Received: 18 March 2019 | Revised: 4 September 2019 | Accepted: 26 September 2019

DOI: 10.1002/ldr.3454

RESEARCH ARTICLE

WILEY

Determining the effect of land consolidation on agricultural production using a novel assessment framework

Changqiao Hong[1,2,3,4] | Xiaobin Jin[1,2,3] | Yeting Fan[1,5] | Xiaomin Xiang[1] | Shuai Cao[1] | Changchun Chen[4] | Guang Zheng[6] | Yinkang Zhou[1]

[1]School of Geographic and Oceanographic Sciences, Nanjing University, Nanjing, 210023, PR China

[2]Key Laboratory of Coastal Zone Exploitation and Protection, Ministry of Natural Resources, Nanjing, 210023, PR China

[3]Natural Resources Research Center, Nanjing University, Nanjing, 210023, PR China

[4]School of Geographic Sciences, Nanjing University of Information Science & Technology, Nanjing, 210044, PR China

[5]School of Public Administration, Nanjing University of Finance & Economics, Nanjing, 210023, PR China

[6]International Institute for Earth System Science, Nanjing University, Nanjing, 210023, PR China

Correspondence
X. Jin, School of Geographic and Oceanographic Sciences, Nanjing University, Nanjing 210023, PR China.
Email: jinxb@nju.edu.cn

Funding information
National Natural Science Foundation of China (NSFC), Grant/Award Number: 41971234; National Science and Technology Support Program of China, Grant/Award Number: 2015BAD06B02; Program B for Outstanding PhD Candidate of Nanjing University, Grant/Award Number: 201802B073

Abstract

Land consolidation (LC) is regarded as a useful tool to improve agricultural production. Measuring the effect of LC on agricultural production (ELC_{AP}) is helpful for the planning of LC activities. In the past, it is difficult to measure ELC_{AP} at regional level due to the lack of field observation, the change of crop planting structure, and high cost of sample collection. Satellite data have large coverage and high spatiotemporal resolution for vegetation observation, which can provide a new idea for estimating ELC_{AP} at regional level. This study aims to build a novel assessment framework to quantitatively investigate ELC_{AP} by developing several satellite-based metrics. In addition, this study also explored the characteristics of ELC_{AP} using the method of spatial autocorrelation and the geographical detector method in 1,281 LC areas in China. Our results show that agricultural productivity in more than 90% of total LC areas shows an increasing trend during 2001–2016. LC could play the positive but limited effects on agricultural production, and its productivity-boosting effect (64.87% of total LC areas) is greater than its stability-improving effect (46.53% of total LC areas). The spatial agglomeration of ELC_{AP} is weak (Moran's I < 0.06), which may be resulted from the differences in field conditions and natural-social–economic situations across LC areas. The interaction between several factors has a greater effect on the ELC_{AP} than each of these factors. Methodology in this study provides a new and useful framework for evaluating ELC_{AP}, and results can be used to guide the planning of LC activities.

KEYWORDS
agricultural production, geographical detector, land consolidation, net primary productivity, regional characteristics

1 | INTRODUCTION

With the growth of population and the level of dietary energy intake, the demand for food has increased dramatically, which has a disadvantageous effect on food security (Nath et al., 2015). Especially in China, cultivated land has decreased significantly due to the expansion of construction land (Fan et al., 2018; Yan, 2010; Zhong et al., 2017), and contemporary agricultural productivity in many areas is still far below the corresponding agricultural production potential (Foley et al., 2011). Therefore, it is a meaningful choice to improve agricultural production. Methods to improve the agricultural productivity have attracted a great deal of attention and have been considered to be crucial to fulfill policy goals such as decreasing the 'gaps between the yields,' boosting food production, and relieving the pressure of food security (Suweis, Carr, Maritan, Rinaldo, & D'Odorico, 2015).

Traditionally, land consolidation (LC) is a favorable land management approach integrating segmented parcels into continuous lands in areas where the lands are not efficiently used, misused, unused, or damaged by production, manufacture, or natural disasters (Liu et al., 2019). Nowadays, it is widely applied in the world, but its content changes substantially across countries (Kwinta & Gniadek, 2017). In China, LC formed into shape in the late 1990s (Song & Pijanowski, 2014). In the beginning, farmland quantity declined due to non-agricultural construction (Xu et al., 2015), ecological restoration, and agricultural structure adjustment (Qin et al., 2013). Later on, occupying high-quality farmland and destroying the ecological environment are increasingly severe due to disorder, the rapid expansion of construction land along with the rapid industrialization and urbanization (Chen, Zhou, & Wu, 2017). Meanwhile, farmland fragmentation and extensive utilization have become increasingly serious problem as well as rural hollowing and farmer aging (Sklenicka et al., 2009). To deal with these dilemmas and tough realities, the Chinese Government have been continuously enriching the connotation and denotation of LC in China (Tang, Pan, & Liu, 2017). Nowadays, China's LC has been into a new stage that highlights the equal importance of 'quantity–quality–ecology' (Yan, Xia, & Bao, 2015). It is sound to integrate LC into the national development strategy (Zhang, Zhao, & Gu, 2014). It is emphasized that improving farmland quality and agricultural production is the main aim of LC during 2003–2015 (Li, Liu, Long, & Cui, 2014).

LC activity in China involves some engineering practices such as land leveling, irrigation and drainage updates, road network construction, and farmland protection. These practices could result in the change of farmland use ways, the adjustment of agricultural management modes, and then change agricultural production (Thapa & Niroula, 2008). The extent and magnitude of the impact of LC on agricultural production might rely on some factors such as geographical environment, social and economic backgrounds, and regional development policies (Miranda, Crecente, & Alvarez, 2006).

As an important part of the theory and practice of LC, evaluating LC effectiveness has increasingly drawn great attention from academics and government (Chartin et al., 2013; Demetriou, 2017; Janus & Markuszewska, 2017; Lerman & Cimpoies, 2006; Zheng et al., 2017). Specifically, changes in the agricultural production caused by LC have been counted as an important indicator in evaluating the effectiveness of LC. Previously, the effect of LC on agricultural production was mainly evaluated with local statistics report and point-to-area verification by relevant agencies in China. Those studies discussed the impact of LC on agricultural production mainly focusing on farmland quality classification (Bitencourt et al., 2016), production monitoring system (Guan et al., 2014), agricultural production capacity (Gu, Dai, & Chen, 2008), potential land productivity (Zhang, Yan, Zhao, & Zhao, 2013), and household survey. Those studies explored the basic contents and theoretical method of agricultural production assessment related to LC. However, they mainly conducted the effectiveness evaluation of single LC area because of the limitation of sample data, and their methods have disadvantages in objectivity, coverage, and cost. The study on estimating the effect of LC on agricultural production at regional level has been still in the stage of "description–interpretation," and the quantitative research revealed by characteristics and regularity of the effect is still rare. The status of crop growth can be monitored by satellite data (Hong, Jin, Ren, Gu, & Zhou, 2019); moreover, the spatial resolution and coverage of satellite data have been continuously increasing in China during the past decades, which shows the great potential to solve the question at regional level compared with the traditional method.

The 'National Land Consolidation Plan (2016–2020)' requires that LC should focus on ensuring to build 266,700-km^2 farmland with the high-quality and stable yield. To better realize that purpose, we need to measure the effect of LC activities carried out in the past on agricultural production and select suitable region to plan the LC activities in the future. The goals in this study are to provide a helpful methodology for the evaluation of LC effectiveness on agricultural production (ELC_{AP}) at regional level and explore the characteristics of ELC_{AP}. To achieve these goals: (a) the assessment framework for regional LC effectiveness based on satellite data was constructed from the

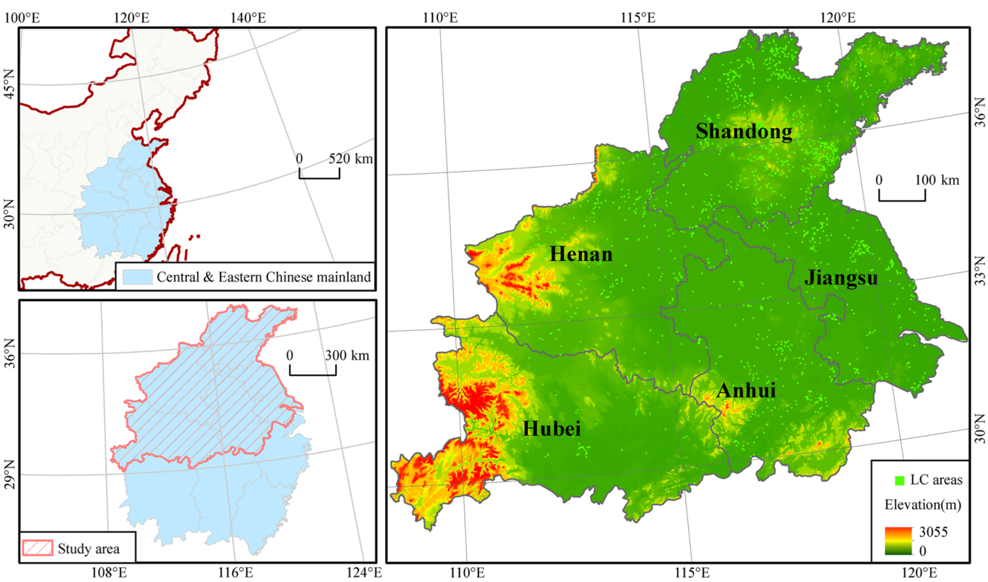

FIGURE 1 The study area and spatial distribution of land consolidation (LC) areas. China's and provincial boundaries come from the Ministry of Natural Resources of China (http://bzdt.ch.mnr.gov.cn). Elevation come from the digital elevation model (http://datamirror.csdb.cn). These maps were made in ARCGIS 9.3 software environment (ESRI, Redlands, USA)

aspects of agricultural productivity and production stability; (b) the influence of characteristics of LC on agricultural production in China's important grain-producing area was explored based on the method of spatial autocorrelation; and (c) we tried to reveal the characteristics of the relationship between ELC_{AP} and natural–social–economic environment by using the geographical detector method.

2 | MATERIALS AND METHODS

2.1 | The study area

Our study area locates in five provinces (Henan, Hubei, Shandong, Anhui, and Jiangsu) in North Central and Eastern China, and each province includes several counties. Besides several mountains in the southwest and the south, most of the study area locates in North China Plain with a total amount of 758,100 km^2 (Figure 1).

The study area has characteristics such as having a muggy and rainy season with concentrated precipitation and single round or maximal double rounds of cropping. The proper environmental factors and climate conditions enable very harmonious agriculture development in this area that make it an essential part of national food production. In 2016, this area produced almost one third of the national grain production (Henan Provincial Bureau of Statistics, 2017, Hubei Provincial Bureau of Statistics, 2017, Shandong Provincial Bureau of Statistics, 2017, Anhui Provincial Bureau of Statistics, 2017, and Jiangsu Provincial Bureau of Statistics, 2017). Meanwhile, almost 393 million people, about 28.59% of the total national population, reside in this region (China's National Bureau of Statistics, 2017). Therefore, food security always takes priority in this area.

The study area has been tried to design as a critical LC area of strategic significance for the nation. The actual implementation of LC in the region has attracted widespread attention. Therefore, analyzing the effectiveness of LC in our study area is of great reference value to some kinds of studies related to LC.

2.2 | Data sources and preprocessing

The LC areas carried out during 2006–2013 come from the Ministry of Natural Resources of China (http://www.mnr.gov.cn/), and their location and coverage were checked based on high-resolution (15 m) Landsat/OLI images. After taking the farmland area of LC that is larger than 1 km^2 as the screening criterion, the 1,281 LC areas were selected as the example in this study. ArcGIS 9.3 (ESRI, Redlands, USA) was used to make buffer analysis for finding the neighbourhood farmland (the farmland did not experience the LC activity, area > 1 km^2) within 3 km around the LC area. Taking the neighbourhood farmland as the control area, then the 1,281 control areas were made.

Farmland (2005) in China comes from the ESA project; it is raster data with 300-m resolution (http://due.esrin.esa.int/page_globcover.php) and can be resampled to 250-m resolution. Farmland (2014) in China with a scale of 1:5,000 comes from the Ministry of Natural Resources of China, which was converted to raster data with 250-m resolution by using ARCGIS 9.3. The farmland raster (250 m) in LC areas and the control areas can be obtained by using overlay analysis of ARCGIS 9.3. Annual Farmland net primary productivity (NPP) in the LC areas and the control areas can be calculated by using the Carnegie–Ames–Stanford Approach (CASA) model described in Section 2.4, normalized difference vegetation index (NDVI), farmland raster data, and the meteorology data (i.e., monthly mean temperature/precipitation and monthly solar radiation). NDVI (16 days, 250 m) data during 2001–2016 come from the MOD13Q1 product (http://www.edc.usgs.gov), after smoothed by using the S-G method and composed by employing the maximum value composition (Hong et al., 2019), and the final NDVI dataset (monthly, 250 m) was made. The meteorology data during 2001–2016 in observation sites come from the Chinese Meteorological Data Sharing Network (http://data.cma.cn/), and the monthly meteorology dataset with the spatial resolution of 250 m can be obtained based on the observation data using the Kriging interpolation method in the ARCGIS 9.3 software environment.

Besides the multiyear average of NPP (*X*1) and coefficient of variation (*CV*; *X*2) before consolidation in the LC areas, the data of LC areas were from the ones listed in Table 1 and in both vector and raster data formats. We rerasterized all vector data with the spatial resolution of 1 km and computed the values of each variable in the LC area using the ARCGIS 9.3. The probability of correlation between ELC_{AP} and natural–social–economic factors was measured by *p* value, which was provided by the geographical detector. The significant test for the spatial autocorrelation also was measured by *p* value, which was provided by the tool 'Spatial Autocorrelation' in ARCGIS 9.3.

2.3 | General framework

The workflow of our study is shown in Figure 2. First, farmland NPP was used to indicate the agricultural productivity, and it was modeled using the CASA model integrating the satellite remote sensing data with high-resolution and large coverage. Second, the change slope of farmland NPP in several years was calculated to reflect the change of agricultural productivity, and the *CV* of farmland NPP in several years was measured, which was used to show the production stability. Third, the neighbourhood farmland around LC area was taken as the control area, and the differences on the change slope and *CV* of farmland NPP between the control area and LC area were regarded as the effect of LC on agricultural production (ELC_{AP}). In addition, we also set up four indicators including the productivity amplitude (*P*), productivity amplitude ratio (*PR*), stability amplitude (*S*), and stability amplitude ratio (*SR*) to capture the changes of *CV* and NPP values. Finally, the spatial variability of ELC_{AP} at regional level was derived by the method of spatial autocorrelation, and the relationship between ELC_{AP} and natural–social–economic factors was explored by the method of geographical detector.

TABLE 1 The data sources in this study

Variable	Expression	Explanation/scale/format	Data source
Multiple cropping index (*X*3)	The number of cropping in a year	Raster, 1-km resolution	Ding, Chen, Xin, Li, and Li (2015)
Total nitrogen (*X*4)	The content of total nitrogen in soil		The National Earth System Science Data Sharing Infrastructure (http://www.geodata.cn/)
Total potassium (*X*5)	The content of total potassium in soil		
Organic matter (*X*6)	The content of organic matter in soil		
Sand (*X*7)	The content of sand in soil		The Harmonized World Soil Database Version 1.1 (http://www.fao.org/home/en/)
Clay (*X*8)	The content of clay in soil		
St_0 (*X*9)	Soil temperature in the depth of 0 cm		The National Earth System Science Data Sharing Infrastructure (http://www.geodata.cn/)
St_40 (*X*10)	Soil temperature in the depth of 40 cm		
Cumulative temperature (*X*11)	The sum of the temperature whose value is greater than 0°C in a year		
Humidity level (*X*12)	The multiyear average of humidity index		
Frost-free period (*X*13)	The number of frost-free days in a year		The Resources and Environment Science Data Center of the Chinese Academy of Science (http://www.resdc.cn/)
Precipitation (*X*14)	The multiyear average of precipitation		The National Earth System Science Data Sharing Infrastructure (http://www.geodata.cn/)
Surface rolling (*X*15)	The value was calculated by using ARCGIS 9.3 and DEM (30 m)	The LC area	http://datamirror.csdb.cn
Slope (*X*16)			
Farmland quality (*X*17)	The quality grade of farmland		The Ministry of Natural Resources of China (http://www.mnr.gov.cn/)
Zone (*X*18)	Chinese agricultural zoning for crop	Vector	The Resources and Environment Science Data Center of the Chinese Academy of Science (http://www.resdc.cn/)
Distances RL (*X*19)	The distances between rural settlements and the LC areas was calculated by using ARCGIS 9.3	The LC area	Beijing City Lab (https://www.beijingcitylab.com/)
Investment intensity (*X*20)	Investment/area of the LC area		The Ministry of Natural Resources of China (http://www.mnr.gov.cn/)
Population density (*X*21)	Population/total land area	County	The Statistical Yearbook (Henan, Hubei, Shandong, Anhui, and Jiangsu Provincial Bureau of Statistics, China, 2006)
Road density (*X*22)	Main road length/total land area		Beijing City Lab (https://www.beijingcitylab.com/)
Fertilization level (*X*23)	Chemical fertilizers/farmland area		The Statistical Yearbook (Henan, Hubei, Shandong, Anhui, and Jiangsu Provincial Bureau of Statistics, China, 2006)
Village electricity level (*X*24)	Village electricity/farmland area		
Machinery level (*X*25)	Agricultural machinery power/farmland area		
Farmland resource (*X*26)	Farmland area/total land area		
Farmland per capita (*X*27)	Farmland area/population		

Abbreviations: DEM, digital elevation model; LC, land consolidation.

2.4 | Measurement of agricultural productivity and production stability

NPP is defined as the organic matter accumulation after photosynthesis and respiration of green vegetation in the unit time and area (Lieth & Whittaker, 1975). NPP can reveal contemporary agricultural productivity directly and is regarded as an effective indicator for monitoring high-, medium-, and low-yield field (Yan et al., 2016). In this paper, to determine agricultural productivity and production stability, farmland NPP has been simulated by the CASA model and remote sensing data, and the *CV* was calculated based on simulated NPP.

The CASA model, proposed by Potter et al. (1993), has become one of the models being widely used to simulate farmland NPP

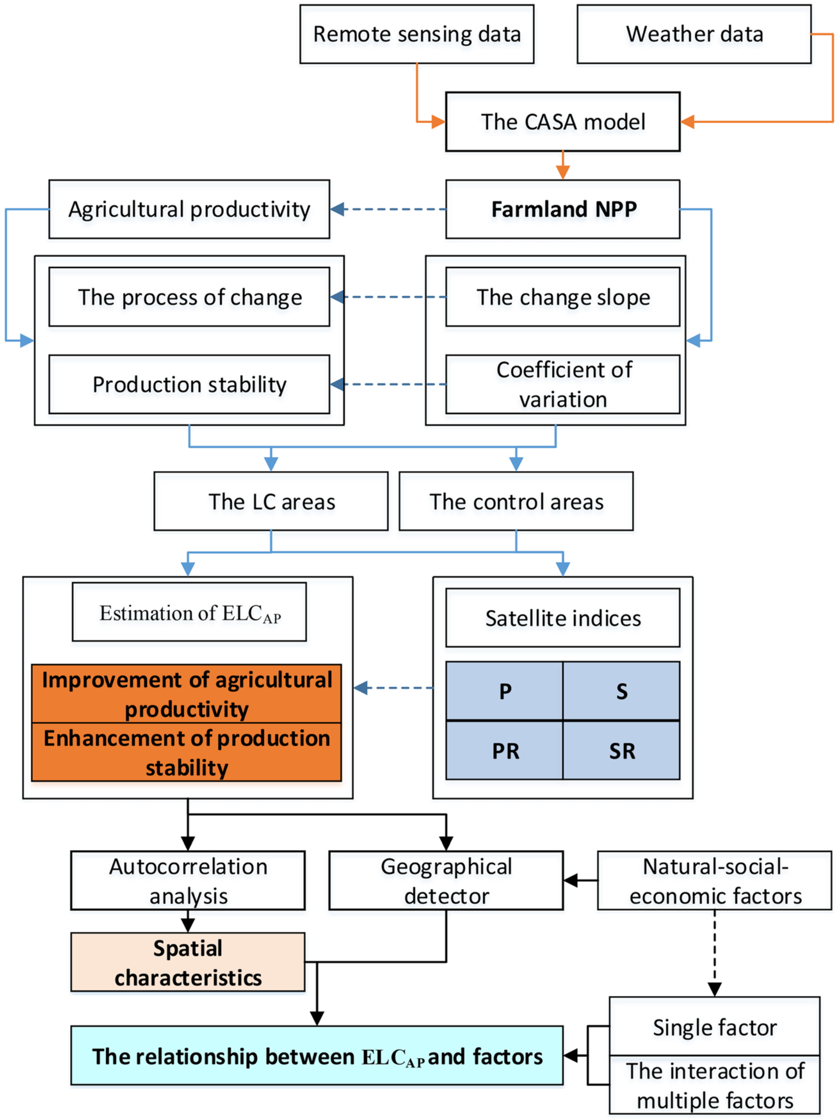

FIGURE 2 The workflow of this study. CASA, Carnegie–Ames–Stanford Approach; LC, land consolidation; NPP, net primary productivity

through recalibration upon the coefficient for regionalization (He, Liu, Xu, Ma, & Dou, 2017; Yu, Shi, Shao, Zhu, & Pan, 2009). The model had been mainly expressed as (Equations (1)–(7)):

$$NPP = APAR \times \varepsilon, \tag{1}$$

$$APAR = FPAR \times PAR, \tag{2}$$

$$FPAR = (FPAR_{NDVI} + FPAR_{SR})/2 \tag{3}$$

$$FPAR_{NDVI} = (NDVI - NDVI_{MIN})/(NDVI_{MAX} - NDVI_{MIN})* (FPAR_{MAX} - FPAR_{MIN}) + FPAR_{MIN}, \tag{4}$$

$$FPAR_{SR} = (SR - SR_{MIN})/(SR_{MAX} - SR_{MIN})*(FPAR_{MAX} - FPAR_{MIN}) + FPAR_{MIN}, \tag{5}$$

$$SR = (1 + NDVI)/(1 - NDVI), \tag{6}$$

$$\varepsilon = \varepsilon max \times T1 \times T2 \times W, \tag{7}$$

where $APAR$ is photosynthetically active radiation of crop's absorption; ε is the coefficient for actual light use efficiency; $FPAR$ is a key parameter, which represents photosynthetic active radiation proportion of crop's absorption, estimated by satellite data (NDVI); PAR is photosynthetically active radiation; εmax is the maximum of light use efficiency; and $T1$, $T2$, and W are the limits of the conditions of low temperature, high temperature, and moisture to light use efficiency of crop, respectively. Detailed calculation steps can be checked in Los (1998) and Yu et al. (2009).

Production stability can be estimated by the CV. The formula can be expressed as (Equation (8)):

$$CV = \sigma/\mu, \tag{8}$$

where σ is the standard deviation of annual NPP and μ is the average value of multiyear NPP.

2.5 | Evaluating the effect of LC on agricultural production (ELC_{AP})

To avoid interferences from other factors besides LC, we set up the neighbourhood farmland within 3 km around LC area as the control area and thus evaluated the effectiveness of regional LC by comparing the differences between LC areas and those control areas.

To reveal the difference in terms of agricultural productivity, learning from the method in the existing literature (Zhang et al., 2016), this study intends to build the productivity amplitude (*P*), productivity amplitude ratio (*PR*), stability amplitude (*S*), and stability amplitude ratio (*SR*) as indices to assess the effects of LC on agricultural productivity and its stability comprehensively. Whereas *P* and *S* respectively represent the net changes of agricultural productivity and production stability, *PR* and *SR* stand for significance degrees of agricultural productivity and production stability change, respectively. These indices can be formulated as (Equations (9)–(13)):

$$P = (Kz2 - Kz1) - (Kc2 - Kc1), \tag{9}$$

$$PR = P/|KC2 - KC1|, \tag{10}$$

$$K = \frac{n\sum_{i=1}^{n} iNPPi - \sum_{i=1}^{n} i \sum_{i=1}^{n} NPPi}{n\sum_{i=1}^{n} i^2 - \left(\sum_{i=1}^{n} i\right)^2}, \tag{11}$$

$$S = (CVz1 - CVz2) - (CVc1 - CVc2), \tag{12}$$

$$SR = S/|CVc1 - CVc2|, \tag{13}$$

where *K* represents the average change slope of *NPP*; *i* represents the *i*th year; *n* represents the number of year; *Kz*1 and *Kz*2 represent the average change slopes of *NPP* before and after consolidation in the LC areas, respectively; *Kc*1 and *Kc*2 are the average change slopes of *NPP* before and after consolidation in the control areas, respectively; CV_{z1} and CV_{z2} are respectively the coefficients of variation of *NPP* before and after consolidation in LC areas; and CV_{c1} and CV_{c2} respectively denote the coefficients of variation of *NPP* before and after consolidation in control areas. The tipping point between before and after consolidation is the year when LC activity was carried out.

2.6 | Analyzing the ELC_{AP} characteristics and the relationship between ELC_{AP} and factors

Spatial autocorrelation (i.e., Moran's *I*) method is used to measure whether the spatial dependence in the effect of LC on agricultural production exists in general (Moran, 1950; Xiao, Hu, Li, & Yang, 2018). Moran's *I* index has been defined as (Equation (14)):

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} Wij(xi - \bar{x})(xj - \bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} Wij \sum_{i=1}^{n}(xi - \bar{x})^2}, \tag{14}$$

where *n* is the number of LC areas; *xi* and *xj* are the observed values of the *i*th and *j*th LC areas, respectively; $\bar{x}$ is the arithmetic mean of *xi*; and *Wij* is the spatial weight matrix. The value of Moran's *I* shall be between −1 and 1. When the value is >0, it shows a spatial positive correlation. Values show a strong spatial autocorrelation with numbers closer to 1. When values are <0, values approaching −1 show that the spatial negative autocorrelation is stronger.

The geographical detector method was first proposed in 2010 (Wang et al., 2010). The idea of this method is to measure the similarity in spatial variety between the response variable and the suspected determinant. This method also provides a novel way to determine interactions between different variables for the response variable. The association described in the above text is mainly measured as follows (Equation (15)):

$$PD = 1 - \frac{\sum_{j=1}^{z}\sum_{i=1}^{n_j}(y_{ji} - \bar{y}_j)}{\sum_{i=1}^{n}(y_i - \bar{y})} = 1 - \frac{\sum_{j=1}^{z} n_j \sigma_j^2}{n\sigma^2} \tag{15}$$

where *PD* represents the power of determinant (*q* statistic); *z* and n_j represent the units in the region and subregion, respectively; and σ^2 and σ_j^2 represent the variance in the whole region and in each subregion. The value of *PD* is between 0 and 1. The higher *PD* indicates that the one or multiple factor has larger effect on the response variable. Detailed steps can be found on the website (http://www.geodetector.org/) and some references (Wang et al., 2010; Luo et al., 2016).

3 | RESULTS

3.1 | Agricultural productivity in the LC areas

The agricultural productivity from 2001 to 2016 across these 1,281 LC areas was calculated (Table 2). The annual average farmland NPP

TABLE 2 Descriptions of agricultural productivity in these land consolidation areas

Variable	Max.	Min.	Mean	CV
NPP_A	771.21	374.72	597.58	0.10
CV	25.00	4.00	9.00	0.22
NPP_C	805.58	358.36	595.72	0.10
CV_C	17.66	4.00	8.43	0.25

Note. NPP_A represents the average farmland net primary productivity (NPP) in total land consolidation areas during 2001–2016 (g C m^{-2} yr^{-1}); *CV* represents the average coefficient of variation of farmland NPP in total land consolidation areas from 2001 to 2016 (%); NPP_C represents the average farmland NPP in total control areas during 2001–2016; CV_C represents the average coefficient of variation of farmland NPP in total control areas from 2001 to 2016; Max., Min., and *CV* represent the maximum, minimum, and coefficient of variation, respectively.

(NPP_A) is 597.58 g C m^{-2} $year^{-1}$, and the maximum value of NPP_A is approximately twice than the minimum one in these LC areas. The smallest and average values of *CV* in these LC areas are 4% and 9% in these LC areas, respectively. The *CV* is larger than that of NPP_A during the study period. It was shown in Figure 3 that almost 90% of LC areas demonstrated an increasing trend, whereas farmland NPP was decreasing in the rest of LC areas.

Focusing on the timing of LC practice, the study period can be divided into two phases: one before consolidation and the other after consolidation. As shown in Figure 4, the NPP of farmland accounting for 85.87% of total LC areas before consolidation showed an increasing trend, whereas a reducing trend was observed for the NPP of farmland accounting for 21.94% of total LC areas after consolidation. The changing trend of farmland NPP after consolidation is larger than that before consolidation in 41.45% of total LC areas. *CV* after consolidation is less than that before consolidation in 58.24% of total LC areas. The smaller CV_{z1}, the more possibility of that CV_{z2} is larger than CV_{z1} in the LC area (Table 3).

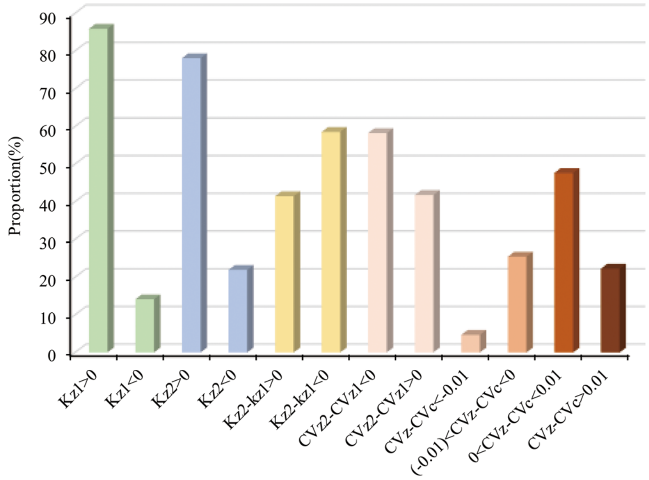

FIGURE 4 The *K* and *CV* of farmland net primary productivity (NPP) in the land consolidation areas and the control areas. K_{z1} and K_{z2} represent the change slope of farmland NPP before and after consolidation, respectively; CV_{z1} and CV_{z2} represent the *CV* of farmland NPP before and after consolidation, respectively; and CV_z and CV_c represent the *CV* of farmland NPP during 2001–2016 in the land consolidation area and the control area, respectively

3.2 | The comparison of agricultural production between LC areas and their control areas

During the study periods (2001–2016), the average of NPP_A in total LC areas is greater, about 1.86 g C m^{-2} $year^{-1}$, than that in their control areas (Table 2). A total of 69.87% of total LC areas are of larger *CV* than that in their control areas, and the differences of *CV* between total LC areas and their control areas are mainly (about 73.07% of total pairs) between −1% and 1% (Figure 4). Similar to the LC areas, an increasing trend occurred in farmland NPP from 2001 to 2016 in the majority (91.10%) of total control areas (Figure 3). About 54.18% of total LC areas are of a greater trend of farmland NPP than that in their control areas (Figure 3). Change of farmland NPP in the LC areas and their control areas before and after consolidation can be divided into four big (Table 4) and 16 small (Table 5) types. Proportions of each of these four big types demonstrate that IV_NPP (81.43%) > I_NPP (10.38%) > II_NPP (6.71%) > III_NPP (1.48%; Table 5), and the *CV* before and after consolidation in LC areas and their control areas can also be divided into four types, whereas their proportions are of the order III_*CV* > I_*CV* > II_*CV* > IV_*CV* (Table 6).

3.3 | The effect of LC on agricultural production

As shown in Figure 5, the result shows that the value of *P* in 64.87% of total LC areas is positive, of which 59.57% are between 0 and 5, whereas 73.11% of negative *P* are from −5 to 0. The value of *S* in 46.53% of total LC areas is positive, of which 62.58% is less than 1%. *PR* and *SR* in more than 75% of total LC areas are between −1 and 1. Based on the value of *P* and *S*, the effect of LC on agricultural productivity can be classified into four types (Table 7). Proportions of each of these four types demonstrate that I > II > III > IV, namely, LC has a positive effect on both agricultural productivity and its stability in 26.62% of total LC areas, whereas LC has a negative effect on both agricultural productivity and its stability in 15.22% of total LC areas.

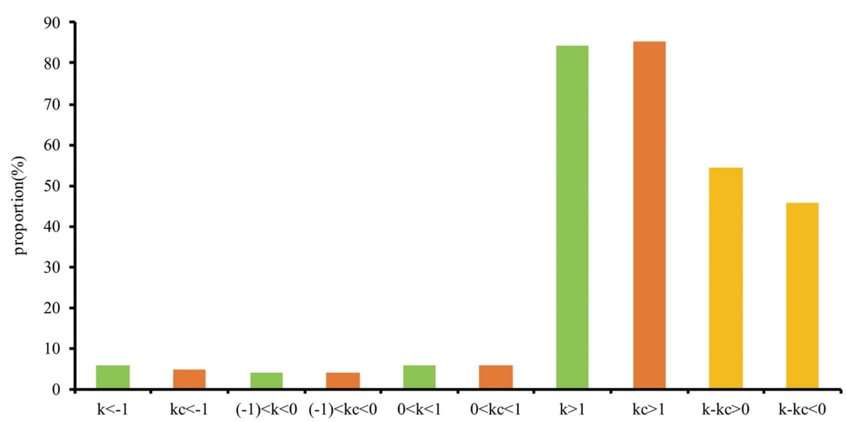

FIGURE 3 The change trend of farmland net primary productivity (NPP) during 2001–2016. *k* represents the change trend of farmland NPP in the land consolidation area, and k_c represents the change trend of farmland NPP in the control area, respectively

TABLE 3 The situation after consolidation in land consolidation areas with different CV_{z1}

Type	CV_{z1} <0.05	0.05–0.08	0.08–0.10	0.10–0.15	>0.15
$P\ (CV_{z2} - CV_{z1} > 0)$	87.84%	56.92%	24.14%	8.51%	0%

Note. CV_{z1} and CV_{z2} represent the coefficient of variation of farmland net primary productivity before and after consolidation, respectively. $P\ (CV_{z2} - CV_{z1} > 0)$ represent in land consolidation areas with CV_{z1}, the proportion of the land consolidation areas whose CV_{z2} is larger than CV_{z1}.

TABLE 4 The description of the big types of farmland NPP change before and after consolidation

Type	Description
I_NPP	The trend of farmland NPP change before consolidation in the LC areas is similar to that in their control areas, whereas the trend of farmland NPP change after consolidation in the LC areas shows an opposite direction of that in their control areas
II_NPP	The trend of farmland NPP change before consolidation in the LC areas shows an opposite direction of that in their control areas, whereas the trend of farmland NPP change after consolidation in the LC areas is similar to that in their control areas
III_NPP	The trend of farmland NPP change before and after consolidation in the LC areas shows an opposite direction of that in their control areas
IV_NPP	The trend of farmland NPP change before and after consolidation in the LC areas is similar to that in their control areas

Abbreviations: LC, land consolidation; NPP, net primary productivity.

TABLE 5 The small types of farmland NPP change before and after consolidation

Type	Before consolidation		After consolidation		
	The LC areas	The control areas	The LC areas	The control areas	Proportion (%)
I_NPP	↑	↑	↑	↓	5.23
	↑	↑	↓	↑	3.43
	↓	↓	↑	↓	0.31
	↓	↓	↓	↑	1.41
II_NPP	↑	↓	↓	↓	0.31
	↓	↑	↑	↑	3.51
	↑	↓	↑	↑	1.72
	↓	↑	↓	↓	1.17
III_NPP	↑	↓	↑	↓	0.16
	↑	↓	↓	↑	0.23
	↓	↑	↑	↓	0
	↓	↑	↓	↑	1.09
IV_NPP	↑	↑	↑	↑	**62.61**
	↑	↑	↓	↓	**12.18**
	↓	↓	↑	↑	4.53
	↓	↓	↓	↓	2.11

Note. ↑ and ↓ represent an increasing and declining trend, respectively.
Abbreviations: LC, land consolidation; NPP, net primary productivity.

3.4 | The characteristics of LC effectiveness on agricultural production

Results of spatial autocorrelation analysis for four variables are shown in Table 8. The *P*, *S*, and *PR* of total LC areas in the study areas are of a low spatial autocorrelation, whereas the *SR* of total LC areas is of an insignificant spatial autocorrelation.

We used a geographical detector to determine the relationships between LC effectiveness (*P*, *PR*, *S*, and *SR*) and 27 social–economic–natural factors (see Table 1). As shown in Table 9, results show that 13 factors have a significant effect on spatial distribution of *P*, and these factors can be divided into four levels in a descending order in terms of the effect: P_1(*X*1), P_2(*X*20, *X*25, *X*27), P_3(*X*2, *X*9, *X*10, *X*11, *X*13, *X*18, *X*21, *X*23), P_4(*X*5). *X*2, *X*3, and *X*19 have a significant effect on the spatial distribution of *PR*, and *X*3 shows the most obvious effect. Fifteen factors have made a contribution to the spatial distribution of *S*, and these factors also can be divided into four levels in a descending order in terms of the effect: S_1(*X*2), S_2(*X*17, *X*18), S_3(*X*9,

TABLE 6 The *CV* before and after consolidation in LC areas and their control areas

Type	*CV* in the LC areas–*CV* in their control areas: Before consolidation	After consolidation	Proportion (%)
I_*CV*	<0	>0	25.45
II_*CV*	>0	<0	19.59
III_*CV*	>0	>0	39.19
IV_*CV*	<0	<0	15.77

The proportion is relatively large, are the use of the bold emphasis.
Abbreviation: LC, land consolidation.

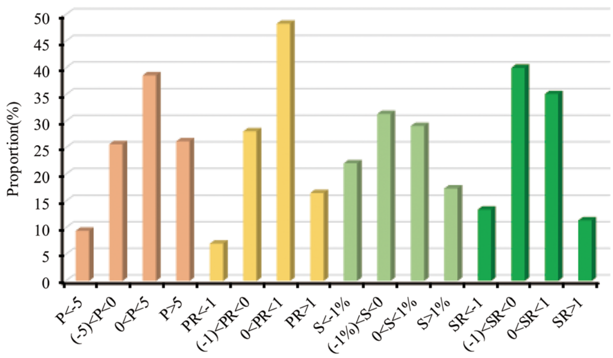

FIGURE 5 The effect of land consolidation on agricultural productivity and production stability. *P* and *S* respectively stand for the net changes of agricultural productivity and production stability, and *PR* and *SR* respectively represent significance degrees of agricultural productivity and production stability change

TABLE 7 The types of the effect of land consolidation on the agricultural productivity in total land consolidation areas

Type	*P*	*S*	Proportion (%)
I	>0	<0	38.25
II	>0	>0	26.62
III	<0	>0	19.91
IV	<0	<0	15.22

Note. *P* and *S* respectively stand for the net changes of agricultural productivity and production stability.

TABLE 8 Spatial autocorrelation analysis of the agricultural productivity in total land consolidation areas

The observation index	*P*	*PR*	*S*	*SR*
Moran's *I*	0.056	0.010	0.025	−0.007
p value	.000	.026	.000	.183

Note. *P* and *S* respectively stand for the net changes of agricultural productivity and production stability; *PR* and *SR* respectively represent significance degrees of agricultural productivity and production stability change.

*X*10, *X*11, *X*12, *X*13, *X*14), S_4(*X*1, *X*5, *X*15, *X*26). Both *X*22 and *X*24 in 27 factors are important factors affecting the spatial distribution of *SR*.

Results from the geographical detector also provided us the effect of the interaction of various factors on the spatial distribution of ELC_{AP}. Some factors have an effect on the spatial distribution of LC effectiveness, but a larger effect could be created by the interaction of these factors. The interactions between *X*18 and *X*1/*X*23 make more contribution (8%) to spatial changes of *P* than themselves (Figure 6). The interactions between *X*3 and *X*4/*X*6/*X*7/*X*8/*X*11 can make over 40% of contribution to spatial changes of *PR* (Figure 7). The interactions between *X*2 and *X*11/*X*13/*X*17/*X*18 create more contribution (10%) to spatial changes of *S* than themselves (Figure 8). The interaction between *X*2 and *X*17 and the interaction between *X*18 and *X*24 have more contribution (12%) to spatial changes of *SR* than themselves (Figure 9).

4 | DISCUSSION

4.1 | The estimation of agricultural productivity

Because of the change of crop types and planting modes, it is not perfect and convenient taking the crop yield as the indicator of agricultural productivity. NPP can reflect the productivity of ecosystem directly; therefore, it can be regarded as the appropriate metric of agricultural productivity (Luo, Yan, & Niu, 2018). The CASA model was built in 1993; it has been regarded as the typical model to estimate NPP and has been widely used in different areas of China (Yu et al., 2009). The simulated value indicates average farmland NPP from 2001 to 2016 in the LC areas, and the control area is between 358.36 and 805.58 g C m^{-2} $year^{-1}$ (Table 2); it is in a reasonable interval and is consistent with the previous studies (Feng et al., 2007; Hong et al., 2019). The difference of average farmland NPP among various LC areas or the control areas may result from the differences in regional/local production conditions, crop types, and/or field input (Huang, Zhang, Sun, & Zheng, 2007). Besides, the study employed the relative amount (e.g., change trend of NPP and variable coefficient of NPP) based on satellite data to analyze the change of agricultural productivity and production stability, which is of positive significance for evaluating the change of agricultural production at regional level.

4.2 | The evaluation of ELC_{AP}

During 2001–2016, the changing trend of farmland NPP indicates an increasing process in more than 90% of total LC areas, the same in the control areas (Figure 3). This result implies that except the LC activity, in the LC area, the change of agricultural productivity may be affected by other factors, such as the changes of production technology (Huang et al., 2007), the art of field management (Eyles, Ives, Hardie, Corkrey, & Boersma, 2018), farmers' intention, and production condition (e.g., climate conditions; Hong et al., 2019). During the whole study period, the difference of production stability between more than 70% of total LC areas and their control areas is small (Figure 4), which may be mainly resulted from the similar meteorological condition and land management modes in the LC areas and their control areas. Besides, the change direction of farmland NPP before consolidation in 8.19% of total LC areas is contrary to that in their control areas (Table 5), namely, the situation of agricultural production before consolidation in some LC areas is significantly different from that in their control areas, and production stability after consolidation in more than 60% of total LC areas is smaller than that in their control areas (Table 6), which can be caused by the disturbance of water–soil environment in these LC areas in a few years after consolidation. Therefore, it can be inferred that the truth of LC effectiveness on agricultural production cannot be revealed correctly when only use the difference of agricultural productivity between before and after consolidation in the LC area to evaluate the LC effectiveness.

In addition, according to Tobler's First Law of Geography (Tobler, 1970), theoretically, the change after consolidation results from other factors except for LC activity in the control area is the same as the LC area. Therefore, the differences after consolidation between the LC area and the control area should be made up of the difference before consolidation, the change caused by LC activities, and the change resulted from other factors. Only taking the difference after consolidation between the LC area and the control area to represent the ELC_{AP} without considering the difference before consolidation may be inappropriate.

Since considering the differences between before and after consolidation and between the LC areas and their control areas simultaneously, satellite indicators (*P*, *PR*, *S*, and *SR*) can be used to reflect the changes of agricultural productivity and production stability caused by the LC activities. In general, the differences in agricultural productivity and production stability between the LC areas and their control areas are not apparent in the study period (Table 2), and the change trends of farmland NPP before and after consolidation in both the LC area and its control area are the same in 81.43% of total LC areas (Table 5). The results imply that LC has a limited effect on agricultural productivity and production stability, which is similar to a previous study (Hong et al., 2019).

From the results of the quantitative assessment (Table 7), the proportion of the LC areas whose *P* are positive in total LC areas is 18.34% more than that of the LC areas whose *S* are positive in total LC areas. This means that the productivity-boosting effect is more significant than stability boosting effect in total LC areas. The absolute value of both *PR* and *SR* in less than 25% of total LC areas is larger than 1 (Figure 5), which indicates that there are only a few LC areas on which LC has a significant effect on agricultural productivity and production stability. In more than 84% of total LC areas, LC has a positive effect on agricultural productivity or production stability (Table 7), which indicates that the LC activity may be beneficial to improve management, soil environment, and irrigation and drainage systems (Chartin et al., 2013; Harasimowicz, Janus, Bacior, & Gniadek, 2017; Thapa & Niroula, 2008), and so on. It is worth considering that the LC activity for improving

TABLE 9 The relationship between land consolidation effectiveness on agricultural production and each of the social–economic–natural factors

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14
The relationship between *P* and social–economic–natural factors														
q statistic	0.047	0.014	0.004	0.002	0.009	0.005	0.003	0.005	0.015	0.014	0.014	0.005	0.017	0.007
p value	.000	.000	.101	.742	.024	.156	.444	.201	.000	.000	.000	.142	.000	.081
The relationship between *PR* and social–economic–natural factors														
	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14
q statistic	0.005	0.009	0.035	0.003	0.007	0.004	0.004	0.004	0.007	0.007	0.004	0.003	0.005	0.001
p value	.158	.025	.000	.410	.064	.226	.243	.329	.055	.057	.342	.500	.186	.849
The relationship between *S* and social–economic–natural factors														
	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14
q statistic	0.008	0.048	0.003	0.006	0.008	0.002	0.001	0.001	0.012	0.011	0.012	0.013	0.014	0.010
p value	.031	.000	.188	.128	.049	.618	.935	.794	.004	.008	.004	.002	.000	.015
The relationship between *SR* and social–economic–natural factors														
	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14
q statistic	0.002	0.005	0.001	0.003	0.003	0.003	0.001	0.002	0.003	0.003	0.002	0.005	0.006	0.006
p value	.659	.197	.718	.441	.521	.483	.796	.676	.489	.506	.599	.165	.098	.093

TABLE 9 The relationship between land consolidation effectiveness on agricultural production and each of the social–economic–natural factors

	The relationship between *P* and social–economic–natural factors												
	X15	***X16***	***X17***	***X18***	***X19***	***X20***	***X21***	***X22***	***X23***	***X24***	***X25***	***X26***	***X27***
q statistic	0.001	0.003	0.010	0.017	0.002	0.023	0.013	0.005	0.016	0.003	0.020	0.002	0.021
p value	.941	.389	.290	.036	.576	.000	.002	.165	.000	.491	.000	.624	.000
	The relationship between *PR* and social–economic–natural factors												
	X15	*X16*	*X17*	*X18*	*X19*	*X20*	*X21*	*X22*	*X23*	*X24*	*X25*	*X26*	*X27*
q statistic	0.002	0.001	0.004	0.003	0.009	0.002	0.003	0.004	0.003	0.002	0.000	0.006	0.001
p value	.755	.877	.872	.967	.037	.634	.382	.340	.357	.619	.976	.093	.830
	The relationship between *S* and social–economic–natural factors												
	X15	*X16*	*X17*	*X18*	*X19*	*X20*	*X21*	*X22*	*X23*	*X24*	*X25*	*X26*	*X27*
q statistic	0.008	0.003	0.017	0.016	0.005	0.002	0.011	0.006	0.012	0.002	0.004	0.009	0.006
p value	.048	.395	.023	.027	.185	.551	.008	.101	.005	.615	.297	.025	.140
	The relationship between *SR* and social–economic–natural factors												
	X15	*X16*	*X17*	*X18*	*X19*	*X20*	*X21*	*X22*	*X23*	*X24*	*X25*	*X26*	*X27*
q statistic	0.001	0.003	0.008	0.005	0.002	0.002	0.000	0.014	0.002	0.012	0.002	0.007	0.005
p value	.762	.400	.404	.784	.684	.660	.990	.002	.733	.008	.661	.051	.158

Note. P and *S* respectively stand for the net changes of agricultural productivity and production stability; *PR* and *SR* respectively represent significance degrees of agricultural productivity and production stability change. $p<0.01$, which represents extremely significant correlation; $0.01<p<0.05$, which represents significant correlation; $p>0.05$, which represents no significant correlation.

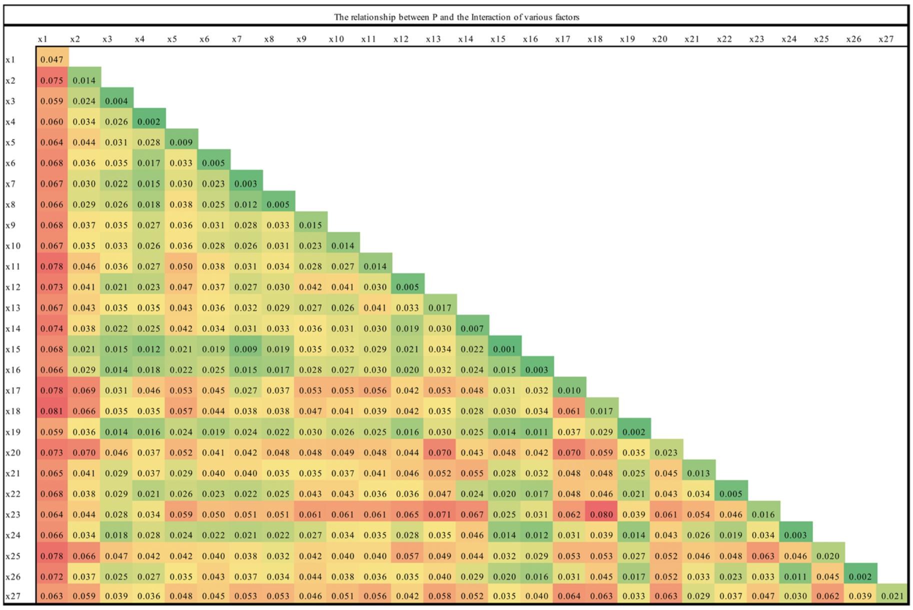

FIGURE 6 The relationship between the effect of land consolidation on agricultural productivity and the interaction of various factors. *P* stands for the net changes of agricultural productivity

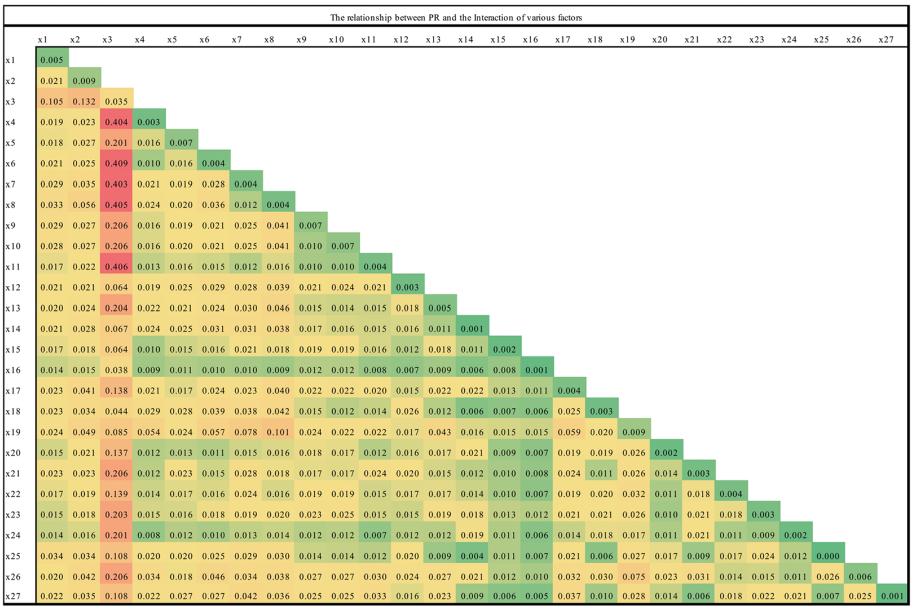

FIGURE 7 The relationship between *PR* and the interaction of various factors. *PR* represents significance degrees of agricultural productivity change

agricultural quality can be arranged in the areas/counties where LC has positive effects on both agricultural productivity and production stability, and maybe it can be considered carrying out the LC activity for increasing farmland area or/and improving the ecosystem in other areas/counties.

4.3 | The characteristics of ELC_{AP}

The spatial agglomeration of ELC_{AP} is weak (Moran's I < 0.1; Table 8). The reason may be that the LC areas are so scattered and they are not in close proximity, and most of them are located in different counties with the differences of natural–social–economic factors, and ELC_{AP} may be closely related to the effect of these factors.

The agricultural system is a complex system that involved in human activity factors, natural factors, and economic factors (Zhang, Yuan, & Xia, 2017). To find the regularity of ELC_{AP} distribution and provide the references for LC planning as comprehensive and reliable as possible, the relationship between ELC_{AP} and 27 potential factors has been explored by a new method that is different from multivariate linear regression. Although multivariate linear regression can show the effect of each factor, it cannot provide the interaction of various factors properly. The new method, geographical detector, is not affected by the multicollinearity of input factors and can offer the effect of each factor and the relationship between ELC_{AP} and the interaction of various factors (Wang et al., 2010).

There are 10 factors that have a significant effect on both *P* and *S* (Table 9), which implied that these 10 factors need to be considered

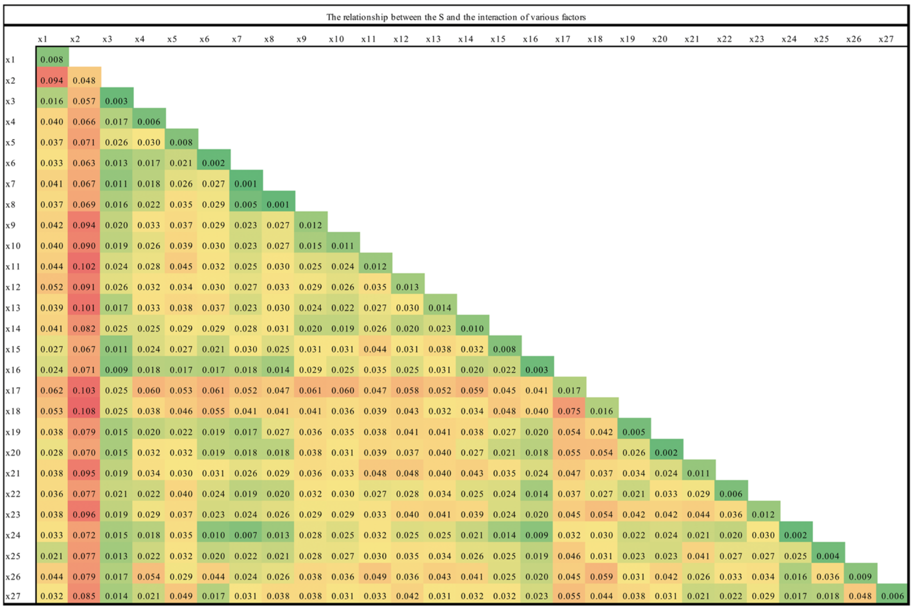

FIGURE 8 The relationship between the effect of land consolidation on production stability and the interaction of various factors. *S* stands for the net changes of production stability

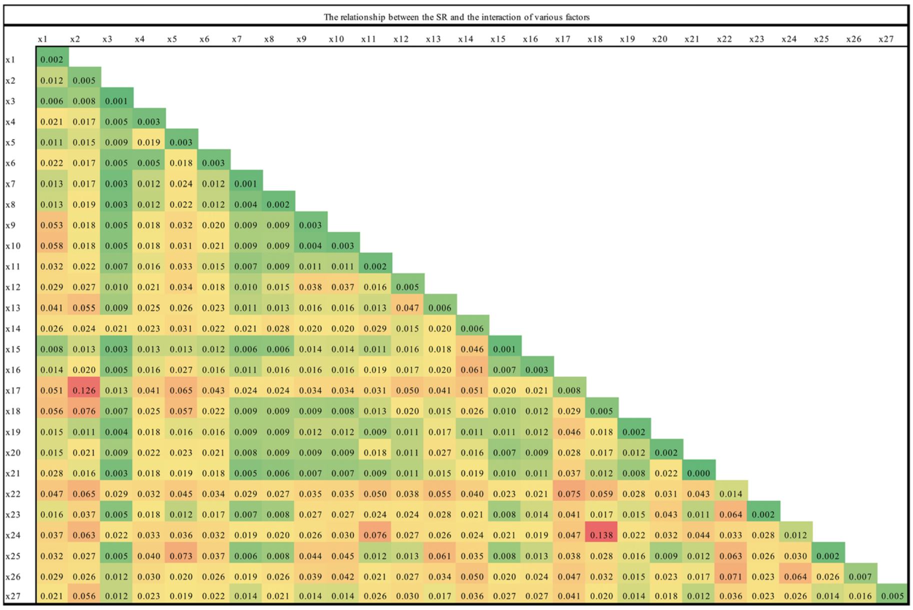

FIGURE 9 The relationship between the *SR* and the interaction of various factors. *SR* represents significance degrees of production stability change

in the areas where both agricultural productivity and production stability need to be improved. *X*1 has the most effect on *P*, and *X*2 has the most effect on *S*, which means that the ELC_{AP} has a close relationship with agricultural production before consolidation and is in agreement with the results in Table 3. This phenomenon may be related to the theory of diminishing marginal effect (Yang, Yang, Yao, & Yuan, 2012). Multiple cropping index in 27 factors has the most effect on the spatial difference of the *PR*. The reason is that the improvement of production condition caused by LC may result in increasing of multiple cropping index and then making a significant improvement of agricultural productivity (Thapa & Niroula, 2008). Road density and rural electricity consumption have significant effects on the spatial difference of the *SR*. The reasons are as follows. Road density and rural electricity consumption can reflect the rural economy indirectly. The difference of economic attraction between urban and rural area can result in the transfer of agricultural labors, which have significant effects on farmland management level and the capacity for resisting natural disasters and further result in the variation of production stability (Hou & Yao, 2018; Wu et al., 2017). And the improvement of production condition caused by LC may make a contribution to the advance of land management level and then promote the enhancement of production stability markedly.

The interactions between 27 factors have more contribution to ELC_{AP} than each of them (Figures 6–9), which indicates that spatial distribution of ELC_{AP} is not only affected by single factor but also affected by the common action of different factors. Especially, the interactions between the six factors (i.e., the multiyear average of NPP before consolidation, farmland quality, investment intensity, fertilization level, machinery level, and farmland per capital) and other factors have more significant contribution to *P* than that between other factors, and the interactions between the six factors show considerable effect on *P* (Figure 6), which explains that the farmland output and comprehensive quality before consolidation and social–economic situation are the main factors to affect spatial patterns of *P*. The contribution of the interactions between these six factors to agricultural productivity has attracted increasing attention, such as comprehensive consideration of investment intensity and farmland quality has been used for farmland consolidation planning with the subject of improving agricultural productivity (Tang et al., 2017). The interactions between multiple cropping index/distance RL and other factors (e.g., the content of total nitrogen, organic matter, sand, and clay in soil) may make a greater contribution to increase the improvement of *PR* than that among other factors (Figure 7), which explains that utilization level, facility of farming, soil fertility, and field water holding capacity are the main factors to affect spatial patterns of *PR* and imply that *PR* has close relationship with the interactions between the factors at the project area or micro level (Abubakari, van der Molen, Bennett, & Kuusaana, 2016; Jiang, Wang, Yun, & Zhang, 2015). The interactions between the factors (i.e., the multiyear average of *CV* before consolidation and farmland quality) and other factors have more considerable contribution to *S* than that between other factors, and the interaction between the multiyear average of *CV* before consolidation and meteorological condition (e.g., cumulative temperature and frost-free period) is particularly outstanding (the contribution to *S* may be the largest one; Figure 8). The reason may be that meteorological condition has significant effect on farmland production (Scudiero et al., 2014), especially at the farmland with low quality, and LC can improve production condition by taking engineering measures and further promote the stability of production (Hong et al., 2019). Besides, the interactions between the factors (i.e., the multiyear average of *CV* before consolidation, farmland quality, road density, and agricultural zone) show more significant effect on *SR* than that between other factors, and the contribution of the interaction between the multiyear average of *CV* and farmland quality to *SR* is more than that of main factor (e.g., road density; Figure 9), which indicates that the contribution of single main factor to spatial distribution of ELC_{AP} may be less than that of the interactions between other factors.

Comprehensively, these phenomena concerning the interaction between various factors indicate that (a) the synergetic action of multiple factors has a more significant effect on ELC_{AP} than each of themselves; (b) different factors of interactions should be concerned for various subjects of LC (increasement of *P*, *PR*, *S*, or *SR*); thus, we may concern more factors of interactions to achieve more subjects of LC; (c) when evaluating potential ELC_{AP}, we need to consider contribution degree from single factor and the interactions between various factors. Overall, it is worth considering sorting these interactions and planning the appropriate LC areas based on the intensity of these interactions. In addition, although some factors were not introduced due to the unavailable of data, the regularity phenomenon and the characteristics of ELC_{AP} have been uncovered and the analysis in this paper focused on the main factors can provide the necessary basis for further study.

5 | CONCLUSIONS

Several significant information can be indicated in this study: First, the change of agricultural production in the majority of the LC areas is consistent with that in their control areas where LC is not implemented. Second, LC has a limited effect on agricultural production and has more effect on boosting the agricultural productivity than improving production stability in the study area, and the spatial correlation of ELC_{AP} between various LC areas is not high due to the dispersed distribution of the LC areas. Third, agricultural productivity and production stability before consolidation have the most effects on the ELC_{AP}, and the effects of the interaction between various factors on ELC_{AP} are more significant than the effects of single factors, and the intensity among these effects exists difference that can be used to guide the planning of the LC activities.

The framework in this study for evaluating LC effectiveness on agricultural productivity and production stability can be taken as the supplement of traditional sample evaluation. The evaluation model combined this framework and the sample evaluation may be one of the most appreciative plans to provide services for the planning of the LC activities. When improving agricultural production is the main aim, the intensity of the relationship between ELC_{AP} and the interaction of various factors can be considered as the reference in the priority of site selection of the LC areas. To achieve multiobjectives of improving 'quantity–quality–ecology' in regional level in the future, it is suggested to take the improvement of agricultural production as the main objective in the area with increasement of both *P* and *S* and take the objectives of the increasement of farmland area and/or the protection of ecology into consideration in the area with reduction of both *P* and *S*.

ACKNOWLEDGMENTS

This work was supported by the National Natural Science Foundation of China (41971234) from National Natural Science Foundation of China (NSFC), the Program B for Outstanding PhD Candidate of Nanjing University (201802B073) from Nanjing University, China, and the National Science and Technology Support Program of China (2015BAD06B02) from Ministry of Science and Technology of China. The constructive and helpful comments of the anonymous reviewers and the editors are appreciated.

ORCID

Changqiao Hong https://orcid.org/0000-0002-8912-3255

REFERENCES

Abubakari, Z., van der Molen, P., Bennett, R. M., & Kuusaana, E. D. (2016). Land consolidation, customary lands, and Ghana's Northern Savannah Ecological Zone: An evaluation of the possibilities and pitfalls. *Land Use Policy*, *54*, 386–398. https://doi.org/10.1016/j.landusepol.2016.02.033

Anhui Provincial Bureau of Statistics (2017). *Jiangsu statistical yearbook*. Beijing: Chinese Statistical Press.

Bitencourt, D. G. B., Barros, W. S., Timm, L. C., She, D., Penning, L. H., Parfitt, J. M. B., & Reichardt, K. (2016). Multivariate and geostatistical analyses to evaluate lowland soil levelling effects on physico-chemical properties. *Soil and Tillage Research*, *156*, 63–73. https://doi.org/10.1016/j.still.2015.10.004

Chartin, C., Evrard, O., Salvador-Blanes, S., Hinschberger, F., Van Oost, K., Lefèvre, I., … Macaire, J. J. (2013). Quantifying and modelling the impact of land consolidation and field borders on soil redistribution in agricultural landscapes (1954–2009). *Catena*, *110*, 184–195. https://doi.org/10.1016/j.catena.2013.06.006

Chen, D., Zhou, S., & Wu, S. (2017). Impacts of urban sprawl on agricultural land quality grade structure and potential production based on remote sensing. *Transactions of the Chinese Society of Agricultural Engineering.*, *33*(13), 264–269. https://doi.org/10.11975/j.issn.1002-6819.2017.13.035

China's National Bureau of Statistics (2017). *China statistical yearbook*. Beijing: Chinese Statistical Press.

Demetriou, D. (2017). A spatially based artificial neural network mass valuation model for land consolidation. *Environment and Planning B: Urban Analytics and City Science.*, *44*(5), 864–883. https://doi.org/10.1177/0265813516652115

Ding, M. J., Chen, Q., Xin, L. J., Li, L. H., & Li, X. B. (2015). Spatial and temporal variations of multiple cropping index in China based on SPOT-NDVI during 1999–2013. *Acta Geographica Sinica*, *70*(7), 1080–1090. https://doi.org/10.3321/j.issn:0375-5444.2005.04.004

Eyles, A., Ives, S., Hardie, M., Corkrey, R., & Boersma, M. (2018). Impact of enhanced efficiency fertilizers on potato productivity in a temperate cropping system. *Soil Use and Management*, *34*(4), 439–448. https://doi.org/10.1111/sum.12459

Fan, Y., Jin, X., Gan, L., Jessup, L. H., Pijanowski, B. C., Yang, X., … Zhou, Y. (2018). Spatial identification and dynamic analysis of land use functions reveals distinct zones of multiple functions in eastern China. *Science of The Total Environment.*, *642*, 33–44. https://doi.org/10.1016/j.scitotenv.2018.05.383

Feng, X., Liu, G., Chen, J. M., Chen, M., Liu, J., Ju, W. M., … Zhou, W. (2007). Net primary productivity of China's terrestrial ecosystems from a process model driven by remote sensing. *Journal of Environmental Management*, *85*, 563–573. https://doi.org/10.1016/j.jenvman.2006.09.021

Foley, J. A., Ramankutty, N., Brauman, K. A., Cassidy, E. S., Gerber, J. S., Johnston, M., … Zaks, D. P. M. (2011). Solutions for a cultivated planet. *Nature*, *478*(7369), 337–342. https://doi.org/10.1038/nature10452

Gu, X., Dai, B., & Chen, B. (2008). Landscape effects of land consolidation projects in central China: A case study of Tianmen City, Hubei Province. *Chinese Geographical Science*, *18*(1), 41–46. https://doi.org/10.1007/s11769-008-0041-5

Guan, X., Jin, X. B., Wei, D. Y., Chen, Y., Yang, X. Y., & Zhou, Y. K. (2014). Discussion on the construction of comprehensive monitoring system for land consolidation project. *China Land Science*, *28*(4), 71–76. https://doi.org/10.13708/j.cnki.cn11-2640.2014.04.011

Harasimowicz, S., Janus, J., Bacior, S., & Gniadek, J. (2017). Shape and size of parcels and transport costs as a mixed integer programming problem in optimization of land consolidation. *Computers and Electronics in Agriculture*, *140*, 113–122. https://doi.org/10.1016/j.compag.2017.05.035

He, C., Liu, Z., Xu, M., Ma, Q., & Dou, Y. (2017). Urban expansion brought stress to food security in China: Evidence from decreased cropland net primary productivity. *Science of the Total Environment*, *576*, 660–670. https://doi.org/10.1016/j.scitotenv.2016.10.107

Henan Provincial Bureau of Statistics (2017). *Jiangsu statistical yearbook*. Beijing: Chinese Statistical Press.

Hong, C., Jin, X., Ren, J., Gu, Z., & Zhou, Y. (2019). Satellite data indicates multidimensional variation of agricultural production in land consolidation area. *Science of the Total Environment*, *653*, 735–747. https://doi.org/10.1016/j.scitotenv.2018.10.415

Hou, M. Y., & Yao, S. B. (2018). Spatial spillover effects and threshold characteristics of rural labor transfer on agricultural eco-efficiency in China. *Resources Science.*, *40*(12), 149–160. https://doi.org/10.18402/resci.2018.12.14

Huang, Y., Zhang, W., Sun, W., & Zheng, X. (2007). Net primary production of Chinese croplands from 1950 to 1999. *Ecological Applications*, *17*(3), 692–701. https://doi.org/10.1890/05-1792

Hubei Provincial Bureau of Statistics (2017). *Jiangsu statistical yearbook*. Beijing: Chinese Statistical Press.

Janus, J., & Markuszewska, I. (2017). Land consolidation—A great need to improve effectiveness: A case study from Poland. *Land Use Policy*, *65*, 143–153. https://doi.org/10.1016/j.landusepol.2017.03.028

Jiang, G. H., Wang, X., Yun, W., & Zhang, R. (2015). A new system will lead to an optimal path of land consolidation spatial management in China. *Land Use Policy*, *42*, 27–37. https://doi.org/10.1016/j.landusepol.2014.07.005

Jiangsu Provincial Bureau of Statistics (2017). *Jiangsu statistical yearbook*. Beijing: Chinese Statistical Press.

Kwinta, A., & Gniadek, J. (2017). The description of parcel geometry and its application in terms of land consolidation planning. *Computers and Electronics in Agriculture*, *136*, 117–124. https://doi.org/10.1016/j.compag.2017.03.006

Lerman, Z., & Cimpoies, D. (2006). Land consolidation as a factor for rural development in Moldova. *Europe-Asia Studies*, *58*(3), 439–455. https://doi.org/10.1080/09668130600601933

Li, Y., Liu, Y., Long, H., & Cui, W. (2014). Community-based rural residential land consolidation and allocation can help to revitalize hollowed villages in traditional agricultural areas of China: Evidence from Dancheng County, Henan Province. *Land Use Policy*, *39*, 188–198. https://doi.org/10.1016/j.landusepol.2014.02.016

Lieth, H., & Whittaker, R. H. (1975). *Primary productivity of the biosphere*. Berlin, Germany: Springer-Verlag.

Liu, J., Jin, X., Xu, W., Fan, Y., Ren, J., Zhang, X., & Zhou, Y. (2019). Spatial coupling differentiation and development zoning trade-off of land space utilization efficiency in eastern China. *Land Use Policy*, *85*, 310–327. https://doi.org/10.1016/j.landusepol.2019.03.034

Los, S. O. (1998). *Linkages between global vegetation and climate: An analysis based on NOAA Advanced Very High Resolution Radiometer Data*. National Aeronautics and Space Administration (NASA): PhD dissertation.

Luo, L., Yan, H. M., & Niu, Z. E. (2018). Comparative analysis on three multi-source remote sensing data fusion models in monitoring farmland productivity. *Journal of Geoinformation Science.*, *20*(2), 268–279. https://doi.org/10.12082/dqxxkx.2018.170068

Luo, W., Jasiewicz, J., Stepinski, T., Wang, J., Xu, C., & Cang, X. (2016). Spatial association between dissection density and environmental factors over the entire conterminous United States. *Geophysical Research Letters*, *43*, 692–700. https://doi.org/10.1002/2015GL066941

Miranda, D., Crecente, R., & Alvarez, M. F. (2006). Land consolidation in inland rural Galicia, N.W. Spain, since 1950: An example of the formulation and use of questions, criteria and indicators for evaluation of rural development policies. *Land Use Policy*, *23*, 511–520. https://doi.org/10.1016/j.landusepol.2005.05.003

Moran, P. A. P. (1950). Notes on continuous stochastic phenomena. *Biometrika*, *37*(1-2), 17–23. https://doi.org/10.1093/biomet/37.1-2.17

Nath, R., Luan, Y., Yang, W., Yang, C., Chen, W., Li, Q., & Cui, X. (2015). Changes in arable land demand for food in India and China: A potential threat to food security. *Sustainability.*, *7*, 5371–5397. https://doi.org/10.3390/su7055371

Potter, C. S., Randerson, J. T., Field, C. B., Matson, P. A., Vitousek, P. M., Mooney, H. A., & Klooster, S. A. (1993). Terrestrial ecosystem production: A process model based on global satellite and surface data. *Global*

Biogeochemical Cycles, *7*(4), 811–841. https://doi.org/10.1029/93GB02725
Qin, Y., Yan, H., Liu, J., Dong, J., Chen, J., & Xiao, X. (2013). Impacts of ecological restoration projects on agricultural productivity in China. *Journal of Geographical Sciences*, *23*(3), 404–416. https://doi.org/10.1007/s11442-013-1018-6
Scudiero, E., Teatini, P., Corwin, D. L., Dal Ferro, N., Simonetti, G., & Morari, F. (2014). Spatiotemporal response of maize yield to edaphic and meteorological conditions in a saline farmland. *Agronomy Journal*, *106*(6), 2163–2174. https://doi.org/10.2134/agronj14.0102
Shandong Provincial Bureau of Statistics (2017). *Jiangsu statistical yearbook*. Beijing: Chinese Statistical Press.
Sklenicka, P., Hladík, J., Střeleček, F., Kottová, B., Lososová, J., Číhal, L., & Šálek, M. (2009). Historical, environmental and socio-economic driving forces on land ownership fragmentation, the land consolidation effect and project costs. *Agricultural Economics*, *55*(12), 571–582. Prague, Czech Republic: Czech Academy of Agricultural Sciences.
Song, W., & Pijanowski, B. C. (2014). The effects of China's cultivated land balance program on potential land productivity at a national scale. *Applied Geography*, *46*, 158–170. https://doi.org/10.1016/j.apgeog.2013.11.009
Suweis, S., Carr, J. A., Maritan, A., Rinaldo, A., & D'Odorico, P. (2015). Resilience and reactivity of global food security. *Proceedings of the National Academy of Sciences*, *112*(22), 6902–6907. https://doi.org/10.1073/pnas.1507366112
Tang, X., Pan, Y., & Liu, Y. (2017). Analysis and demonstration of investment implementation model and paths for China's cultivated land consolidation. *Applied Geography*, *82*, 24–34. https://doi.org/10.1016/j.apgeog.2017.03.002
Thapa, G. B., & Niroula, G. S. (2008). Alternative options of land consolidation in the mountains of Nepal: An analysis based on stakeholders' opinions. *Land Use Policy*, *25*, 338–350. https://doi.org/10.1016/j.landusepol.2007.09.002
Tobler, W. R. (1970). A computer movie simulating urban growth in the Detroit region. *Economic Geography*, *46*(Supp 1), 234–240. https://doi.org/10.2307/143141
Wang, J. F., Li, X. H., Christakos, G., Liao, Y. L., Zhang, T., Gu, X., & Zheng, X. Y. (2010). Geographical detectors-based health risk assessment and its application in the neural tube defects study of the Heshun region, China. *International Journal of Geographical Information Science*, *24*(1), 107–127. https://doi.org/10.1080/13658810802443457
Wu, J. J., Geng, G. P., Zhou, H. K., Liu, J. H., Wang, Q. F., & Yang, J. H. (2017). Global vulnerability to agricultural drought and its spatial characteristics. *Science China Earth Sciences*, *60*, 910–920. https://doi.org/10.1007/s11430-016-9018-2
Xiao, G., Hu, Y., Li, N., & Yang, D. (2018). Spatial autocorrelation analysis of monitoring data of heavy metals in rice in China. *Food Control*, *89*, 32–37. https://doi.org/10.1016/j.foodcont.2018.01.032
Xu, G., Huang, X., Zhong, T., Chen, Y., Wu, C., & Jin, Y. (2015). Assessment on the effect of city arable land protection under the implementation of China's National General Land Use Plan (2006–2020). *Habitat International*, *49*, 466–473. https://doi.org/10.1016/j.habitatint.2015.06.017
Yan, H., Ji, Y., Liu, J., Liu, F., Hu, Y., & Kuang, W. (2016). Potential promoted productivity and spatial patterns of medium- and low-yield cropland land in China. *Journal of Geographical Sciences*, *26*(3), 259–271. https://doi.org/10.1007/s11442-016-1267-2
Yan, J., Xia, F., & Bao, H. X. H. (2015). Strategic planning framework for land consolidation in China: A top-level design based on SWOT analysis. *Habitat International*, *48*, 46–54. https://doi.org/10.1016/j.habitatint.2015.03.001
Yan, J. M. (2010). *China's land use and planning research strategy*. Beijing: China Land Press.
Yang, L. X., Yang, G. S., Yao, S. M., & Yuan, S. F. (2012). A study on the spatial heterogeneity of grain yield per hectare and driving factors based on ESDA-GWR. *Economic Geography*, *32*, 120–126. https://doi.org/10.15957/j.cnki.jjdl.2012.06.020
Yu, D., Shi, P., Shao, H., Zhu, W., & Pan, Y. (2009). Modelling net primary productivity of terrestrial ecosystems in East Asia based on an improved CASA ecosystem model. *International Journal of Remote Sensing*, *30*(18), 4851–4866. https://doi.org/10.1080/01431160802680552
Zhang, P. D., Yuan, S., & Xia, X. (2017). Influence factor analysis for collaborative development of "5-tasks" and agricultural modernization. *Economic Geography*, *27*(3), 152–157. https://doi.org/10.15957/j.cnki.jjdl.2017.03.020
Zhang, Y., Hu, Z., Qi, W., Wu, X., Bai, W., Li, L., … Zheng, D. (2016). Assessment of effectiveness of nature reserves on the Tibetan Plateau based on net primary production and the large sample comparison method. *Journal of Geographical Sciences*, *26*(1), 27–44. https://doi.org/10.1007/s11442-016-1252-9
Zhang, Z., Yan, J., Zhao, W., & Zhao, W. (2013). An evaluation system for arable land consolidation potential and its application in China. *Outlook on Agriculture.*, *42*(4), 265–272. https://doi.org/10.5367/oa.2013.0147
Zhang, Z., Zhao, W., & Gu, X. (2014). Changes resulting from a land consolidation project (LCP) and its resource–environment effects: A case study in Tianmen City of Hubei Province, China. *Land Use Policy*, *40*, 74–82. https://doi.org/10.1016/j.landusepol.2013.09.013
Zheng, H. G., Qiao, F. R., Li, Y. Q., Zhang, J. S., Liao, L. J., Wang, D. J., & Yu, J. X. (2017). The evaluation of the sustainability of land consolidation and remediation in Funing County. *Bulgarian Chemical Communications*, Special Edition H, *49*, 53–58.
Zhong, T., Mitchell, B., Scott, S., Huang, X., Li, Y., & Lu, X. (2017). Growing centralization in China's farmland protection policy in response to policy failure and related upward-extending unwillingness to protect farmland since 1978. *Environment and Planning C: Politics and Space.*, *35*(6), 1075–1097.

How to cite this article: Hong C, Jin X, Fan Y, et al. Determining the effect of land consolidation on agricultural production using a novel assessment framework. *Land Degrad Dev*. 2020;1–16. https://doi.org/10.1002/ldr.3454