German Journal of Agricultural Economics Vol. 73 (2024), No. 2, 1-20

Original Research Article

https://doi.org/10.52825/gjae.v73i2.1409

Submitted: 16 Nov. 2023 | Accepted: 24 May 2024 | Published: 04 Jul. 2024

Technical Efficiency Versus Land-Use Efficiency: A Spatio-Temporal Efficiency Analysis of China's Crop Production

Fang Yin [1], Zhanli Sun [2], Liangzhi You [3,4], and Vivian Wei Huang [5*]

[1] Shandong Academy of Agricultural Sciences, Gongyebei Road 23788, 250100, Jinan, China

[2] Leibniz Institute of Agricultural Development in Transition Economies (IAMO), TheodorLieser-Str. 2, 06120 Halle (Saale), Germany

[3] International Food Policy Research Institute (IFPRI), 1201 Eye Street, NW, Washington, DC 20005, USA

[4] Macro Agriculture Research Institute, College of Economics and Management, Huazhong Agricultural University, Wuhan, Hubei 430070, China

[5] Department of Economics, Swedish University of Agricultural Sciences, Uppsala, Sweden

*Correspondence: Vivian Wei Huang, Vivian.wei.huang@slu.se

Abstract: Improved land-use efficiency in agricultural production is crucial to meet increasing demand for agricultural commodities using the finite area of arable land worldwide. By applying a spatial autoregressive stochastic frontier methodology to county-level data spanning from 1980 to 2011, we conducted an analysis to investigate changes in both the spatial and temporal dimensions of technical efficiency and land-use efficiency within Chinese crop production. During this period, China achieved a remarkable upsurge in food production, notably within the first three decades of the rural reform that began in 1978. There were substantial transformations in agricultural land use that encompassed changes in cropland areas, shifts in the composition of various crops, alterations in their geographical distributions and enhancements in crop yields. Based on the results of this analysis, land-use efficiency increased slightly from 0.47 to 0.56 in most regions of China during that period and became convergent over time, with spatial gaps narrowing. National technical efficiency increased by 20 % on average, but with substantial regional variations, e.g. lower technical efficiency gains in northeast and northwest China and greater technical efficiency in the north and south. Urbanisation was found to be positively associated with lower technical efficiency, while a greater distance from provincial capitals resulted in higher technical efficiency. Efficient land use can lead to greater agricultural productivity, which, in turn, can boost rural economies and contribute to overall economic growth. These results could help in the design of effective regional policies to optimise land-use efficiency in crop production.

Keywords: Spatial Spillover, Spatial Autoregressive Model, Stochastic Frontier Analysis, Production Function

1 Introduction

Chinese agriculture has witnessed a drastic and rapid transformation in recent decades. Cropland in China is relatively limited. Despite a gradual increase in crop yield since the introduction of the household responsibility system in 1978, a slight decrease in cropland along with soil degradation have led to high intensity and less sustainability. For a sustainable and food-secure future, China needs to boost the productivity and efficiency of agricultural production while substantially reducing its environmental footprint (Viana et al, 2022; Zhang et al., 2022; Wang et al., 2023). Technical efficiency (TE) and land-use efficiency (LUE) in cropping production both optimise production processes. TE, a key measure of overall production performance, quantifies the capacity of a production unit to convert inputs, such as land, labour and capital, into outputs. The idea is to achieve maximum output levels from a given set of inputs or to produce a given level of output with the minimum use of inputs. In the context of agriculture, the assessment of TE can provide important insights into how efficiently resources are being used, and thus pave the way for adjustments that could lead to more sustainable and productive farming systems. Apart from overall production performance, examining the efficiency of individual inputs enables the identification of specific areas where improvements can be made for the sustainable development of agriculture.

Agricultural production in China has increased substantially through the intensive use of inputs such as irrigation (Zhu et al., 2019), fertilisers (Huang and Jiang, 2019) and machines (Qiu et al., 2022). However, high or excessive usage of natural resources and chemical inputs can be the cause of severe ecological and environmental issues (Zahoor et al., 2022), including the depletion of water resources, water pollution (Ouassanouan et al., 2022) and soil degradation (Seeger, 2023). To tackle these problems, we measured the efficiency of single input use, specifically in this paper land-use efficiency (LUE). The basic concept of LUE originated from the theory of environmental efficiency as a quantitative management tool for studying both economic and environmental aspects (Reinhard et al., 2002). LUE is a tool used to gauge the effectiveness of cropland use, which is measured by comparing the actual area of cropland to the optimal area needed for best-practice cultivation, with LUE usually defined as the ratio between the two. A higher LUE score implies that less land is required to yield a certain level of agricultural output, signifying better use of the land. Conversely, a lower LUE indicates that more land is needed for the same output, indicating a larger gap between the current and ideal use of the land. Thus, striving for a higher LUE can lead to better land management and sustainable agricultural practices. Considering its importance in achieving food self-sufficiency and maintaining food security for China's population of 1.4 billion, improvements in overall performance (i.e. TE) and single input efficiency (i.e. LUE) are vital for efficient agricultural production.

Agricultural production activities vary due to heterogeneous biophysical conditions, such as soil type, topography, climate and hydrological setting (Grau et al., 2013). These non-uniform conditions result in spatial differences in agricultural production efficiency (Neumann et al., 2010; Bharadwaj K, 1982). For example, Yang (1996) found a wide spatial variation in the factor productivities of maize production under natural conditions, while Chen et al. (2009) found that the frontier production functions of Chinese farms have a statistically different structure in different regions. Omitting this spatial heterogeneity can lead to biased and inaccurate TE estimates since the estimated values may capture not just the true inefficiency of the operations, but also intrinsic farm- or regional-specific heterogeneity (Greene 2005). Moreover, agricultural outputs and production factors often exhibit unique spatial clustering patterns owing to geographical spillover effects. Understanding these spatial clustering patterns and spatial autocorrelations offers a more nuanced insight into the dynamics of agricultural production and can improve the accuracy of TE estimates and agriculture-related analysis.

Spatial stochastic frontier analysis (SFA) models account for such spatial autocorrelation effects by incorporating spatial dependence. These models can be divided into two types: one explaining efficiency in terms of exogenous determinants analysing heterogeneity and another that accounts for spatial dependence by incorporating a spatial autoregressive specification (LeSage and Pace, 2009). Druska and Horrace (2004) developed a spatial error model using SFA for rice farming, calculated the time-invariant technical inefficiency and concluded that spatial correlation can affect TE. Cho et al. (2010) analysed the TE of agricultural performance in China using spatial lag models with county-level cross-sectional datasets, while Jiang et al. (2017) introduced spatial dependency to the determinants of a single-factor efficiency model with provincial data for the period 2003-2011. Pede et al. (2018) investigated the role of the spatial dependency of the dependent variable in a TE estimation of rice farmers, using panel data for the Philippines, and concluded that a spatial autoregressive stochastic frontier analysis model (SAR-SFA) outperforms models that do not account for spatial spillover. Glass et al. (2016) proposed a SAR-SFA for panel data and introduced the concept of efficiency spillover where the technical inefficiency term is homoscedastic. Ramajo and Hewings (2018) developed a SAR-SFA model with a time-varying decay efficiency specification, and used it to estimate regional development performance in western Europe. Skevas (2023) presents a novel modelling framework that allows the dependence of TFP growth and its components on certain factors to be built into the SFA framework. Tsukamoto (2018) examined the Japanese manufacturing industry using a SAR-SFA model and simultaneously estimated the determinants of technical inefficiency. Glass et al. (2016) extended the SAR-SFA model by including true fixed effects with balanced panel data, and concluded that an SFA model with a spatial lag structure combined with a model of technical inefficiency can estimate parameters correctly. Collectively, these studies underline how neglecting spatial dependencies may lead to biased estimates of agricultural efficiency. This recognition of spatial effects has not only improved model precision, but also broadened the understanding of the complex dynamics involved in agricultural productivity.

We extended the SAR-SFA model developed by Glass et al. (2016) by incorporating a spatially dependant component to measure the TE of crop production, the determinants of technical inefficiency and the LUE of crop production at county level in China for the period 1980-2011. To our knowledge, this is the first empirical study of changes in TE and land-use efficiency, and of the determinants of technical inefficiency for agricultural crop production in China using extensive, long-term county-level data and accounting for spatial spillover. Our aim was to identify efficiency pathways by analysing how TE and LUE varied spatially and temporally, with our findings helping inform agricultural policies and strategies at both local and national levels in China, and guiding targeted interventions tailored to the specific needs of different regions, potentially leading to improvements in agricultural efficiency and productivity.

2 Methodology

2.1 Technical Efficiency and Land-Use Efficiency

TE is defined as the ratio of observed output to the optimal output, given current technology and observed inputs (Farrell, 1957), using the formula:

$$\mathrm{TE}_{it} = \frac{y_{it}}{y_{it}^{opt.}} \tag{1}$$

where $\mathrm{y_{it}}$ is the observed output of unit *i* at time *t*, and $\mathrm{y_{it}^{opt.}}$ is the optimal output.

When referring to input efficiency, LUE is defined as the ratio of the optimal amount feasible to the observed use of an environmentally detrimental input, given existing technology and observed levels of output and inputs (Reinhard et al., 2002). When referring to agricultural efficiency, LUE can be interpreted as the partial efficiency of land use, defined as the ratio of optimal land area needed for the observed crop production to the observed land area in use (Reinhard et al., 2002):

$$LUE_{it} = \frac{optimal\ land\ area_{it}}{observed\ land\ area_{it}} \tag{2}$$

2.2 The Spatial Autoregressive Stochastic Frontier Model

To estimate TE and LUE, we applied a SAR-SFA model, for which we developed a production function and nested test to find the most suitable logarithmic functional form. This is a more flexible approach and imposes fewer assumptions on the functional form and its elasticities than the Cobb-Douglas function (Christensen et al., 1973). The SAR-SFA model for panel data takes the form:

$$Lny_{it} = \alpha_i + \eta(t)_t + TL(x)_{it} + \rho \sum_{j=1}^{N} w_{ij} Lny_{ijt} + v_{it} - u_{it};\ i,j = 1, \dots, N;\ t = 1, \dots, T \tag{3}$$

where $\mathrm{Lny}_{\mathrm{it}}$ is log-normalised output of the i^{th} unit; α_i is a fixed effect; $\eta(\mathrm{t})_{\mathrm{t}}$ is a time period effect; $TL(x)_{it}$ represents the technology as the translog approximation of the log of the production function where x is a vector of log normalised inputs; ρ is the spatial autoregressive parameter; $\sum_{j=1}^{N} w_{ij} Lny_{ijt}$ is the endogenous spatial lag of the dependent variable which shifts the frontier technology where w_{ij} is the non-negative element of the spatial weight matrix W; $\varepsilon_{it} = v_{it} - u_{it}$ is an error term, independent and identically distributed $(i.i.d.)$ for i and t with zero mean and variance σ^2; and $(\mathrm{v_{it}}\text{-}\mathrm{u_{it}})$ is the composed error term, which has two components (Aigner et al., 1977; Meeusen and van Den Broeck, 1977), where v_{it} accounts for stochastic effects, including statistical noise and measurement errors, and $v \sim i.i.d.N(0, \sigma_v^2)$, and u_{it} is the technical inefficiency term, which is a non-negative random variable, and $\mathrm{u} \sim \mathrm{i.i.d.N}^+(\mu, \sigma_u^2)$. This equation could be estimated using maximum likelihood in a procedure following Lee and Yu (2010).

A spatial weight matrix W is a $N \times N$ matrix of pre-specified non-negative constants that describes the spatial arrangement of the cross-sectional units and the strength of the spatial interaction between *n* units. It represents the spatial structure of the data. All the results are conditional on the specification of W (Dubin, 1998). The element of the matrix $\mathrm{W} = (\mathrm{w_{ij}}, \mathrm{i}, \mathrm{j} = 1, \dots, \mathrm{N})$, $\mathrm{w_{ij}}$, typically reflects the "spatial influence" of unit *j* on unit *i*. In the present study, all the elements on the main diagonal of W were set to zero to exclude "self-influence", by assumming $\mathrm{w_{ij}} = 0, \forall \mathrm{i} = \mathrm{j}$. The spatial weight matrix was used to capture the spatial arrangement and spatial interaction between the counties represented in the dataset. The commonly used spatial weight matrices are based on distance, contiguity or a combination of these. The weight is row-normalised so that each row in the weight matrix adds up to 1, and the endogenous spatial lag of the dependent variable is the weighted average of observation values for the dependent variable of neighbouring units.

2.3 Technical Inefficiency and Determinants of Technical Inefficiency

As the technical inefficiency component is heteroscedastic, it accounts for the determinants of efficiency in the estimation (Kumbhakar and Lovell, 2000). By allowing for heteroscedasticity in the inefficiency component, the model accounts for the possibility that different determinants, such as environmental factors or managerial skills, can affect the level of inefficiency differently. This can lead to a more comprehensive understanding of the factors affecting efficiency and allow for a more robust analysis. Once the variations in TE across production units were estimated, the determinants of technical inefficiencies were estimated simultaneously, i.e. the exogenous factors explaining the variation between production units. Assuming a linear relationship between technical inefficiency and its explanatory variables, the technical inefficiency term $\mathrm{u_{it}}$ can be estimated as:

$$u_{it} = \tau_0 + \sum_{m=1}^{M} \tau_m z_{mit}, m = 1, \dots, M \quad (4)$$

where z_{mit} is an explanatory variable for county *i* at time *t* associated with technical inefficiency; *M* is the number of explanatory variables; and τ_m is the coefficient for the m^{th} explanatory variable. As the dependent variable *u* is technical inefficiency, instead of TE a positive value of the coefficient, i.e. $\tau_m > 0$, indicates a negative effect on TE and vice versa.

3 Data and Empirical Model Specification

Data for the analysis were taken from the China Statistics Yearbooks and Chinese Agricultural Statistic Yearbooks from 1980 to 2011. This period was significant in China due to economic and political transformations that brought about remarkable changes in the country following the introduction of the Reform and Opening-Up Policy in 1978. The household responsibility system (HRS) was a pivotal component in China's Reform and Opening-Up Policy that profoundly changed the rural economy. There were substantial transformations in agricultural land use, encompassing changes in cropland areas, shifts in the composition of various crops, alterations in their geographical distributions and enhancements in crop yields. Each of these shifts would have had an impact on both the technical efficiency (TE) and land-use efficiency (LUE) of agricultural production in China. An evaluation of these changes can provide valuable insights into China's agricultural transformation, and offer lessons for future farming policies and practices. The balanced panel data contained 22,077 observations covering 2,007 counties in China for the period 1980-2011 at three-year intervals. To minimise the impact of non-representative outliers, we removed counties in provinces with an average cropland area below 10,000 ha between 1980 and 2011, and counties where cropland accounted for less than 10 % of the total area. As a result, Inner Mongolia, Xinjiang, Qinghai, Tibet, Hainan, Beijing and Tianjin were excluded from the analysis. The area included in the final analysis is shown in Appendix Figure A1. We calculated three-year moving averages of all variables to smooth out short-term fluctuations and highlight longer-term trends, and then picked the data at three-year intervals. Before estimation, we log-transformed and then normalised all the variables around the sample mean to reduce the influence of unit changes. To account for inflation and make monetary values comparable over time, we converted all the variables with monetary values to the constant price in 2010.

3.1 Output and Input Variables

The output variable used was the aggregated cropping output of a county, measured in Chinese Yuan (*y*) in constant 2010 prices. It was calculated by multiplying the quantity of crops produced by the consumer prices in the respective year. The consumer prices index increased from around 19.3 to 105.4, a 4.5-fold increase, during the study period. This indicates a significant increase in overall price levels as it provides essential information about inflation.

The input variables were the amounts of agricultural labour (x_1), machinery power in agriculture (x_2), land (sown area x_3), fertiliser (x_4) and pesticide (x_5) (Coelli and Rao, 2005). Labour (x_1) included the amount of labour for farming activities; machinery (x_2) was estimated as the total horsepower of agricultural machinery to reduce the bias of different sizes of machine, including all farm machinery for harvesting, irrigation and transportation; and land (x_3) was estimated as the total sown area for all annual crops, including grain, oil, cotton, sugar crops, vegetables, melons, fibre crops and medicine crops. Since double-cropped areas were counted twice, the sown area reflected the effective usage of cultivated land in agriculture. Multiple cropping was common in the Middle-Lower Yangtze River Valley in south and southwest China (Hou et al., 2012). Use of fertiliser (x_4) was measured as the annual quantity of chemical fertilisers (nitrogen, phosphorus, potassium and potash contained in combined fertilisers) used for crop production, while the use of pesticides (x_5) was estimated as the annual quantity of pesticides used in crop production. Detailed descriptive statistics on all the variables used are presented in Table 1.

Table 1. Selected variables and summary statistics

Variable description	Unit	Notation	Mean	Std.	Min.	Max.
Variables in the production function						
Output - farming output value	10^6 Yuan	y	747	768	0	8,819
Input - agricultural labour	10^3 Person	x_1	151	113	0	1,013
Input - machinery power in agriculture	10^6 Watt	x_2	209	253	0	3,049
Input - sown area	10^3 ha	x_3	69	51	0	405
Input - fertilisers	10^3 tonne	x_4	17	19	0	250
Input - pesticides	10^3 tonne	x_5	1	8	0	362
Variables in the technical inefficiency model						
Population	10^3	z_1	535	408	3	7,682
Urbanisation rate	%	z_2	18	17	0	97
Elevation	m	z_3	614	774	0	4,512
Suitable soil for farming	10^3 ha	z_4	75	88	0	927
Road length	km	z_5	80	68	5	1,343
Distance to nearest provincial capital	km	z_6	143	93	0	759
Livestock output value	10^6 Yuan	z_7	414	535	0	7,712
Forestry output value	10^6 Yuan	z_8	55	81	0	1,976
Temperature	°C	z_9	14	5	-4	24
Accumulated temperature over 10 degrees (growing degree days, GDD)	°C	z_{10}	499	143	40	889
Rainfall	mm	z_{11}	1000	471	23	2,979
Share of irrigated area	%	z_{12}	33	20	0	100
Share of machinery-farmed area	%	z_{13}	32	22	0	100

Source: authors' own calculation

3.2 Determining Variables of Technical Inefficiency

Technical inefficiency in the stochastic frontier approach was related to socio-economic variables, ecological considerations and climate factors. The socio-economic variables were population (z_1), urbanisation (z_2), road length (z_5), livestock outputs (z_7) and forestry outputs (z_8). The total population of a county (z_1) is an important factor for demand, as well as a source of labour and non-agricultural uses for land, consequently influencing TE in agricultural production. The urbanisation rate (z_2) was calculated as the urban population divided by the total population to represent the changes driving the use of new agronomic techniques (Masters et al., 2013; Yang et al., 2022). Road length (z_5) was taken as the length of all roads in the county, including national-level, provincial-level and county-level paved roads, to reflect changes in transportation and market access. Livestock output value (z_7) and forestry output value (z_8) can promote the use of agricultural practices for intensifying production sustainably, and thus have an influence on efficiency (Alves et al., 2017).

To capture ecological and climate-related effects, we included elevation (z_3), soil quality (z_4), temperature (z_9), growing degree days (GDD) (z_{10}) and rainfall (z_{11}). The elevation median (z_3) was devised from the global digital elevation model (DEM), i.e. a digital representation of ground surface topography or terrain. DEM and county boundaries were overlaid to calculate the average elevation of each county. Land area with suitable soil for farming (z_4) was taken from the Soil and Terrain Database (SOTER) for China, v1.0. The soil information was interpreted and divided into suitable areas (better soil quality for crops) and unsuitable areas. Climate variables influence the performance of agricultural production, e.g. rainfall has an impact on irrigation (Demir and Mahmud, 2002; Pilevneli et al., 2023). Data on mean annual temperature (z_9), GDD (accumulated temperature over ten degrees, z_{10}) and rainfall (z_{11}) were obtained from China's meteorological office. In addition, the irrigation rate (proportion of irrigated land, z_{12}) and machinery rate (proportion of machinery-farmed land, z_{13}) represented water and machine accessibility. To represent physical accessibility, we calculated the straight-line distance from the geographic centroid of the county to the nearest provincial capital (z_6) as the distance to that capital.

3.3 Empirical Model Specification

We assumed a Hicks-neutral technical change for the production function with a linear time trend variable t and its square t^2, with the respective parameters η_1 and η_2 (Ramajo and Hewings, 2018). Based on Equation 3, the production function was specified as follows:

$$Lny_{it} = \alpha_i + \rho \sum_{j=1}^{2007} w_{ij} Lny_{ijt} + \eta_1 t + \eta_2 t^2 + \sum_{l=1}^{5} \beta_l Lnx_{lit} + \frac{1}{2} \sum_{l=1}^{5} \sum_{k=1}^{5} \beta_{lk} Lnx_{lit} Lnx_{kit} + v_{it} - \left(\tau_0 + \sum_{m=1}^{13} \tau_m z_m \right); \; i,j = 1, \dots, 2007; t = 1, \dots, 32; l,k = 1, \dots, 5; \; m = 1, \dots, 13 \tag{5}$$

where y_{it} Lny_{it} is the natural log of agricultural production output value and x_{lit} is one input x_l in county i at time t of five inputs (amount of agricultural labour (x_1), machinery power in agriculture (x_2), sown area (x_3), fertiliser (x_4) and pesticide (x_5)); l is the index of the (1×5) vector of exogenous independent variables; t is time trend; β_l is an unknown coefficient to be estimated for input x_l; and β_{lk} is the coefficient for the translog term of inputs x_l and x_k, assuming $\beta_{lk} = \beta_{kl}$.

As the output and input variables were normalised by sample means, the estimated first-order parameters can be interpreted as production elasticities at the sample mean (Kumbhakar and Lovell, 2000). Based on the estimates of the production function, the term elasticity of output with respect to inputs can be calculated by the marginal effects (LeSage and Pace, 2009):

$$\varepsilon_{x_l} = \frac{\partial Lny}{\partial Lnx_l} = (I - \rho W)^{-1} \left\{ \beta_l + \sum_{k=1}^{5} \beta_{lk} Lnx_k \right\} \tag{6}$$

where ε_{x_l} is the elasticity of one input x_l. Since the elasticity of each input factor depends on the other input factors if $l \neq k$, elasticities are no longer fixed and identical for all counties and periods.

This means that TE could be calculated as followed:

$$\mathrm{TE}_{it} = \frac{y_{it}}{y_{it}^{opt.}} = e^{-u_{it}^{total}} = e^{-(I-\rho W)^{-1} u_{it}} = (I - \rho W)^{-1} e^{-u_{it}} \tag{7}$$

3.4 LUE

For the study area, LUE was calculated as the difference between the natural log of input x_3, i.e. the actual land area used, and the optimal land input $x_3^{'}$ for the observed level of production:

$$Ln\ LUE = Ln \left(\frac{x_3'}{x_3} \right) = Lnx_3' - Lnx_3 \tag{8}$$

Setting *u=0* and letting the output of the land use-efficient producer equal that in Equation (5) (Reinhard et al., 2002), then:

$$Lny_{it} = (I-\rho W)^{-1}\left\{\alpha + \eta_1 t + \eta_2 t^2 + \sum_{l=1}^{5}\beta_l Lnx_{lit} + \frac{1}{2}\sum_{l=1}^{5}\sum_{k=1}^{5}\beta_{lk} Lnx_{lit} Lnx_{kit} + v_{it} - u_{it}\right\} = (I-\rho W)^{-1}\left\{\beta_3 Lnx'_{3it} + \frac{1}{2}\beta_{33} Lnx'_{3it} Lnx'_{3it} + \beta_{13} Lnx_{1it} Lnx'_{3it} + \beta_{23} Lnx_{2it} Lnx'_{3it} + \beta_{34} Lnx'_{3it} Lnx_{4it} + \beta_{35} Lnx'_{3it} Lnx_{5it} + \sum_{l\neq 3}^{5}\beta_l Lnx_{lit} + \frac{1}{2}\sum_{l\neq 3}^{5}\sum_{k\neq 3}^{5}\beta_{lk} Lnx_{lit} Lnx_{kit} + v_{it}\right\} \tag{9}$$

The logarithm of the stochastic land input efficiency measure ($LnLUE_{it} = Lnx'_{3it} - Lnx_{3it}$) can be isolated. Setting Equation 5 and Equation 9 as equal yielded:

$$(I-\rho W)^{-1}\left\{\frac{1}{2}\beta_{33}(Lnx'_{3it} Lnx'_{3it} - Lnx_{3it} Lnx_{3it}) + (\beta_3 + \beta_{13} Lnx_{1it} + \beta_{23} Lnx_{2it} + \beta_{34} Lnx_{4it} + \beta_{35} Lnx_{5it})(Lnx'_{3it} - Lnx_{3it}) + u_{it}\right\} = 0 \tag{10}$$

which can be solved for *LnLUE* to obtain:

$$LnLUE_{it} = (I-\rho W)^{-1}\left\{\frac{-(\beta_3 + \sum_{k}^{5}\beta_{3k} Lnx_{kit}) \pm \sqrt{(\beta_3 + \sum_{k}^{5}\beta_{3k} Lnx_{kit})^2 - 2\beta_{33} u_{it}}}{\beta_{33}}\right\} \tag{11}$$

LUE was calculated using the positive root in Equation 11 (Reinhard et al., 2002).

4 Results

4.1 Empirical Model Selection and Testing

The development of the SAR-SFA model comprised two steps: 1) the estimation of the production function and technical inefficiency simultaneous model to obtain coefficients of inputs and determinants of technical inefficiency, and 2) the calculation of spatial TE and land-use efficiency scores. Prior to the final model selection, we compared different settings of spatial weights and conducted three tests – Hausman test, LR test and Variance Inflation Factor (VIF) Test – for endogeneity for the non-spatial stochastic frontier model to determine the specification of a suitable econometric model (Kutlu et. al., 2020). In terms of spatial weight selection, we conducted 15 kinds of spatial weights and calculated Moran's I for output y (see details in Appendix Table 1). Four types were contiguity weights and the others were inverse distance weights. We found contiguity weights had a better autocorrelation for the explained variable. Finally, we conducted rook contiguity and found that there was one county isolated, so selected the first order of the queen contiguity weight for the following regression. The queen weights consider as neighbours all observations that share a common boundary or vertex point. The ij^{th} component in the matrix *W* equals 1 if units *i* and *j* are neighbours and $i \neq j$, otherwise the elements are set to 0. We then normalised the values so that each row in the weight matrix added up to 1 and all neighbours had the same weight, so that the endogenous spatial lag of the dependent variable was a simple average of observation values for the dependent variable of neighbouring counties, which preserved the scaling of the data.

In terms of production function model selection, we used a truncated inefficiency term for estimation. First, we used the Hausman test to assess whether a fixed-effects model or random-effects model was more appropriate. Second, we applied the likelihood ratio test to assess whether the Cobb-Douglas production function or translog production function was the better choice. We also used the likelihood ratio test to select the technical inefficiency model specification and spatial dependence. The test results showed that the empirical model matched the data very well (Appendix Table 2). We used the Akaike information criterion (AIC) to choose between the fitted SFA and SAR-SFA models. To check the robustness of model selection, we used the Schwarz/Bayesian information criterion (BIC). Both criteria are based on the concept of minimising information loss and properly separating noise from structural information, where the smaller the AIC or BIC value, the less information loss. Based on the Hausman test, we rejected the hypothesis of no difference in coefficients, resulting in the fixed-effects model being preferred for the analysis. Based on the likelihood ratio test results, three null hypotheses (referring to translog terms, technical inefficient items and spatial dependency items) were rejected, and consequently the SAR-SFA translog function was selected. The AIC/BIC results gave a strong preference (low values) for an SAR-SFA model with a technical inefficiency determinant model, compared with a normal SFA model and an SAR-SFA model without technical inefficiency determinant models (higher AIC and BIC values). The local spatial parameter ρ was significant at the 1 % level, indicating that the spatial dependence of dependent variable y was affected by the model specification. The results presented below were obtained using the fitted SAR-SFA model.

4.2 Estimates for the SAR-SFA and Technical Inefficiency Model

The estimates obtained using SAR-SFA with fixed effects are presented in Table 2. The estimated first-order coefficients for the inputs labour (x_1), machinery (x_2), land (x_3), fertiliser (x_4) and pesticide (x_5) had the expected positive signs, with values of 0.06, 0.05, 0.25, 0.10 and 0.01 respectively. The estimated coefficient of spatial lag ρ for the dependent variable was positive and had a value of 0.52, showing that agricultural production had substantial spillover effects. The patterns of the production elasticities of inputs were spatially heterogeneous with respect to the output. The average elasticity of inputs x_1, x_2, x_3, x_4 and x_5 was 0.10, 0.06, 0.56, 0.19 and 0.01 respectively. Based on the magnitude of these coefficients, the most important input for production was land (x_3), followed by fertiliser (x_4), machinery (x_2), labour (x_1) and pesticides (x_5) in that order. This shows the essential role of land in crop production, which is consistent with the situation of arable land being comparatively scarce in China (Chen et al., 2009). Increases in land input over time were due to the expansion and intensification (multiple cropping) of cultivated land, but some regions in which production inputs were limited showed a decrease in the extent of multi-cropping (Yan et al., 2009). Fertiliser, at the second highest magnitude, was particularly important in regions with scarce land resources in crop production. The estimates of elasticities confirmed that the most important input was land, followed by fertiliser, machinery, labour and pesticides (Figure 1). Similarly to the results reported by Fan (1997) and Gong (2018), we found that input elasticities of land and labour decreased by 0.4 % and 5.9 % respectively from 1981 to 2011, while input elasticities of fertiliser, machinery and pesticides increased by 0.2 %, 2.1 % and 1 %, respectively. The decline in the elasticity of labour inputs was particularly apparent in the model for the whole of China, but was also evident in all regions except for northeast China. In the south and southwest, where the terrain is dominated by hilly landscapes that require higher labour input per area, labour still played a larger role than machinery.

Population (z_1), urbanisation (z_2) and road length (z_5) were found to be negatively associated with technical inefficiency, i.e. they had a negative association with TE. A 1 % increase in population was associated with a 0.6 % decrease in TE of crop production, while a 1 % increase in urbanisation could be associated with a 0.14 % decrease in TE. Population increase and urbanisation were correlated with a decrease in cropland area and occupation of high-quality cropland, although the total decrease was small. The coefficient for rainfall (z_{11}) suggested that 1 % more rainfall would be negatively correlated with agricultural TE by 0.76 %.

The climate factors temperature (z_9) and growing degree days (z_{10}) had positive influences on the TE score, with a 1 % increase in these increasing TE by 0.25 % and 1.1 % respectively. Compared with rainfall, a temperature increase during the growing season had a positive impact on agricultural production. The association relationship of geographical factors on technical inefficiency was negative, but relatively small, for elevation (z_3; -0.15), suitable soil for farming (z_4; -0.01) and distance to the nearest provincial capital (z_6; -0.14). Meanwhile, the development of other parts of the primary economy besides crop farming, such as a 1 % increase in forestry (z_7) and livestock (z_8) outputs, was positively correlated with TE of crop production by 0.95 % and 0.28 %, respectively.

Table 2. Parameter estimates for the spatial autoregressive production function and technical inefficiency model

Spatial autoregressive production function				**Technical inefficiency model**			
Dependent variable: ln(y)				Dependent variable: inefficiency relevant variable			
Parameters		Coeff.	Confidence intervals	Parameters		Coeff.	Confidence intervals
t	η_1	-0.04	[-0.041,-0.037]	lnz1	τ_1	0.60	[0.52,0.67]
t2	η_2	0.00	[0.0012,0.0013]	lnz2	τ_2	0.14	[0.093,0.18]
lnx1	β_1	0.06	[0.038,0.081]	lnz3	τ_3	-0.15	[-0.18,-0.13]
lnx2	β_2	0.04	[0.028,0.055]	lnz4	τ_4	-0.01	[-0.043,0.022]
lnx3	β_3	0.25	[0.22,0.28]	lnz5	τ_5	0.02	[-0.068,0.10]
lnx4	β_4	0.10	[0.084,0.12]	lnz6	τ_6	-0.14	[-0.19,-0.091]
lnx5	β_5	0.01	[0.0022,0.017]	lnz7	τ_7	-0.91	[-0.96,-0.86]
lnx1lnx1	β_{11}	0.03	[0.011,0.046]	lnz8	τ_8	-0.28	[-0.32,-0.25]
lnx2lnx2	β_{22}	0.01	[0.0041,0.016]	lnz9	τ_9	-0.25	[-0.41,-0.081]
lnx3lnx3	β_{33}	0.07	[0.054,0.078]	lnz10	τ_{10}	-1.10	[-1.35,-0.84]
lnx4lnx4	β_{44}	0.01	[-0.0034,0.019]	lnz11	τ_{11}	0.76	[0.64,0.88]
lnx5lnx5	β_{55}	0.00	[-0.0044,0.0031]	lnz12	τ_{12}	-0.03	[-0.086,0.019]
lnx1lnx2	β_{12}	-0.05	[-0.061,-0.033]	lnz13	τ_{13}	-0.09	[-0.12,-0.065]
lnx1lnx3	β_{13}	0.01	[-0.0071,0.030]	_cons	τ_0	-3.60	[-3.69,-3.51]
lnx1lnx4	β_{14}	0.01	[-0.0029,0.029]	Vsigma			
lnx1lnx5	β_{15}	0.01	[0.0016,0.019]	_cons	v	-3.89	[-3.95,-3.84]
lnx2lnx3	β_{23}	0.03	[0.017,0.049]				
lnx2lnx4	β_{24}	-0.01	[-0.018,0.00025]	*Model performance*			
lnx2lnx5	β_{25}	0.01	[0.0067,0.019]	AIC			7534
lnx3lnx4	β_{34}	-0.02	[-0.041,-0.0058]	BIC			23898
lnx3lnx5	β_{35}	-0.03	[-0.041,-0.020]	Likelihood value			-1722
lnx4lnx5	β_{45}	0.01	[0.0026,0.015]	No. of observations			22,077
Spatial lag	ρ	0.52	[0.51,0.53]				

Note: 95 % confidence intervals in brackets
Source: authors' own calculation

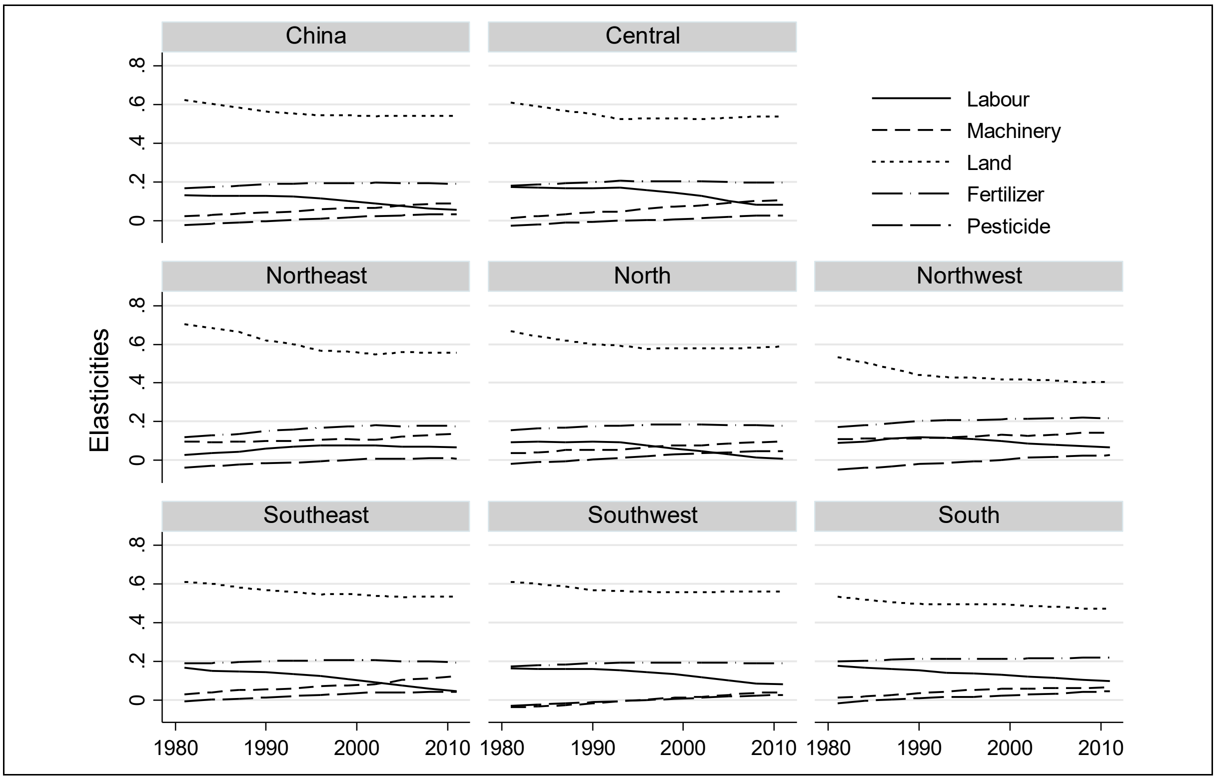

Figure 1. Annual elasticities in the period 1981-2011 in crop production inputs for the whole of China and for its main regions (see Appendix Figure A1 in Supplementary Material)

Source: authors' own calculation

4.3 Spatio-Temporal Patterns of TE

Based on the estimated parameters and production function, TE was estimated for each county in each year. The average TE was 0.8 for the whole study region and period, but the TE distribution was negatively skewed. During the period, TE increased from 0.68 to 0.84, i.e. by 20 %, and the standard deviation in TE decreased from 0.27 to 0.12, which could be interpreted as indicating a decreasing regional gap.

Spatial and temporal changes in TE of crop production from 1981 to 2011 are shown in Figure 2. TE for the regions varied from 0 to 0.99, with values above 0.8 for the provinces of Shandong, Sichuan, Chongqing, Fujian and Guangxi, while for Heilongjiang, Jilin, Shanxi and Shaanxi the TE values were below 0.8. One reason for the lower TE in northeast China (the provinces of Heilongjiang and Jilin) is that large tracts of unused wetland and unused barren land were converted to cultivated land during the period (Hou et al., 2012, Yao et al., 2008). In the north (Shanxi and Shaanxi provinces), an ecologically fragile area, cropland was converted to grassland and forest as part of environmental programmes. Since a lower TE value indicates greater potential for increasing production performance through improved TE, TE was more likely to increase in regions such as the northeast when crop productivity was improved.

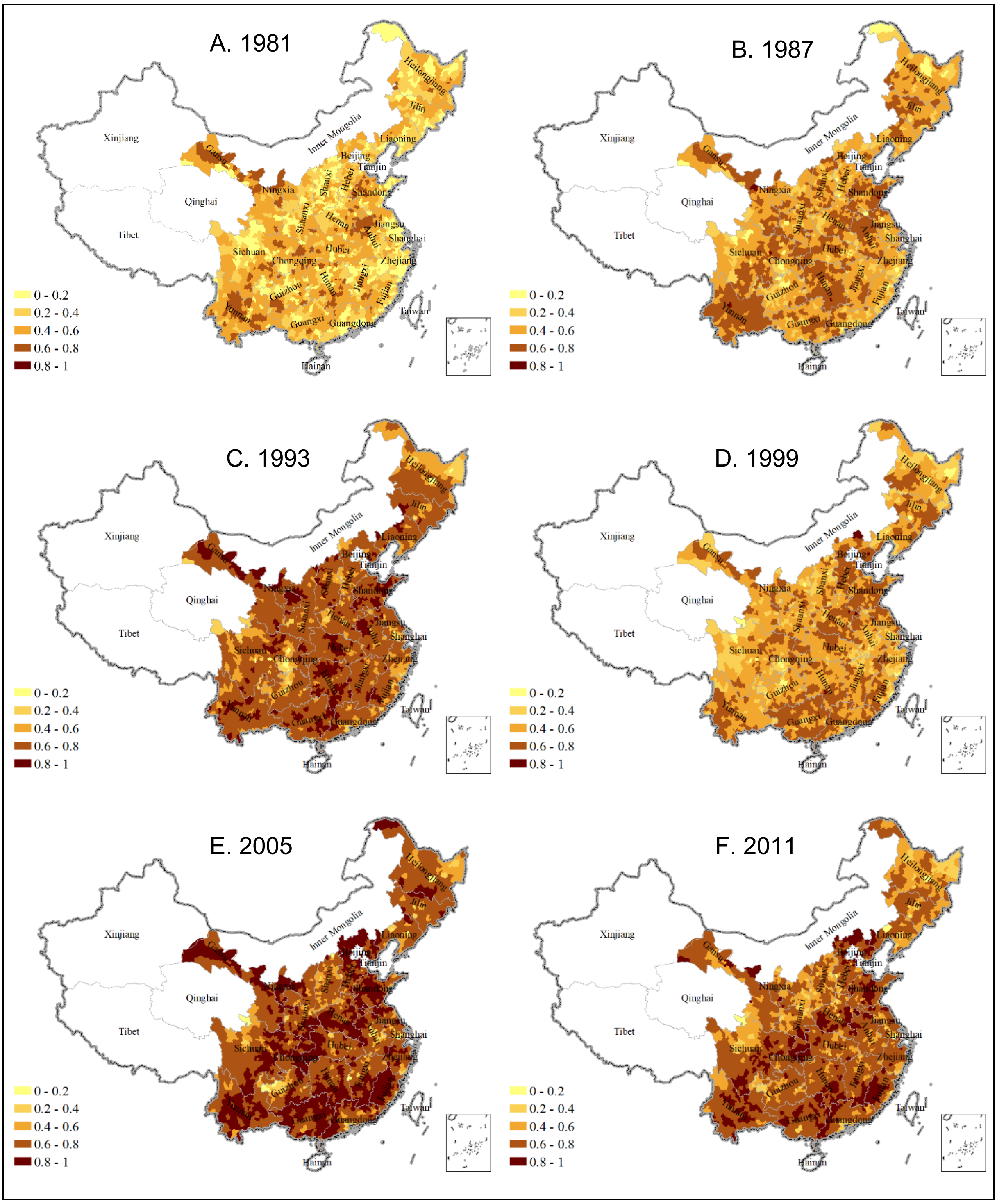

Figure 2. Spatial distribution of technical efficiency (TE) at six-year intervals from 1981 to 2011

Source: authors' own graph based on calculated technical efficiency

4.4 Spatio-Temporal Patterns of LUE

The results showed that the national average LUE was 0.54, i.e. substantially lower than 1, indicating ample scope to improve LUE (Liu et. al. 2019). LUE also varied over time, ranging from 0.52 in 1980 to 0.59 in 2011. During this period, LUE reached its highest level (0.65) in 2005, while in 1999 it was only 0.44, the lowest level observed in the study period. After 2008, there was an apparent downward trend in LUE. Overall, LUE increased slightly over time by 18 %, but there was no clear overall trend and a series of upwards and downward turns. LUE fluctuated and remained well below 1 during the study period, which implies untapped potential, but also difficulties in improving LUE. LUE is one of the efficiency components in overall TE. As expected, LUE and TE were positively correlated. Thus, the increase in LUE probably resulted in the increase of TE. At the same time, LUE also correlated highly with crop yields. The increase in LUE through improvements in agricultural practices and technologies also allows for a reduction in cultivated land area in those marginal regions, which brings about positive environmental externalities.

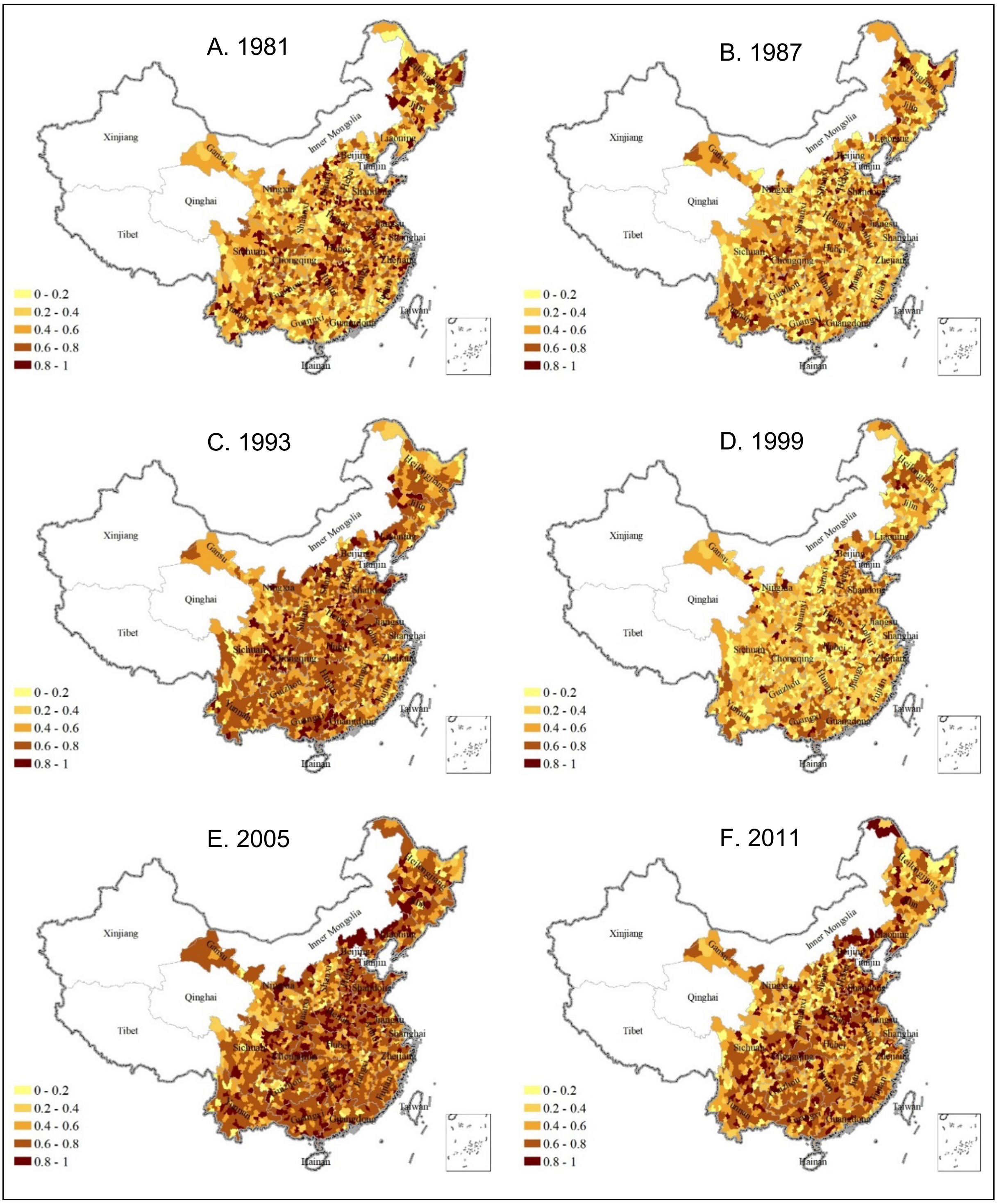

Figure 3. Distribution of changes in land-use efficiency (LUE) at six-year intervals from 1981 to 2011

Source: author's own graph based on calculated land-use efficiency

The spatial pattern of LUE in 2011 revealed heterogeneity between regions (Figure 3), e.g. a low LUE in Gansu, Heilongjiang, Jiangxi and Shanxi provinces (below 0.5). The provinces of Shandong and Chongqing had the highest LUE (0.61 on average for 1980-2011), while Gansu had the lowest (0.41). Jiangsu, Anhui, Henan and Shandong provinces are China's main breadbaskets, and their LUE was relatively high at above 0.55 in all cases. However, the LUE of Heilongjiang, also an important breadbasket, was only 0.51. A low LUE may be due to the conversion of land within a region (Hou et al., 2012). For example, Deng et al. (2006) found that large tracts of unused wetland and unused barren land in northeast China were converted to cultivated land between 1986 and 2000. As previously mentioned, the breadbasket regions showed a high LUE (0.65-0.7), including the provinces of Hebei, Shandong and Henan. These major food production areas have been prioritised in government policy on cropland conservation.

4.5 Discussion

Using an SAR-SFA approach, we estimated changes in LUE and TE and in the determinants of technical inefficiency for crop production in China based on county-level data for the period from 1980 to 2011. We found that the average TE increased by 20 % over the study period, indicating improvements in the ability of the agriculture to use inputs effectively to produce output. However, this gain was not uniform across the country, with substantial regional variations characterised by a lower TE gain in northeast and northwest China and a higher TE gain in the north and south. In the study period, LUE increased overall by 18 %, but again with substantial regional variations. There is a positive correlation with TE. Since the spatial heterogeneity of land-use efficiency is well observed for counties, policies could promote the development of customised support and incentives for counties with a lower land-use efficiency. In northeast China, for large-scale farms, the development of advanced machines and technologies for land management would enhance efficiency. In the southwest of the country, where small farms and hilly fragments are ubiquitous, the planting of specific crops could increase the output value. With spatial spillover, greater collaboration and cooperation between counties to leverage their advantages and shortcomings could be encouraged. This could involve establishing inter-county partnerships, knowledge-sharing networks and joint initiatives to promote sustainable land-use practices and agricultural development.

Urbanisation resulted in a lower TE, which could be due to the loss of arable land and a possible reallocation of resources away from cropping. A greater distance from provincial capitals was associated with a higher TE, which might be due to factors such as lower land costs, less competition for alternative land uses, or farm-scale fitting for different agricultural practices. We also found an association between TE and geographical and economic factors, underscoring the complexity of agricultural efficiency and the need for region-specific approaches. One way to increase production performance could be better networking or integration between regions, from farm level to province level. Moreover, developing other components of the primary sectors, including forestry and livestock, could bolster efficiency in crop production, advocating a more holistic approach to agriculture.

The elasticities of key production inputs varied between regions. There was an overall decline in the elasticity of labour, which was good from another perspective since declining labour availability, or a fall in the demographic dividend, represents a major challenge for farming in China. China has the highest fertiliser use per hectare globally, but productivity remains moderate by global standards. Consequently, fertiliser-use efficiency is lower than the global average (Wu et al., 2018; Huang and Jiang, 2019). In addition, excessive use of synthetic fertilisers is causing increasing and widespread water pollution (Yu et al., 2019). To achieve sustainability in crop production, the use of fertiliser needs to be reduced by adopting better management practices in fields (Cui et al., 2018). Pesticides are other critical chemicals in agriculture, with average pesticide use per hectare of cropland in China 1.3 times the global average in 2011 (FAO, 2019). Decreasing pesticide use would not only increase efficiency, as our results demonstrated, but also reduce the environmental impact of crop production. To address the overuse of inputs such as fertilisers and pesticides, integrated pest management, organic farming and the use of bio-fertilisers have been promoted as part of the government's agricultural green development. These findings suggest that there are opportunities to improve the sustainability and efficiency of China's agricultural sector through careful management and policy interventions that are tailored to the specific needs and conditions of different regions.

5 Conclusions

This is the first empirical analysis to apply a SAR-SFA model to estimate spatio-temporal changes in TE and LUE of crop production in China using county-level data over a long period (30 years). We examined spatial dependency in crop production by introducing a spatial lag in the model, which substantially improved the estimates obtained by accounting for the strong positive influence of spatial spillover effects. Identifying and quantifying the effects of the determinants on production performance can help design effective policies for improving the TE and LUE of crop production. Improving TE and LUE in agricultural production is crucial if China is to feed its vast population with the limited area of arable land available and achieve the government goal of domestic self-sufficiency. More detailed analyses at a finer resolution, possibly using primary farm-level data, would provide deeper insights into TE and LUE efficiency in crop farming in China.

This study has some limitations. We measured crop output in monetary terms, which made the outputs for different crops comparable. However, most of the rural labour force also perform off-farm work, and a major limitation of this study was that we could not determine how much of their time was devoted to working in agriculture. Another limitation was that the spatial weight matrix used in this study was based on geographical contiguity, without consideration being given to the economic interaction between counties. This would be an interesting area for further study, but we lacked data and information about the nature of these interactions. We are also aware that the use of county-level data for crop production has drawbacks in terms of depth and data quality, which we could not address, but county-level and long-term statistical data were the only available data for the type of analysis presented here. More detailed, fine-scale analyses, possibly using primary farm-level data, would deepen the insights gained here by providing additional knowledge on efficiency in crop farming in China.

Acknowledgements

We gratefully acknowledge anonymous reviewers for their critical and constructive comments. We thank PD. Dr. Daniel Müller for his help in interpreting the results of the study.

Funding

The authors highly appreciated the Swedish Foundation for International Cooperation in Research and Higher Education (STINT) for the funding support on Joint China-Sweden Mobility program (Dnr: MG2021-9098). This research is also partially supported by the Youth Project funded by Shandong Foundation of Natural Sciences (No. ZR2022QD149).

References

Aigner, D.J., Lovell, C.A.K., Schmidt, P. (1977): Formulation and estimation of stochastic frontier production function models. Journal of Econometrics 6 (1): 21-37. https://doi.org/10.1016/0304-4076(77)90052-5.

Alves, B.J.R., Madari, B.E., Boddey, R.M. (2017): Integrated crop-livestock-forestry systems: prospects for a sustainable agricultural intensification. Nutrient Cycling in Agroecosystems 108 (1): 1-4. https://doi.org/10.1007/s10705-017-9851-0.

Bharadwaj, K. (1982): Production conditions in Indian agriculture. In: Harriss, J.: Rural Development: Theories of Peasant Economy and Agrarian Change. 1st edition. Routledge, London: 269-288. https://doi.org/10.4324/9781003431763.

Chen, Z., Huffman, W.E., Rozelle, S. (2009): Farm technology and technical efficiency: Evidence from four regions in China. China Economic Review 20 (2): 153-161. https://doi.org/10.1016/j.chieco.2009.03.002.

Cho, S.-H., Chen, Z., Poudyal, N.C. (2010). Spatial structure of agricultural production in China. Applied Economics 42 (16): 2031-2040. https://doi.org/10.1080/00036840701765320.

Christensen, L.R., Jorgenson D.W., Lau L.J. (1973): Transcendental Logarithmic Production Frontiers. Review of Economics and Statistics 55 (1): 28-45. https://doi.org/10.2307/1927992.

Coelli, T.J., Rao, D.S.P. (2005): Total Factor Productivity Growth in Agriculture: A Malmquist Index Analysis of 93 Countries, 1980-2000. Agricultural Economics 32 (SUPPL. 1): 115-134. https://doi.org/10.1111/j.0169-5150.2004.00018.x.

Cui, Z., Zhang, H., …, Dou, Z. (2018): Pursuing sustainable productivity with millions of smallholder farmers. Nature 555 (7696): 363-366. https://doi.org/10.1038/nature25785.

Demir, N., Mahmud, S.F. (2002): Agro-Climatic Conditions and Regional Technical Inefficiencies in Agriculture. Canadian Journal of Agricultural Economics 50 (3): 269-280. https://doi.org/10.1111/j.1744-7976.2002.tb00337.x.

Deng, X., Huang, J., Rozelle, S., Uchida, E. (2006): Cultivated land conversion and potential agricultural productivity in China. Land Use Policy 23 (4): 372-384. https://doi.org/10.1016/j.landusepol.2005.07.003.

Druska, V., Horrace, W.C. (2004): Generalized Moments Estimation for Spatial Panel Data: Indonesian Rice Farming. American Journal of Agricultural Economics 86 (1): 185-198. http://www.jstor.org/stable/3697883.

Dubin, R.A. (1998): Spatial Autocorrelation: A Primer. Journal of Housing Economics 7 (4): 304-327. https://doi.org/10.1006/jhec.1998.0236.

Fan, S. (1997): Production and Productivity Growth in Chinese Agriculture: New Measurement and Evidence. Food Policy 22 (3): 213-228. https://doi.org/10.1016/S0306-9192(97)00010-9.

FAO (Food and Agriculture Organization of the United Nations) (2019): FAOSTAT Database on Agriculture.

Farrell, M.J. (1957): The Measurement of Productive Efficiency. Journal of the Royal Statistical Society. Series A (General) 120 (3): 253. https://doi.org/10.2307/2343100.

Glass, A.J., Kenjegalieva, K., Sickles, R.C. (2016): A Spatial Autoregressive Stochastic Frontier Model for Panel Data with Asymmetric Efficiency Spillovers. Journal of Econometrics 190 (2): 289-300. http://dx.doi.org/10.1016/j.jeconom.2015.06.011.

Gong, B. (2018): Agricultural Reforms and Production in China: Changes in Provincial Production Function and Productivity in 1978-2015. Journal of Development Economics 132 (October 2017): 18-31. https://doi.org/10.1016/j.jdeveco.2017.12.005.

Grau, R., Kuemmerle, T., Macchi, L. (2013): Beyond ‘Land Sparing versus Land Sharing’: Environmental Heterogeneity, Globalization and the Balance between Agricultural Production and Nature Conservation. Current Opinion in Environmental Sustainability 5 (5): 477-483. https://doi.org/10.1016/j.cosust.2013.06.001.

Greene, W. (2005): Reconsidering Heterogeneity in Panel Data Estimators of the Stochastic Frontier Model. Journal of Econometrics 126 (2): 269-303. https://doi.org/10.1016/j.jeconom.2004.05.003.

Hou, L., Zhang, Y., Zhan, J., Glauben, T. (2012): Marginal Revenue of Land and Total Factor Productivity in Chinese Agriculture: Evidence from Spatial Analysis. Journal of Geographical Sciences 22 (1): 167-178. https://doi.org/10.1007/s11442-012-0919-0.

Huang, W., Jiang, L. (2019): Efficiency Performance of Fertilizer Use in Arable Agricultural Production in China. China Agricultural Economic Review 11 (1): 52-69. https://doi.org/10.1108/CAER-12-2017-0238.

Jiang, L., Folmer, H., Ji, M., Tang, J. (2017): Energy Efficiency in the Chinese Provinces: A Fixed Effects Stochastic Frontier Spatial Durbin Error Panel Analysis. The Annals of Regional Science 58 (2): 301-319. https://doi.org/10.1007/s00168-016-0782-5.

Kumbhakar, S.C., Lovell, C.A.K. (2000): Stochastic frontier analysis. Cambridge University Press. https://doi.org/10.1017/CBO9781139174411.

Kutlu, L., Tran, K.C., Tsionas, M.G. (2020): A spatial stochastic frontier model with endogenous frontier and environmental variables. European Journal of Operational Research 286 (1): 389-399. https://doi.org/10.1016/j.ejor.2020.03.020.

LeSage, J., Pace, R.K. (2009): Introduction to Spatial Econometrics. Chapman and Hall/CRC, New York. https://doi.org/10.1201/9781420064254.

Lee, L.F., Yu, J. (2010): Estimation of spatial panel model with fixed effects. Journal of Econometrics 154: 165-185. https://doi.org/10.1016/j.jeconom.2009.08.001.

Liu, J., Jin, X., Xu, W., Gu, Z., Yang, X., Ren, J., Fan, Y., Zhou, Y. (2020): A new framework of land use efficiency for the coordination among food, economy and ecology in regional development. Science of The Total Environment 710 (2019): 135670. https://doi.org/10.1016/j.scitotenv.2019.135670.

Masters, W.A., Djurfeldt, A.A., De Haan, C., Hazell, P., Jayne, T., Jirström, M., Reardon, T. (2013): Urbanization and farm size in Asia and Africa: Implications for food security and agricultural research. Global Food Security 2 (3): 156-165. https://doi.org/10.1016/j.gfs.2013.07.002.

Meeusen, W., Broeck, J. (1977): Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error. International Economic Review 18 (2): 435-444. https://doi.org/10.2307/2525757.

Neumann, K., Verburg, P.H., Stehfest, E., Müller, C. (2010): The Yield Gap of Global Grain Production: A Spatial Analysis. Agricultural Systems 103 (5): 316-326. https://doi.org/10.1016/j.agsy.2010.02.004.

Ouassanouan, Y., Fakir, Y., Simonneaux, V., Kharrou, M.H., Bouimouass, H., Najar, I., Benrhanem, M., Sguir, F., Chehbouni, A. (2022): Multi-decadal analysis of water resources and agricultural change in a Mediterranean semiarid irrigated piedmont under water scarcity and human interaction. Science of The Total Environment 834: 155328. https://doi.org/10.1016/j.scitotenv.2022.155328.

Pede, V.O., Areal, F.J., Singbo, A., McKinley, J., Kajisa, K. (2018): Spatial Dependency and Technical efficiency: An Application of a Bayesian Stochastic Frontier Model to Irrigated and Rainfed Rice Farmers in Bohol, Philippines. Agricultural Economics 49 (3): 301-312. https://doi.org/10.1111/agec.12417.

Pilevneli, T., Capar, G., Sánchez-Cerdà, C. (2023): Investigation of climate change impacts on agricultural production in Turkey using volumetric water footprint approach. Sustainable Production and Consumption 35: 605-623. https://doi.org/10.1016/j.spc.2022.12.013.

Qiu, T., Choy, S.T.B., Luo, B. (2022): Is small beautiful? Links between agricultural mechanization services and the productivity of different-sized farms. Applied Economics 54 (4): 430-442. https://doi.org/10.1080/00036846.2021.1963411.

Ramajo, J., Hewings, G.J.D. (2018): Modelling Regional Productivity Performance across Western Europe. Regional Studies 52 (10): 1372-1387. https://doi.org/10.1080/00343404.2017.1390219.

Reinhard, S., Lovell, C.A.K., Thijssen, G. (2002): Analysis of Environmental Efficiency Variation. American Journal of Agricultural Economics 84 (4): 1054-1065. https://www.jstor.org/stable/1244745.

Seeger M. (2023): Agricultural Soil Degradation in Germany. In: Pereira, P., Muñoz-Rojas, M., Bogunovic, I., Zhao, W. (eds.): Impact of Agriculture on Soil Degradation II. The Handbook of Environmental Chemistry, vol 121. Springer, Cham. https://doi.org/10.1007/698_2022_948.

Skevas, I. (2023): A novel modeling framework for quantifying spatial spillovers on total factor productivity growth and its components. American Journal of Agricultural Economics 105 (4): 1221-1247. https://doi.org/10.1111/ajae.12360.

Tsukamoto, T. (2018): A Spatial Autoregressive Stochastic Frontier Model for Panel Data Incorporating a Model of Technical Inefficiency. Japan & The World Economy 50 (July): 1-12. https://doi.org/10.1016/j.japwor.2018.11.003.

Viana, C.M., Freire, D., Abrantes, P., Rocha, J., Pereira, P. (2022): Agricultural Land Systems Importance for Supporting Food Security and Sustainable Development Goals: A Systematic Review. Science of The Total Environment 806 (February): 150718. https://doi.org/10.1016/j.scitotenv.2021.150718.

Wang, J., Wang, Z., Li, K., Li, C., Wen, F., Shi, Z. (2023): Factors affecting phase change in coupling coordination between population, crop yield, and soil erosion in China's 281 cities. Land Use Policy 132: 106761. https://doi.org/10.1016/j.landusepol.2023.106761.

Wu, Y., Xi, X., Tang, X., Luo, D., Gu, B., Lam, S.K., Vitousek, P.M., Chen, D. (2018): Policy distortions, farm size, and the overuse of agricultural chemicals in China. Proceedings of the National Academy of Sciences (PNAS) 115 (27):7010-7015. https://doi.org/10.1073/pnas.1806645115.

Yan, H., Liu, J., Huang, H., Tao, B., Cao, M. (2009): Assessing the Consequence of Land Use Change on Agricultural Productivity in China. Global and Planetary Change 67 (1-2): 13-19. https://doi.org/10.1016/j.gloplacha.2008.12.012.

Yang, H. (1996): China's Maize Production and Supply from A Provincial Perspective. Chinese Economies Research Centre (CERC) Working Papers. University of Adelaide, Chinese Economies Research Centre.

Yang, B., Zhang, Z., Wu, H. (2022): Detection and attribution of changes in agricultural eco-efficiency within rapid urbanized areas: A case study in the Urban agglomeration in the middle Reaches of Yangtze River, China. Ecological Indicators 144: 109533. https://doi.org/10.1016/j.ecolind.2022.109533.

Yao, S., Liu, Z. (2008): Determinants of Grain Production and Technical efficiency in China. Journal of Agricultural Economics 49 (2): 171-184. https://doi.org/10.1111/j.1477-9552.1998.tb01262.x.

Yu, C., Huang, X., …, Taylor, J. (2019): Managing nitrogen to restore water quality in China. Nature, 567 (7749): 516-520. https://doi.org/10.1038/s41586-019-1001-1.

Zahoor, Z., Latif, M.I., Khan, I., Hou, F. (2022): Abundance of natural resources and environmental sustainability: the roles of manufacturing value-added, urbanization, and permanent cropland. Environmental Science and Pollution Research 29 (54): 82365-82378. https://doi.org/10.1007/s11356-022-21545-8.

Zhang, B., Li, X., Chen, H., Niu, W., Kong, X., Yu, Q., Zhao, M., Xia, X. (2022): Identifying opportunities to close yield gaps in China by use of certificated cultivars to estimate potential productivity. Land Use Policy 117: 106080. https://doi.org/10.1016/j.landusepol.2022.106080.

Zhu, W., Jia, S., Devineni, N., Lv, A., Lall, U. (2019): Evaluating China's Water Security for Food Production: The Role of Rainfall and Irrigation. Geophysical Research Letters 46 (20): 1-12. https://doi.org/10.1029/2019GL083226.

Contact Author

Dr. Vivian Wei Huang
Swedish University of Agricultural Sciences, Department of Economics
Box 7013, 75007 Uppsala, Sweden
e-mail: vivian.wei.huang@slu.se

Appendix

Table A1. Spatial weights selection and related Moran's I value

No.	Spatial weight	Moran's I of y
1	One order of queen contiguity	0.383
2	Two orders of queen contiguity	0.309
3	One order of rook contiguity	0.384
4	Two orders of rook contiguity	0.311
5	Neighbour within 150 km	0.29
6	Neighbour within 200 km	0.259
7	Neighbour within 250 km	0.233
8	One neighbour for each county	0.310
9	Two neighbours for each county	0.327
10	Three neighbours for each county	0.336
11	Four neighbours for each county	0.346
12	Five neighbours for each county	0.356
13	Six neighbours for each county	0.361
14	Seven neighbours for each county	0.352
15	Eight neighbours for each county	0.347

Source: authors' own calculation

Table A2. Results of model specification tests

Test Hypothesis	LL	AIC	BIC
1. Specification of effects: $chi^2(7)$ = 1040.43 / Prob>chi^2 = 0.00			
H0: Difference in coefficients not systematic (RE)	-10372.11	20766.21	20854.24
H1: Difference in coefficients systematic (FE)	-5654.381	15340.76	31473.38
2. Selection of production function LR $chi^2(15)$ = 450.68 / Prob > chi^2 = 0.00			
H0: Cobb-Douglas production function	-5654.381	15340.76	31473.38
H1: Translog production function	-5429.039	14920.08	31172.73
3. Specification of technical inefficiency model LR chi2(11) =2840.27 / Prob > chi^2 =0.00			
H0: No technical inefficiency effect	-5429.039	14920.08	31172.73
H1: Final specification as Model 1	-4008.902	12101.8	28442.48
4. Specification of SAR LR $chi^2(1)$ =4533.84 / Prob > chi^2 =0.00			
H0: ρ=0 no spatial dependency	-4008.902	12101.8	28442.48
H1: Final specification as Model 2	-1741.983	7569.966	23918.65

Note: AIC Akaike information criterion, BIC Bayesian information criterion, LL log likelihood value
Source: authors' own calculation

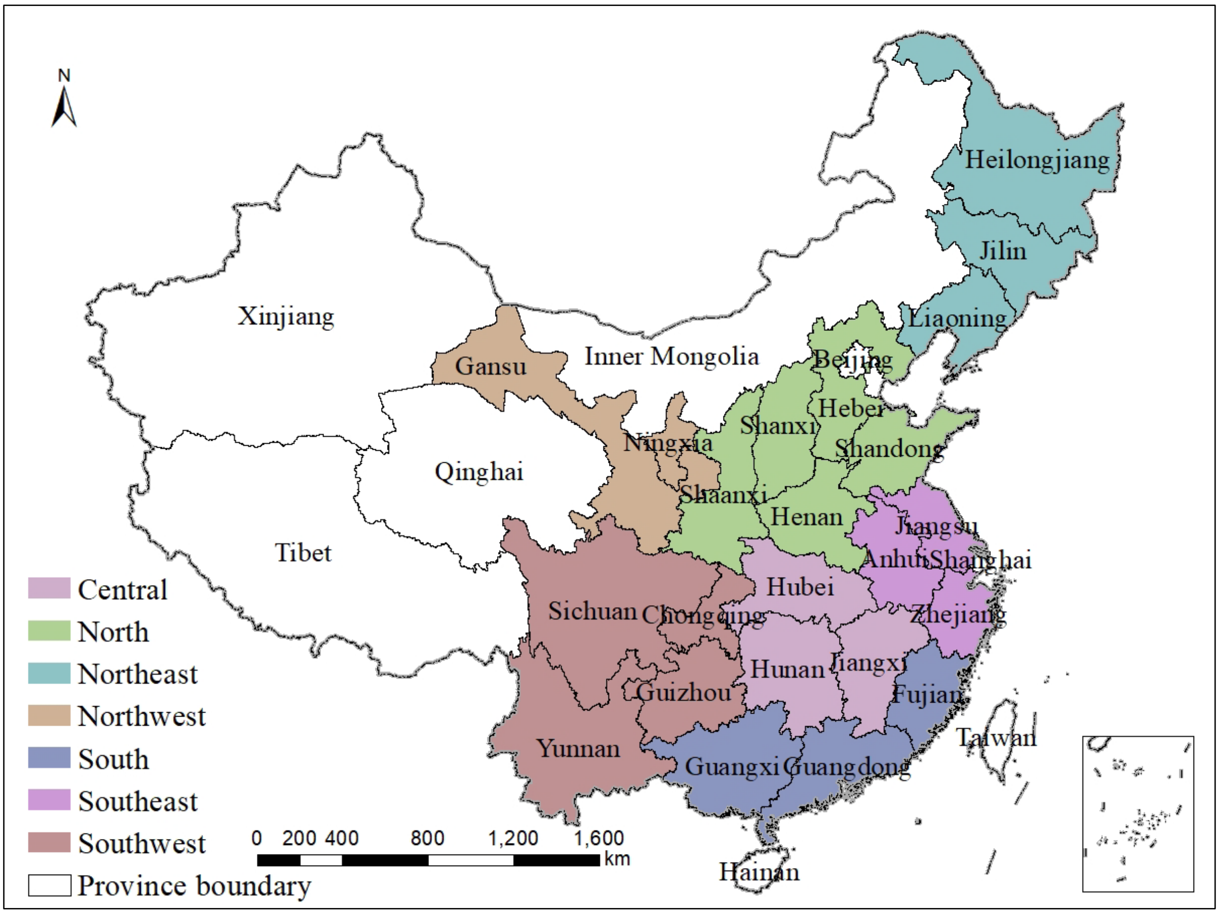

Figure A1. Agricultural regions of China and the provinces included in this study

Source: author`s own graph