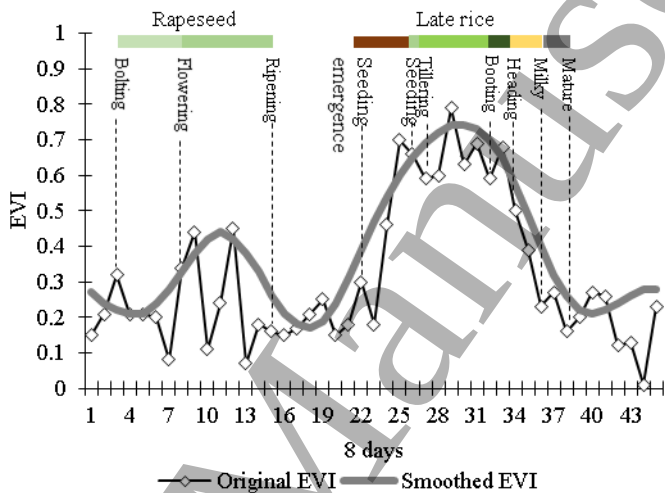


Figure 1. The original and smoothed EVI at the Yugan station (116°40'59"E, 28°42' 00" N) with rotation of rapeseed and late rice. The crop calendar of two crops were also provided.

2.2.2. Accuracy assessment and comparison of MODIS-based cropping intensity maps

To assess the accuracy of MODIS-based cropping intensity maps at both pixel and regional scales, we collected ground reference samples and the government agricultural census data. The ground reference samples were visually interpreted from time series multiple-source high spatial resolution images, including Landsat 4-5 TM, Landsat 7 ETM+, Landsat 8 OLI, and Sentinel-2 time series images in 2000 and 2015. The government agricultural census data at the provincial level in 2000, 2005, and 2010 were used in this study.

The combined Landsat-like sensors provide relatively high frequency of land surface observations at the spatial resolutions from 10 to 30 meters, which provides a chance to visually

interpret cropping cycles at relatively fine scales. Considering the very small area proportion (~2% of total cropland area) of triple-cropped area in China, the accuracy assessment was conducted for single- and double-cropping practices. Firstly, 200 ground samples were generated using stratified random sampling in ArcGIS based on cropping intensity map in 2015 (Figure S2). The sample numbers for single- (146 pixels) and double-cropping (54 pixels) areas were approximately consistent with the area proportion of these cropping systems. Secondly, visual interpretation of cropping intensity for these samples was conducted for 2000 and 2015 using a combination of all available Landsat-like images. Based on the phenology characteristics of single- and double-cropping systems (see Figure S3 and S4), the visual interpretation was performed using the LandLook Viewer (<https://landlook.usgs.gov/>), which is a prototype tool for rapid online viewing and interactively explore Landsat and Sentinel-2 archives at up to full resolution. Thirdly, we generated a confusion matrix for cropping intensity maps in 2000 and 2015 and cropping intensity change from 2000 to 2015, and we then calculated the overall accuracy, user accuracy, and producer accuracy. Area estimates (uncertainties) were also calculated from the confusion matrix using the method described in (Olofsson et al., 2014).

At the regional scale, agricultural sown areas estimated from this study and the government agricultural census were compared at the provincial level for 2000, 2005, and 2010. Pixel-level agricultural sown area was calculated by multiplying cropland area by cropping intensity for each pixel in 2000, 2005, and 2010. Provincial agricultural sown areas were the sum of agricultural sown area of each grid cell. Finally, linear relationships between agricultural sown areas estimated from this study and the government agricultural census were analyzed for 2000, 2005, and 2010.

2.2.3. Methods for characterizing the spatial pattern of cropping intensity trends

To characterize the changes in the spatial and temporal patterns of cropping intensity, we

aggregated the 500-m cropping intensity maps into 5-km gridcells using two aggregation approaches. In the first approach, we generated annual 5-km cropping intensity maps using the average aggregation method in the period of 2000-2015. In the second approach, we generated for the same period annual 5-km area fractional maps of single- and double-cropping based on the sum aggregation method. Then, we performed trend analysis for annual 5-km cropping intensity maps using linear regression models with t test at the 5% significance level.

Two landscape metrics were applied to quantify spatial fragmentation of cropping pattern, which were calculated using software FRAGSTATS 4.2 (McGarigal et al., 2012). Patch density (PD) and Landscape Fragmentation Index (LFI) were used to quantify the degree of fragmentation at the landscape and regional scales, respectively.

$$PD = \frac{N_i}{S_i} \quad (2)$$

where N_i represents the patch numbers of landscape i ; S_i represents the area of landscape i .

$$LFI = \frac{N}{S} \quad (3)$$

where N refers to the total number of patches; S refers to the total landscape area of the region.

3. Results

3.1 Accuracy assessment and comparison of MODIS-based cropping intensity maps in China

According to the confusion matrix (Table 2), the MODIS-based cropping intensity maps were assessed with relatively high accuracy in 2000 and 2015. The overall accuracy of the MODIS-based cropping intensity map was 95.5% for each year. The user accuracy and producer accuracy of single- and double-cropping area were 97.2% and 96.5%, and 91.2% and 92.9% in 2000, respectively. The user accuracy and producer accuracy of single- and double-cropping area were

96.6% and 97.2%, and 92.6% and 90.9% in 2015. The cropping intensity changes also showed good accuracy between 2000 and 2015. The overall accuracy of change in cropping intensity was 91.5%. Both the user accuracy and producer accuracy of single-cropping converted to double-cropping were 75% and the user accuracy and producer accuracy of double-cropping to single-cropping were 73.7% and 82.4%.

Table 2. Confusion matrix of MODIS-based cropping intensity maps based on ground reference samples from visual interpretation of time series Landsat and Sentinel-2 images in 2000 and 2015. Overall, user and producer accuracies are provided.

Year			Ground reference		Total pixels	User accuracy
			Single-cropping	Double-cropping		
2000	Cropping intensity	Single-cropping	139	4	143	97.20%
		Double-cropping	5	52	57	91.23%
	Total pixels		144	56		
	Producer accuracy		96.53%	92.86%		
	Overall accuracy		95.50%			
2015	Cropping intensity	Single-cropping	141	5	146	96.58%
		Double-cropping	4	50	54	92.59%
	Total pixels		145	55		
	Producer accuracy		97.24%	90.91%		
	Overall accuracy		95.50%			

Table 3. Confusion matrix of MODIS-based cropping intensity change from 2000 to 2015.

		Ground reference				Total pixels	User accuracy
		Single to Single	Single to Double	Double to Single	Double to Double		
Cropping intensity	Single to Single	122	3	1	1	127	96.06%
	Single to Double	2	12	0	2	16	75.00%
	Double to Single	4	0	14	1	19	73.68%
	Double to Double	0	1	2	35	38	92.11%
	Total pixels	128	16	17	39	200	
Producer accuracy		95.31%	75.00%	82.35%	89.74%		
Overall accuracy		91.5%					

According to Figure 2, the agricultural sown areas calculated from the MODIS cropping

intensity maps and from the government agricultural census data had reasonably good and stable linear relationships in 2000 ($R^2 = 0.88$, $p < 1e^{-5}$), 2005 ($R^2 = 0.86$, $p < 1e^{-5}$), and 2010 ($R^2 = 0.89$, $p < 1e^{-5}$), respectively (Figure 2). The slopes ranged from 0.75 to 0.86 and the RMSE was $8.44 \times 10^6 \text{ km}^2$, $6.73 \times 10^6 \text{ km}^2$, and $7.95 \times 10^6 \text{ km}^2$ for 2000, 2005, and 2010, respectively. The crop planting area estimated by MODIS data in our study was larger than the reported area by agricultural census data, which was also found in previous studies (Frolking et al. 1999). Two factors may contribute to the uncertainty: (1) the underestimate of cropland area in China from official agricultural census (Frolking et al. 1999; Liu et al. 2005; Seto et al. 2000; Xiao et al. 2003), which may be due to political and policy factors (Seto et al. 2000; Xiao et al. 2003; Zhang et al. 2017), and (2) the inherent overestimate of cropland area in remote-sensing estimates due to the coarse spatial resolution for small field patches (Frolking et al. 1999; Seto et al. 2000).

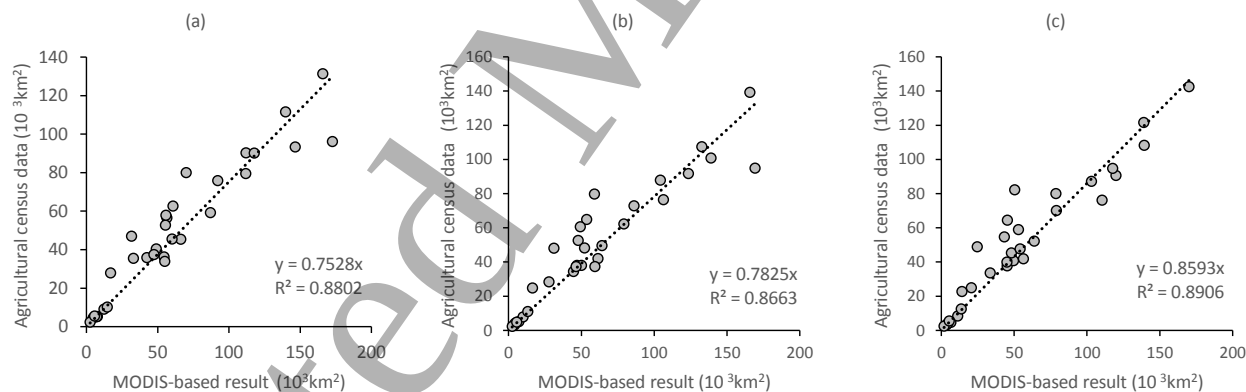


Figure 2. The scatter plots for the comparison of provincial agricultural sown area between MODIS-based result and agricultural census data in 2000 (a), 2005 (b), and 2010 (c).

3.2 Spatial distribution of MODIS-based cropping intensity in China in 2015

The MODIS-based cropping intensity map showed clear spatial patterns of cropping intensity in China in 2015. Single-cropping had the largest area of approximately $1.28 \pm 0.027 \times 10^6 \text{ km}^2$,

accounting for 70.14% of the total cropland area, which was concentrated in northern China and slatternly distributed in southern China (Figure 3). The double-cropping area was $0.52 \pm 0.027 \times 10^6$ km², accounting for 27.74% of the total cropland area. Double-cropping was mainly distributed in the Huang-Huai-Hai Region (37.71%) and the Middle and Lower Reaches of the Yangtze River Region (30.93%). Figure 3 showed triple-cropping areas occupied a small proportion of cropland (~2% of total cropland area), so we mainly focused on the single- and double-cropping areas in the following analyses.

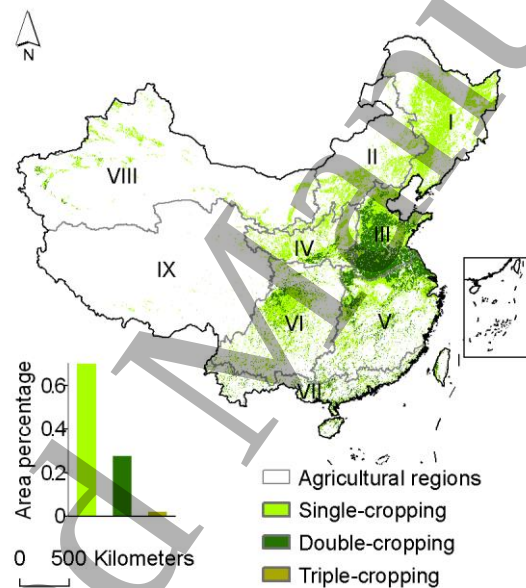


Figure 3. Spatial distribution of single-, double-, and triple-cropping in 2015. Agricultural regions include the Northeast Region (I), Inner Mongolia and the Great Wall Region (II), Huang-Huai-Hai Region (III), Loess Plateau Region (IV), Middle and Lower Reaches of the Yangtze River Region (V), Southwest Region (VI), South China Region (VII), Gan-Xin Region (VIII), and Qinghai-Tibet Region (IX).

3.3 Changes in the spatio-temporal distribution of cropping intensity

At the country scale, the total single-cropping ($1.24 \pm 0.027 \times 10^6$ km² in 2000 to $1.28 \pm 0.027 \times 10^6$ km² in 2015) and double-cropping ($0.54 \pm 0.027 \times 10^6$ km² in 2000 to $0.52 \pm 0.027 \times 10^6$ km² in 2015) areas remain relatively stable. However, there was a noticeable

spatial transition of cropping intensity between 2000 and 2015. About $0.164 \pm 0.026 \times 10^6 \text{ km}^2$ of single-cropped land was converted to double-cropped land, mainly in the Huang-Huai-Hai Region. About $0.193 \pm 0.028 \times 10^6 \text{ km}^2$ of double-cropped land was converted to single-cropped land, which mainly occurred in the southern part of China (Figure 4a).

The spatial pattern of change in cropping intensity during 2000-2015 was shown in Figure 4b. Approximately 85.42% of cropland with decreased cropping intensity was in the southern part of China. About 79.96% of cropland with increased cropping intensity was distributed in the Huang-Huai-Hai Region and the northern part of the Middle and Lower Reaches of the Yangtze River region. In addition, we determined the spatial pattern of area changes of single- and double-cropping systems during 2000-2015. Significant expansion of single-cropping occurred in the southern part of China (the Middle and Lower Reaches of the Yangtze River Region and the Southwest Region), while single-cropping area significantly shrank in the Huang-Huai-Hai Region (Figure 4c). The reverse trend was observed for double-cropping areas (Figure 4d). Single-cropping was dominate in Northern China and was relatively stable.

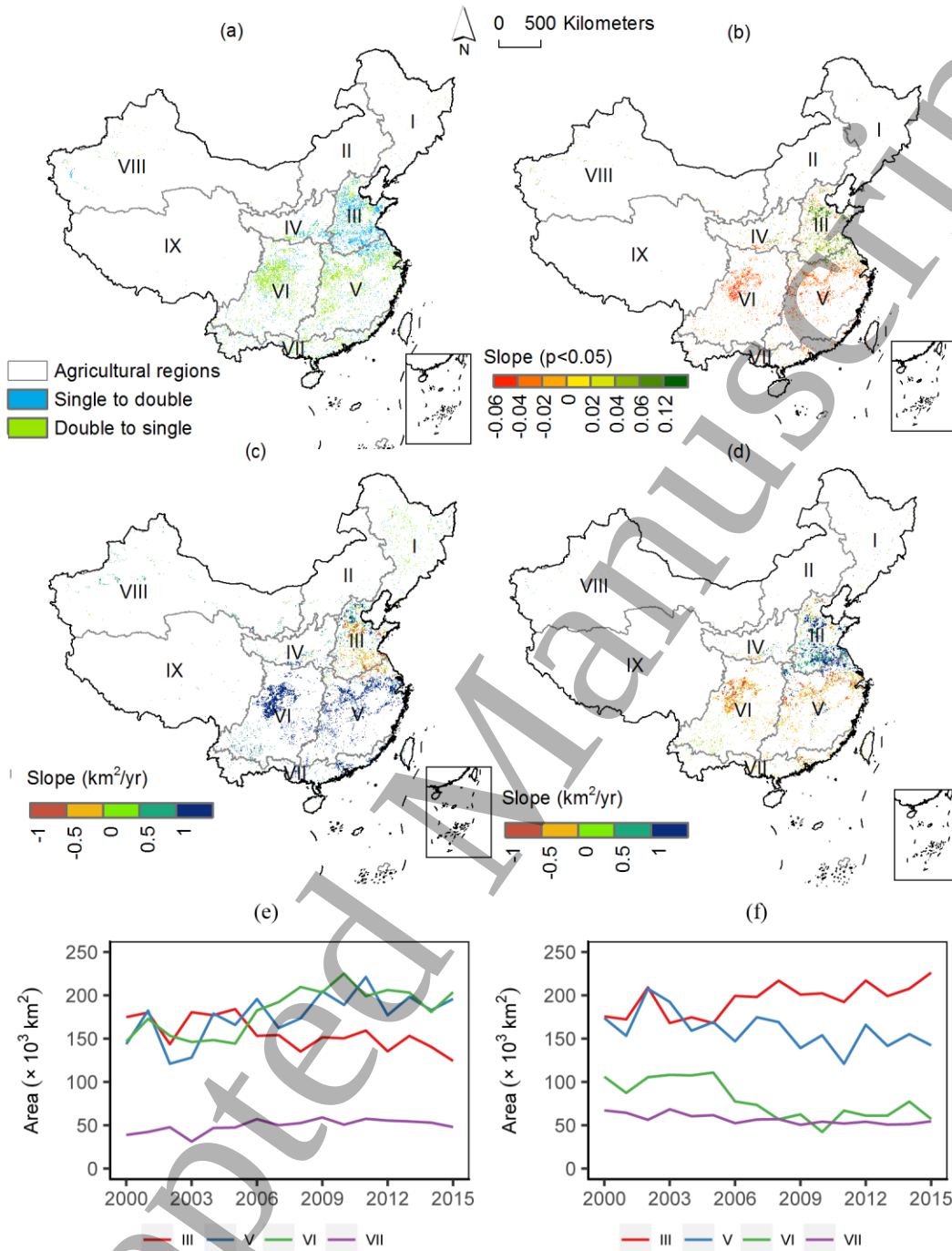


Figure 4 Significant change ($p < 0.05$) in cropping intensity at multiple scales during 2000-2015. (a) Spatial distribution of conversion between single-cropping and double-cropping between 2000 and 2015; (b) Significant trend in cropping intensity at $5\text{km} \times 5\text{km}$ grid cell ($p < 0.05$) during 2000-2015; Significant trend in area of single- (c) and double-cropping (d) at $5\text{km} \times 5\text{km}$ grid cell ($p < 0.05$); Inter-annual changes of single- (e) and double-cropping (f) area by agricultural

regions ($p<0.05$). Cropping intensities in regions with insignificant changes were not displayed in the figure.

At the regional scale, regional variations in cropping intensity changes were also detected (Table 3, Figure 4c and 4d). The Huang-Huai-Hai Region had a significant increased cropping intensity ($p<0.05$) through the expansion of double-cropping area and a slight reduction in single-cropping area. The Middle and Lower Reaches of the Yangtze River Region, the Southwest Region, and the South China Region experienced significant decreases in cropping intensity ($p<0.05$), with an increase in single-cropping area and a decrease in multiple-cropping area. In the other agricultural regions, there was a general absence of any significant trends both in average cropping intensity and area of different cropping systems.

Table 3 Inter-annual variations of mean cropping intensity during 2000-2015 by agricultural regions

Region	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
I	1.01	1.01	1.00	1.01	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.01	1.01	1.01	1.01
II	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
III**	1.51	1.50	1.60	1.50	1.50	1.48	1.57	1.57	1.62	1.57	1.58	1.55	1.62	1.57	1.62	1.65
IV	1.12	1.13	1.14	1.17	1.14	1.14	1.13	1.14	1.11	1.11	1.10	1.11	1.18	1.08	1.19	1.20
V**	1.67	1.50	1.71	1.70	1.50	1.55	1.44	1.56	1.51	1.41	1.46	1.36	1.49	1.44	1.49	1.45
VI**	1.52	1.39	1.47	1.51	1.49	1.51	1.35	1.29	1.23	1.25	1.16	1.27	1.24	1.26	1.37	1.27
VII*	1.72	1.68	1.66	1.83	1.64	1.62	1.52	1.62	1.57	1.51	1.63	1.52	1.53	1.58	1.60	1.66
VIII	1.06	1.03	1.04	1.05	1.04	1.10	1.02	1.02	1.02	1.04	1.04	1.03	1.04	1.03	1.09	1.10
IX	1.06	1.04	1.03	1.05	1.05	1.05	1.03	1.03	1.03	1.03	1.03	1.03	1.04	1.03	1.08	1.08

Note: ** represents significant change with $p<0.01$; * represents significant change with $p<0.05$.

4. Discussion

4.1. Improvement to previous cropping intensity methods and products

The cropping intensity calculated based on the agricultural census data at the administrative level (Xie and Liu, 2015) has large uncertainty, restricted by spatial resolution, cost, and the knowledge of census people. Our remote sensing approach provided a detailed spatial and spatiotemporal dynamics of cropping intensity and has high efficiency to track cropping intensity through time

(Yan et al. 2014).

Compared with previous research on change in cropping intensity in China based on remote sensing since 2000 (Ding et al. 2015; Ding et al. 2016; Qiu et al. 2017), our study incorporated crop-phenology information from *in situ* field observations into the algorithm and quantified the area, area uncertainties, and spatiotemporal changes of cropping intensity. Our results showed improvements in two aspects: higher accuracy and more reasonable results for cropping intensity in China.

First, our improved methodology incorporated crop-phenology information and led to higher accuracy. Ding et al. (2015) performed the NDVI peak-based algorithm using SPOT NDVI at 1 km spatial resolution with an overall accuracy of 91.95%. Qiu et al. (2017) applied the wavelet feature-based method to calculate cropping intensity using MODIS EVI with an overall accuracy of 91.63% (in 2013). We incorporated the crop-phenology information from *in situ* field stations to improve the EVI peak-based algorithm, which helped make our rule-based algorithm and helped determine reasonable peak numbers in the EVI profiles. We set the thresholds for possible minimum peak value, the minimum temporal interval between two probable peaks, and the possible earliest and latest dates that the peaks reasonably occur according to the field-observed crop calendar information to avoid misclassification. The overall accuracy of cropping intensity in 2000 and 2015 in our study were 95.5% for each year, which was higher than the previous two studies. Additionally, the previous studies didn't have accuracy assessments for the spatiotemporal changes of cropping intensity in China, which is important to analyze the uncertainty of their cropping intensity change results. In our study, we not only evaluated the accuracy of cropping intensity in 2000 and 2015, but also the accuracy of change in cropping intensity from 2000-2015 based on the ground references. The accuracy of change in cropping intensity from 2000 to 2015

was 91.5%.

Second, a more accurate cropping intensity product leads to more reasonable results of the spatiotemporal change of cropping intensity in China. For the trend in cropping intensity in China, Ding et al. (2015) found that cropping intensity increased significantly by 1.3% per year during 1999-2013 in China, while Qiu et al. (2017) found that the cropping intensity slightly declined during 2001-2013. According to the accuracy assessment, we carried out uncertainty analysis for the cropping intensity change in China (Olofsson et al., 2014). Our results showed that the total cropping intensity was relatively stable. The single-cropping area changed from $1.24 \pm 0.027 \times 10^6$ km² in 2000 to $1.28 \pm 0.027 \times 10^6$ km² in 2015 and the double-cropping area changed from $0.54 \pm 0.027 \times 10^6$ km² in 2000 to $0.52 \pm 0.027 \times 10^6$ km² in 2015. This meant the total cropping intensity was relatively stable in China from 2000 to 2015. For example, our product didn't show many significant changes in cropping intensity in the Loess Plateau. However, both Ding et al. (2016) and Qiu et al. (2017) showed that significant increases in cropping intensity occurred in the revegetation area in Loess Plateau (Chen et al. 2015; Feng et al. 2016), where large areas of farmland and barren land have been converted to woodland and grassland under the "Grain for Green" project (Liu et al., 2014). Additionally, rising labor scarcity leads to decline in cropping intensity, the rising out-migrant population in southern part of China (Figure 6d and 6e) will aggregate the labor shortage and then result in decreasing cropping intensity (Jiang et al., 2013). Therefore, it is reasonable that our product and Qiu, et al. (2017) showed significant decreasing trends of cropping intensity in Southern China.

Our previous work mainly focused on the algorithm and spatial distribution of cropping intensity in 2002 (Yan et al., 2014). This study extended our previous efforts to generate the annual cropping intensity maps during 2000-2015 and address the trend of cropping intensity since 2000.

The accuracy assessment of the algorithm was firstly provided in this paper not only in terms of cropping intensity mapping in 2000 and 2015, but also that of the change analysis, which have demonstrated the consistency and robustness of the algorithm for tracking spatiotemporal changes of cropping intensity in China. Based on the annual cropping intensity products, we analyzed the spatiotemporal changes of cropping intensity and improved the previous knowledge about the cropping intensity in China since 2000.

4.2 Change in Landscape pattern of cropping systems

Spatiotemporal changes in cropping intensity not only include the land use changes of different cropping systems, but also on the change in the spatial configuration pattern of cropping systems. The annual fragmentation of cropland decreased in China but the change was statistically insignificant ($p>0.05$). However, the spatial fragmentation in the Huang-Huai-Hai Region and the Middle and Lower Reaches of the Yangtze River Region significantly declined by 61.51% and 34.16% ($p<0.05$) (Figure 5a), implying that cropping systems tended to be homogenized and cropland with the same cropping system tended to be more distributed in 2015 than in 2000 (Figure 6).

We observed a negative trend in patch density in single-cropped lands of China ($p<0.05$), declining from 2000 to 2015 by 32.49% (Figure 5b). Regionally, a significant decreasing trend was also detected in the Huang-Huai-Hai Region, the Middle and Lower Reaches of the Yangtze River Region, and the Southwest Region, where the patch densities have declined by 66.75%, 69.07%, and 34.55%, respectively (Figure 5c). This decrease implied that the degree of fragmentation of single-cropped land declined and that these areas tended to be more concentratedly distributed (Figure 5b). We detected no trend in patch density of double-cropping cropland across China (Figure 5b). Regionally, double-cropped lands tended to be more

concentrated in the Huang-Huai-Hai Region and the Middle and Lower Reaches of the Yangtze River Region and more dispersed in the South China Region (Figure 5c).

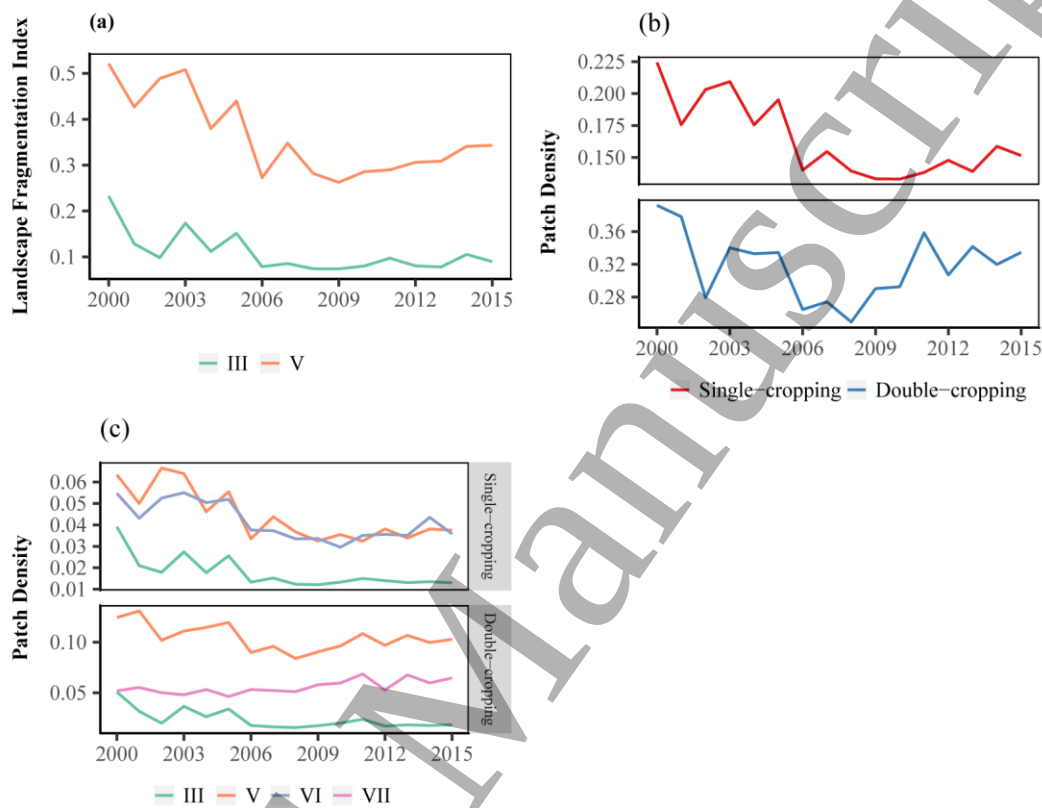


Figure 5. Change in landscape index of cropping systems during 2000-2015. (a) Inter-annual variations of landscape fragmentation index among agricultural regions ($p<0.05$). Patch density of single- and double-cropping in China (b) and agricultural regions (c) ($p<0.05$). The labels of agricultural regions refer to Figure 1. The trend analysis of LFI and PD was conducted in the nine agricultural regions, but only the regions with significant change ($p<0.05$) was displayed in the figure.

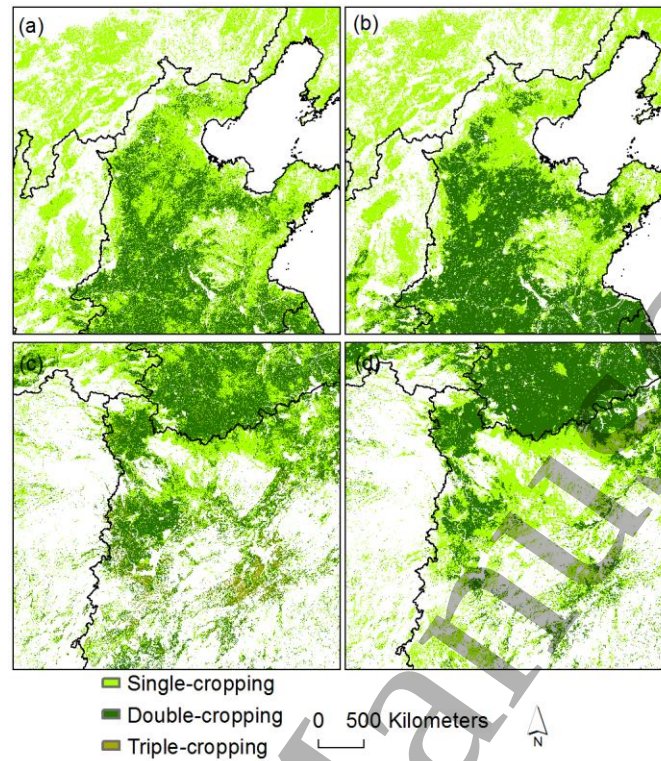


Figure 6. Spatial heterogeneity of cropping systems in the Huang-Huai-Hai Region (a, b) and the Middle and Lower Reaches of the Yangtze River Region (c, d) at 500m×500m grid cell in 2000 (a, c) and 2015 (b, d).

4.3. Possible factors influencing the cropping intensity change

The potential factors contributing to the spatio-temporal changes of cropping intensity in China are complex. In the long run, climate changes have also been found to have effects on cropping intensity (Lizumi and Ramankutty, 2015). Climate warming in China have increased the potential cropping intensity in the last 50 years (Liu et al., 2013), including the Tibetan Plateau (Zhang et al., 2013). Meanwhile, crop mixes and crops distribution were also influenced by climate change (Yin et al., 2016; Zhang et al., 2018). For example, climate warming has made the planting boundary shift northward for maize and rice in Northeast China and rice in Southern China (Liu et al. 2013; Ye et al., 2015; Lu et al., 2017).

Socio-economic factors also effected the trend of cropping intensity change in two opposite

ways. On one hand, a series of new agricultural policies implemented the early 21st century benefited farmers and increased farmers' enthusiasm for growing grain, including the elimination of the agricultural tax, increasing agricultural subsidies, and increasing grain price (Figure 7a). These policies were supposed to increase farmers' incomes and investment in agriculture, which would positively contribute to intensification of cropland (Zuo et al. 2014; Gale et al. 2005; Huang et al. 2013). Also, institutional innovation and policy support will increase farm operational scale in China through land transfer, land consolidation, and mechanization (Huang and Ding, 2016), which would help the distribution of croplands become homogenized. On the other hand, urban expansion and growth in out-migrant agricultural workers would lead to lower cropping intensity (Xie and Jiang 2016; Jiang et al 2013). The increasing out-migrant population and rising wages (Figure 7d, 7e) caused declines in available farm workers and a continuous growth in labor cost for major crops (Figure 7b). Although there were fewer farm workers, the land owner often preferred to retain their land for family farming (Xie and Jiang, 2016), which would lead to decreased cropping frequency (Su et al., 2016). Among agricultural regions, the out-migrant population trend was consistent with the distribution of hotspots of decline in cropping intensity. From 2000 to 2010, more provinces in the southern part of China, except for coastal provinces, became the main sources of migrant workers (Figure 7d and 7e). Meanwhile, the cost-profit ratio of major crops, i.e. the rate of profit, soared to the highest level in 2004 and then exhibited a decreasing trend (Figure 7c). The decline in the rate of profit would reduce the enthusiasm of farming. This variation might explain the decrease in the area of multiple-cropping starting in 2004.

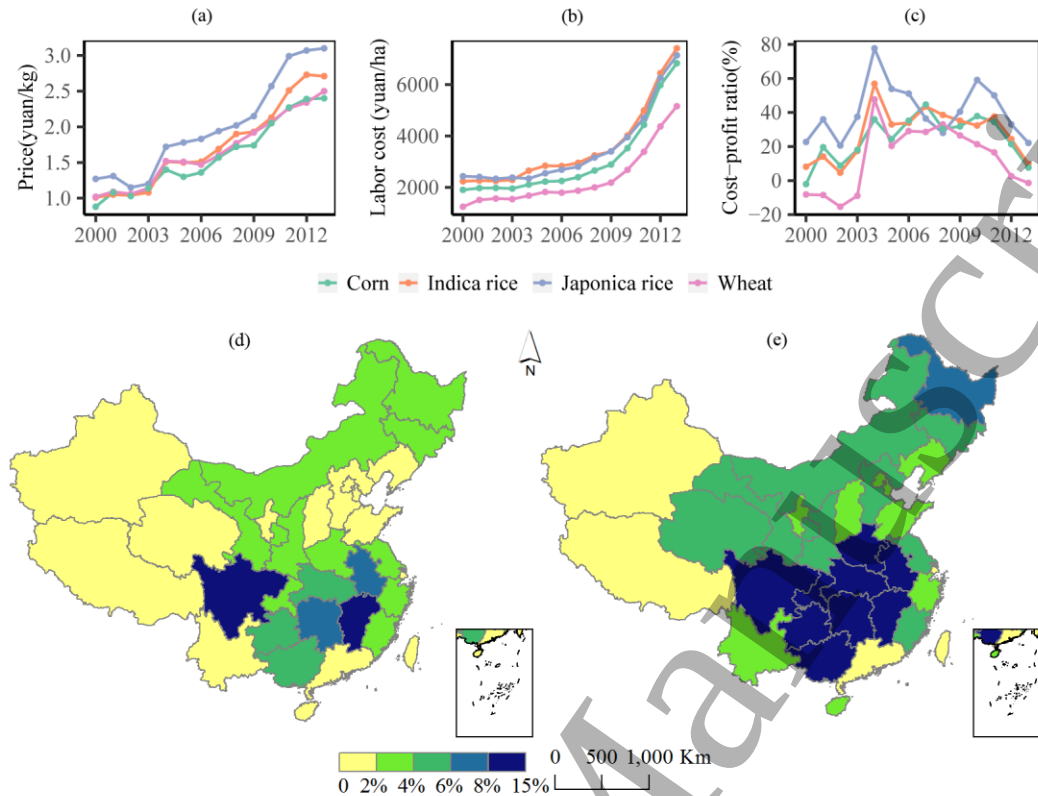


Figure 7. Possible factors influencing the change of cropping intensity. (a) Price of main crops. (b) Labor cost of main crops. (c) Cost-profit ratio of main crops. Out-migrant population percent in every province in 2000 (d) and 2010 (e).

4.4. Linkage with food security

In an effort to achieve food security, a series of agricultural programs were launched to provide agricultural subsidies, increase grain price, and improve soil quality and crop varieties to increase farmers' enthusiasm for growing grain (Huang et al., 2013). Although the agricultural areas with multiple-cropping systems decreased, grain production continued to increase according to the agricultural census, mainly due to increased grain yield and cropland reclamation. The average grain yield increased from about 5000 kg/ha in 2000 to 6000 kg/ha in 2013, which can be largely attributed to increased investment in agriculture (Huang et al. 2017). However, a large gap remains between grain production and demand in China (Wei et al., 2015) and about 1.2×10^8 t of grain

(20% of grain production in China) was imported in 2015.

Cropping intensity is an important indicator of agricultural land use efficiency (Licker et al., 2010; Neumann et al., 2010; Rudel et al., 2009). Although improving cropping intensity is an effective way to increase grain production, suitable cropping systems still depend on the local natural environment and socio-economic conditions. The spatio-temporal change of cropping intensity from our study clearly showed the regions that had significant decreases and increases in cropland area from 2000 to 2015. According to the changes in cropping intensity, increased cropping intensity in some regions would be a potential way to increase grain if the ecological and environmental conditions are suitable (Zuo et al., 2014). For example, we should evaluate the potential for improving cropping intensity in Southwest China despite ecological and environmental limitations, such as intensive soil erosion (Zuo et al., 2014). Some agricultural regions show increased cropping intensity, such as the Huang-Huai-Hai Region, a region with high grain production. In this region, the increasing grain production is based on the use of excessive fertilizer, underground water, and biocides, which reduce the sustainability of cropland production and food security (Guo et al., 2010; Rodell et al., 2018), as well as ecosystems (Ellis and Ramankutty, 2008; Foley et al., 2005; Kareiva et al., 2007; Sanderson et al., 2002). Therefore, a balance should be reached between cropland sustainable production and ecosystem services.

5. Conclusions

This study explored changes in cropping intensity and fragmentation of different cropping systems across China during 2000-2015. In 2015, single-cropping had the largest area of approximately $1.28 \pm 0.027 \times 10^6 \text{ km}^2$, accounting for 70.14% of the total cropland area and double-cropping area was $0.52 \pm 0.027 \times 10^6 \text{ km}^2$, accounting for 27.74% of the total cropland area. From 2000 to 2015, the total area of single-cropped and double-cropped lands was relatively stable at

the country scale. However, the distribution of cropping intensity significantly changed between 2000 and 2015. About $0.164 \pm 0.026 \times 10^6$ km² of single-cropped land was converted to double-cropped land, mainly occurring in the Huang-Huai-Hai Region. About $0.193 \pm 0.028 \times 10^6$ km² of double-cropped land was converted to single-cropped land, which occurred mainly in the southern part of China. Substantial changes occurred through spatial comparison: cropping intensity stabilized in Northern China, increased in the Huang-Huai-Hai Region, and decreased in Southern China. Single-cropping increased in Southern China, which was opposite to the decrease observed in the Huang-Huai-Hai Region. We also found that the trend in double-cropping reversed. The decline in the cropping intensity in Southern China was correlated with the increased out-migrant population trend in the region. Regional cropping system patterns tended to increase in spatial consistency and landscapes of the same cropping practices became less fragmented in the main agricultural regions (the Huang-Huai-Hai Region and the Middle and Lower Reaches of the Yangtze River Region).

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