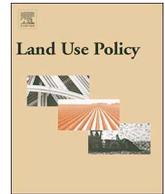




ELSEVIER

Contents lists available at ScienceDirect

## Land Use Policy

journal homepage: [www.elsevier.com/locate/landusepol](http://www.elsevier.com/locate/landusepol)

## Spatial pattern of arable land-use intensity in China

Ye Sijing<sup>a,b,1</sup>, Song Changqing<sup>a,b</sup>, Shen Shi<sup>a,b</sup>, Gao Peichao<sup>a,b</sup>, Cheng Changxiu<sup>a,b,\*</sup>, Cheng Feng<sup>c</sup>, Wan Changjun<sup>b</sup>, Zhu Dehai<sup>d</sup><sup>a</sup> State Key Laboratory of Earth Surface Processes and Resource Ecology, Beijing Normal University, Beijing, 100875, China<sup>b</sup> Center for Geodata and Analysis, Beijing Normal University, Beijing, 100875, China<sup>c</sup> Centre of Land Consolidation, Ministry of Natural Resources, Beijing, 100035, China<sup>d</sup> Key Laboratory of Agricultural Land Quality (Beijing) Ministry of Land and Resources, China Agricultural University, Beijing, 100083, China

## ARTICLE INFO

## Keywords:

Land-use intensity  
Land-use  
Arable land quality  
Arable land protection  
Agricultural productivity  
Land computing  
K-means

## ABSTRACT

In recent years, the sustainable utilization of China's arable land has been confronted with several challenges. The China government has been very strict in arable land protection, and a package of policies and measures have been promulgated. All these endeavors are of great significance for proposing an innovative policy system for sustainable land use in China. However, above stated policies are all designed from the perspective of space control with the purpose of reducing arable land loss or increasing arable land area, few policies have been designed from the perspective of utilization control, namely guide the actual arable land farming in sustainable ways and constraint unreasonable land use behavior such as overuse, rough use, land abandonment. In this paper, we analyze spatial distribution of average land-use intensity (ALUI) at the county-level in Mainland China, which can be used as a significant index for evaluating the rationality of arable land use and providing effective decision-making supporting information for design of regional arable land protection policy. Based on the experimental results, there is still considerable room for yield improvement as the ALUI of ~73.1 % counties are lower than 0.7 while the 53.60 % counties are lower than 0.6. Furthermore, the ALUI dataset shows significant global spatial autocorrelation characteristic. Boundaries of regions that aggregated by counties with high ALUI are more consistent with that of provincial administrative districts, comparing with that of sub-standard farming system regions. On the other hand, counties with low ALUI are mostly cluster in mountains, hills, or plateaus, where grain yield is mainly limited by regional hydrothermal conditions. In addition, counties with different ALUI status have been divided into six classes, using k-means clustering algorithm. This will facilitate the understanding of appropriate arable land protection and utilization paths for different regions and the rethinking of current support policies on farmland protection.

## 1. Introduction

Food security has been a concern worldwide since it is a fundamental requirement for human survival and development (Rosegrant and Cline, 2003). Despite this, nearly one billion people regularly fail to consume sufficient calories to lead active healthy lives (Food and Agriculture Organization (FAO), 2012). Due to rising population and income, the United Nations Food and Agriculture Organization (FAO) projects a growth in the global food demand by ~70 % from 2000 to 2050 (Alexandratos and Bruinsma, 2012), while Tilman et al. (2011) projects a growth of 100–110 %. In 2019, IPCC "Climate Change and Land Report" points out that the degradation of arable Land endangers food security and aggravates climate change. Sustainable use of arable

land plays an important role in reducing soil erosion, eliminating hunger and coping with climate change. This poses a daunting challenge for scientists and policymakers around the world, namely how to protect the stability of arable land ecosystems and meet sustainable agricultural and socio-economic development while increasing food production (Coyle et al., 2016; Valujeva et al., 2016). As a country of huge population and scarce per capita land resources, food security in China has been the focus of several researchers and scholars for a long time (Cheng et al., 2014). Despite rapid urbanization and the loss of high-quality farmlands, China has been making efforts to feed 21 % of the world's population with 7% of the world's arable land (Jin et al., 2018). Moreover, it has made outstanding contributions to the United Nations Millennium Development Goals in its efforts to reduce poverty

\* Corresponding author at: State Key Laboratory of Earth Surface Processes and Resource Ecology, Beijing Normal University, Beijing, 100875, China.  
E-mail addresses: [yesj@bnu.edu.cn](mailto:yesj@bnu.edu.cn) (S. Ye), [chengcx@bnu.edu.cn](mailto:chengcx@bnu.edu.cn) (C. Cheng).

<sup>1</sup> Ye Sijing (1988–), Assistant Professor, specialized in arable land evaluation and protection.

<https://doi.org/10.1016/j.landusepol.2020.104845>

Received 22 July 2019; Received in revised form 26 April 2020; Accepted 8 June 2020

Available online 18 June 2020

0264-8377/ © 2020 Elsevier Ltd. All rights reserved.

and increase food production (UNICEF, 2014; Deng et al., 2015). In this situation, exploration of arable land sustainable utilization path in China is significant for sustainable human development and national stability.

With rapid urbanization in recent decades, arable land gradually become focal points of contradictions among population, natural resources, environment and economic development of China (Bai et al., 2014). Chinese government attaches importance to protecting arable land, and regard “treasuring and employing every inch land, protecting arable land” as national basic policy. According to the strictest arable land protection system, a package of policies and measures including ‘requisition-compensation balance of arable land’, ‘rural land consolidation’, ‘economical and intensive land use’, ‘National land consolidation planning (2011–2015)’ have been promulgated. In spite of some disadvantages (e.g., occupied arable land is always more productive and larger than supplementary arable land (Gao et al., 2018); regardless of peasants’ real need and concern (Liu and Li, 2017); lacks overall planning, theoretical guidance and systematical technical support (Li et al., 2018); lagging rural institutional innovation and rural land protection mechanism (Cheng et al., 2019), all these endeavors are of great significance for proposing an innovative policy system for sustainable land use and economic development in China in the future (Liu, 2018a). However, above stated policies are all designed from the perspective of space control with the purpose of reducing arable land loss or increase arable land area, another serious problem that threatening the sustainable use of arable land has been long-term lack of attention and policy control, namely arable land degradation.

Arable land degradation is the result of comprehensive effect of natural system and utilization system, which contains not only natural factors and socio-economic factors that affect arable land productivity, but also the unstable factors caused by human activities. The unreasonable use of arable land and the overemphasis on grain yield are important reasons for arable land degradation. In last four decades, overuse of fertilizer, herbicides and pesticides, promotion of heavy agricultural machinery equipment and high multi-cropping degree have induced continuous increase of arable land-use intensity and grain output at the expense of serious arable land degradation including decrease in soil organic matter content (Zhao et al., 2013), serious soil erosion and nutrient loss (Fan et al., 2005), increased soil acidification and pollution (Liu, 2016a,b), decay of soil bio-characteristics and expansive soil salinization area. While conservation tillage strategies such as crop rotation, deep plowing do not receive enough attention. In consequence, innovative arable land protection policies and implementing schemes should be promulgated with considering many factors including regional climatic conditions, soil properties, cultivation and site management technologies, farming willingness, economic benefits, ecological capacity, environmental status, etc. as well as the interactions among them (Ye et al., 2019), for guiding and restraining peasants to adopt sustainable farmland management strategies and farming intensity.

Land-use intensity can be a significant index for evaluating the rationality of arable land use and providing effective decision-making supporting information for design of regional arable land protection policy from the perspective of utilization control. Research on land-use intensity reaches back to the mid-19th century when Malthus (1798) explicitly addressed agricultural intensification in the context of population growth. Brookfield (1993) defined agricultural intensification as the substitution of inputs of capital, labour and skills for land, so as to gain more production from a given area, use it more frequently, and hence make possible a greater concentration of production. In early studies of agricultural intensification, land-use intensity is rooted in the land rent theory (von Thunen, 1826) and the law of diminishing (Ricardo, 1815), and measured in terms of production inputs (pesticides, fertilisers, seed, fuel or labour) or outputs per unit of land. Subsequently, land-use intensity researches gradually focus on different topics including drivers of agricultural change, potentially detrimental

ecological consequences of land-use intensification and systemic interrelation between intensification and land expansion (Erb et al., 2013). This situation renders an explicit valuation of the benefits and trade-offs of land-use intensification important and calls for innovative ways of measuring and assessing intensification (Tilman et al., 2011; Foley et al., 2011). Nevertheless, how to calculate arable land-use intensity with distinguishing influence of human activities from climate conditions and apply it to develop detailed arable land management strategies?

Given the complexity of land-use intensity, methods are proposed from multidimensional perspective to measure it for different purposes, which can be summarized into four aspects (Erb et al., 2013; Kuemmerle et al., 2013): input intensity (Shao et al., 2006; Zhang et al., 2008b; Chen et al., 2011; Yin et al., 2019; Liu et al., 2014a, b; Wang et al., 2014; Yao et al., 2014; Xie et al., 2014), output intensity (Turner and Doolittle, 1978; Hunt, 2000; Shriar, 2000), combined of inputs and outputs (Feon et al., 2010; Smith, 2013; Liu, 2016a,b) and altered ecosystem services (Reidsma et al., 2006; Niedertscheider et al., 2016; Stjernman et al., 2019). There into, output intensity is more applicable to express the exploitation degree of arable land potential as it represents the purpose of cultivation (Turner and Doolittle, 1978; Hunt, 2000;) and no presumptions about the efficiency of inputs on productivity are made (Shriar, 2000). However, comparability is limited if output intensity is directly defined as annual crop yield per land unit due to the huge yield variation of different crops, climate conditions, soil conditions, crop management history. Results of output intensity also strongly depend on the unit of measurement (e.g. in mass, energy, calorific value, monetary value per area) and the methodology used to measure output consistently (Hunt, 2000). To manage this comparability better, methods have been developed that assess the ‘yield gap’ as the ratio between actual yield (observed yields) and a reference yield that is attained under similar conditions of production and standardized management (Neumann et al., 2010; Dietrich et al., 2012). Reference yields can either be derived by statistical analysis or crop models (Dietrich et al., 2012), whereas such data are usually not readily available or are often connected to considerable uncertainty. (Erb, 2012; Siebert et al., 2010). Statistical data are frequently only available at the national scale, systematic ground-based data collection covers only a few regions since manual investigation is costly and inefficient, and remote sensing struggles to capture the often subtle spectral effects of land use intensity changes (Kuemmerle et al., 2013). Dietrich et al. (2012) calculates reference yields in a global context by using the “Lund-Potsdam-Jena dynamic global vegetation model with managed Land” (Bondeau et al., 2007), while especially crop models typically suffer from systematic errors and biases caused by the high complexity of the modeled system. Hence, relevant researches rarely work out uniformly county level comparable output intensity in nationwide studies.

In this paper, we calculate land-use intensity (LUI) as the ratio of actual investigated yield (per unit) of specific arable land plot to the maximum yield (per unit) of the standard farming system sub-region it belongs to. And then we analyze the spatial distributions of the average land-use intensity (ALUI) and relative standard deviation of land-use intensity (VLUI) of China’s arable land at the county level and their correlations with arable land area (ALA) in Mainland China. The external farming conditions (including soil properties, cultivation, and site management technologies) and internal farming willingness are then comprehensively expressed. Counties with different ALUI-VLUI-ALA status have been divided into six classes using k-means clustering algorithm, to facilitate the understanding of relatively appropriate arable land protection and utilization paths and strategies for different regions, as well as developing utilization control policies on farmland protection. Furthermore, this research can provide effective decision-making supporting information for implementation of “store grain in the ground, store grain in technology” strategy.

## 2. Material and methods

### 2.1. Data source

In recent decades, the Ministry of Natural Resources of China has launched national field-scale evaluation of arable land productivity project (Cheng et al., 2014; GB/T, 28407-, 2012; Wang and Yun, 2011; Gao and Ma, 2002) based on “the second national land survey” as well as a cumulative investment of ~0.43 billion RMB and 1.3 million investigators. Thus, a uniformly comparable multi-factor spatial pattern of arable land in Mainland China (Zhang et al., 2008a; Kong et al., 2013; Feng et al., 2014; Wu et al., 2008c) has been achieved for the first time. Considering that China has a vast territory with diversified factors that impact arable land productivity, the whole territory is divided into 12 standard farming system regions (SFSR) and 51 sub-regions (sub-SFSR) in the first step of this research according to spatial heterogeneity of regional hydrothermal conditions (An et al., 2002). Suitable cropping systems are then developed for different counties based on regional socio-economic conditions and crop type as well as structure characteristics (An et al., 2002). In the design process, this research complies with the standard which stipulates that “the designed cropping system can take full advantage of regional arable land production potential on the premise of not damaging the sustainability of arable land use” (An et al., 2002). For instance, Changsha city of Hunan Pro is located in Jiangnan district (SFSR) – a western hilly region (Sub-SFSR). The suitable cropping system of its irrigable land is designed as oilseed rape –early rice –late rice (three crops per year), while the cropping system of its dry land is corn–potato (two crops per year). Thus, four modules (i.e. climate conditions module, nature quality mark module, utilization coefficient module and economic coefficient module) have been adopted in the evaluation of the arable land productivity (see SI Appendix A.1 for details). The evaluation unit is arable land plots.

Thereinto, utilization coefficient module is designed to calculate arable land-use intensity  $K$  as the ratio of actual investigated yield (per unit) of specific arable land plot to the maximum yield (per unit) of the sub-SFSR (extracted from 2005 to 2010 county-level statistical yearbook) it belongs to (Zhang et al., 2002; Kong et al., 2008a). This ratio can objectively and comprehensively express the external farming conditions (including soil properties, cultivation, and site management technologies) and internal farming willingness of different arable land plots. Computational formula of  $K$  is listed in Eq. (1).  $\beta_i$  is coefficient for converting yield per unit of specific species of crop  $i$  to a uniform crop (Kong et al., 2008b, 2009; Wang et al., 2006);  $Y_i$  and  $Y_{i-max}$  respectively are actual investigated yield (per unit) and maximum yield (per unit) of crop  $i$ ; and  $n$  is crop count.

$$K = \frac{\sum_{i=1}^n Y_i * \beta_i}{\sum_{i=1}^n Y_{i-max} * \beta_i} \tag{1}$$

In this paper, arable land plots-based LUI dataset generated by the above-mentioned utilization coefficient module has been used as the experimental data. The quantity of plots is ~67 million, and the relevant actual yield (per unit) data is investigated during 2011–2012. Detailed dataset information has been listed in Table 1.

### 2.2. Spatial autocorrelation analysis model

Spatial autocorrelation is commonly used to measure the correlation of the same spatial variable in different spatial positions. It describes the spatial aggregation of its attribute values, including global spatial autocorrelation and local spatial autocorrelation (Legendre, 1993; Ord and Getis, 2001). Both Moran’s I and LISA (local indicators of spatial association) are conventional spatial autocorrelation indexes that use the same principles. However, their scope of application and focus are different. The global spatial autocorrelation (Moran’s I) evolved from Pearson correlation coefficient. The relationship between the two

**Table 1**  
Detailed dataset information related to arable land plots-based LUI calculation.

No.	data set name	definition	data source	applications
1	arable land plots	arable land plots of each county generated by remote sensing and field investigation	“the second national land survey” of China during 2007 – 2009; (Cheng et al., 2014) (An et al., 2002)	(Zhang et al., 2008a; Kong et al., 2013; Wu et al., 2008c; Ma et al., 2018; Wang et al., 2006,2007;Xue et al., 2014; Ye et al., 2019) (Wang, 2013a,b;Zhang et al., 2014; Li et al., 2017; Cui et al., 2010)
2	SFSR and sub-SFSR	standard farming system regions divided according to spatial heterogeneity of regional hydrothermal conditions	(Wang, 2006; Kong, 2008b, 2009)	(Kong et al., 2009; Zhang et al., 2009; Li et al., 2018)
3	$\beta$	yield ratio coefficient which is used to convert yield per unit of different crops to a uniform crop		
4	$Y_i$	actual yield (per unit) of specific arable land plot for crop $i$	field investigation	(Zhang et al., 2002; Wu et al., 2008a, 2008b;Feng et al., 2014)
5	$Y_{i-max}$	maximum yield (per unit) in specific sub-SFSR for crop $i$	county-level statistical yearbook from agricultural administrations	(Feng et al., 2014; Ye et al., 2014; Yao et al., 2016; Wang et al., 2008)

variables  $x$  and  $y$  in Eq. (2) is expressed by  $x$ , while the corresponding  $y$  value is replaced by the adjacent  $x$  value. Moran's  $I$  can then be obtained with a slight modification (Eq. (3)), where  $w_{ij}$  is a spatial weight matrix. If the regional units  $i$  and  $j$  are adjacent, the value of  $w_{ij}$  is 1; otherwise, its value is 0;  $x_i$  and  $\bar{x}$  represent the value of the variable  $x$  in the unit  $i$  and the mean value in the entire study area, respectively;  $N$  represents the total number of regional units. The calculated Moran's  $I$  value ranges from  $[-1:1]$ . Meanwhile, the positive value of  $I$  indicates positive correlation; the negative value of  $I$  indicates negative correlation; while the zero value of  $I$  indicates uncorrelation. Moreover, the greater the absolute value, the higher the significance.

$$\text{Pearson} = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_i (x_i - \bar{x})^2 \sum_i (y_i - \bar{y})^2}} \quad (2)$$

$$\text{Moran's } I = \frac{N \sum_i \sum_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{ij} w_{ij} \sum_i (x_i - \bar{x})^2} \quad (3)$$

Under the normal distribution hypothesis, Moran's  $I$  is normalized for significance test.  $Z(I)$  is a normalized statistic (Eq. (4)), where  $E(I)$  is the expected value of Moran's  $I$ ;  $\sigma(I)$  is the standard deviation of Moran's  $I$  for all variable values. At 5% significance level, if  $Z(I) > 1.96$ , there is a positive correlation in the study subjects; if  $-1.96 < Z(I) < 1.96$ , there is no spatial correlation in the study subjects such that they exhibit a random distribution state; if  $Z(I) < -1.96$ , there is a negative correlation.

$$Z(I) = \frac{[I - E(I)]}{\sigma(I)} \quad (4)$$

The global spatial autocorrelation hypothesis space is stationary, i.e., only a state fills the entire region, and it can only detect whether there is spatial correlation in the whole study area. Thus, it is impossible to accurately locate the aggregation area (Getis and Ord, 2010). It is therefore necessary to detect the aggregation area using a local spatial autocorrelation index (such as LISA) to reflect the degree of association between the same attribute value of one regional unit and the adjacent unit (Anselin, 1995; Anselin et al., 2006). The local spatial autocorrelation index is defined as  $LISA_i$  (Eq. (5)), where  $Z_i$  indicates the degree of deviation between the observed value and the mean value (Eq. (6)), and  $I_i$  is the weighted average product of  $Z_i$  and the unit observations around the unit  $i$ .

$$LISA_i = Z_i \sum_{j=1}^n W_{ij} Z_j \quad (5)$$

$$Z_i = \frac{x_i - \bar{x}}{\sqrt{\frac{1}{n} \sum_i (x_i - \bar{x})^2}} \quad (6)$$

### 2.3. k-means clustering algorithm

The k-means clustering algorithm was originally derived from a vector quantization method in signal processing and is one of the most widely used algorithms in cluster analysis (MacQueen, 1967). The algorithm is easy to describe, and its processing efficiency is high in large datasets. Moreover, it can produce a good clustering result when the sample distribution is close within the classes and far away between the classes. It has been widely used in soil analysis and natural language processing at home and abroad (Wilpon and Rabiner, 1985; Kanungo et al., 2002; Brus et al., 2006). The core idea is to divide  $n$  samples into  $k$  cluster categories, minimizing the sum of the square distance of each sample with its cluster center, i.e., within-cluster sum of squares is the smallest sum that satisfies the clustering result (Eq. (7)), where  $x$  is the sample value;  $Y$  is the category set;  $y_j$  is a category in the category set, and  $z_j$  is the cluster center in the category  $y_j$ .

$$\text{arg}_Y \min \sum_{j=1}^k \sum_{x \in y_j} \|x - z_j\|^2 \quad (7)$$

The algorithm steps are as follows:

- i Determine the appropriate number of categories  $k$  based on prior knowledge. The category set  $Y$  is  $\{y_1, y_2, \dots, y_k\}$ ;
- ii The observation sets  $\{x_1, x_2, x_3, \dots, x_n\}$  are the known samples while the optional  $k$  samples are given as the initial cluster center  $\{z_1, z_2, \dots, z_k\}$ , corresponding to  $k$  number of categories;
- iii Calculate the distance between the sample  $x_i$  and each cluster center  $z_j$ . Determine the closest cluster center  $z_j$ , and assign  $x_i$  to the category  $y_j$  to which  $z_j$  belongs;
- iv After all samples are allocated, the samples in each category  $y_j$  ( $j = 1, 2, \dots, k$ ) are recalculated to obtain a new cluster center  $z_j$ ;
- v Finally, if all the category center positions  $\{z_1, z_2, \dots, z_k\}$  remain unchanged and the results tend to converge, then the output category set is  $\{y_1, y_2, \dots, y_k\}$ . Otherwise, go to step (iii) for further iterative calculations until the classification result converges.

### 2.4. Calculation of arable land-use intensity

In this study, we use outputs-oriented method to evaluate arable intensity of arable land plots in Mainland China. Fig. 1 expresses connotation and calculation thought of arable land-use intensity (LUI). Theoretically, LUI should be considered as the ratio of actual investigated crop yield (per unit) to theoretical capacity (per unit) (Zhang et al., 2002). It indicates that arable land plot is completely utilized if LUI is approximately equal to 1. While in practice, we replace theoretical capacity with maximum yield of the sub-SFSR it belongs to because the former is difficult to be estimated accurately (Kong et al., 2008a).

### 2.5. Statistics of ALUI-VLUI-ALA

The ALUI, VLUI and ALA of ~67 million arable land plots are calculated using county as a statistical unit, to analyze the histogram distribution features and spatial patterns of them as well as the pairwise correlations among them. Eq. (8) expresses the calculation process of ALUI, VLUI, and ALA for a specific county  $j$ , where  $L_i$  represents the area of each arable land plot  $i$  in county  $j$  (unit: ha.),  $n$  represents plot quantity of county  $j$ ,  $K_i$  represents LUI of each arable land plot,  $VLUI_j$  represents the dispersion degree of  $K_i$  in county  $j$  (for each county, the lower the  $VLUI_j$ , the more similar  $K_i$  is).

$$\begin{aligned} ALA_j &= \sum_{i=1}^n L_i, \quad ALUI_j = \frac{\sum_{i=1}^n K_i * L_i}{ALA_j}, \quad VLUI_j \\ &= \frac{\sqrt{\sum_{i=1}^n [L_i * (K_i - ALUI_j)^2]}}{\sqrt{(1 + \sum_{i=1}^n L_i)}} \\ &= \frac{\sqrt{\sum_{i=1}^n [L_i * (K_i - ALUI_j)^2]}}{ALUI_j} \end{aligned} \quad (8)$$

### 2.6. Experimental environment

An Arable Land Productivity Data Applied Analysis Platform (ALPDAAP) has been constructed to support the massive data processing and analysis of the polygon-based unstructured arable land productivity data. Fig. 2 shows the logical architecture of the ALPDAAP infrastructure, including the data storage layer, network transportation layer, computing service layer, and application layer. In the data storage layer, the distributed metadata model-based file system was deployed on two name nodes and six data nodes. The arable land productivity data processing (e.g., coordinate transformation (Ye and Yan, 2016a), re-organization (Ye, 2016b; Ye et al., 2018), and visualization (Yao and Ye, 2017b)) are directly executed between computing service machines and data nodes, while name nodes are only used for metadata

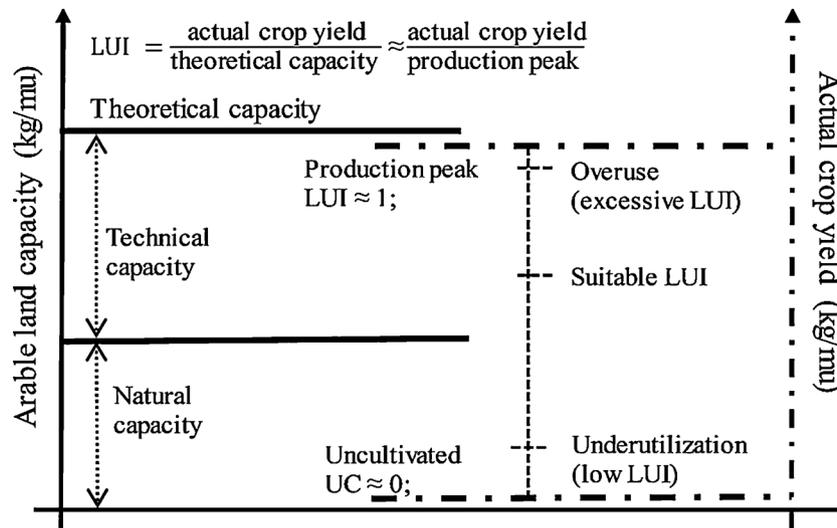


Fig. 1. Connotation and calculation thought of LUI.

Note: for a region over a period of time, its theoretical capacity is theoretical grain output capacity under the comprehensive input of natural capacity and technical capacity.

management and data addressing. The storage capacity is 200 TB, and both name nodes and data nodes can be horizontally extended. In the network transportation layer, gigabit switches and CAT6 cables were used for data reading, analysis, and outputting, while optical fibers were deployed for the arable land productivity data download. In the computing service layer, a MapReduce-based computing cluster involving five computers was established for parallel data extraction and statistics (Yao et al., 2017a, 2018). Meanwhile, the application layer integrates the task request interface and result output interface.

### 3. Results

#### 3.1. Spatial pattern and correlation of ALUI-VLUI-ALA

Since the same sub-SFSRs share similar topographic features and hydrothermal conditions, the ALUI can eliminate the impact of climatic conditions on arable land productivity, objectively and comprehensively express external farming conditions (including soil properties,

cultivation, and site management technologies) and internal farming willingness of different arable land plots, which is uniformly comparable in the national scale. Fig. 3 shows the normal distribution characteristics of ALUI in Mainland China, where the mean value  $\mu = 0.58946$  and standard deviation  $\delta = 0.18105$ . Despite the fact that China's food self-sufficiency ratio reached more than 95%, there is still a significant room for yield improvement. The ALUI of ~68.2% counties belong to  $[\mu - \delta, \mu + \delta]$  and is lower than 0.6 for 53.60% counties. Moreover, it is lower than 0.7 for ~73.1% counties. By setting  $[\mu - 1.96\delta, \mu - \delta, \mu, \mu + \delta, \mu + 1.96\delta]$  as interval, we divide the ALUI of all counties into six levels to obtain the spatial pattern of ALUI. From an overall perspective, the spatial pattern of ALUI shows significant differences between China's eastern and western regions. Counties with ALUI higher than 0.5895 are mainly distributed in east of Hu's line (Hu, 1935) (e.g., Heilongjiang, Zhejiang, Jiangxi, Guangxi, Guizhou, Shaanxi, Henan, Hubei, Chongqing), and form accumulation regions of highly utilized arable land in Heilongjiang Pro, Jiangsu Pro, Hubei Pro etc. However, there is distinct "depressions" feature in

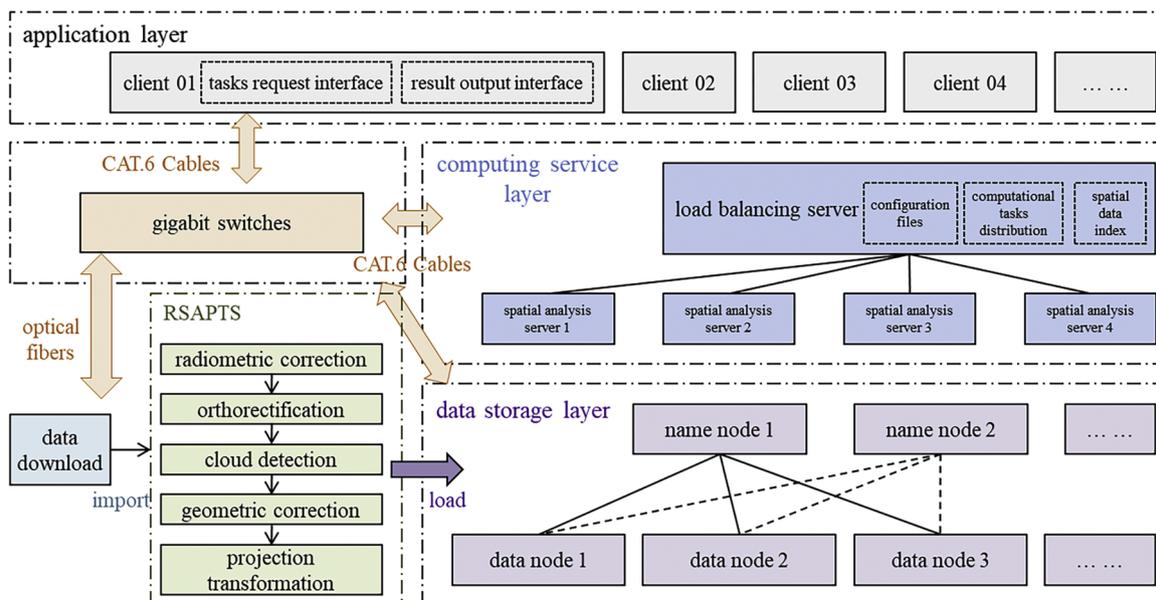


Fig. 2. Logical architecture of ALPDAAP infrastructure.

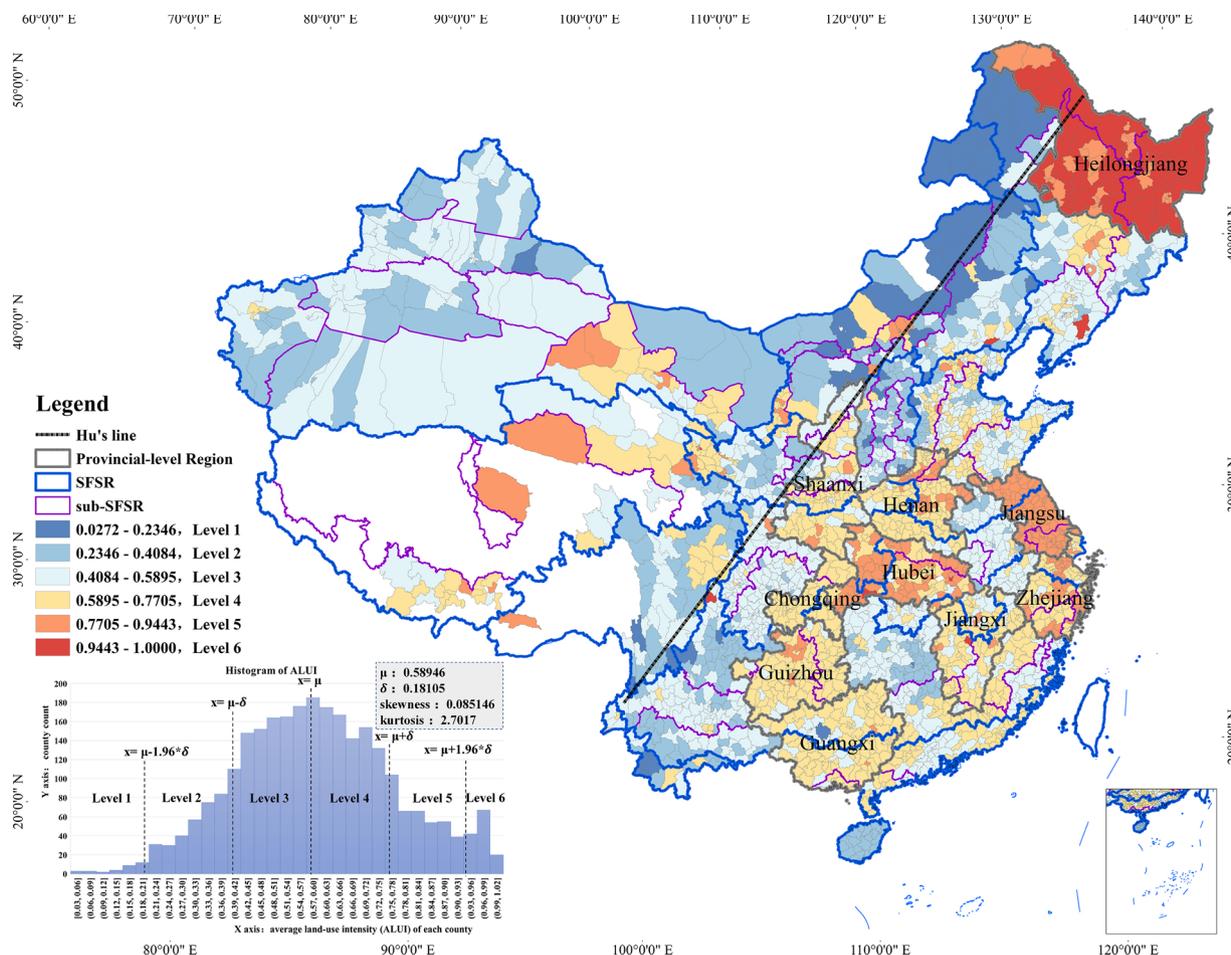


Fig. 3. Normal distribution characteristic and spatial pattern of ALUI. Blank area expresses few arable land (e.g. Qinghai-Tibet Plateau, urban region) or no data (e.g. Taiwan).

Hunan Pro, Anhui Pro, Hainan Pro, and Shanxi Pro, as the ALUI of the counties is significantly lower than the surrounding provinces. Hence, is there some correlation between ALUI dataset and its corresponding ALA dataset and VLUI dataset?

Based on the statistical histogram features of ALA (Fig. 4a), the ALA dataset conforms to the law of heavy-tailed distribution (Jiang and Liu, 2012a). Few counties (low frequency) have extremely large ALA (and therefore form the head counties), while the ALA of abundant counties (high frequency) are less than that of the head counties and therefore constitute the tail. Influenced by Gaussian mode of thinking, traditional classification methods focus on high frequency events (HF-Es) and separate low frequency events (LF-Es) from these HF-Es. However, there are significant faults between HF-Es (with different levels) and LF-Es, which form the basis of natural classification (Fisher, 1958). Meanwhile, for heavy-tailed distributions, LF-Es tend to be more important and more noteworthy than HF-Es (e.g., there are rare extreme events in natural and social systems which are commonly known as “black swan events” (Taleb, 2007)). Furthermore, for heavy-tailed distributions, first-order mathematical expectation and second-order variance have no mathematical significance, which render the classification methods (Fisher, 1958; Jenks, 1963) based on these indicators inapplicable. Hence, we divide the ALA of all counties into six levels using head/tail breaks model (Jiang, 2012b), as shown in Fig. 4b (see SI Appendix A.2 for detailed classification process). Moreover, we also analyze the spatial pattern of ALA in SI Appendix A.3. The correlations between normalized ALUI/VLUI and normalized ALA are analyzed, as shown in Fig. 5c and d, respectively. Based on the experiment result, there is no significant correlation between ALUI/VLUI and ALA, especially for

levels 1–5. Hence, ALA is not a critical factor that affects ALUI and VLUI. Moreover, counties with extremely large ALA (level 6) are more likely to have high ALUI and low VLUI, which constitute core regions of arable land use.

The histogram distribution of VLUI is roughly normal with high skewness and kurtosis. Using Geodetector model (Wang et al., 2010, 2016), we progressively divide the VLUI of all counties into four levels, as shown in Fig. 5a (see SI Appendix A.4 for detailed classification process). Fig. 5b shows the correlation between VLUI and ALUI. Most counties have low VLUI (namely ALUI of arable land plots in these counties have small differences). Only a few counties express relatively high VLUI (levels 3–4), whose corresponding ALUI are generally low. Furthermore, for counties with high ALUI, the farming conditions and willingness of their internal arable land plots are more likely to be consistent. While for counties with low ALUI, things get more complicated. Hence, VLUI can be used as an important indicator for developing regional appropriate arable land protection and utilization paths, especially for counties with low ALUI.

### 3.2. Spatial autocorrelation analysis of ALUI-VLUI

In this paper, we used Moran’s I model and LISA model to analyze global and local spatial autocorrelation of ALUI, respectively. In Mainland China, the county-based ALUI dataset shows significant global spatial autocorrelation characteristic (Moran’s I is 0.700825,  $Z = 76.0677$ ,  $P = 0.001$ ), as shown in Fig. 6. It indicates that for counties with high ALUI, their contiguous counties also tend to have high ALUI and form high-high concentration (HHC), and vice

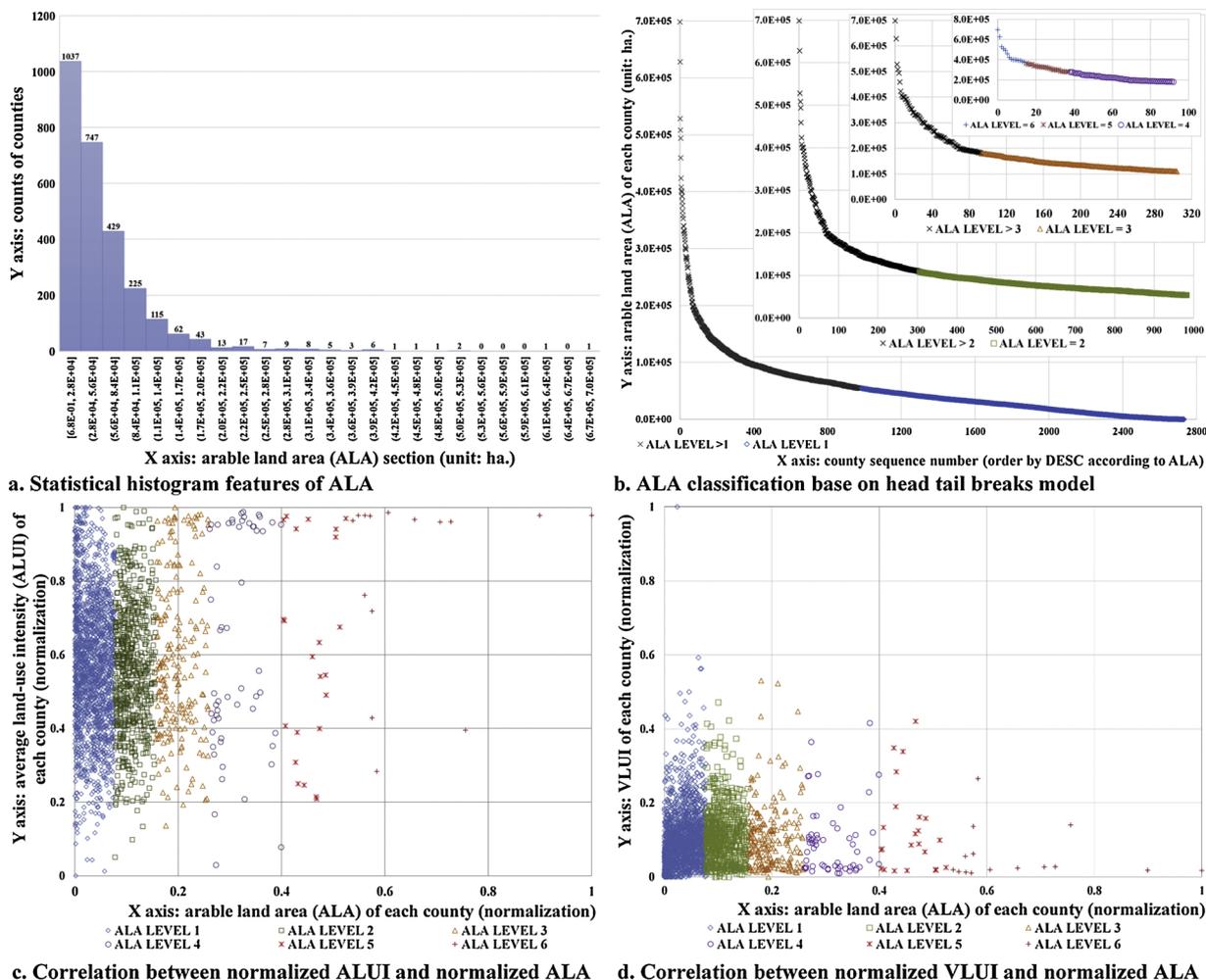


Fig. 4. Statistical histogram features of ALA and its correlations with ALUI and VLUI.

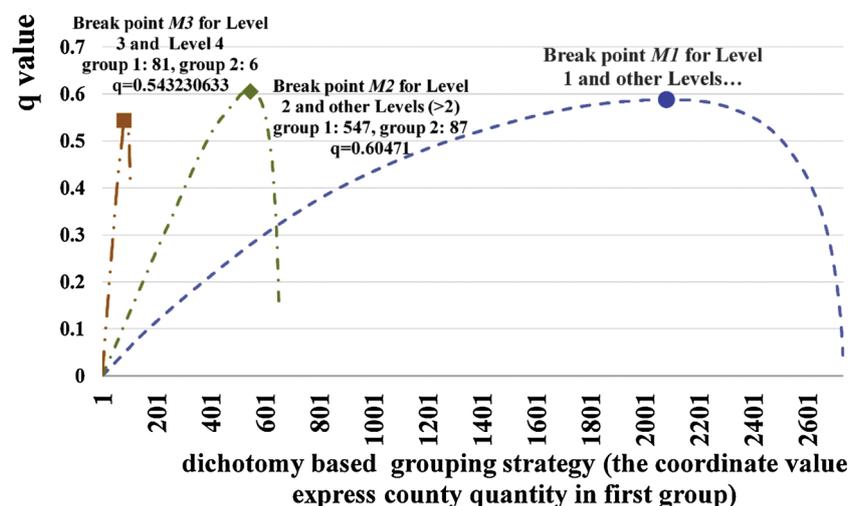
versa-form low-low concentration (LLC). The HHC region mainly covers nearly all the regions of Heilongjiang Pro, Jiangsu Pro, Hubei Pro, Zhejiang Pro, and central-north area of Henan Pro, Guizhou Pro, etc. In addition, boundaries of HHC regions are more consistent with that of provincial administrative districts, comparing with that of sub-SFSR. The reason is that local government is playing an important role in improving land-use intensity. For instance, the Huanghuai Plain sub-SFSR covers part counties of Jiangsu Pro, Anhui Pro, and Henan Pro. Although these counties share similar hydrothermal conditions, their ALUI accumulation characteristics in different provinces may be opposite: form HHC northern Jiangsu Pro and eastern Henan Pro, and form LLC in northern Anhui Pro (see SI Appendix A.5 for details). In addition, the terrain of Zhejiang Pro is complicated as it consists of northern Yangtze plain sub-SFSR, western low mountainous sub-SFSR, southern mountainous sub-SFSR, and eastern low hilly sub-SFSR. There are relatively large differences in hydrothermal conditions and external farming conditions among these sub-SFSRs. However, the HHC pattern is not affected by these differences and covers nearly the whole province. (see SI Appendix A.6 for details). Therefore, the formation of HHC characteristic is more likely to be influenced by the composite effect of provincial policy, administration management methods as well as social and economic conditions. In some cases, this effect may cover up the climate effect. On the other hand, LLC regions of ALUI are mainly distributed in Yunnan Pro, Hainan Pro, Shanxi Pro, Xinjiang Pro, southern Sichuan Pro, southern Hunan Pro, northern Anhui Pro, eastern Inner Mongolia. The relevant landscape types of these regions are mostly mountains, hills, or plateaus, where grain yield is mainly

limited by regional hydrothermal conditions. Thereinto, Anhui, Sichuan, Hunan, and Inner Mongolia belong to major grain producing provinces of China.

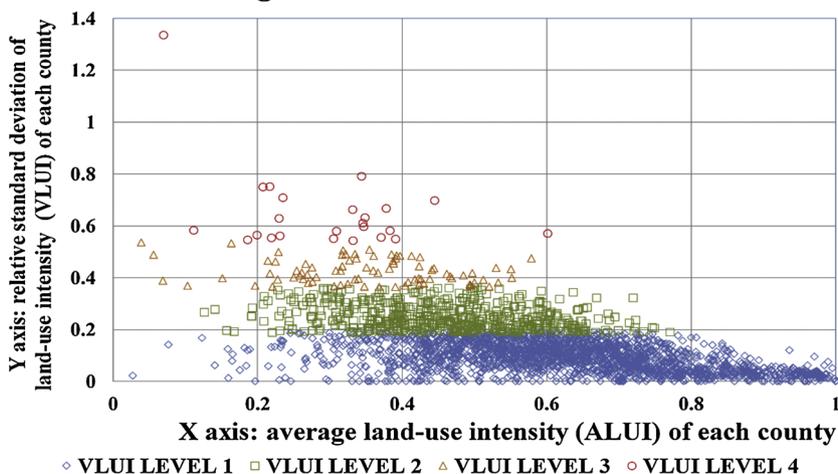
Furthermore, the global spatial autocorrelation characteristic (Moran's I) of county-based VLUI dataset is 0.467822 ( $Z = 54.488$ ,  $P = 0.001$ ) (Fig. 7). HHC regions of VLUI are mainly distributed in Yunnan Pro, Hainan Pro, Hebei Pro, southern Sichuan Pro, eastern Inner Mongolia, eastern Gansu Pro, and southern Ningxia Pro. For counties in these regions, the spatial pattern of the ALUI of the arable land spots is more uneven than elsewhere because of differences in farming conditions and farming willingness among famers. Some farmers may achieve better grain production in better farming conditions or by being more industrious. Hence, local governments should investigate these differences and relevant specific driving factors when policies are being designed to promote local agriculture development or arable land protection. For instance, if the difference is caused by cultivation and site management technologies, local governments should help farmers promote technological capacity or guide farmers to implement other suitable agricultural practices to ensure that farmers do not lose confidence or aggravate contradiction in unbalanced comparisons.

### 3.3. Spatial heterogeneity of ALUI-VLUI-ALA and corresponding arable land utilization path

Using k-means clustering algorithm to perform classification, we propose that Mainland China should be divided into six classes with



**a. Statistical histogram features of VLUI**



**b. Correlation between VLUI and ALUI**

Fig. 5. Statistical histogram features of VLUI and its correlations with ALUI.

comprehensively considering county-based normalized ALUI-VLUI-ALA, as shown in Fig. 8. High-level policy intervention, if done properly, can be a powerful force for good. But to succeed, a tailored and adaptive policy approach that engages with local social, environmental, economic and cultural contexts and allows local innovation will be crucial (Liu et al., 2018b).

For Class A, both normalized ALA and VLUI is relatively low, normalized ALUI is in the average level, and ALUI local mean (~0.55) is close to ALUI global mean. Counties belonging to Class A are mainly distributed in Guangxi Pro, Guangdong Pro, Fujian Pro, Jiangxi Pro, Shandong Pro, Hebei Pro, Anhui Pro, central Liaoning Pro, and central Sichuan Pro. There is considerable room for improvement of ALUI in these counties.

Classes B, D, and F all possess highly normalized ALUI and relatively low VLUI. Their ALUI local mean are 0.706, 0.889, and 0.868, respectively. Counties belonging to Class F are mainly distributed in Heilongjiang Pro and northern Jilin Pro, corresponding to higher normalized ALA. This indicates that the protection of the sustainable ALUI of arable land is particularly important in these regions. Class D presents even higher ALUI local mean in comparison with Class F. However, its ALA local mean is significantly lower. It mainly covers Jiangsu Pro and northern Hubei Pro while Class B mainly covers Zhejiang Pro, Henan Pro, Hubei Pro, Chongqing Pro, Guizhou Pro, eastern Guangxi, and southern Shaanxi. It is not that the higher ALUI the better. For regions covered by Class D and Class F, local governments and scientists should pay more attention to the high land-use

intensity in tackling problems such as soil erosion, pesticide and chemical fertilizer pollution, land degradation, groundwater recession, and therefore explore sustainable arable land use paths.

Class C represents counties that possess low ALUI and relatively high ALA, which are mainly distributed in Hunan, Anhui, Liaoning, Xinjiang, Sichuan, Yunnan, and Shanxi provinces. It has a higher effectiveness and efficiency in enhancing the ALUI of these counties because of their high ALA and extremely low ALUI. Furthermore, since the VLUI of these counties are not high (VLUI local mean is ~0.1), a single factor is likely to be responsible for the low ALUI. Therefore, it is important to explore and improve core factors that restrict ALUI and thereby improve arable land grain yield in these counties.

For counties belonging to Class E, the ALUI is low while VLUI is high, thereby indicating that arable land within these counties has a remarkably different ALUI. In this case, factors that lead to low ALUI are more diverse and complicated, including poor soil conditions, inefficient farming technologies, unsuitable farming systems, inferior agricultural facilities, low agricultural income, etc. For some counties, there is another possibility that low and uneven ALUI indicates inappropriate land use type. Thus, it may be appropriate to convert some low ALUI arable land to other land use types (e.g., grassland). Therefore, uniform agricultural subsidy policy is probably not applicable in these counties. Local governments and scientists should analyze specific reasons that lead to low ALUI status when researching possible improvement paths and control methods of arable land productivity.

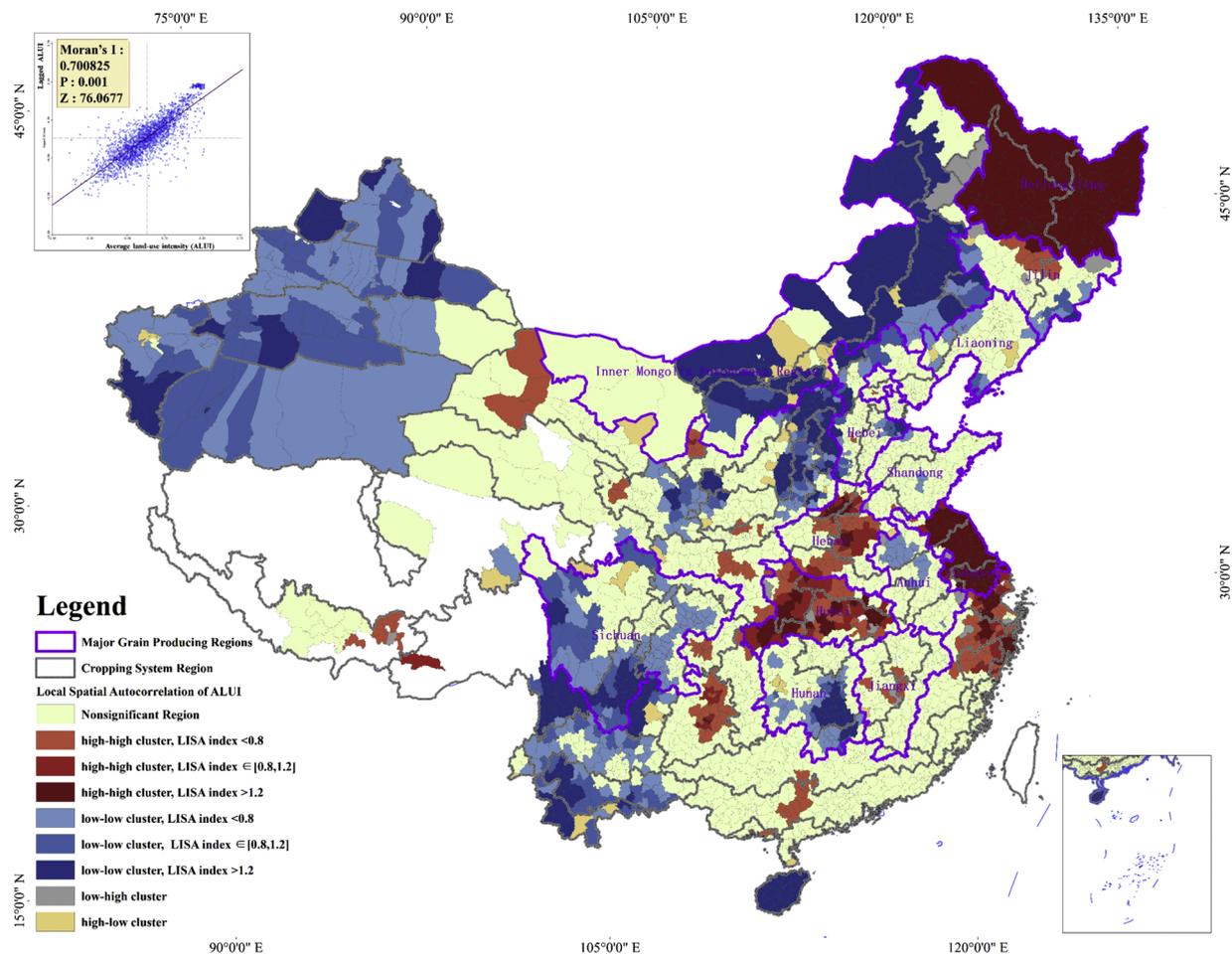


Fig. 6. Global and local spatial autocorrelations of ALUI.

## 4. Discussion

### 4.1. Spatial differentiation characteristics of arable land-use intensity

According to the distribution characteristics of ALUI, there is still a significant room for yield improvement. ALUI is lower than 0.7 for ~73.1 % counties. Therefore, it is more preferable to enhance the ALUI of counties than to develop saline land, waste grassland, slope land, and other kinds of unused land to supplement the total arable land. Moreover, the spatial pattern of ALUI shows significant local spatial autocorrelation characteristics and imbalance between East and West.

Counties with high ALUI are mainly distributed in southeastern coastal provinces, northeast provinces, middle provinces and Qinghai-Tibet plateau. Economically developed southeastern coastal provinces have relatively high farming conditions, and the disadvantage of high labour costs can be remedied by funds and technology (Hu and Huang, 2002). Peasants in northeast provinces and middle provinces generally have relatively high farming willingness because other employment options are scarce (Zhang et al., 2006). High ALUI in Qinghai-Tibet plateau is mainly because large quantity of inferior arable land has been transformed according to ecological de-farming policy (Chen, 2001). Counties with low ALUI are mainly distributed in northern provinces, southern Yunnan province and Hainan province (Xu et al., 2016; Liu et al., 2014b). For these areas, farming conditions are poor because of insufficient inputs and low management level (Yao et al., 2004); And limited by climatic conditions, topographic features and water resources carrying capacity, construction of high-standard agriculture is difficult and costly.

### 4.2. Using the arable land-use intensity in future policy making

As our research shows, local government is playing an important role in improving ALUI of arable land. The accelerated rural hollowing driven by vast and increasing out-migration of rural labors (the number reached 168.84 million in 2015 and has then exacerbated villagers' insufficient care and input to the farmland (Liu, 2018a)) under urban-rural dual-track system has imposed huge obstacles on improving land use intensity (Li et al., 2014), which needs special attention from local governments. Another factor that restricts the improvement of land use intensity is severe land fragmentation caused by the household responsibility system, which can be improved by land engineering and land consolidation (Yang et al., 2018). Continuous work by government at all levels to reform land systems and research of land use by different divisions should be adopted according to local conditions.

Liu et al. (2014a) has proposed a strategic land-use policy system to construct reciprocities and multi-layer connections among main arable land protection policies, which possesses Chinese characteristics and consists of strategic layer, policy layer and protection layer. The ALUI can be integrated in strategic layer to provide effective decision-making supporting information for making and implementing different regional arable land protection policies: regions with extensive high ALUI are crucial area for implementation of "store grain in the ground, store grain in technology" strategy, local governments should pay more attention in tackling problems such as soil erosion, pesticide and chemical fertilizer pollution, land degradation, groundwater recession, and thereby promote conservation tillage technique; while for regions with extensive low ALUI, implementing of local regional policies should focus on arable land consolidation, management and control of arable

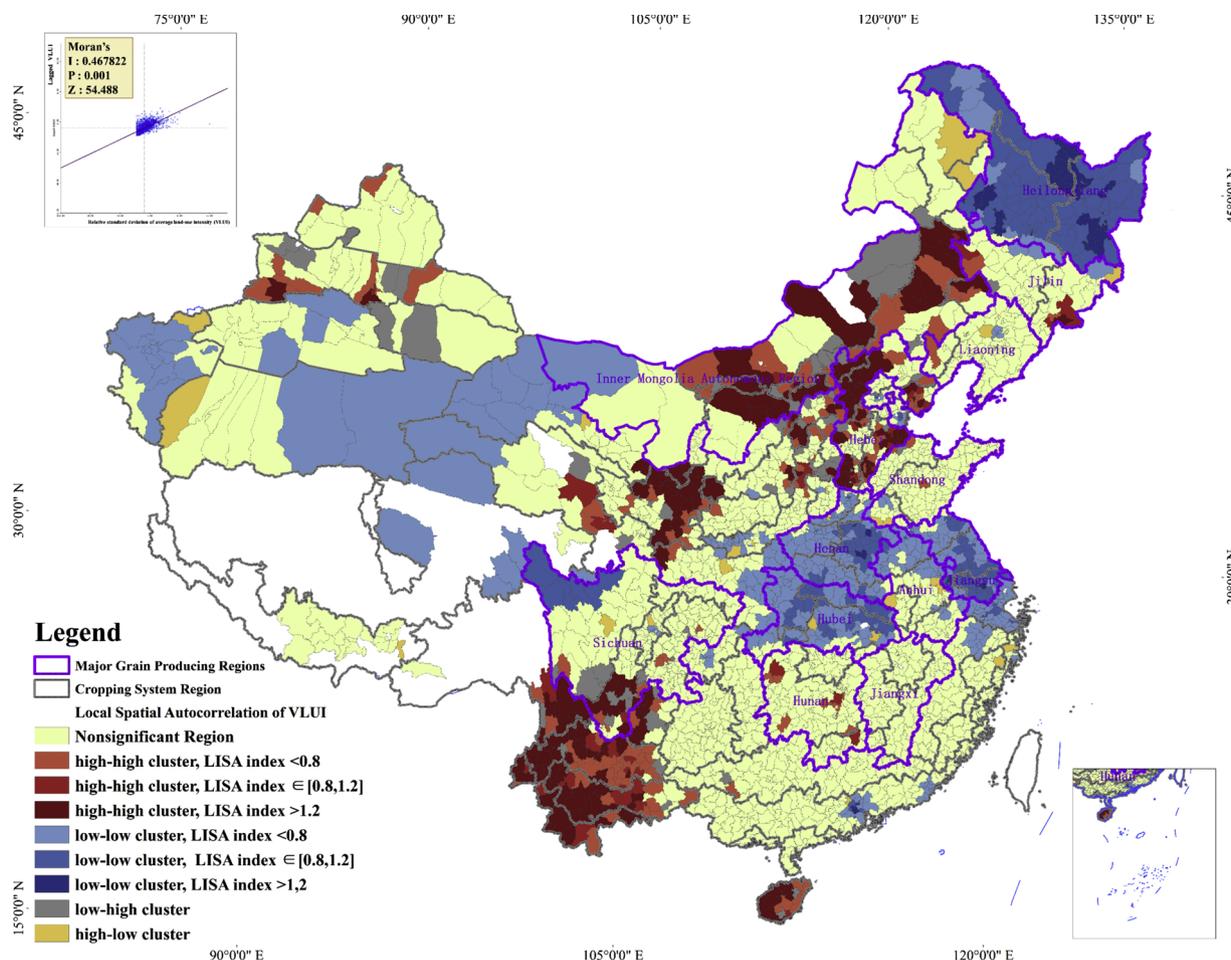


Fig. 7. Global and local spatial autocorrelations of VLUI.

land abandonment, and appropriate arable land conversion.

### 4.3. Shortages and prospect

In the face of globalization, climate change, food security concerns and development inequalities, the better understanding of key questions related to sustainable land use, and putting forward countermeasures favouring sustainability are becoming crucially important to the world (Liu, 2018a). In this paper, we have analyzed spatial distributions and autocorrelation characteristics of average ALUI of China's arable land at the county level and their correlations with ALA and VLUI in Mainland China. The results can provide effective decision-making supporting information for developing regional arable land use patterns and policies from the perspective of utilization control. Shortages of this study have been listed as follows.

(1) Arable land protection is a systematic project of which people's livelihood, public facilities, farmland and rural environmental conditions must be considered. This paper does not discuss the tradeoff between regional appropriate intensity for the sustainable utilization of arable land and food security (Justin et al., 2014) as well as the specific reasons that impact the ALUI of counties. Hence, our future research will focus on exploring sustainable utilization paths of arable land by synthesizing regional climate conditions, external farming conditions, farmers' willingness, economic benefit, and water resource-carrying capacity.

(2) The arable land system is a complex giant system composed of various elements, with complex organizational structure, diverse evolution direction, and regional difference (Song et al., 2018; Cheng et al., 2018) Thus, it needs the theory and method innovation of land

computing science to realize sustainable land use. In the future, we will research critical factors that influence ALUI and their impact mechanism, and thereby put forward more concrete countermeasures. Furthermore, we will study the methods for dividing multi-level red line of farmland protection, explore regional key tasks and analyze changes in ALUI by integrating the achievements of "the third national land survey."

(3) It is difficult to determine the factors relevant to ALUI nationwide as manual surveys have a disadvantage of low efficiency and low cost. In recent years, we have constructed a remote sensing (RS) data automatic pretreatment system (RSAPTS) to support near real-time GF RS data application (Zhao et al., 2018), including automatic radiometric correction, orthorectification (Ye et al., 2017), cloud detection, geometric correction (Wang and Ye, 2015) and projection transformation (Ye and Yan, 2016a). In the future, we will develop RS technology-based arable land production capacity indicators monitoring using RSAPTS.

### 5. Conclusions

In this paper, we have analyzed spatial distributions of ALUI of China's arable land at the county level and their correlations with ALA and VLUI in Mainland China, which can be used as a significant indicator for evaluating the arable land use rationality and providing effective decision-making supporting information for design of regional arable land protection policy. According to the experimental results, there is still significant room for yield improvement as the ALUI of ~73.1 % counties is lower than 0.7 while the ALUI of 53.60 % counties is lower than 0.6. Moreover, there is no significant correlation between

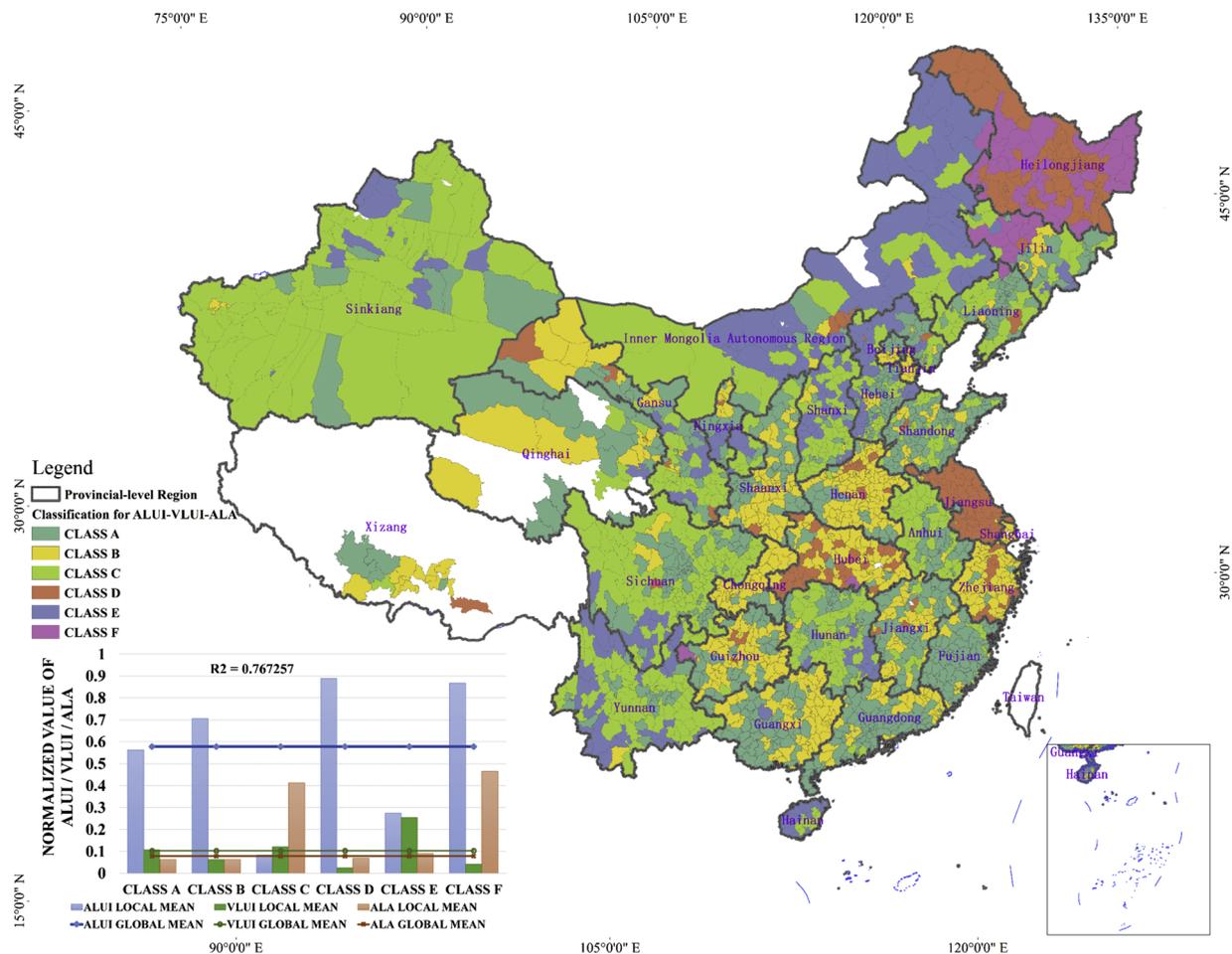


Fig. 8. Spatial heterogeneity of ALUI-VLUI-ALA.

**Note:** ALUI / VLUI / ALA GLOBAL MEAN is average ALUI / VLUI / ALA of all counties, ALUI / VLUI / ALA LOCAL MEAN is average ALUI / VLUI / ALA of counties belong to the same class. For Class A, both normalized ALA and VLUI is relatively low, normalized ALUI is in the average level, and ALUI local mean (~0.55) is close to ALUI global mean. Classes B, D, and F all possess highly normalized ALUI and relatively low VLUI. Their ALUI local mean are 0.706, 0.889, and 0.868, respectively. Class C represents counties that possess low ALUI and relatively high ALA. For counties belonging to Class E, the ALUI is low while VLUI is high.

ALUI/VLUI and ALA. Thus, ALA is not a critical factor that affects ALUI and VLUI. In addition, for most counties, ALUI is highly consistent.

ALUI dataset shows significant global spatial autocorrelation characteristic, and high-high concentration (HHC) region mainly covers nearly all the regions of Heilongjiang Pro, Jiangsu Pro, Hubei Pro, Zhejiang Pro, and central-north area of Henan Pro, Guizhou Pro, etc. Meanwhile, HHC regions have a high relationship with provincial administrative district but are less affected by sub-SFSR. On the other hand, low-low concentration (LLC) regions of ALUI are mainly distributed in Yunnan Pro, Hainan Pro, Shanxi Pro, Xinjiang Pro, southern Sichuan Pro, southern Hunan Pro, northern Anhui Pro, eastern Inner Mongolia. The relevant landscape types of these regions are mostly mountains, hills, or plateaus, where grain yield is mainly limited by regional hydrothermal conditions.

Counties with different ALUI-VLUI-ALA status have been divided into six classes, using k-means clustering algorithm. This will facilitate the understanding of appropriate arable land protection and utilization paths for different regions and provide effective decision-making supporting information for making and implementing different regional arable land protection policies. Furthermore, ALUI is a practical indicator for evaluating arable land productivity and identifying marginal land. It can comprehensively determine external farming conditions (including soil properties, cultivation, and site management technologies) and internal farming willingness. It also can be used as a constrained variable for crop yield simulation. Hence, the results of this

study can provide support information for developing spatialized arable land protection red line.

### Funding

This work was supported by the Strategic Priority Research Program of the Chinese Academy of Sciences [grant number XDA23100303]; National Natural Science Foundation of China [grant number 41801300, 41901316]; and the Fundamental Research Funds for the Central Universities [grant number 2018NTST03].

### CRediT authorship contribution statement

**Ye Sijing:** Conceptualization, Data curation, Formal analysis, Methodology, Visualization, Writing - original draft, Writing - review & editing. **Song Changqing:** Project administration, Conceptualization. **Shen Shi:** Investigation, Methodology. **Gao Peichao:** Investigation, Methodology. **Cheng Changxiu:** Methodology, Supervision. **Cheng Feng:** Funding acquisition, Resources. **Wan Changjun:** Writing - original draft. **Zhu Dehai:** Resources.

### Acknowledgments

This work was supported by the Strategic Priority Research Program of the Chinese Academy of Sciences [grant number XDA23100303];

National Natural Science Foundation of China [grant number 41801300, 41901316]; and the Fundamental Research Funds for the Central Universities [grant number 2018NTST03]. We would like to thank the high-performance computing support from the Center for Geodata and Analysis, Faculty of Geographical Science, Beijing Normal University [<https://gda.bnu.edu.cn/>]. The first author would also like to thank Jiang Bin and Wang Jinfeng for helpful discussions.

## Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:<https://doi.org/10.1016/j.landusepol.2020.104845>.

## References

- Alexandratos, N., Bruinsma, J., 2012. World Agriculture Towards 2030/2050: The 2012 Revision. Food and Agriculture Organization, Rome.
- An, P.L., Zhang, F.R., Chen, F., 2002. Determination of the standard farming system for farmland grading. *Geog. Territo. Res.* 18 (2), 45–48 (in Chinese with English abstract).
- Anselin, L., 1995. Local indicators of spatial association-LISA. *Geogr. Anal.* 27 (2), 93–115.
- Anselin, L., Syabri, I., Kho, Y., 2006. GeoDa: an introduction to spatial data analysis. *Geogr. Anal.* 38, 5–22.
- Bai, X., Shi, P., Liu, Y., 2014. Realizing China's urban dream. *Nature* 509 (7499), 158–160.
- Bondeau, A., Smith, P., Zaehle, S., et al., 2007. Modelling the role of agriculture for the 20th century global terrestrial carbon balance. *Glob. Chang. Biol.* 13, 679–706.
- Brookfield, 1993. Brookfield H.C. NOTES on the Theory of Land Management 1. PLEC News and Views, pp. 28–32.
- Brus, D.J., De Grijter, J.J., Van Groenigen, J.W., 2006. Designing spatial coverage samples using the k-means clustering algorithm. *Dev. Soil Sci.* 31, 183–192.
- Chen, B., 2001. The Comprehensive Productivity and Population Carrying Capacity of Agricultural Resources in China. Weather Press, Beijing (in Chinese).
- Chen, Y., Lei, G., Wang, Y., 2011. Spatial differentiation and evaluation on intensive use of cultivated lands in Heilongjiang Province. *Bull. Soil. Water Conser.* 31 (5), 154–456 (in Chinese with English abstract).
- Cheng, F., Wang, H.B., Yun, W.J., 2014. Study on investigation and assessment of cultivated land quality grade in China. *China Land Sci.* 28 (2), 75–82 (in Chinese with English abstract).
- Cheng, C.X., Shi, P.J., Song, C.Q., Gao, J.B., 2018. Geographic big-data: a new opportunity for geography complexity study. *Acta Geographica Sinica.* 73 (8), 1397–1406 (in Chinese with English abstract).
- Cheng, M., Liu, Y., Zhou, Y., 2019. Measuring the symbiotic development of rural housing and industry: a case study of Fuping County in the Taihang Mountains in China. *Land Use Policy* 82, 307–316.
- Coyle, C., Creamer, R.E., Schulte, R., et al., 2016. A Functional Land Management conceptual framework under soil drainage and land use scenarios. *Environ. Sci. Policy* 56, 39–48.
- Cui, Q., Wu, Y., Li, Q., 2010. Construction of the classification and grading index system of cultivated land based on the viewpoint of sustainable development. *Asian Agri. Res.* 2 (09), 1–5.
- Deng, X.Z., Huang, J.K., Rozelle, S., Zhang, J.P., Li, Z.H., 2015. Impact of urbanization on cultivated land changes in China. *Land Use Policy* 45, 1–7.
- Dietrich, J.P., Schmitz, C., Muller, C., et al., 2012. Measuring agricultural land-use intensity—a global analysis using a model-assisted approach. *Ecol. Model.* 232 (10), 109–118.
- Erb, K., 2012. How a socio-ecological metabolism approach can help to advance our understanding of changes in land-use intensity. *Ecol. Econ.* 76, 8–14.
- Erb, K., Martin, H., Jepsen, R., et al., 2013. A conceptual framework for analysing and measuring land-use intensity. *Curr. Opin. Environ. Sustain.* 5 (5), 464–470.
- Fan, H., Cai, Q., Chen, G., et al., 2005. Comparative study of the soil erosion and control in the three major black soil regions in the world. *J. Nat. Res.* 20 (3), 387–393 (in Chinese with English abstract).
- Feng, T., Zhang, F.R., Li, C., et al., 2014. Spatial distribution of prime farmland based on cultivated land quality comprehensive evaluation at county scale. *Tran. Chinese Soc. Agri. Eng.* 30 (1), 200–210 (in Chinese with English abstract).
- Feon, V., Schermann-Legionnet, A., Delettre, Y., et al., 2010. Intensification of agriculture, landscape composition and wild bee communities: a large scale study in four European countries. *Agric. Ecosyst. Environ.* 137, 143–150.
- Fisher, W.D., 1958. On grouping for maximum homogeneity. *J. Am. Stat. Assoc.* 53, 789–798.
- Foley, J., Ramankutty, N., Brauman, K.A., et al., 2011. Solutions for a cultivated planet. *Nature* 478, 337–342.
- Food and Agriculture Organization (FAO), 2012. The State of Food Insecurity in the World. FAO Soil Bulletin, Rome, pp. 52.
- Gao, X.J., Ma, R.H., 2002. Research advances of gradation and evaluation of agricultural land in China. *Tran. Chinese Soc. Agri. Eng.* 18 (1), 165–168 (in Chinese with English abstract).
- Gao, J., Chen, W., Liu, Y., 2018. Spatial restructuring and the logic of industrial land redevelopment in urban China: a case study of the redevelopment of a local state-owned enterprise in Nanjing. *Land Use Policy* 70, 24–33.
- GB/T 28407-2012, 2012. Regulation for Gradation on Agriculture Land Quality. Beijing: General Administration of Quality Supervision, Inspection and Quarantine of the People's Republic of China and Standardization Administration of China (in Chinese).
- Getis, A., Ord, J.K., 2010. The analysis of spatial association by use of distance statistics. *Perspectives on Spatial Data Analysis.* Springer, Berlin, Heidelberg, pp. 127–145.
- Hu, H.Y., 1935. Population distribution in China - attached statistical tables and density maps. *Acta Geographica Sinica.* 2, 33–74.
- Hu, R., Huang, J., 2002. Study on technical structure and development of agriculture in China from resources of cultivated lands and labors. *Impact Sci. Soc.* 2, 30–36 (in Chinese with English abstract).
- Hunt, R., 2000. Labor productivity and agricultural development: boserup revisited. *Human Ecol.* 28, 251–277.
- Jenks, G.F., 1963. Generalization in statistical mapping. *Ann. Assoc. Am. Geogr.* 53 (1), 15–26.
- Jiang, B., 2012b. Head/Tail breaks: a new classification scheme for data with a heavy-tailed distribution. *Prof. Geogr.* 65 (3), 482–494.
- Jiang, B., Liu, X., 2012a. Scaling of geographic space from the perspective of city and field blocks and using volunteered geographic information. *Int. J. Geogr. Inf. Sci.* 26 (2), 215–229.
- Jin, J.J., He, R., Wang, W.Y., Gong, H.Z., 2018. Valuing cultivated land protection: a contingent valuation and choice experiment study in China. *Land Use Policy* 74, 214–219.
- Justin, A.J., Carlisle, F.R., Benjamin, S., et al., 2014. Global agriculture and carbon trade-offs. *PNAS* 111 (34), 12342–12347.
- Kanungo, T., Mount, D.M., Netanyahu, N.S., et al., 2002. An efficient k-means clustering algorithm: analysis and implementation. *IEEE Trans. Pattern Anal. Mach. Intell.* 7, 881–892.
- Kong, X.B., Lin, J., 2008b. Study on productive ratio in farmland classification. *Res. & Indus.* 10 (5), 77–82 (in Chinese with English abstract).
- Kong, X.B., Liu, L.W., Qin, J., 2008a. Arable land evaluation based on the household land use behavior in Daxing District of Beijing. *Acta Geographica Sinica.* 8, 856–868 (in Chinese with English abstract).
- Kong, X.B., Lin, J., Wang, J., et al., 2009. Impacts of productive ratio coefficient on grade of farmland classification. *Tran. Chinese Soc. Agri. Eng.* 25 (1), 237–243 (in Chinese with English abstract).
- Kong, X.B., Zhang, Q.P., Yun, W.J., et al., 2013. Integration method of accomplishments of arable land from province level to national level based on equal standard crop yields. *Tran. Chinese Soc. Agri. Eng.* 29 (16), 238–246 (in Chinese with English abstract).
- Kuemmerle, T., Erb, K., Meyfroidt, P., 2013. Challenges and opportunities in mapping land use intensity globally. *Curr. Opin. Environ. Sustain.* 5 (5), 484–493.
- Legendre, P., 1993. Spatial autocorrelation: trouble or new paradigm? *Ecology.* 74 (6), 1659–1673.
- 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. *Land Use Policy* 39, 188–198.
- Li, P., Du, Z., Zhang, G., et al., 2017. Space difference analysis of cultivated land quality grade in Beijing-Tianjin-Hebei region. *Tran. Chinese Soc. Agri. Eng.* 48 (2), 150–157 (in Chinese with English abstract).
- Li, Y., Wu, W., Liu, Y., 2018. Land consolidation for rural sustainability in China: practical reflections and policy implications. *Land Use Policy* 74 (5), 137–141.
- Liu, Y., 2018a. Introduction to land use and rural sustainability in China. *Land Use Policy* 74 (5), 1–4.
- Liu, Y., Li, Y., 2017. Revitalize the world's countryside. *Nature* 548 (7667), 275–277.
- Liu, Y., Fang, F., Li, Y., 2014a. Key issues of land use in China and implications for policy making. *Land Use Policy* 40, 6–12.
- Liu, Y., Hao, X., Pan, Y., 2014b. Evaluating and zoning of cultivated land intensive use in Henan Province at county level. *Scientia Geographica Sinica.* 34 (10), 1218–1225 (in Chinese with English abstract).
- Liu, G., Wang, H., Cheng, Y., et al., 2016a. The impact of rural out-migration on arable land use intensity: evidence from mountain areas in Guangdong. *China. Land Use Policy.* 59, 569–579.
- Liu, P., Wu, K., Luo, M., et al., 2016b. Evaluation of agricultural land soil heavy metal elements exceed standards and safe utilization zones. *Tran. Chinese Soc. Agri. Eng.* 32 (23), 254–262 (in Chinese with English abstract).
- Liu, Y., Li, J., Yang, Y., 2018b. Strategic adjustment of land use policy under the economic transformation. *Land Use Policy* 74 (5), 5–14.
- Ma, R.M., Ma, R.H., Han, D.M., et al., 2018. Construction of cultivated land quality evaluation system in provincial level based on multilevel indicators. *Trans. CSAE.* 34 (16), 249–257 (in Chinese with English abstract).
- MacQueen, J., 1967. Some methods for classification and analysis of multivariate observations. *Proceedings of the 5th Berkeley Symposium on Mathematical Statistics and Probability.* University of California Press, Berkeley, pp. 281–297.
- Malthus, T.R., 1798. An Essay on the Principle of Population. Printed for J. Johnson, in St. Paul's Church-Yard, London.
- Neumann, K., Verburg, P.H., Stehfest, E., Muller, C., 2010. The yield gap of global grain production: a spatial analysis. *Agric. Syst.* 103, 316–326.
- Niedertscheider, M., Thomas, K., Tamara, F., et al., 2016. Mapping and analysing cropland use intensity from a NPP perspective. *Environ. Res. Lett.* 11 (1), 014008.
- Ord, J.K., Getis, A., 2001. Testing for local spatial autocorrelation in the presence of global autocorrelation. *J. Reg. Sci.* 41 (3), 411–432.
- Reidsma, P., Tekelenburg, T., van den Berg, M., et al., 2006. Impacts of land-use change on biodiversity: an assessment of agricultural biodiversity in the European Union. *Agric. Ecosyst. Environ.* 114 (1), 86–102.

- Ricardo, D., 1815. An Essay on the Influence of a Low Price of Corn on the Profits of Stock. John Murray, London.
- Rosegrat, M.W., Cline, S.A., 2003. Global food security: challenges and policies. *Science* 302, 1917–1919.
- Shao, X., Liu, Q., Zhang, Y., 2006. Advances and expectations of intensive land use researches. *Prog. Geogr.* 25 (2), 85–94 (in Chinese with English abstract).
- Shriar, A., 2000. Agricultural intensity and its measurement in frontier regions. *Agrofor Syst.* 49, 301–318.
- Siebert, S., Portmann, F.T., Doll, P., 2010. Global patterns of cropland use intensity. *Remote Sens. (Basel)* 2, 1625–1643.
- Smith, P., 2013. Delivering food security without increasing pressure on land. *Glob. Food Sec.* 2 (1), 18–23.
- Song, C.Q., Cheng, C.X., Shi, P.J., 2018. Geography complexity: new connotations of geography in the new era. *Acta Geographica Sinica.* 73 (7), 1204–1213 (in Chinese with English abstract).
- Stjerner, M., Sahlin, U., Olsson, O., et al., 2019. Estimating effects of arable land-use intensity on farmland birds using joint species modeling. *Ecol. Appl.* 29 (4), e01875.
- Taleb, N.N., 2007. *The Black Swan: the Impact of the Highly Improbable*. Allen Lane, London.
- Tilman, D., Balzer, C., Hill, J., Befort, B.L., 2011. Global food demand and the sustainable intensification of agriculture. *Proc. Natl. Acad. Sci. U.S.A.* 108 (50), 20260–20264.
- Turner, B.L., Doolittle, W., 1978. The concept and measure of agricultural intensity. *Prof. Geogr.* 30, 297–301.
- UNICEF, 2014. The millennium development goals report 2015. Midwifery. 30, 1043–1044.
- Valtjeva, K., O'Sullivan, L., Gutzler, C., et al., 2016. The challenge of managing soil functions at multiple scales: an optimisation study of the synergistic and antagonistic trade-offs between soil functions in Ireland. *Land Use Policy* 58, 335–347.
- Von Thunen, J.H., 1826. *Der Isolierte Staat in Beziehung Auf Landwirtschaft Und Nationalökonomie Oder Untersuchungen Über Den Einfluss, Den Die Getreidepreise, Der Reichtum Des Bodens Und Die Abgaben Auf Den Ackerbau Ausüben*. Friedrich Berthes, Hamburg.
- Wang, Y., Ye, S.J., et al., 2015. Contrast of automatic geometric registration algorithms for GF-1 remote sensing image. *Trans. Chinese Soc. Agri. Mach.* 46 (1), 260–266 (in Chinese with English abstract).
- Wang, G.Q., Yun, W.J., 2011. A briefly review and prospects on the land quality evaluation research. *China Land Sci.* 25 (7), 92–96 (in Chinese with English abstract).
- Wang, Y., Huang, J., Zhu, D., Liu, Y., Huang, C., Hou, H., 2006. Calculation Method of  $\beta$  Coefficient for Agricultural Land Classification. *Chinese J. soil Sci.* 37 (5), 837–840 (in Chinese with English abstract).
- Wang, G.Q., Wang, L., Tian, Y., et al., 2007. Foundation and method for gathering agricultural land classification achievements at provincial level. *Tran. Chinese Soc. Agri. Eng.* 23 (6), 271–275 (in Chinese with English abstract).
- Wang, H.B., Yun, W.J., Wu, C.F., et al., 2008. Farmland productivity monitoring system based on farmland gradation. *Trans. CSAE* 4 (24), 122–126 (in Chinese with English abstract).
- Wang, J.F., Li, X.H., Christakos, G., et al., 2010. Geographical detectors-based health risk assessment and its application in the neural tube defects study of the Heshun region. *China. Int. J. Geog. Inf. Sci.* 24 (1), 107–127.
- Wang, X.P., Jiang, G.H., Zhang, R.J., et al., 2013a. Zoning approach of suitable areas for high quality capital farmland construction. *Tran. Chinese Soc. Agri. Eng.* 29 (10), 241–250 (in Chinese with English abstract).
- Wang, L., An, P., Pan, Z., He, D., Dong, Z., 2013b. Cultivated land quality change of Wuchuan county in Inner Mongolia under background of climate change in semi-arid regions during recent 20 years. *Tran. Chinese Soc. Agri. Eng.* 29 (11), 224–231 (in Chinese with English abstract).
- Wang, G., Liu, Y., Chen, Y., 2014. Dynamic trends and driving forces of land-use intensification in the cultivated land of China. *Acta Geographica Sinica.* 7 (69), 907–915 (in Chinese with English abstract).
- Wang, J.F., Zhang, T.L., Fu, B.J., 2016. A measure of spatial stratified heterogeneity. *Ecol. Indic.* 67, 250–256.
- Wilpon, J.G., Rabiner, L.R., 1985. A modified K-means clustering algorithm for use in isolated word recognition. *IEEE Trans. Acoust.* 33 (3), 587–594.
- Wu, K., Cheng, X.J., et al., 2008b. Comprehensive productivity of agricultural land based on the agricultural land classification. *Trans. CSAE* 24 (11), 51–56 (in Chinese with English abstract).
- Wu, K., Jiao, X., Liang, S., et al., 2008a. Framework of the arable-land quality dynamic monitoring sites through national gathering of standard farmland. *Trans. CSAE* 10 (24), 74–79 (in Chinese with English abstract).
- Wu, Y.P., Yun, W.J., Zou, R., 2008c. Model for calculation of cultivated land productivity. *Tran. Chinese Soc. Agri. Eng.* 24, 108–113. (in Chinese with English abstract). Suppl.2.
- Xie, H., Zou, J., Jiang, H., et al., 2014. Spatiotemporal pattern and driving forces of arable land-use intensity in China: toward sustainable land management using emergy analysis. *Sustainability* 6 (6), 3504–3520.
- Xu, Y., Pan, Y., Liu, Y., 2016. Spatial-temporal variance of cultivated land use intensity in Hainan Province. *J. Cap. Normal Uni. (Natural Science Edition)* 37, 78–83 (in Chinese with English abstract).
- Xue, J., Han, J., Zhang, F.R., et al., 2014. Development of evaluation model and determination of its construction sequence for well-facilitated capital farmland. *Tran. Chinese Soc. Agri. Eng.* 30 (5), 193–203 (in Chinese with English abstract).
- Yang, Y., Liu, Y., Li, Y., et al., 2018. Measure of urban-rural transformation in Beijing-Tianjin-Hebei region in the new millennium: population-land-industry perspective. *Land Use Policy* 79, 595–608.
- Yao, X.C., Ye, S.J., et al., 2017b. Parallel algorithm for partitioning massive spatial vector data in cloud environment. *J. Wuhan Uni. (Information Science Edition)*. 10, 1–6 (in Chinese with English abstract).
- Yao, H., Zhang, L., Zhang, F., Kong, X., An, P., 2004. Calculation method of land use coefficient in agricultural land gradation. *J. Nat. Resour. Life Sci. Educ.* 26 (4), 89–95 (in Chinese with English abstract).
- Yao, C., Huang, L., Lv, X., et al., 2014. Temporal and spatial change of cultivated land use intensity in China based on emergy theory. *Tran. Chinese Soc. Agri. Eng.* 8, 1–12 (in Chinese with English abstract).
- Yao, X.C., Zhu, D.H., Ye, S.J., et al., 2016. A field survey system for land consolidation based on 3S and speech recognition technology. *Comput. Electron. Agric.* 127, 659–668.
- Yao, X.C., Mokbel, M.F., Ye, S.J., et al., 2017a. Spatial coding-based approach for partitioning big spatial data in Hadoop. *Comput. Geosci.* 106, 60–67.
- Yao, X.C., Mokbel, M.F., Ye, S.J., et al., 2018. LandQv2: a MapReduce-Based system for processing arable land quality big data. *ISPRS* 7 (7), 271.
- Ye, S.J., 2016b. Research on application of Remote Sensing Tupu - take monitoring of meteorological disaster for example. *Acta Geodaetica et Cartographica Sinica.* 47 (6) (in Chinese with English abstract).
- Ye, S.J., Yan, T.L., et al., 2016a. Developing a reversible rapid coordinate transformation model for the cylindrical projection. *Comput. Geosci.* 89 (4), 44–56.
- Ye, S.J., Zhu, D.H., Yao, X.C., et al., 2014. Development of a highly flexible mobile GIS-based system for collecting arable land quality data. *Ieee J. Sel. Top. Appl. Earth Obs. Remote Sens.* 5 (14), 4432–4441.
- Ye, S.J., et al., 2017. Design and implementation of automatic orthorectification system based on GF-1 big data. *Tran. Chinese Soc. Agri. Eng.* 33, 266–273 (in Chinese with English abstract).
- Ye, S.J., Cheng, C.X., Song, C.Q., et al., 2018. RDCRMG: a raster dataset clean & reconstitution multi-grid architecture for remote sensing monitoring of vegetation dryness. *Remote Sens. (Basel)* 10 (1376), 1–24.
- Ye, S.J., Song, C.Q., Cheng, F., et al., 2019. Cultivated land health-productivity comprehensive evaluation and its pilot evaluation in China. *Tran. Chinese Soc. Agri. Eng.* 35 (22), 66–78. <https://doi.org/10.11975/j.issn.1002-6819.2019.22.008>. (in Chinese with English abstract).
- Yin, G., Lin, Z., Jiang, X., Yan, H., Wang, X., 2019. Spatiotemporal differentiations of arable land use intensity — a comparative study of two typical grain producing regions in northern and southern China. *J. Clean. Prod.* 208, 1159–1170.
- Zhang, F.R., Yun, W.J., Kong, X.B., et al., 2002. Discussion on the land use coefficient of regulations for classification and gradation on agricultural land. *China Land Science.* 16 (1), 16–19 (in Chinese with English abstract).
- Zhang, J., Zhang, F., Zhang, L., et al., 2006. Comparison between the potential grain productivity and the actual grain yield of cultivated lands in mainland China. *Scientia Agricultura Sinica* 39 (11), 2278–2285 (in Chinese with English abstract).
- Zhang, L.N., Yun, W.J., Su, Q., et al., 2008a. Methods for productivity calculation based on agricultural land classification. *Tran. Chinese Soc. Agri. Eng.* 24 (Suppl.1), 133–136 (in Chinese with English abstract).
- Zhang, L., Zhang, F., An, P., 2008b. Comparative study of cultivated land use intensity degree and its change law at different economic levels. *Tran. Chinese Soc. Agri. Eng.* 24, 108–112 (in Chinese with English abstract).
- Zhang, L., Wu, K., Rao, C., Chen, L., 2009. Research on the  $\beta$  coefficient of agricultural land classification on provincial bordering: a case of Hubei province. *China Land Sci.* 23 (2), 52–55 (in Chinese with English abstract).
- Zhang, B., Kong, X., Xiang, H., Zhang, Q., 2014. Distribution characteristics and representative test of national standard farmland in Western China. *Tran. Chinese Soc. Agri. Eng.* 30 (7), 227 235 (in Chinese with English abstract).
- Zhao, Y., Chang, Q., Li, Z., et al., 2013. Spatial characteristics and changes of soil organic matter for cultivated land in suburban area of Xi'an from 1983 to 2009. *Tran. Chinese Soc. Agri. Eng.* 29 (2), 254–262 (in Chinese with English abstract).
- Zhao, Z.L., Zhe, L., Ye, S.J., et al., 2018. Spatial layout of multi-environment test sites: a case study of maize in Jilin Province. *Sustainability.* 10, 1424.