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# Increasing concentration of major crops in China from 1980 to 2011

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## ABSTRACT

The concentration of crop cultivation can be measured in terms of spatial clustering and of inequality in the distribution of the cropland area. We used official agricultural statistics at the county level ( $N = 2,354$ ) for each year from 1980 to 2011 for all of China to analyse the changes in spatial clustering and inequality of overall cropland and of the harvested areas of the five major crops (rice, maize, wheat, soybean, and potato). We quantified the spatial clustering with global and local Moran's  $I$  and assessed the inequality in the distribution of crop cultivation with the generalized entropy index. The results showed that the cropland area and harvested areas of the major crops indeed became more homogeneous over time, and the major crops concentrated in fewer areas and in the major historic breadbaskets. Increasing concentration may offer opportunities in specialization and positive agglomeration effects but can reduce the resilience of food systems and agricultural sustainability.

## ARTICLE HISTORY

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## KEYWORDS


Land use; spatial clustering; spatial heterogeneity; crop production; Moran's  $I$ ; Generalized Entropy Index (GEI); inequality

## 1. Introduction

Global agricultural land use has transformed substantially in recent decades. One of the key changes was the concentration of production activities on fewer and more profitable crops (DeFries et al., 2015; Jepsen et al., 2015). Besides changes in farm structure and farm orientation, the global transformation of agriculture led to increasing concentration of agricultural land use around populated places and in areas with favourable natural endowments (fertile soils, favourable climate conditions, and abundant water resources). In short, spatial structures of commercially oriented agricultural land use are increasingly following the paradigms put forward by von Thünen and Ricardo (Alexander et al., 2015; Bren d'Amour et al., 2016a; Ricardo, 1817; Thünen and Hall, 1966).

David Ricardo showed that crop production attains higher rents in more fertile locations (Ricardo, 1817). Over time, populations are in increasingly concentrated densities in and around the areas suitable for crop production, which create further opportunities for agricultural growth, as these larger settlements act as major centres of demand. Positive externalities, such as those from knowledge and technology spillovers, add force to the creation of spatial clusters around the fertile areas (Irwin & Bockstael, 2002).

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 Supplemental data for this article can be accessed [here](#).

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Spatial clusters of crop production occur not only because of high Ricardian rents but also can emerge in surroundings of strategically established settlements, for example, at coastal ports or close to major trade hubs, as a result of low transport costs to these urban centres, in accordance with von Thünen's theory of land rent (Thünen and Hall, 1966). Recent evidence suggests that spatial clusters of crop production, particularly in developed and emerging economies, are increasingly polarized to fertile and accessible areas with good infrastructure, while much land in naturally less favoured areas and with lower quality of infrastructure is left abandoned (Kuemmerle et al., 2016).

While much research has focused on the patterns of spatial clustering of land use in general and on changes in the clustering of agricultural production in particular, less attention has been paid to the increasing spatial concentration of crop production among regions. However, evidence suggests that commercial agricultural land use is increasingly concentrated in fewer but highly productive areas, leading to a higher inequality of land use with a few producing regions dominating much of the output (Monfreda, Ramankutty, & Foley, 2008; Ramankutty et al., 2018). The concept of concentration, in this case, is akin to economic concentration, that is, an increasing share of the market is controlled by a shrinking number of firms. In terms of agricultural production, if only a few regions cultivate a large share of a crop, then the cultivation pattern of this crop is highly unequal, regardless of whether these regions are located next to each other. The increasing inequality in agricultural production often reflects the process of regional specialization, facilitated by agglomeration of knowledge and skills in production and processing in a few pockets of production. Increasing productivity and higher efficiency in agricultural production archetypally go in hand with higher specialization at the farm and regional levels (Levers et al., 2018; Václavík, Lautenbach, Kuemmerle, & Seppelt, 2013).

Higher spatial clustering and increasing inequality in the distributions of crops are complementary concepts, although the two processes may share the same underlying drivers. Nevertheless, a high degree of spatial clustering does not correspond to high inequality and vice versa. High spatial clustering of a variable can be observed with fairly equal distributions among regions (i.e. small variance in terms of distribution), for example, when regions with a high share in the cultivation of a particular crop are next to each other. On the other hand, a few important producing regions may host a high share of the production of one specific crop (i.e. high inequality), but these few regions are not spatially connected to each other (i.e. low spatial clustering). Combined, the spatial clustering and inequality in the distribution of cultivation among regions can yield important insights into the overall concentration of cropland use and crop production.

The concentration of agricultural production has important implications. Increasing specialization and spatial clustering of production can have manifold economic advantages, such as positive effects on agricultural productivity because of technology spillovers and the emergence of service and knowledge centres (Brühlhart & Traeger, 2005; Fujita & Thisse, 2009). However, the increasing concentration on fewer crops and on fewer places of production may also infringe on domestic food security, bring higher production risks, and affect environmental conditions (Mehrabi & Ramankutty, 2018). The increasing concentration may also render countries and regions more vulnerable to production shocks, such as from crop diseases that spread more easily due to adverse weather events or in response to economic shocks, such as through price volatility (Bren d'Amour, Wenz, Kalkuhl, Christoph Steckel, & Creutzig, 2016b). Therefore, an improved understanding of the degree and spatial locations of crop concentration and their changes over time is urgently needed.

China presents a good case in point with its dynamic land-use changes in recent decades and its uneven distribution of cropland (Yu, Hu, van Vliet, Verburg, & Wu, 2018a). Only 15% of the territory of China is suitable for cultivation, which is mainly in the east of China (Liu et al., 2014). The spatial patterns of cropland and especially crop production, however, experienced notable changes in China, particularly since the introduction of the household responsibility system in 1978, although the overall area of cropland did not change much (Liu et al., 2014; Liu, Xu, Zhuang, Chen, & Li, 2013; Xie & Liu, 2015). In many areas, particularly away from urban centers and in less fertile places,

cropland has been abandoned since approximately the turn of the millennium due to labour emigration from rural areas, an ageing rural society, and less reliance on agricultural incomes (Fraye, Müller, Sun, Munroe, & Xu, 2014; Long, Li, Liu, Woods, & Zou, 2012; Xu et al., 2013). The degree of abandonment already jeopardizes the red line of minimum domestic cropland area, which was set by the Chinese government at 1.8 billion mu, equivalent to 120 million hectares (Li, Deng, Yin, & Yang, 2015). Land-use intensity was also reduced in many of the more marginal areas, witnessed among others by a reduction in the extent of multi-cropping (Yu et al., 2018a), leading to further reduction in harvested area. Another proximate cause for the reduction of cropland is the expansion of urban areas, which causes permanent loss of fertile cropland especially in economically developed regions, such as in the rapidly developing coastal areas in eastern and southern China (Bren d'Amour et al., 2016a). Finally, large-scale ecological conservation projects, such as the Sloping Land Conversion Program, contributed to the reduction in considerable amounts of marginal lands mainly in hilly and mountainous areas (Fraye et al., 2014).

At the same time, arable land increased in the northeast and southwest of China because of the expansion of irrigation facilities (He et al., 2015). Moreover, state and private investments into the agricultural sector have contributed to intensified land use in some areas. Agricultural production has shifted to higher yielding crops that are cultivated at high input intensities, especially in the country's main agricultural areas, and generate agricultural products with high value added (Xie & Liu, 2015; Yan, Liu, Huang, Tao, & Cao, 2009; Yu et al., 2018a). China's accession to the World Trade Organization (WTO) in 2001 also influenced the crop structures and the spatial distribution of land use in China. A notable example is soybean production. Because of the lower yields, inferior oil extraction rate, and high production cost compared to genetically modified soybeans produced in the USA, Brazil, and Argentina, soybean production in China became less profitable after the accession to the WTO, and the harvested area of soybeans was reduced significantly.

National agricultural policies also play a critical role in shaping the spatial distribution of the crops. For example, the setting of a minimum purchase price on maize by the government to protect farmers' revenue led to rapid expansion of maize cultivation. Similarly, the rapid growth of potato cultivation in recent years was caused by a national support policy that promoted potatoes as a major staple food (traditionally only eaten as a vegetable by the Chinese, not as a source of carbohydrates). Many of these changes arguably led to an increasing polarization of land use, with a higher concentration of profitable, highly intensive production in some areas, such as the concentration of vegetable production in Shandong and Hainan (Ji et al., 2018; Zhang, Jin, & Zheng, 2016). Nevertheless, it remains unclear to what degree and in which locations crop production has concentrated and how this concentration process evolved over time, especially at a fine spatial scale.

To improve the understanding of the evolution of cropping patterns, we analysed the changes in the spatial concentration of overall cropland area and of the harvested area of the main crops (rice, maize, wheat, soybean, and potato) using annual statistics at the county level for all of China from 1980 to 2011. We aimed to answer the following questions: How did the spatial clustering of all cropland and of the harvested areas of the five major crops change between 1980 and 2011? Second, how did the inequality of the distribution of the harvested area of the five crops evolve between 1980 and 2011? The two research questions correspond to the two perspectives on concentration that we aimed to address, namely, spatial clustering and inequality of distribution in terms of cropland area and harvested areas of crops.

## 2. Materials and methods

### 2.1. Data

We used county-level agricultural statistics from the China Compendium of Statistics, China statistical yearbooks, and various provincial statistical yearbooks (<http://tongji.cnki.net/kns55/>

Navi/NaviDefault.aspx). These data are available for each year from 1980 to 2011 for all 2,354 counties of China. We extracted the area covered by crops (cropland area henceforth) and the harvested area for the five major crops that we defined as those crops with the largest harvested area in 2011, which were wheat, maize, rice, soybean, and potato. Note that when more than one harvest per year occurs on the same cropland, the harvested area may exceed the cropland area due to the multi-cropping. The data revealed the major agricultural areas of the selected five crops were in the northeast, north, and southeast (Figure 1), which are also the areas that most rapidly urbanize and industrialize (for a map of the seven regions and the province names in China, see Figure 1). The spatial distribution of the five major crops in 2011 showed the clustering of maize and wheat in northern and northeastern China, rice in the northeast and the south, soybean in the northeast, and potato along the boundary of regions.

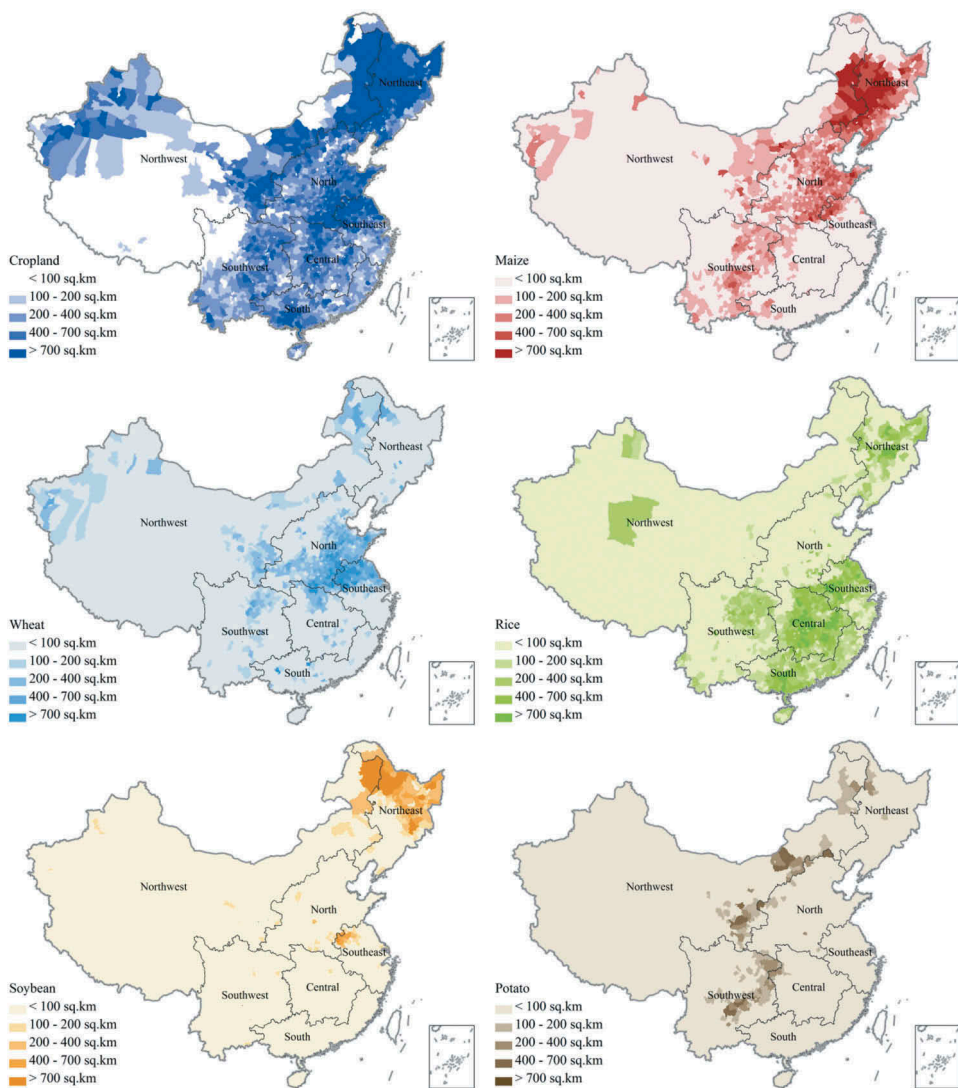


Figure 1. Distribution of cropland and the five major crops in 2011.

### 2.2. Spatial clustering

We quantified the concentration of land use from two perspectives, that is, spatial clustering and inequality of distributions of cropland and of the harvested areas of the five crops (Figure 2).

Spatial clustering is a frequent pattern of many geographic phenomena and an important justification for the use of spatial statistical analysis. We used Moran’s I and local Moran’s I to quantify the spatial clusters among neighbouring values. The Moran’s I index is the extension of Pearson’s correlation coefficient with a spatial weights matrix that defines the neighbourhood structure (Moran, 1950). Moran’s I ranges between -1 and +1. Positive values indicate spatial clusters and negative values signal that neighbouring observations have dissimilar values.

The global Moran’s I is a summary measure for the presence of spatial clustering across a study area, but the index cannot show where hot spots (spatial clusters of high values) and cold spots (spatial clusters of low values) are located. We captured local clustering patterns with local indicators of spatial association (LISA, Anselin, 1995), which visualize the spatial location of hot spots and cold spots on a map. Compared to alternative local measures of spatial associations, for example, Getis-Ord  $G_i^*$ , the local Moran’s I can also identify spatial outliers, that is, when high values are surrounded by low values or vice versa.

We calculated the global Moran’s I, and we mapped the local Moran’s I for each year of our study period to reveal changes in the spatial clustering of the five crops and of the overall cropland area. We calculated the global Moran’s I according to equation 1:

$$I = \frac{N \sum_i \sum_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{W \sum_i (x_i - \bar{x})^2} \tag{1}$$

where N, in our case, is the number of counties in China indexed by  $i$  and  $j$  ( $N = 2,354$ );  $x$  is the variable to be investigated (cropland area and harvested area of the selected crops);  $\bar{x}$  is the mean of the areas in neighbouring counties;  $w_{ij}$  is a matrix of spatial weights with zeroes on the diagonal (i.e.  $w_{ij} = 0$  if  $i = j$ ) and ones indicating the spatial neighbours.  $W$  is the sum of all  $w_{ij}$ . We settled on first-order rook contiguity matrix as the neighbourhood specification. We assessed the sensitivity of the results to the neighbourhood specification by carrying out identical calculations with a queen contiguity matrix and with a second-order rook matrix. The choice of the matrix did not change the results fundamentally, and the differences between rook and queen contiguity were, as expected, very minor (Figure S4). For the sake of brevity, we only report the first-order rook case.

The LISA allowed mapping the local clusters. LISA were defined as:

$$I_i = z_i \sum_j w_{ij} z_j \tag{2}$$

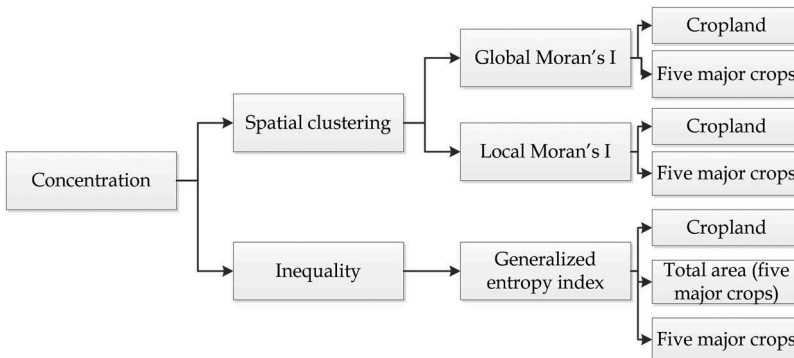


Figure 2. Two perspectives on concentration and methods for quantification.

where  $z_i$  and  $z_j$  are deviations from the mean. A positive  $I$  indicates a clustering pattern, i.e. an entity and its neighbouring entities have similar values; a negative value for  $I$  indicates spatial outliers, i.e. an observation is surrounded by observations with dissimilar values. A permutation approach that yields pseudo-significance levels using z-scores and p-values assessed the statistical significance of  $I$ . The permutation involves a random spatial assignment of all observations in the neighbourhood, as defined by the spatial weights matrix  $w_{ij}$ . The resulting distributions capture spatial randomness, which are then compared to the actual distributions (Anselin, 1995).

### 2.3. Inequality of distribution of cropland and harvested area of crops

Inequality is measured in several ways, with the most famous the Gini index and the Theil index (Lerman, 1984; Mussard, Seyte, & Terraza, 2003). In this study, we quantified inequality with the generalized entropy index (GEI). The GEI is from the family of generalized entropy measures of which the Theil index is a special case. We preferred the GEI for our purposes because of its additive decomposability (e.g. by groups or by sources), which allows to attribute the individual contributions of groups to the overall inequality into within and between elements (Shorrocks & Wan, 2005; Shorrocks, 1984). In our case, decomposing the inequality of the harvested areas of the five crops combined into its components was useful to understand the contribution of each crop to total inequality. The GEI is defined as:

$$GEI = \begin{cases} -\sum_i f_i \log\left(\frac{y_i}{\mu}\right), & c = 0 \\ \sum_i f_i \left(\frac{y_i}{\mu}\right) \log\left(\frac{y_i}{\mu}\right), & c = 1 \\ \frac{1}{c(c-1)} \sum_i f_i \left[\left(\frac{y_i}{\mu}\right)^c - 1\right], & c \neq 0, 1. \end{cases} \tag{3}$$

where  $f_i$  is the population share of unit  $i$ ,  $y_i$  is the considered variable's value of unit  $i$ ,  $\mu$  is the average of values of  $y_i$ , and  $c$  is a parameter that has to be selected. In our case,  $f_i$  was  $1/N$  ( $N = 2354$ ) for the share of one county among the whole country, and  $y_i$  would be areas such as harvested areas of wheat, rice, maize, soybean, potato and the combined five crops. If  $c = 0$  or  $c = 1$ , GEI becomes a special case, called the Theil index, where  $y_i$  needs to be strictly positive. Because some crops were not planted in certain countries in our study, which means  $y_i$  can be zero, we could not use the Theil index with  $c = 0$  or  $c = 1$ . Therefore, we set  $c = 2$  following standard practice (Bellù & Liberati, 2006a, 2006b), which yields one half of the squared coefficient of variation, CV:

$$GEI(2) = \frac{1}{2} CV^2 \tag{4}$$

where

$$CV = \frac{1}{\mu} \left[ \frac{1}{N} \sum_{i=1}^N (y_i - \mu)^2 \right]^{1/2} \text{ and } 0 \leq GEI(2) \leq \frac{1}{2}(N - 1)$$

Since the logic of the decomposition by source is the same as in the case of the decomposition by subgroups, the GEI can be decomposed into individual contributions as follows:

$$GEI = \frac{1}{c(c-1)} \left[ 1 - \sum_j g_j \left(\frac{\mu_j}{\mu}\right)^c \right] + \sum_j GEI_j g_j \left(\frac{\mu_j}{\mu}\right)^c \quad c \neq 0, 1 \tag{5}$$

where  $j$  refers to each subgroup,  $\mu_j$  refers to the area share of the group  $j$ , and  $GEI_j$  refers to the index in group  $j$ . The between-group component of concentration is captured by the first term  $\frac{1}{c(c-1)} \left[ 1 - \sum_j g_j \left(\frac{\mu_j}{\mu}\right)^c \right]$ : the level of inequality between groups. The second term  $GEI_j g_j \left(\frac{\mu_j}{\mu}\right)^c$  gives the within-group inequality. Theoretically, the GEI can range from zero to infinite, with zero indicating perfectly equal distribution and large values indicating high inequality. We calculated the GEI for every year of the study period to reveal the changes in the inequality distribution of cropland and the five crops among all counties of China.

### 3. Results

#### 3.1. Spatial clustering

Moran's I indices for cropland and for the harvested areas of the five crops were consistently above zero for each year from 1980 to 2011, indicating positive spatial clustering of county-level harvested areas (Figure 3). The harvested area of wheat exhibited the strongest clustering with a Moran's I close to 0.8 since 2000, followed by soybean and maize, all with modest increases in the spatial clustering. Cropland was less strongly clustered than the harvested areas of the individual crops, except for potatoes. In addition, cropland and the harvested areas of the individual crops except rice became more spatially clustered, particularly between 1980 and 2000 (Figure 3). Since approximately 2000, no clear trends were visible, apart from the decrease in the clustering of the harvested area of potatoes.

Figure 4 shows the LISA cluster maps for cropland in ten-year steps, and two prominent hot spots of cropland are clearly visible in northeast China (the Northeast China Plain) and in central east China (the North China Plain). These two areas have long been breadbaskets of China. The southern part of the North China Plain has been cultivated for over 4000 years and is widely regarded as the cradle of Chinese civilization. Over time, the clusters in northeast China expanded, while the hot spots in the North China Plain shrank in spatial extent. The two smaller hot spots in Inner Mongolia and around Ningxia (see Figure S1 for a map with provincial names) also contracted. Unsurprisingly, cold spots were observed in west China (Yunnan, Sichuan, Tibet, and Qinghai) and in the hilly areas in the south (Zhejiang, Fujian, Guizhou, and Guangxi) due to less favourable natural endowments and higher emigration rates from rural areas. The low-high outliers (counties with low values surrounded by counties with high values) were mainly located on the peripherals of the hot spots in northeast China and Inner Mongolia. The high-low outliers (counties with high values surrounding by counties with low values) were mainly located in southern China, where basins and small plains in the hilly regions often have high shares of cropland area, while their neighbours have low shares of cropland.

We calculated the local Moran's I for the harvested areas of the five major crops over the study period and for each year from 1980 to 2011. Because of space limits, we take maize as the example

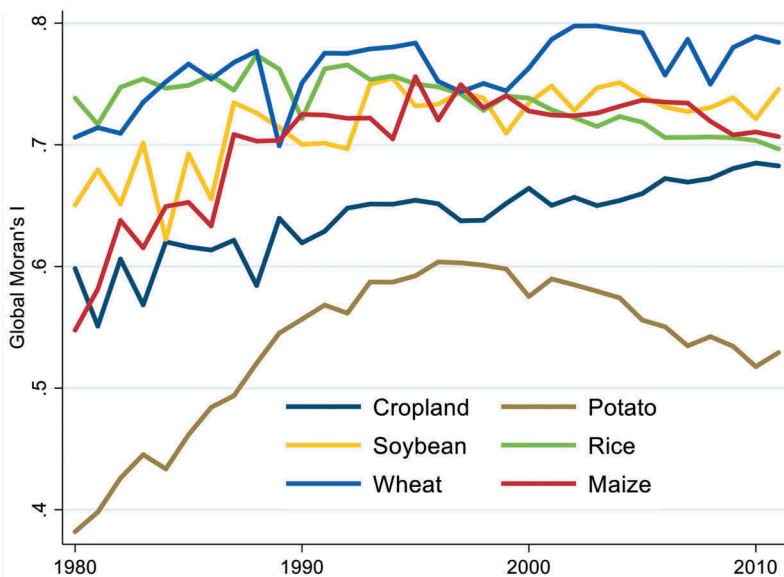


Figure 3. Global Moran's I of cropland and five crops from 1980 to 2011.



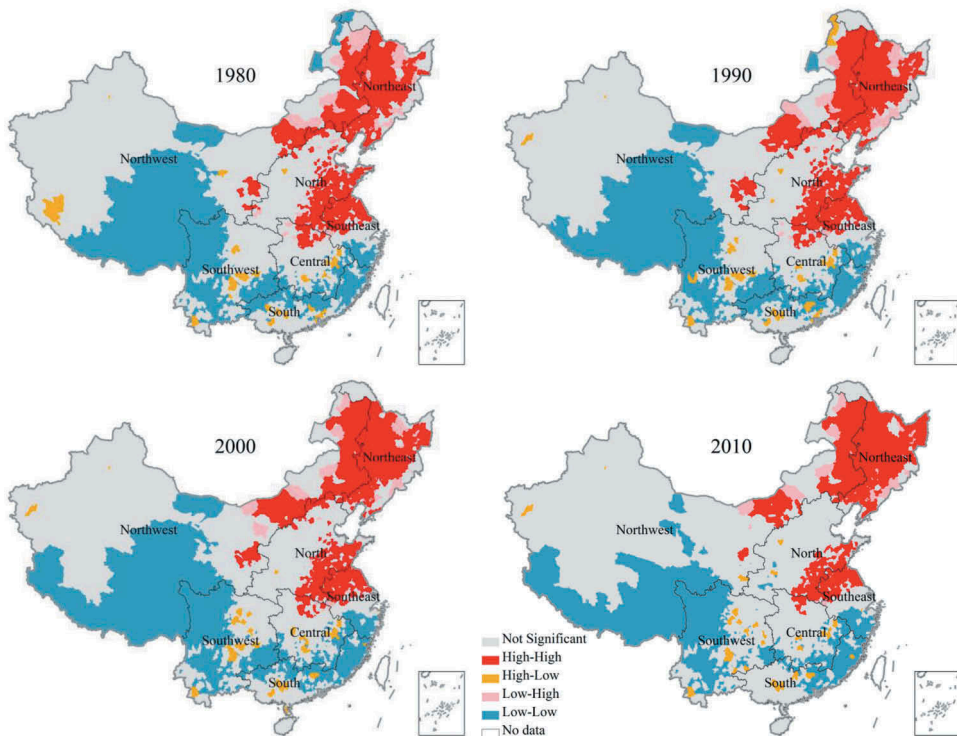


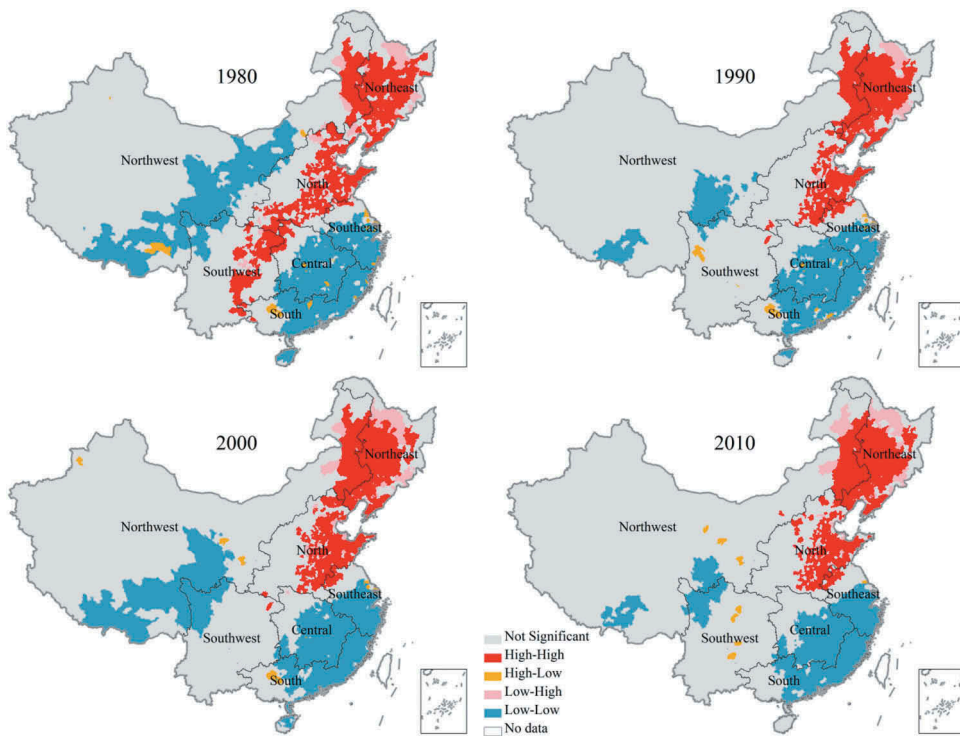
Figure 4. LISA cluster maps for cropland area from 1980 to 2010 in 10-year intervals.

to present our results (Figure 5; results for the other crops are found in the supplementary information in Figure S2). From Figure 5, the harvested area of maize in 1980 clustered in a diagonal belt stretching from southwest to northeast and sandwiched between two cold spot zones, one stretching from Tibet to Inner Mongolia in the northwest region and one that covered much of south, central, and southeast China. In subsequent time steps, the hot spot belt substantially contracted, particularly in the hilly areas of the southwest where it had already disappeared by 1990. The maize hot spots increasingly concentrated in Inner Mongolia, the northeast, and north China. Figure 5 also shows a contraction of the cold spot belt in the northwest, while the large cold spot in southeastern China remained largely intact.

### 3.2. Inequality of distribution of cropland and harvested area of crops

Figure 6 shows inequality trends for cropland and for the harvested areas of the five major crops. Figure 6(a) reveals that all cropland was distributed fairly equally (low inequality), implying few changes in the overall distribution of cropland among counties. In contrast, inequality of the harvested areas of the five major crops consistently increased. Soybean was the most unequally distributed and had the largest increase in inequality, suggesting that the area harvested with soybeans was concentrating in ever fewer counties. The increasing spatial clustering of soybean in northeast China corroborated this result (shown in Figure S2d). Potato cultivation was also unequally distributed in China, with a rise in inequality since 1990, as measured by the GEI. The other three crops were more equally distributed and showed less obvious changes over time.

The inequality in the distribution of cropland and harvested areas of crops is shown in Figure 6(a). The GEI of the total harvested area of the five crops increased rapidly after 2000 (shown by the cumulative amount of the GEI in Figure 6(b)). Note that the GEI of the total area of the five crops was



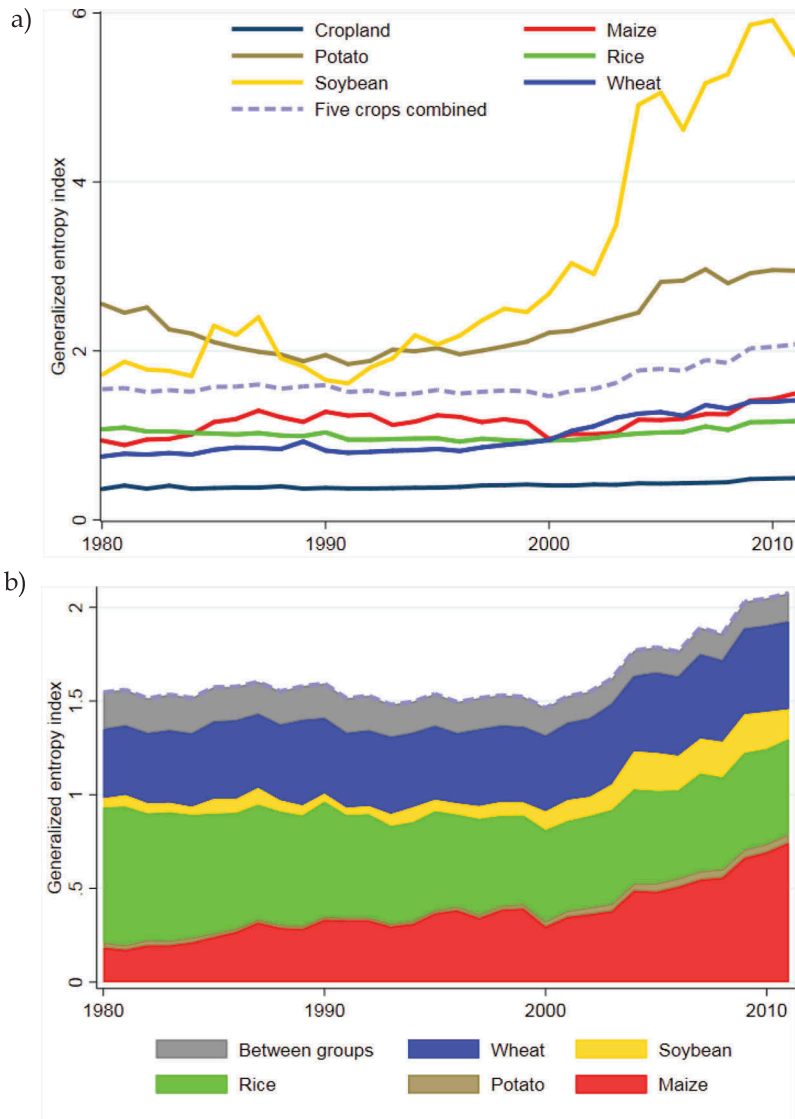
**Figure 5.** LISA cluster maps for harvested area of maize for 1980, 1990, 2000, and 2010.

not equal to the average of the GEIs of the five crops; rather, the GEI of the total area of the five crops was decomposed and attributed to individual crops based on the individual GEI values together with harvested areas as weights (see Methods section). From the decomposition of the GEI in Figure 6(b), rice and wheat accounted for more than 60% of the total inequality before 2000, while the contribution of maize increased steadily from 11% to 48%. In contrast, the contribution of rice to total inequality declined by 15% from 1980 to 2011, mostly because of total area changes in rice and maize. In addition, the rising inequality of soybean contributed to the overall rise in the inequality of crop cultivation, although the overall contribution of soybean was low due to its relatively small harvested area.

#### 4. Discussion

Our study revealed that the cultivation patterns of the major crops in China became increasingly concentrated between 1980 and 2011, albeit the increase in concentration has been small for some (e.g. rice) and larger for other crops (e.g. soybean). Even though a high spatial concentration may be beneficial for more profitable agriculture, a decrease in crop diversity can bear negative consequences, such as increased susceptibility to diseases and pests and vulnerability to weather shocks (Li et al., 2009; Sheng et al., 2017). Conversely, since overall cropland has been controlled under many of China's agricultural policies, including initiatives to maintain the red line of 1.8 billion mu (i.e. 120 million hectares) of cropland (Long, 2014), the development of all cropland was much less dynamic but still showed some tendencies of concentration.

The global Moran's I revealed increasing spatial clustering, particularly in the period from 1980 to 2000 and for wheat, maize and soybean but less so for rice and potatoes. Possibly, many of these changes towards increased concentration were brought about by the transition from a centrally



**Figure 6.** Generalized entropy index for cropland and for the harvested areas of the five selected crops (a) and decomposed harvested area of the five crops with the sum indicating total inequality (b).

planned to a market-oriented economy, which facilitated the gradual transition to more commercial-oriented farming starting in the early 1990s. During the transition, farmers were able to choose which crops to produce (and typically selected the most profitable ones) and were able to purchase agricultural inputs on the markets. For example, the spatial clustering of rice decreased since the early 1990s because farmers in hilly areas in the south increasingly diversified and converted rice paddies, in particular on sloping land, to higher-value and labour-saving crops (e.g. tea, fruits); hence, the area harvested by rice was reduced (Yu et al., 2018b). At the same time, rice production increased in northeast China due to the higher quality of rice in the region, which stimulated more market demand and thus higher price premiums.

Potato is not only a staple food for hundreds of millions of people but also a cash crop. The increase in the spatial clustering of potato can be explained by the increasing contribution of

returns from potato production to households as altitude increases. However, the spatial patterns of potato cultivation correlate not only with agroecological site conditions but also with poverty, which tends to be higher in the hilly and mountainous areas. Likely, potato cultivation will further expand in the future in response to national policies that promote potatoes as a major staple food. Nevertheless, the level of spatial clustering in potatoes was still lower than that of other crops because potatoes are more insensitive to soil and climatic conditions.

We showed that crop production in China increasingly clustered towards fewer core cultivation zones. These zones were characterized by high natural suitability for agriculture and by beneficial market access (Li, Coates, Li, Ye, & Leipnik, 2017; Weinzettel, Hertwich, Peters, Steen-Olsen, & Galli, 2013). They were located to the east of the so-called Hu Line (Figure S1), where most economic output concentrates and where more than 90% of the population resides (Hu, 1990). This region is where the earliest traces of agricultural cultivation have been found in China (Yang, Guo, Jin, Long, & Zhou, 2015). Interestingly, the cultivation of the major crops seems to increasingly concentrate in these cradles of Chinese agriculture. The economic transition, from a largely agricultural country to one where an increasing share of the workforce is employed in industry and in the service sector, has been a key underlying driver for the increasing concentration of the cultivation of major crops to the east of the Hu line. In addition, some of these regions (e.g. the north China plain and northeast China plain) have more suitable topography for the use of machinery and thus attract investments into capital-intensive agricultural intensification.

China's government postulated self-sufficiency in grain production in 1995 (Brown, 2012) and heavily subsidized grain production since then (Huang, Wang, Zhi, Huang, & Rozelle, 2011; Li, Deng, Yin, & Yang, 2015). These subsidies focused on the important grain production regions, i.e. the abovementioned plain areas. As a result, major grain crops are increasingly concentrated in these regions. In contrast, rural areas, where profitable agriculture is compromised by difficult topography, low fertility, or adverse market accessibility, increasingly lose out because of emigration of the workforce in search of better income opportunities and the associated ageing of the rural population that are left behind. Nature conservation policies, such as the Sloping Land Conversion Programme, reinforce this development by encouraging the retirement of marginal land from agricultural production. However, some centres of intensive agriculture disappeared from the local cluster maps (Figure 4). For example, the Sichuan basin, the most important agricultural region in western China, disappeared from the hot spot maps of the major crops, especially for the case of maize (Figure 5). The Sichuan basin is very densely populated and characterized by extremely small farm sizes. Most agricultural production focuses on crops with high value added, such as vegetables and fruits, and on intensive livestock production.

Our analysis on inequality revealed rising inequality of cropland and of harvested areas of the five major crops, albeit only slightly for most crops except soybean. Hence, crop cultivation was increasingly concentrated in fewer counties, irrespective of changes in the size of the harvested area. For example, the inequality of the harvested area of soybean soared after 1995, while the total harvested area of soybean decreased during this period. The increasing globalization of agricultural production mainly caused the dynamics in the concentration of harvested areas of soybean. China became a member of the WTO in 2001. Since then, the Chinese demand for soybean skyrocketed, mainly to meet protein consumption of the growing monogastric livestock numbers. By 2011, soybean imports satisfied 70% of the total soybean consumption (FAO, 2015), because soybean imports from the large farms in the Americas achieve far higher profit margins than those of Chinese soybean producers (Sly, 2017; Song, Marchant, Reed, & Xu, 2009). The decomposition of inequality (Figure 6(b)) illustrated that maize became the preponderant crop for the growing overall inequality because of the increase in its harvested area share over the five major crops combined and because of increasing domestic demand and rising prices for maize as a feed source for livestock (Meng, Hu, Shi, & Zhang, 2006).

Subnational statistics on agriculture in China may not convey the complete truth due to inaccuracies in measurement and biased reporting (Gale, 2002). As a result, the spatial patterns

that we revealed for the five main crops and for overall cropland may bear considerable uncertainty. Moreover, we were not able to examine the diversity of less important crops with lower harvested area, because data for these crops frequently suffer from missing values and high measurement inaccuracies. While most previous assessments had to rely on provincial-level data, we relied on county-level data with much higher spatial resolution. However, the scale of our analysis remained coarse. Unfortunately, national crop maps that rely on wall-to-wall remote sensing imagery are, to the best of our knowledge, not available to date. Such maps would provide a better database for more accurate assessments of the concentration patterns of China's agricultural production.

## 5. Conclusions

Crop production in China became increasingly concentrated in terms of its spatial distribution since 1980. All cropland and the harvested area of the major crops gradually concentrated in the major historic breadbaskets of eastern China, especially since 1990. Maize and soybean changed most dynamically since 1990, with both increasingly unequally distributed, despite diverging trends in their harvested areas that substantially increased for maize but decreased for soybean. Agricultural policies, such as the rural land reform, changes in trade patterns, and nature conservation policies as well as changing domestic diets all played an important role in shaping the spatial clustering and inequality among crops and in the overall concentration of cropland.

The increasing concentration can have positive effects on crop productivity through effects of technology spillover, processing facilities, and knowledge. In addition, with the increasing concentration, the recovery of nature may benefit in areas where crop production contracted in terms of area used and of cultivation intensity. However, a higher concentration of production of major staple crops may also lead to higher vulnerability to climate change, natural hazards, and disease outbreaks. This research revealed the complex dynamics of the spatial concentration in cropland and major crops with the example of China, and we envision these results to foster the implementation of mitigation measures that reduce agricultural production risks and increase the resilience of the agricultural production system.

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## Disclosure statement

No potential conflict of interest was reported by the authors.

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## References

- Alexander, P., Rounsevell, M.D.A., Dislich, C., Dodson, J.R., Engström, K., & Moran, D. (2015). Drivers for global agricultural land use change: The nexus of diet, population, yield and bioenergy. *Global Environmental Change*, 35, 138–147.
- Anselin, L. (1995). Local indicators of spatial association -LISA. *Geographical Analysis*, 27, 93–115.

- Bellù, L.G., & Liberati, P. (2006a). *Policy impacts on inequality decomposition of income inequality by subgroups policy impacts on inequality* (pp. 1–23). EASYPol.
- Bellù, L.G., & Liberati, P. (2006b). *Policy impacts on inequality decomposition of income inequality by income source* (p. 14). EASYPol.
- Bren d'Amour, C., Reitsma, F., Baiocchi, G., Barthel, S., Güneralp, B., Erb, K.-H., ... Seto, K.C. (2016a). Future urban land expansion and implications for global croplands. *Proceedings of the National Academy of Sciences of the United States of America*, 114, 201606036.
- Bren d'Amour, C., Wenz, L., Kalkuhl, M., Christoph Steckel, J., & Creutzig, F. (2016b). Teleconnected food supply shocks. *Environmental Research Letters*, 11, 035007.
- Brown, L. R. (2012). *Full planet, empty plates: The new geopolitics of food scarcity*. W. W. Norton & Company.
- Brühlhart, M., & Traeger, R. (2005). An account of geographic concentration patterns in Europe. *Regional Science and Urban Economics*, 35, 597–624.
- DeFries, R., Fanzo, J., Remans, R., Palm, C., Wood, S., & Anderman, T.L. (2015). Metrics for land-scarce agriculture. *Science*, 349, 238–240.
- FAO. (2015). Data from: FAOSTAT database on agriculture. *Journal of Food and Agricultural Organization*. United Nations. Retrieved from <http://www.fao.org/faostat/en/#home>
- Frayser, J., Müller, D., Sun, Z., Munroe, D., & Xu, J. (2014). Processes underlying 50 years of local forest-cover change in Yunnan, China. *Forests*, 5, 3257–3273.
- Fujita, M., & Thisse, J.F. (2009). New economic geography: An appraisal on the occasion of Paul Krugman's 2008 nobel prize in economic sciences. *Regional Science and Urban Economics*, 39, 109–119.
- Gale, F. (Ed.). (2002, April). *Market and trade economics division, economic research service* (China's Food and Agriculture: Issues for the 21st Century. Agriculture Information Bulletin No. 775). Washington, DC: U.S. Department of Agriculture. Retrieved from <http://www.ers.usda.gov/Publications/AIB775/>
- He, F., Shi, Y., Luo, R., Zhang, L., Johnson, N., & Rozelle, S. (2015). Irrigation investment in China: Trends, correlates and impacts. *China Agricultural Economic Review*, 7, 344–359.
- Hu, H. (1990). The distribution, regionalization and prospect of China's population. *Acta Geologica Sinica*, 2, 139–145.
- Huang, J., Wang, X., Zhi, H., Huang, Z., & Rozelle, S. (2011). Subsidies and distortions in China's agriculture: Evidence from producer-level data. *Australian Journal of Agricultural and Resource Economics*, 55, 53–71. doi: 10.1111/j.1467-8489.2010.00527.x
- Irwin, E.G., & Bockstael, N.E. (2002). Interacting agents, spatial externalities and the evolution of residential land use patterns. *Journal of Economic Geography*, 2, 31–54.
- Jepsen, M.R., Kuemmerle, T., Müller, D., Erb, K., Verburg, P.H., Haberl, H., ... Reenberg, A. (2015). Transitions in European land-management regimes between 1800 and 2010. *Land Use Policy*, 49, 53–64.
- Ji, L., You, L., See, L., Fritz, S., Li, C., Zhang, S., & Li, G. (2018). Spatial and temporal changes of vegetable production in China. *Journal of Land Use Science*, 00, 1–14.
- Kuemmerle, T., Levers, C., Erb, K., Estel, S., Jepsen, M.R., Müller, D., ... Reenberg, A. (2016). Hotspots of land use change in Europe. *Environmental Research Letters*, 11. doi:10.1088/1748-9326/11/6/064020
- Lerman, R.I. (1984). A note on the calculation and interpretation of the Gini index. *Economics Letters*, 15, 363–368.
- Levers, C., Müller, D., Erb, K., Haberl, H., Jepsen, M.R., Metzger, M.J., ... Kuemmerle, T. (2018). Archetypical patterns and trajectories of land systems in Europe. *Regional Environmental Change*, 18, 715–732.
- Li, C., He, X., Zhu, S., Zhou, H., Wang, Y., Li, Y., ... Zhu, Y. (2009). Crop diversity for yield increase. *PLoS one*, 4, 0–5.
- Li, E., Coates, K., Li, X., Ye, X., & Leipnik, M. (2017). Analyzing agricultural agglomeration in China. *Sustainability*, 9, 313.
- Li, Z., Deng, X., Yin, F., & Yang, C. (2015). Analysis of climate and land use changes impacts on land degradation in the North China plain. *Advances in Meteorology*, 2015, 1–11.
- Liu, J., Kuang, W., Zhang, Z., Xu, X., Qin, Y., Ning, J., ... Chi, W. (2014). Spatiotemporal characteristics, patterns, and causes of land-use changes in China since the late 1980s. *Journal of Geographical Sciences*, 24, 195–210.
- Liu, L., Xu, X., Zhuang, D., Chen, X., & Li, S. (2013). Changes in the potential multiple cropping system in response to climate change in China from 1960–2010. *PLoS one*, 8, 1–12.
- Long, H. (2014). Land use policy in China: Introduction. *Land Use Policy*, 40, 1–5.
- Long, H., Li, Y., Liu, Y., Woods, M., & Zou, J. (2012). Accelerated restructuring in rural China fueled by “increasing vs. decreasing balance” land-use policy for dealing with hollowed villages. *Land Use Policy*, 29, 11–22.
- Mehrabi, Z., & Ramankutty, N. (2018). On the synchronized failure of global crop production. doi:10.1101/287391
- Meng, E.C.H., Hu, R., Shi, X., & Zhang, S. (2006). *Maize in China: Production systems, constraints and research priorities*. D. F.: Cimmyt.
- Monfreda, C., Ramankutty, N., & Foley, J.A. (2008). Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000. *Global Biogeochemical Cycles*, 22. doi:10.1029/2007GB002947
- Moran, P.A.P. (1950). Notes on continuous stochastic phenomena. *Biometrika*, 37, 17.
- Mussard, S., Seyte, F., & Terraza, M. (2003). Decomposition of gini and the generalized entropy inequality measures. *Economic Bulletin*, 4(7), 1–6.

- Ramankutty, N., Mehrabi, Z., Waha, K., Jarvis, L., Kremen, C., Herrero, M., & Rieseberg, L.H. (2018). Trends in global agricultural land use: Implications for environmental health and food security. *Annual Review of Plant Biology*, 69, 789–815.
- Ricardo, D. (1817). On the principles of political economy and taxation. *Batoche Books*. doi:10.1088/1751-8113/44/8/085201
- Sheng, J., Gao, F., Andile, M., Wang, L., Sandhu, H.S., Ouyang, F., & Zhao, Z.H. (2017). Crop diversity and land simplification effects on pest damage in northern China. *Annals of the Entomological Society of America*, 110, 91–96.
- Shorrocks, A., & Wan, G. (2005). Spatial decomposition of inequality. *Journal of Economic Geography*, 5, 59–81.
- Shorrocks, A.F. (1984). Inequality decomposition by population subgroups. *Econometrica*, 52, 1369–1385.
- Sly, M.J.H. (2017). The Argentine portion of the soybean commodity chain. *Palgrave Communication*, 3, 17095.
- Song, B., Marchant, M.A., Reed, M.R., & Xu, S. (2009). Competitive analysis and market power of China's soybean import market. *International Food and Agribusiness Management Review*, 12, 21–42.
- Thünen, J.H., & Von, Hall, P.G. (1966). *Von Thunen's isolated state : An English edition of Der isolierte Staat* (1st ed.). Oxford, London: Pergamon Press.
- Václavík, T., Lautenbach, S., Kuemmerle, T., & Seppelt, R. (2013). Mapping global land system archetypes. *Global Environmental Change*, 23, 1637–1647.
- Weinzettel, J., Hertwich, E.G., Peters, G.P., Steen-Olsen, K., & Galli, A. (2013). Affluence drives the global displacement of land use. *Global Environmental Change*, 23, 433–438.
- Xie, H., & Liu, G. (2015). Spatiotemporal difference and determinants of multiple cropping index in China during 1998–2012. *Acta Geologica Sinica*, 70, 604–614.
- Xu, S., Wu, J., Song, W., Li, Z., Li, Z., & Kong, F. (2013). Spatial-temporal changes in grain production, consumption and driving mechanism in China. *Journal of Integrative Agriculture*, 12, 374–385.
- Yan, H., Liu, J., Huang, H.Q., Tao, B., & Cao, M. (2009). Assessing the consequence of land use change on agricultural productivity in China. *Global and Planetary Change*, 67, 13–19.
- Yang, X., Guo, B., Jin, X., Long, Y., & Zhou, Y. (2015). Reconstructing spatial distribution of historical cropland in China's traditional cultivated region: Methods and case study. *Chinese Geographical Science*, 25, 629–643.
- Yu, Q., Hu, Q., van Vliet, J., Verburg, P.H., & Wu, W. (2018a). GlobeLand30 shows little cropland area loss but greater fragmentation in China. *International Journal of Applied Earth Observation and Geoinformation*, 66, 37–45.
- Yu, Q., van Vliet, J., Verburg, P.H., You, L., Yang, P., & Wu, W. (2018b). Harvested area gaps in China between 1981 and 2010: Effects of climatic and land management factors. *Environmental Research Letters*, 13, 044006.
- Zhang, M., Jin, Y., & Zheng, F. (2016). *Investigating the "one farm household, two production systems" in rural China: The case of vegetable and fruit farmers* (p. 235959). Boston, Massachusetts: Agricultural and Applied Economics Association.