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Determinants of changes in harvested area and yields of major crops in China

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Abstract

Global agricultural production has risen substantially in recent decades and needs to rise further to meet the ever-growing food demand. While higher production can be directly attributed to agricultural expansion and intensification, the underlying factors behind the changes in cultivated areas and yields can be complicated and have not been well understood. China has dramatically increased its food production in past decades, especially during the initial approximately 30 years following the commencement of the rural reform in the late 1970s. The agricultural land use, including cropland areas, the composition of different crops and their spatial distributions, and crop yields have experienced substantial changes. In this research, we quantitatively analysed the changes in the harvested areas and yields of the four most widely cultivated crops in China (rice, wheat, maize, and soybean) at the county level from 1980 to 2011. We used spatial panel regressions to quantify the determinants of the observed changes in harvested area and yields for the major cultivation region of each of the four crops. Results showed that growth in population, gross domestic product, and urbanisation are positively associated with harvested areas. Higher usage of machinery and fertiliser inputs increased yields of the three cereal crops, while the harvested area of soybean decreased, particularly after China's accession to the WTO. Our findings reveal how domestic urbanisation and changes in consumption patterns, coupled with the rising globalisation of agricultural markets, shaped China's agricultural production and land use over the three decades. These insights shed light on the determinants of long-term agricultural dynamics and thus inform evidence-based decision-making.

Keywords Agricultural production · Land-use intensity · Crop productivity · Land-use change · Food security · Spatial panel regression

1 Introduction

Food security continues to be a major concern for humanity and is an intrinsic element of sustainable development (Godfray, Beddington et al., 2010). Future agricultural

production must increase to meet the ever-increasing food demand due to population growth, higher demands for plant-based energy production, and more resource-demanding diets. While the increased food production in the past, particularly after the green revolution started

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in the 1950s, was mainly achieved by agricultural land expansion and intensification, future production increases, however, must be achieved at lower environmental costs (Alexander et al., 2015; Garnett et al., 2013; Popp et al., 2016). A few crops play a particularly important role in food security as they provide the majority of the energy and essential nutrients (Khoury et al., 2014). Overall, humanity obtains 50% of its daily calories from cereals, and more than 40% of these calories are from only three major staple crops: rice, wheat, and maize (FAO, 2019; Kearney, 2010). Moreover, the growing consumption of livestock products, which are increasingly produced in industrial production systems, requires large amounts of feed and fodder, which are mainly sourced from maize, as the source of energy, and soybean, which provides the proteins for animal growth (Cassidy et al., 2013). In 2017, half of the 1.42 billion hectares (Bha) of the global harvested area were cultivated with only four crops: wheat, maize, rice, and soybean (FAO, 2019). Understanding changes in the area dedicated to these major crops and their yields provides critical insights for better understanding the agricultural dynamics that shape the salient changes in the food system.

While the overall share of the four major crops in the global harvested area and production volume has remained stable over the last 50 years, the contribution of the individual crops to the overall production quantities has substantially changed over time. The proportion of wheat in the total harvested area decreased from 22% in 1967 to 15% in 2017. At the same time, the area occupied by maize increased from 11% in 1967 to 14% in 2017, equivalent to an absolute increase of 85 million ha (Mha). The increase in soybean cultivation has been especially drastic, with an increase greater than 95 Mha, or from 3 to 9% of the global harvested area during this 50-year period (FAO, 2019).

The sweeping changes in the global patterns of crop cultivation have been driven by interlinked political, socioeconomic, climate change, and biophysical factors. Where these crops are produced depends on locational factors that shape land rents, including climate, soil, and accessibility, while changes in economic, institutional, political, and demographic characteristics drive the changes in cultivation patterns (Meyfroidt, 2016). For example, the spatial patterns of food production and consumption have been transformed by the globalisation of the food system, manifested by the shift from locally produced food to an increasing reliance on agricultural commodities that are sourced from distant markets (Levers & Müller, 2019).

While the overall cropland area only increased moderately, much of the recent global increase in crop production has been due to higher crop yields, mainly as a result of higher input intensity per unit area (Magliocca et al., 2015; Rudel et al., 2009). The intensification of production has

greatly benefitted global food security because it has saved substantial land resources from being converted into agricultural production (Borlaug, 2007; Burney et al., 2010). However, the intensification may also provoke rebound effects by raising profits from production and lowering food prices, thereby incentivising further expansion (Lambin & Meyfroidt, 2011; Rudel et al., 2009). Understanding the patterns and determinants of intensification processes remains important because of the adverse side effects that can result from higher input intensity, such as nutrient leaching, water pollution, air pollution, and negative effects on human health (Godfray, Crute et al., 2010; Tilman et al., 2011).

China is a particularly interesting case because the country's rapid economic development has had substantial effects on land use (Deng et al., 2015; Jiang et al., 2013; Sun et al., 2018). China has experienced drastic changes in agricultural production and land systems in the past years. Agricultural production has increased dramatically in China following the reforms initiated in 1978 that shifted farmland use rights from communes to millions of farm households—the so-called household responsibility system (Huang & Rozelle, 2018; Lin et al., 2022). Agricultural production has taken off ever since. China's real agricultural output value grew at an annual rate of 5.3 percent between 1978 and 2017 (Sheng et al., 2020).

At present, China is by far the largest producer and consumer of rice and wheat in the world; the government views self-sufficiency in the production of these crops as critical for securing China's "rice bowl" (i.e., producing sufficient food for China) (Zhang, 2019). Maintaining domestic food security, defined by the Chinese government as a 95% degree of grain self-sufficiency, remains a top policy priority and is a strategic goal on China's food security agenda (Huang & Yang, 2017). The lingering COVID pandemic and ongoing Russia-Ukraine conflict have pushed food security even higher on the Chinese government's agenda (Hellegers, 2022; Pu & Zhong, 2020).

To achieve the policy goals, the Chinese government has implemented a strict policy to protect its arable land, the so-called "arable land red line policy", which aims to maintain at least 1.8 billion mu (i.e., 120 Mha) of agricultural land in production. In addition, China set up a guaranteed grain procurement price for wheat, rice, and maize, among others, to foster grain production. While China become the largest food importer, particularly of soybeans and maize, in the world, the key staple crops, wheat and rice, continue to be largely produced domestically, mainly to reduce reliance on imports and to guarantee domestic food security (Huang et al., 2017). However, China faces daunting challenges in striving for the envisaged domestic food security. The domestic demand for agricultural products has been rapidly increasing, mainly because of population growth, and a dietary structural shift from mainly plant-based food

towards diets with a higher reliance on animal proteins—driven by urbanisation and growing affluence (Huang et al., 2015; Jiang et al., 2015; Zhao et al., 2021).

Achieving production increases is hampered by the small farm structure—the average farm size in China was approximately 0.5 ha in 2015 (Wu et al., 2018) and the high fragmentation of farms, which hinders higher capital inputs, agricultural modernisation, and realisation of economies of scale (Lai et al., 2020; Zhang et al., 2013). Cropland per capita amounted to only 0.09 ha per capita in 2016 in China, and the scarcity of land resources becomes even more severe with the loss of arable land caused by urbanisation, land degradation, and soil contamination (Bren d'Amour et al., 2016; Deng & Li, 2016). The contrast between the low income from agriculture and the rising wage levels from urban employment opportunities drives the massive migration from rural to urban areas. Since the 2000s, many rural areas have started to depopulate and are suffering from labour shortages because of the ever-increasing migration from rural areas to the growing cities (Liu et al., 2017). The aging society, partially due to the previous one-child policy, further augments rural labour scarcity and raises the question of who will cultivate China's agricultural land in the future. The fundamental changes in the Chinese countryside have profound effects on the extent and input intensity of agriculture and, consequently, on agricultural production outputs. It is vital to understand the impact of these changes on agricultural production strategies and, thus, on agricultural productivity.

The spatial composition of crop cultivation in China has changed notably in the last three decades. Rice, arguably the most important staple food for the Chinese, has traditionally been cultivated in southern China. However, in recent years, rice cultivation has expanded in Northeast China because the japonica rice grown in the north is in high demand due to its superior nutritional value and good taste (Sun et al., 2018). In contrast, the harvested area of rice in the south has decreased due to multiple factors such as urbanisation, cropland abandonment, and reduced cultivation intensity reflected in the multi-cropping index (Jin & Zhong, 2022; Liu et al., 2013). Combined with climate change, the centroid of the rice plantation area has already shifted 230 km to the northeast (Hu et al., 2019; Li et al., 2015; Liu et al., 2013). Wheat is the main staple crop in northern China. Approximately 126 million metric tons of wheat were produced on 24 Mha in 2011, and most of this wheat was cultivated extensively and rotated with maize. Moreover, China has become the second-largest maize producer in the world. The harvested area of maize increased from 20 Mha in 1980 to 36 Mha in 2011, mainly in response to the increasing demand for maize as a feed crop for China's growing livestock population. Maize production is concentrated in the plain regions stretching from the northeast to the southwest

(Li, 2009; Yin et al., 2018). Overall, rice, wheat, and maize account for 80% of the total harvested area in China, with an increasing trend. Conversely, the area cultivated with soybeans decreased slightly, and yields have remained stable since approximately 1980 (Sun et al., 2018).

The changes in harvested area, crop structures, and yields have stark implications for food security and the environment. However, the existing literature on the patterns, determinants, and drivers of changes in cropland structures in China has focused on individual crops, such as rice (Hu et al., 2019; Jin & Zhong, 2022; Li et al., 2015; You, 2012; Yu et al., 2022) or maize (Li, 2009). To the best of our knowledge, a holistic assessment of the spatial changes in cropping structures and productivity, how these have changed in all of China, and what factors have determined these changes is still lacking. Here we analyse the determinants for the changes in harvested areas and yields of four major crops (rice, wheat, maize, and soybean) at the county level with spatial panel regressions that account for spatial and serial autocorrelations in the data. We aim to answer two key research questions:

1. How did the harvested areas and yields of the four major crops change between 1980 and 2011?
2. What were the main determinants for the changes in the harvested area and yield of each of these crops?

2 Data

We utilised spatial panel data from 2,354 counties and from each year from 1980 to 2011—the first three decades after the rural reform when the most drastic changes in cropland area and crop yields happened. The rural reform of China started from a grassroots initiative in Fengyang County, Anhui province, in 1978 and soon spread to other counties in Anhui and Sichuan provinces. But only in 1980, the household responsibility system (HRS) was officially endorsed by the central government and implemented nationwide (Lin, 1988). Therefore, we purposely chose this period when the sweeping changes in agricultural production happened, mainly driven by institutional reforms. All data were sourced from the statistical yearbooks of the Chinese government. The panel setup allows to control for variables that cannot be observed or measured, such as cultural factors or differences in agricultural practices across observations, and to control for variables that change over time but not across observations (Hsiao, 2007). We focused our analysis on the four major crops, i.e., rice, wheat, maize, and soybean, which covered 90% of the cultivated areas and 92% of the grain production quantity in China in 2011. In total, we estimated eight crop-specific regressions with the annual harvested areas of each of the four crops and their yields as the response variables.

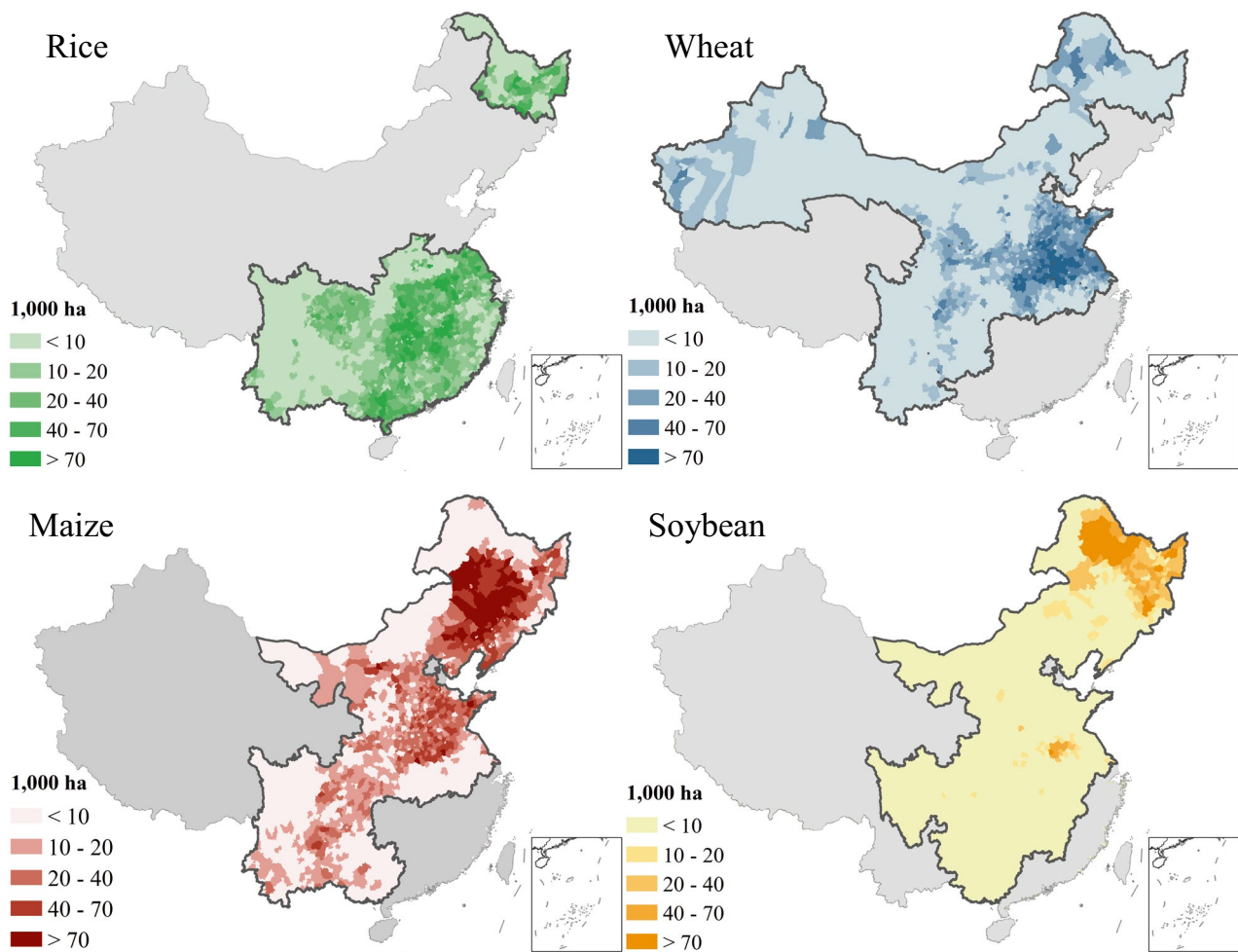


Fig. 1 Main cultivation region of each crop (thick black outline). These regions harboured more than 90% of the entire harvested area of each crop in 2011

Crop production in China is spatially clustered in specific regions (Sheng et al., 2017; Yin et al., 2018). We confined the four crop-specific regressions to the main cultivation region of each crop. To define these regions, we selected the provinces with the largest harvested area in 2011 in descending order until more than 90% of each crop's harvested area was included. The main cultivation regions visualise the most important centres of production for each crop (Fig. 1). Rice clusters in Northeast and South China; wheat is mostly located in the northern part; maize dominates in a belt from the northeast to southwest; soybean is concentrated in the northeast. In contrast to the harvested areas of each of the four crops, the crop yields did not show obvious spatial clusters (Supplementary Fig. S1).

The choice of the explanatory variables was based on a thorough literature review and prior knowledge about land use in China (Shi et al., 2013; Tong et al., 2003; Yu et al., 2016) but was also constrained by data availability. The harvested area and yields of the major crops can be influenced

by many factors, including political, socioeconomic, management, technological, and biophysical factors. We tested the model with different combinations of the variables to attain the most plausible and generalizable model. The socioeconomic variables, which we selected from the Chinese statistical yearbooks, include the gross domestic product (GDP) per county as a proxy for economic performance, road length per county to capture market accessibility, and the population per county (in thousands) to measure the local demand for agricultural products, which may affect the extent and patterns of cultivation. The GDP value was adjusted for inflation by employing the consumers' price index (CPI) with the reference year set as 2010. We hypothesized that the GDP values in preceding years might impact the harvest area and crop yields. Consequently, we used lagged GDP, specifically GDP(t-1), in the model. We accounted for the agricultural labour input (in thousands), the horsepower of machinery (in 1000kw) used in agricultural production, and the use of fertiliser in agricultural production to represent

land-use intensity. We further employed two time-variant biophysical factors that we hypothesised to be important spatial determinants for the location of crop cultivation: the growing degree days as the accumulated temperature over 10 degrees and the total rainfall for every year (Deryng et al., 2014; Hu et al., 2019). Finally, we included a dummy variable that captures the admission of China to the World Trade Organization (WTO) in 2001 as a potentially important variable affecting the amount of crop imports, which may determine the domestic patterns of agricultural production.

All explanatory variables from the statistical yearbooks are available at the county level for every year from 1980 to 2011; we resampled or aggregated the biophysical variables to the county level. As the study areas for each crop differ from each other, the statistics of the explanatory variables also differ for each crop. While the application of capital inputs for agriculture (i.e., machinery, fertiliser), as well as GDP and road length, have increased substantially in the main cultivation regions of all crops, labour input has decreased (Fig. 2). The population increased by 35% over the study period, but agricultural labour decreased by 20%. As expected, rainfall and growing degree days fluctuated over time, with a slightly increasing trend in the number of growing degree days.

3 Methods

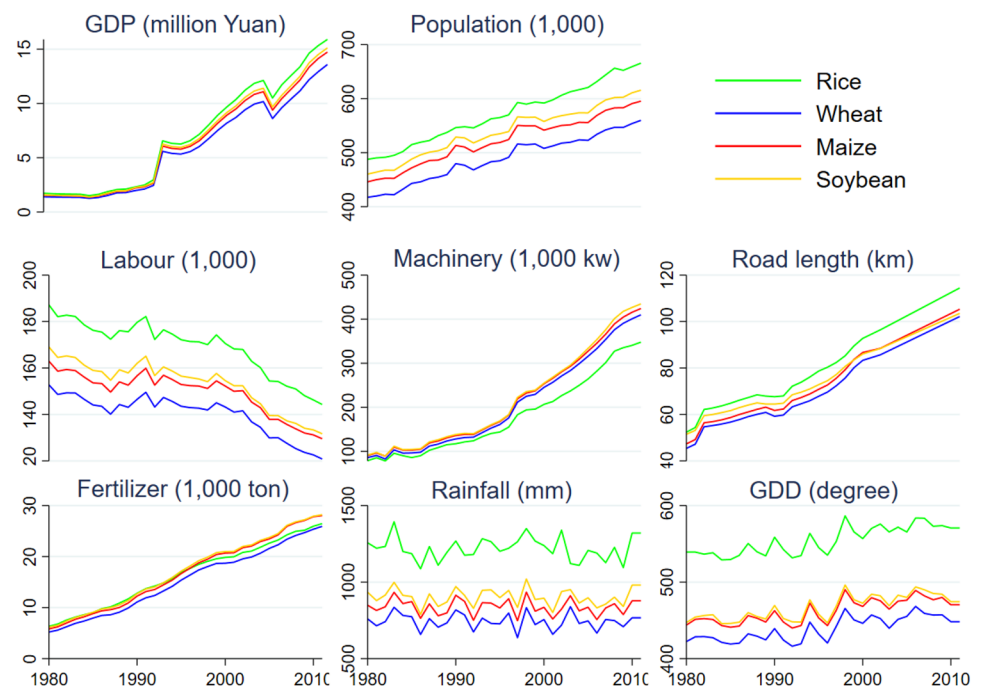
Given the spatial dynamic nature of the changes in the crop-land area and yields, we chose the spatial panel regression model, a state-of-the-art statistical model, in this research.

Regression models must correct for the presence of spatial autocorrelation in the dependent variable because it violates the standard assumption of independent observations in regression analysis, similar to serial correlations in time series data. To test for the presence of spatial autocorrelation in the dependent variables, we calculated Moran's I separately for harvested areas and yields for all cultivation regions of the four crops. We consistently found statistically significant spatial clustering for the harvested areas and yields, implying the existence of positive autocorrelation. We correct for the autocorrelations over time and space with spatial panel models (Belotti et al., 2017; Elhorst, 2010, 2012). We tested different models that controlled for time lags, spatial lags, spatial errors, or a combination thereof. To select the appropriate model, we used the Akaike information criteria (AIC). Finally, we used the Hausman test to decide between random and fixed effect formulations. The results suggested the fixed effects formulation as appropriate and, in consequence, all time-invariant variables cancel out of the regressions. The spatial autoregressive model is as follows:

$$y_t = \rho W y_t + \beta X + \tau t + \varepsilon \quad (1)$$

W is an $n \times n$ (n is the number of the spatial observations, in our case, counties) spatial weights matrix that describes the spatial neighboring relationship: w_{ij} takes a positive value if county i is a neighbor of county j , otherwise 0. w_{ij} is the (i, j) th element of W , where i and $j = (1, \dots, n)$. The spatial lag term $W y_t$ is the spatially weighted average of the value of y in the neighbouring locations, i.e., counties. ρ is the spatial autoregressive coefficient, and ε is the error term, and X the

Fig. 2 Trends of county-level explanatory variables in the main cultivation regions of the major crops



vector of the explanatory variables. To capture the influence of aggregate temporal trends (e.g., the technological progress), we included the year values in the regression with τ denoting the time coefficient.

The spatial weights matrix, W , account for the spatial autocorrelation. There are no universal rules for the choice of the neighbourhood structure, size, and weight of individual neighbours. We, therefore, tested several realisations of the spatial weights matrix to assess the sensitivity of the results to the choice of the neighbourhood structure. Here we reported the results with the first-order rook contiguity weights, which include immediate neighbours that share a common border with the observation of interest. The implementations of the second-order weights (i.e., the inclusion of neighbors of first-order neighbors) and queen contiguity (i.e., shared border and vertexes) had minor effects on the results and do not affect their interpretation (these results can be obtained from the first author upon request). We tested for multicollinearity among explanatory variables with the variance inflation factor (VIF). As a rule of thumb, a variable with a VIF greater than 10 may merit further investigation (Miles, 2014). No major correlative structures of concern occurred in our data, as judged by the VIFs.

Finally, we assessed if our models suffer from Simpson's paradox, that is, the coefficient that relates the explanatory (x) to the response variables (y) changes sign if another variable is added to the model (Pearl, 2014). This allows testing the robustness of the models to additional model formulations by starting with one variable of interest, then consecutively adding other variables until arriving at the full model specification. We did not find any change in the variables' sign when including additional covariates in the models.

4 Results

We present all regression results in log–log form so that we can interpret the variable effects as elasticities, expressed as a percent change. For example, an elasticity of two implies that a 1% increase in the independent variable would result in a

2% increase in the dependent variables. In addition to comparing the size of the influence of each coefficient for all crops, we also calculated the standardised effect sizes that facilitate comparing the strengths of influence across the explanatory variables, irrespective of their measurement units.

4.1 Changes in harvested area and yield

The average harvested area of maize and soybean increased by 78% and 7%, respectively, while the areas of rice and wheat declined by 14% and 9%, respectively, especially between 1998 and 2004 (Fig. 3; note that we present the changes in the main cultivation regions; hence, the numbers may differ from the official statistics). The decline of rice and wheat during this period reflected the crop planting structure shift: many regions, particularly in coastal and western China adjusted the crop structure by reducing the proportion of grain crops, such as wheat and rice, and increasing cash crops and vegetables (Liu et al., 2013). The steady and sharp increase of maize, especially after year 2000, reflects the increased demand of animal feed due to the dietary change (Wang et al., 2019; Zhao et al., 2021). Government subsidies on maize also play a substantial role (Huang et al., 2013). The yields of rice, wheat, maize, and soybean increased by 40%, 46%, 61%, and 26% from 1980 to 2011, respectively. (After cross-referencing the values with other data sources, we conclude that the spikes in maize and wheat yields in 1983 are likely a data artifact; this outlier will not substantially affect the results because we have a long time series).

The area harvested with rice increased in the northeast and declined in southern China (maps with the spatial changes in harvested areas from 1980 to 2011 are in Supplementary Fig. S2 and yield changes in Supplementary Fig. S3). The main areas of wheat cultivation were in northern China, although almost every province has some wheat cultivation. The spatial patterns of changes in wheat cultivation from 1980 to 2011 show few obvious spatial patterns except the increasing spatial clustering around the North China Plain, the traditional wheat cultivation region. Maize

Fig. 3 Changes in harvested areas (left) and yields (right) per crop type in the main cultivation regions

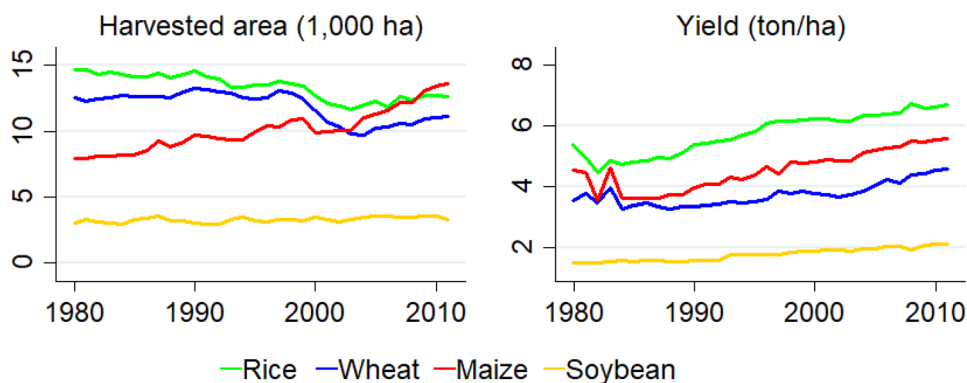
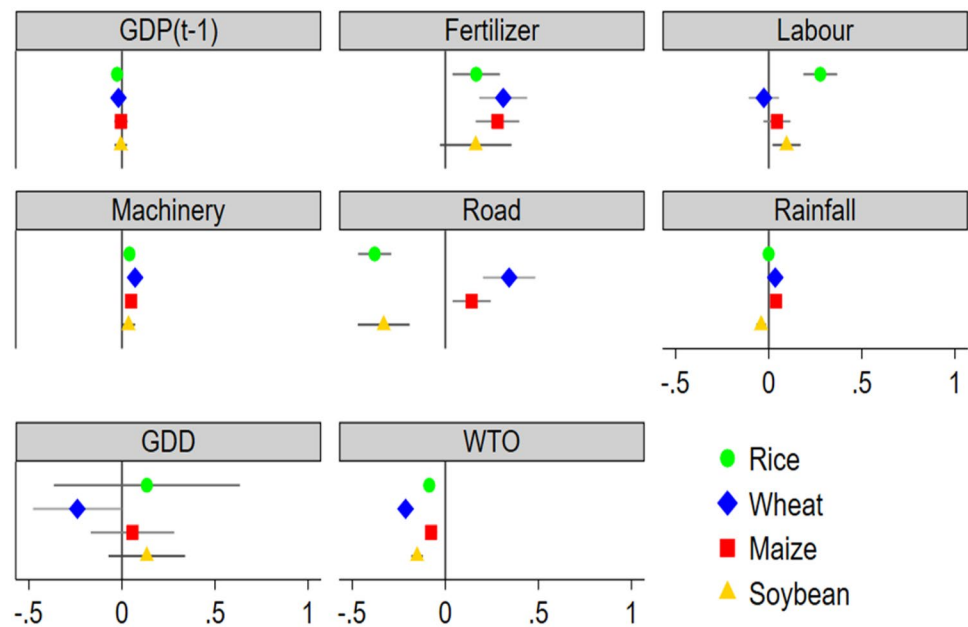


Fig. 4 Percentage change in harvested areas of each crop with a 1% increase in the explanatory variables (or in the years after the accession of WTO for the WTO dummy); markers are coefficient estimates, and whiskers denote the 95% standard errors



cultivation covered large areas stretching from the northeast to the southwest; this area is known as the Chinese maize belt (Meng et al., 2016). Soybean was increasingly concentrated in the northeast.

Crop yields showed a much more heterogeneous distribution than the area harvested. The yields of rice, wheat, and maize increased in most regions in China, while the yield of soybean decreased, especially between 1980 and 1990.

4.2 Determinants of the changes

The spatial lag of the dependent variables has strong and positive effects, which mirror the spatial concentration of the harvested areas (see Supplementary Table S4 for detailed regression results).

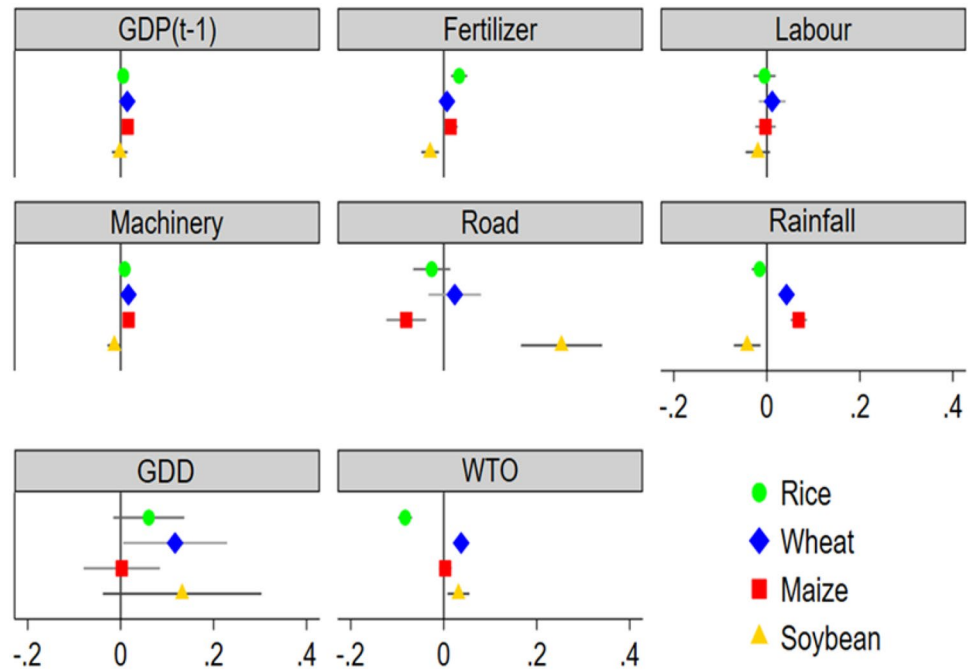
The impacts of time-varying explanatory variables quantify the effects in percent changes (Fig. 4 visualises changes in harvested areas; Fig. 5 shows changes in yields). Population is positively associated with the harvested area of crops; a 1% increase in population is associated with substantial increases in harvested areas for all four crops: 0.16% for rice and soybean, 0.33% for wheat, and 0.27% for maize. Rising agricultural labour per county also has positive influences on all crops except wheat, with the strongest effect on rice, at 0.29% per one percent increase. Road length has a mixed effect on the harvested areas: increasing road length tends to be associated with less harvested areas of wheat, rice and soybean, but the areas of wheat and maize tend to expand in counties with a denser road network. GDD has positive effects on the harvested areas of all crops except wheat, possibly because most wheat cultivation in China is winter

wheat, sown in autumn. WTO accession in 2001 had a universal negative effect on the harvested areas of all crops, particularly wheat and soybean. GDP, agricultural machinery, and rainfall have negligible influences on harvested areas.

In terms of yield changes, GDP has positive, albeit minor effects on crop yields: a 1% growth in GDP is positively associated with the yields of rice (0.02%), wheat (0.02%), maize (0.03%), and soybean (0.01%) (Fig. 5). As for the production inputs, more agricultural labour has little influence on yields; machinery and fertiliser have positive effects on all crops aside from soybean. The increase in road length was positively correlated with the yield growth of soybean, and negatively correlated with rice and maize. Weather conditions were, unsurprisingly, important determinants for yields. GDD is positively associated with crop yields, with particularly strong effects for wheat and soybean at around 0.15%. Higher rainfall is associated with higher yields of wheat and maize, while it has minimal effects on rice and soybean. The WTO accession is associated with an increase in the yields of wheat, maize, and soybean, but it has a negative effect on rice yield.

The comparison of the variables with the standardised regression coefficients reveals the relative influence of each covariate in the crop-specific regression (Fig. 6; see Supplementary Table S5 for the detailed regression results). The population is the most important determinant for all four crops, with more people being associated with more harvested areas for all crops. This reflects the spatial overlapping of population and major agricultural areas. The harvested area of rice is positively affected by more agricultural labour and population and strongly negatively influenced by more roads. The rice production area seems to be associated

Fig. 5 Percentage change in yields of each crop with a 1% increase in the explanatory variables (or after the accession of WTO as WTO is a dummy variable); markers are coefficient estimates, and whiskers denote the 95% standard errors



with less dense road networks. This may be due to the fact that large areas of rice cultivation expanded in Northeast China, where the road network is quite low. Similarly, soybean also exhibits a similar pattern, as the major expansion and planting regions were concentrated in the remote areas of Northeast China.

The wheat area is negatively related to the accession of WTO and higher growing degree days, but positively related to population and road. The harvested area of soybean is

negatively associated with greater road length and, unsurprisingly, accession to the WTO. The import of soybeans by China surged significantly following its accession to the WTO. Presently, China stands as by far the largest importer of soybeans, accounting for approximately two-thirds of the total traded volume (Gale et al., 2019).

As expected, the weather variables are important for the yields of all crops, albeit with varying degrees of influence (Fig. 7). The temperature indicated by GDD is the

Fig. 6 Variable importance for changes in harvested areas of each crop; dots are standardised coefficients, and whiskers denote the 95% standard errors

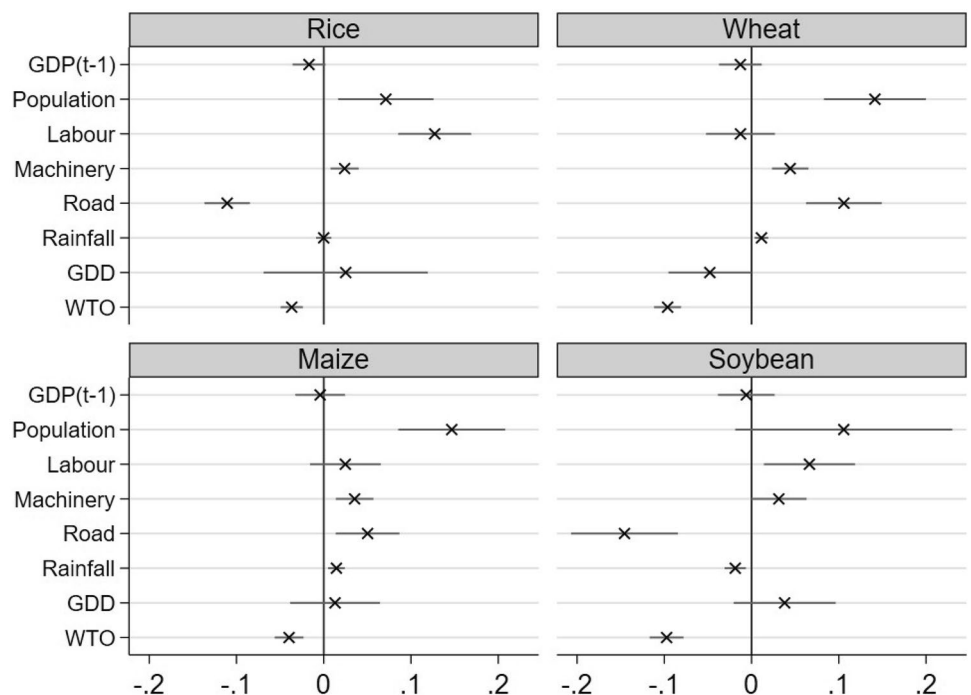
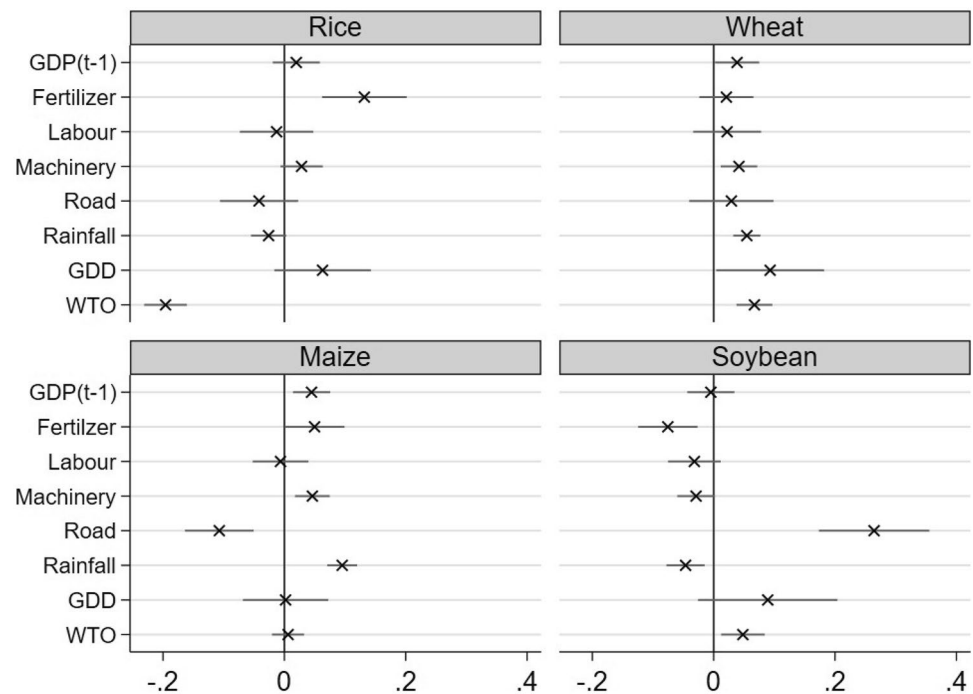


Fig. 7 Variable importance for changes in yields of each crop; dots are standardised coefficients, and whiskers denote the 95% standard errors



most or second-most important explanatory factor for the yields of rice, wheat, and soybean, but it has a relatively minor effect on the yield of maize. Rainfall has a mixed effect on yields and is the most important factor for the yield of maize. The production input variables, i.e., labour, machinery, and fertiliser, have relatively strong effects on yield. However, the negative effects of them on the soybean seem perplexing, possibly because soybeans are a nitrogen-fixing crop that requires low fertiliser inputs. For the yield of rice, the most important factors are fertiliser, GDD with positive effects, and WTO with strong negative effects. For the yield of wheat, GDD stands out as the most important factor with a strong positive effect. Surprisingly, road density is the most important factor for the yield of soybean. That means the higher yield of soybean is associated with better road infrastructure.

5 Discussion

The product of harvested areas and yields of crops determine total crop production. We evaluated the changes in both areas and yields for rice, wheat, maize, and soybean in the major producing regions of these crops in China using county-level data from 1980 to 2011. We use spatial panel regression to quantify the determinants of the observed changes.

We reveal substantial changes in the cropping structures in China over recent decades, with maize occupying more area, mainly at the expense of wheat and rice. Maize has been important in providing energy-rich feed for livestock.

In particular, the increasingly dominant industrial production of pigs and poultry relies on domestic maize production to provide energy for rapid animal growth (Bai et al., 2018). At the same time, protein feed, the second vital feed ingredient for monogastric livestock, comes from soybeans. However, domestic soybean cultivation has even slightly contracted in China, despite the massive increase in pig and poultry production. The rapid increase in demand for soybeans has largely been satisfied by imports from abroad, which was spurred by China's accession to the WTO in 2001. A large amount of soybean imports allows China to save scarce arable land for cultivating other grain crops (Qiang et al., 2013). At the same time, the growing soybean imports from China have contributed to land-use change elsewhere, such as in Latin America, where most of the soybeans imported by China are produced (Porkka et al., 2013; Yu et al., 2016). This is worrying for China's domestic nitrogen balance because soybean, a legume, fixes nitrogen from air and soil in its biomass. Thus, the contraction of soybean production also compels higher nitrogen application to N-demanding crops, such as maize (Sun et al., 2018).

China has dramatically increased grain production in recent decades (You et al., 2011), mainly due to higher yields of rice, wheat, and maize, while the harvested areas of rice and wheat have declined by 14% and 10%, respectively. Yield levels are mainly the result of management as well as higher application of intermediate inputs, such as pesticides and fertilisers. Our analysis corroborates the importance of higher input levels on yield increases. While lower labour intensity is associated with lower crop yields, the decrease

in labour input was compensated by the higher fertiliser use and machinery applications for the three cereal crops. Labour input will likely decrease further as more people migrate from rural areas to cities, possibly contributing to labour shortages in agricultural activities (Huang & Rozelle, 1996; Liu et al., 2016).

Most rice production is located in the coastal areas of South China; this region has been characterised by high rates of economic development and rapid urbanisation. Rice cultivation demands considerable labour input, yet provides comparatively little income. Off-farm jobs hence continuously pull labour out of agricultural production (Peng et al., 2009). GDP growth and rural–urban migration in these regions have led to a decline in the harvested areas of rice, particularly in coastal regions. In addition, as a result of the increasing demand for high-quality rice that is produced in north-eastern China and of the higher average temperatures due to climate change, rice production has expanded substantially in the north in recent years (Li et al., 2015; You, 2012). Our analysis and results on the effects of GDP and growing degree days confirm this narrative and are in line with other findings (Deng et al., 2015; Gornall et al., 2010; Wang et al., 2018). The results proved to be robust and sensible.

One limitation of this research is that the explanatory variables are not crop-specific. As all counties grow several crops, we thus cannot associate the amounts of fertiliser, machinery, and labour that are applied to each of these crops, and we cannot relate the changes in input applications to the changes in crop-specific production patterns. This uncertainty causes inaccuracies and insensitivities in the input variables. For example, soybean was not the dominant crop in most regions except in some counties in north-eastern China; thus, the fertiliser, machinery, and labour data only partly reflect the input intensity of soybean cultivation. This explains some seemingly counterintuitive results, such as that labour has little effect on soybean yield. In addition, the actual labour input is difficult to estimate, as labour has shifted from the agricultural sector to the manufacturing and service sectors. The increase in rural labour does not necessarily imply a higher input of labour in crop production, which may explain the negative effects of labour on yields. Nevertheless, the analysis suggests that labour is not a major constraint for further yield increases in Chinese crop production. Besides, our national-level analysis at the county level, spanning a period of 32 years, clearly reveals some pertinent trends in crop production and their determinants. Although the model is by no means a causal model, the results can nevertheless stimulate further discussion and analysis because such nationwide analysis complements analyses at the level of farms with smaller geographic coverage. Comparisons of the analyses at the micro- and macro-levels are needed

to attain a more holistic picture of the agricultural production dynamics in China. Another limitation of this research is that the four major crops were modelled separately. Consequently, we overlooked the interactions among these crops, both in terms of supply and demand. On the supply side, the growth of one crop might result in the reduction of another crop, given the competition for land. On the demand side, certain crops may exhibit potential substitution effects—which also link the supply and production of two crops. Future research with promise could be structured to tackle these interactions, e.g., by aggregating the production of the major crops.

Although the first three decades after the rural reform represented an interesting case for studying the changes in harvested area and yields of the major crops, research based on more recent data can provide more up-to-date information and relevant policy implications. The COVID-19 and geopolitical conflicts, such as the Russia-Ukraine war may also profoundly affect the agricultural policies and strategies on food security, which in turn affect the cropping structure and patterns. All of these are good topics for future research.

6 Conclusion

China's population growth has gone in hand with rapid urbanisation and rising income levels, which led to a substantial increase in demand for food. In particular, the shift to higher meat consumption resulting from rising affluence by urban consumers has contributed to land conversion away from staple crops towards feed crops such as maize. The development of the road network, better transportation infrastructure, and accession to the WTO facilitated rising food imports. However, there is ample evidence that a further increase in the application of intermediate inputs will not elevate crop yields much more, as the input applications are already very high in many areas of China, leading to levels of air and water pollution that are of rising concern (Wang et al., 2018).

Our analysis demonstrates the complex interactions among intertwined determinants that affect the changes in harvested areas and yields in China. Further research with statistical data of a higher spatial resolution will permit more nuanced insights into the dynamics within the counties. In light of the many impacts of changes in crop production on food security and the environment, it remains pertinent to expose the patterns and determinants of the changes across large areas. Such analysis will also benefit from longer time series and methodological improvements, such as in spatial econometrics, that allow for a deeper analysis of space–time data. Data-driven insights with state-of-the-art statistical models can inform land policies and thus support the sustainable development of agriculture.

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Declarations

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