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Ecological Efficiency of Hog Scale Production under Environmental Regulation in China: Based on an Optimal Super Efficiency SBM-Malmquist–Tobit Model

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Abstract
China's hog production is facing the dual pressures of the market and environment. A systematic analysis on the ecological efficiency (eco-efficiency) of hog cultivation is of great significance for the development of sustainability and distribution optimization in the industry. This paper investigates the eco-efficiency of hog production and the determinants of eco-efficiency in China using a panel data (2004-2018). An optimal Super Efficiency SBM-Malmquist–Tobit model is adopted for hog production analysis, and the empirical results show a great variation in eco-efficiency across provinces, ranging from 0.557 to 1.19 with a mean value of 0.937 in 2018. The predominant production area of hogs is found being transferred from north to south, with small- and medium-scale predominant production areas shifted from east China to southwest China, and large-scale predominant production areas shifted from north China to south-central China. Another finding is that eco-efficiency increased by the improvement of technical efficiency. In addition, the Tobit regression results show that, rural economic development, the government's investment in environmental control, the market advantage index, and transportation conditions had positive effects on the eco-efficiency; meanwhile, the forbidden policy for livestock cultivation in certain areas, the structure of the hog-breeding industry, the density of slaughtered fattened hogs, and the prices of hogs had negative effects on the eco-efficiency.

Keywords Ecological Efficiency; Hog production; Environmental regulation; Optimized super efficiency SBM-Malmquist-Tobit model; China

Introduction

China is the world's largest pork consumer and hog producer. The development of the hog-breeding industry is of great significance to stimulating rural economic growth, ensuring the market supply, and promoting the stability of social development. Since the occurrence of African swine fever, China's hog breeding industry has experienced a tightening trend of supply. Compared with 2018, China's domestic pork production was reduced by 21.25% in 2019. Although imports of pork increased by 45.19%, when excluding exports, there was still a supply gap of 18.6% (about 10.3894 million tons). After the occurrence of COVD-19 in 2020, China's domestic pork production is further reduced by 3.3%, which led to a sharp increase in pork prices (the data are from the *China Statistical Yearbook*, NBSC 2005–2020, and the Ministry of Agriculture and rural areas information website of the People's Republic of China). Improving the efficiency of hog production is the key means to stabilize the market supply, while the continuous development of scale farming provides conditions for the improvement of production efficiency. Data show that the number of scale farms with more than 500 slaughtered fattened hogs rise to 215,502 in 2017 (China Animal Husbandry and Veterinary Yearbook, AHVYEBC 2018). China's hog production is undergoing a great transformation from small backyard, household-based farms towards large-scale breeding zones (Qiao et al. 2016).

However, highly intensive hog production boosts the cost and difficulty of manures treatment (Weiss and McMichael 2004) and inevitably seriously increases the risk of bad air quality through odor (Schiffman and William 2005). High concentrations of hydrogen sulfide, which occur from the anaerobic fermentation of manure, are toxic to human and animal life (Ni et al. 1999; Heederick et al. 2007). Under the strategy of sustainable development, in order to achieve the dual goals of livestock and poultry breeding industry development and ecological environment protection, local governments have successively introduced prohibitions and restrictions policies for livestock cultivation in certain areas, and put forward new development goals for hog production. The No. 1 Central Document formulated by China State Council (CSC 2013) in 2013 explicitly proposed conducting control efforts to prevent agricultural nonpoint source pollution and livestock farming pollution. In 2015, the Chinese government formulated The Action Plan for the Prevention and Control of Water Pollution (CSC 2015), which required local governments to scientifically demarcate forbidden areas of livestock farming, and to close or relocate farms in forbidden areas by the end of 2017. In this context, both environmental cost and production efficiency must be considered in hog production.

Heated discussions have been conducted on how to measure the synergistic growth of productivity and environmental protection. The ecological efficiency (hereinafter referred to as "eco-efficiency") provides a reference for the measurement and quantification of the environmental efficiency of the industry. Compared with the traditional total factor productivity (TFP) evaluation method, eco-efficiency incorporates environmental pollution into the indicator system, which reflects the sustainable development of the industry. Regarding how to incorporate environmental factors into the econometric model, the main practices in the existing literature include: incorporating pollution control input or environmental constraints as independent variables into the model (Ramanathan 2005); or incorporating environmental pollutant emissions (such as carbon emissions, etc.) into the production model as a type of undesired output to estimate the eco-efficiency (Pittman 1983; Chung et al. 1997; Zhao et al. 2015). And some utilized undesired output removal as a proxy for output in pollution (Yang et al. 2008; Yang 2009).

Early research mainly used the radial and angular data envelopment analysis DEA model (contains Charnes-Copper-Rhodes CCR model (Charnes et al. 1979) and Banker-Charnes-Cooper BCC model (Banker et al. 1984)) to estimate eco-efficiency. In traditional DEA model, input and output factors are defined to vary in a same ratio or radial direction. However, typically the input and output factors in reality do not change with the same proportion or radial direction, which makes a great difference between the theory of traditional DEA model and the actual situation. What's more, DEA efficiency measures are often overestimated when there is excessive input or insufficient output. To improve this shortcoming, Tone (2001) put forward a Slacks-based measure of efficiency (SBM), which is non-radial and deals with input/output slacks directly. Since that usually plural decision making units (DMUs) will realize "efficient status", which make the efficiency score unity as 1. Therefore, Tone (2002) proposed super efficiency based on SBM (SE-SBM), which can rank the efficient DMUs by define a DMU as being SBM-efficient. That provides a new approach to analyze the effects of environmental factor inputs.

Recently, eco-efficiency has been gradually applied to the study of efficiency in agricultural production (Li 2014; Meng et al. 2019). In the research of hog production, Wu et al. (2013) used the output-based directional distance function (DDF) to construct a Malmquist–Luenberger productivity index that accounts for the desired output and undesired output as well as the measured eco-efficiency and endogenous power of the efficiency growth of China's 16 main hog-breeding provinces. Based on the same method, Wang et al. (2015) proposed the concept of an environmental technology innovator, made a comparative analysis of eco-efficiency in advantageous hog production provinces, and proposed that environmental regulation would promote the formation of a certain number of environmental technology innovators to promote the outer migration of the production possibility frontier. Zhang et al. (2015) used the stochastic frontier approach (SFA) to calculate the individual technical efficiency, and used the radial output technical efficiency (OTE) function to compare the current output with the maximum possible output and to calculate the technical and eco-efficiency of different scales of hog production across provinces. Zuo et al. (2016) constructed a fixed-window-Malmquist–Luenberger (FWML) index containing the undesired output and measured the efficiency of large-scale hog production in China's 29 provinces based on the variable return to scale (VRS) model from the perspective of the output. Zuo and Feng (2017) analyzed the TFP's spatial-temporal variation and its convergence of scale hog production in China under the view of environmental regulation using the SML index, spatial autocorrelation, and spatial β convergence analysis methods. Du and Wang (2020) constructed evaluation indication systems for the eco-efficiency of hog scale production and evaluated the eco-efficiency of different scales of 17 main hog production provinces in China, applying a non-radical and non-oriented SE-SBM model, and discussed the appropriateness of the hog breeding scale.

The existing research has provided many experiences for the measurement methods of eco-efficiency and enlightenment. However, there are still some improvements needed in the following aspects. First, previous studies only provided the decomposition and calculation value of eco-efficiency, and there are few works on the analysis of the influencing factors of eco-efficiency in hog production of different scales, which would reduce the persuasiveness of the research conclusions and the correctness of the policy recommendations (Wang et al. 2015). Second, undesired output occurs in the whole hog cycle, and the environmental constraints can only act as shock variables to describe changes in the external environment, and a method that only incorporates environmental constraints or undesired output into the econometric model to calculate the eco-efficiency cannot be a complete description of reality.

Based on the discussion above, the marginal contributions of this paper are as follows: First, to strengthen the credibility of research conclusions and provide empirical evidence for subsequent policy enlightenment, we conducted Tobit regression to analyze the influencing factors of eco-efficiency in the hog industry. Second, we incorporated an undesired output and environmental constraints into the analysis framework simultaneous, to analyze the eco-efficiency of the hog industry and its influencing factors to be closer to the actual production conditions. Third, we used the net value of hog production as the desired output. Some studies used the net weight of hogs to express the desired output; however, in reality, interest is the main influencing factor for farmers in deciding on the breeding behavior. Therefore, based on the selection experience of output indicators in the existing literature on the efficiency of livestock farming, this paper chose the net value of hogs as the desired output (Reinhard et al. 1999; Geng and Li 2013; Han et al. 2019), which provides a new discussion perspective for the study of hog production efficiency.

Methodology

To calculate and decompose the eco-efficiency of specific environmentally detrimental outputs, two steps are usually taken. First, the optimal SE-SBM model is used to calculate the eco-efficiency; second, the Malmquist–Luenberger index is decomposed to describe the dynamic trend characteristics of the eco-efficiency. The Tobit regression function was also used to analyze the influencing factors on eco-efficiency at different scales in hog production.

Optimal SE-SBM Model

The process of hog production not only obtains the desired output but also brings certain undesired outputs that have negative external effects on the environment. Färe et al. (2007) constructed an environmental production set that considered both the desired output and undesired output; this set reflects the input–output technological structure, including all types of outputs.

Suppose that there exist n DMUs in the production system, and each DMU has three types of elements: input factor (m), desired output (S_1), and undesired output (S_2). The DMU can be expressed by a vector as $x \in R^m, y^g \in R^{s_1}, y^{gb} \in R^{s_2}$. We define the matrices X, $\mathrm{Y^g}$, and $\mathrm{Y^b}$ as $X = [x_1, \cdots, x_n] \in R^{m \times n}$, $\mathrm{Y^g} = [y_1^g, \cdots, y_n^g] \in R^{s_1 \times n}$, and $\mathrm{Y^b} = [y_1^b, \cdots, y_n^b] \in R^{s_2 \times n}$, where $X > 0$, $\mathrm{Y^g} > 0$, $\mathrm{Y^b} > 0$. Thus, the above production set can be transformed into:

$$\rho = \{(x, \mathrm{y^g}, \mathrm{y^b}) | x > X\theta, \mathrm{y^g} \leq \mathrm{Y^g}\theta, \mathrm{y^b} \geq \mathrm{Y^b}\theta, \theta \geq 0\} \tag{1}$$

where $\theta \in R^n$ is the weight vector, and $\theta > 0$ means that the industry has a constant return to scale; if the equation satisfies both $\theta > 0$ and $\sum \theta = 1$, then the return to scale is variable. In hog production, the returns to scale are changes with the adoption of production technology and the factor input structure (Zheng et al. 1998).

The traditional radial DEA model cannot consider the influence of "slack variables" on the efficiency value, nor can it measure the technical changes that increase the desired output and reduce the non-desired output simultaneously. Thus, the eco-efficiency measured by the traditional radial DEA model is biased. To improve the radial DEA models, Tone (2002) proposed a super-efficient SBM model (a super-efficient DEA model based on modified slack variables) that can further distinguish efficient DMUs. This paper draws on the improvement of the super-efficiency SBM model by Huang et al. (2014), and we set the SBM efficiency model of a specific DMU (x_o, y_o^g, y_o^b) as:

$$\rho^* = min \frac{1 + \frac{1}{m}\sum_{i=1}^{m} \frac{S_i^-}{X_{io}}}{1 - \frac{1}{S_1 + S_2}(\sum_{r=1}^{S_1} \frac{S_r^g}{Y_{ro}^g} + \sum_{k=1}^{S_2} \frac{S_k^b}{Y_{ko}^b})}$$

$$s.t. \quad \begin{cases} x_{io} - \sum_{j=1, j\neq o}^{n} x_{ij}\theta_j + S_i^-; i = 1,2, \cdots, m \\ \sum_{j=1, j\neq o}^{n} Y_{rj}\theta_j - Y_{ro}^g + S_r^g \geq 0; r = 1,2, \cdots, S_1 \\ Y_{ko}^b - \sum_{j=1, j\neq o}^{n} Y_{kj}\theta_j + S_k^b \geq 0; k = 1,2, \cdots, S_2 \\ 1 - \frac{1}{S_1 + S_2}(\sum_{r=1}^{S_1} \frac{S_r^g}{Y_{ro}^g} + \sum_{k=1}^{S_2} \frac{S_k^b}{Y_{ko}^b}) \geq \varepsilon \\ S^- \geq 0, S^g \geq 0, S^b \geq 0, \theta \geq 0 \end{cases} \tag{2}$$

where Equation (2) is a super-efficiency SBM model based on the assumption of variable returns to scale, and ρ^* is the eco-efficiency value of hog production; S^-, S^g, and S^b are slack variables of the input variables, desired output, and undesired output, respectively; x, $\mathrm{y^g}$, $\mathrm{y^b}$ are input, desired output and undesired output values respectively; and o is the DMU being evaluated. To ensure that the denominator is not zero, ε is non-Archimedean infinitesimal.

Malmquist–Luenberger Index

Sten Malmquist (1985) first proposed Malmquist index, as a kind of consumption quantity index. Based on the theory of Malmquist, Cave et al. (1982) proposed a Malmquist productivity index. And then, Färe et al. (1997) decompose the

Malmquist productivity index into the rate of technical progress and the rate of change of technical efficiency. After that, the Malmquist productivity index has been popular applied in multiples study areas. Chung et al. (1997) further develop the Malmquist productivity index to Malmquist–Luenberger Index (ML) which contains environmental factors. The Malmquist–Luenberger Index (ML) not only includes the Malmquist index's requirement for increasing desired output, but also takes environmental factors into account and requires that undesired output continue to decrease.

To analyze the dynamic trend characteristics of eco-efficiency in hog production, we drew on the theory of Malmquist–Luenberger Index (ML) and decompose it into the rate of technical progress and the rate of change of technical efficiency. The specific decomposition formula is as follows:

$$ML_t^{t+1} = [\frac{1+\vec{D}_0^t(x^t,y^t,b^t;y^t,-b^t)}{1+\vec{D}_0^t(x^{t+1},y^{t+1},b^{t+1};y^{t+1},-b^{t+1})} \times \frac{1+\vec{D}_0^{t+1}(x^t,y^t,b^t;y^t,-b^t)}{1+\vec{D}_0^t(x^{t+1},y^{t+1},b^{t+1};y^{t+1},-b^{t+1})}]^{\frac{1}{2}} \tag{3}$$

$$MLTECH_t^{t+1} = [\frac{1+\vec{D}_0^{t+1}(x^t,y^t,b^t;y^t,-b^t)}{1+\vec{D}_0^t(x^{t+1},y^{t+1},b^{t+1};y^{t+1},-b^{t+1})} \times \frac{1+\vec{D}_0^{t+1}(x^t,y^t,b^t;y^t,-b^t)}{1+\vec{D}_0^t(x^{t+1},y^{t+1},b^{t+1};y^{t+1},-b^{t+1})}]^{\frac{1}{2}} \tag{4}$$

$$MLEFFCH_t^{t+1} = [\frac{1+\vec{D}_0^t(x^t,y^t,b^t;y^t,-b^t)}{1+\vec{D}_0^t(x^{t+1},y^{t+1},b^{t+1};y^{t+1},-b^{t+1})} \times \frac{1+\vec{D}_0^{t+1}(x^t,y^t,b^t;y^t,-b^t)}{1+\vec{D}_0^t(x^{t+1},y^{t+1},b^{t+1};y^{t+1},-b^{t+1})}]^{\frac{1}{2}} \tag{5}$$

$$ML_t^{t+1} = MLTECH_t^{t+1} \times MLTECH_t^{t+1} \tag{6}$$

where ML_t^{t+1} (Malmquist–Luenberger) is the total factor productivity, $MLTECH_t^{t+1}$ presents the technical progress rate, and $MLEFFCH_t^{t+1}$ denotes the rate of change in technical efficiency. The index is based on the sample technology in period t and is calculated from the trend of the productivity change in period t to t+1. An index value greater than 1 indicates that productivity is on the rise, equal to 1 indicates that there is no change in productivity, and less than 1 indicates that productivity is on the decline.

The Tobit Regression

According to the model setting, the eco-efficiency calculated by the SE-SBM model and the Malmquist–Luenberger productivity index is a truncated segment value or cut value. That means the ordinary least squares (OLS)regressions estimate is inconsistent and biased. Therefore, we chose the Tobit regression model to analyze the impact factors of eco-efficiency in hog production. We propose the following Tobit regression model:

$$\rho_i^* = \alpha_0 + \sum_{j=1}^{l} \alpha_j x_{ij} + \gamma_i \tag{7}$$

$$\rho_i = \rho_i^* \qquad 0 < \rho_i^* \leq 1$$

$$\rho_i = 0 \qquad \rho_i^* < 0$$

$$\rho_i = 1 \qquad \rho_i^* > 1$$

where ρ_i^* is the latent variable, ρ_i is the actually observed dependent variable, x_{ij} presents the independent variable, α_0 is the constant term, α_j denotes the correlation coefficient vector, and γ_i is the random error term. In particular, we used the maximum and minimum values of eco-efficiency as the upper and lower cutoff points in the Tobit regression.

Data

The input and desired output data for the different scales of hog production of 30 provinces in China from 2004 to 2018 used in the present study were directly obtained from the *China Agricultural Product Cost-Benefit Compilation* (CAPCBC, NDRC 2005–2019), which was issued by the National Development and Reform Commission (NDRC) of China. The cost–benefit data of hog production were collected from individual farms by a three-stage random sampling procedure. The individual farms included traditional backyard households (less than 30 hogs), small-scale farms (raising 30 to 100 hogs), medium-scale farms (100 to 1000 hogs), and large-scale farms (more than 1000 hogs). Due to missing data on traditional backyard households in some provinces, this paper only took small-, medium-, and large-scale farms into consideration. These data contained each slaughtered hog's weight and value, each piglet's weight and cost, feeding days, labor inputs (including days and cost), feed usage, water and fuel cost, medical treatment, epidemic prevention costs, etc. (Zhou et al. 2015).

The data of the undesired outputs were from *The First National Census of Pollution: Manual of Discharge Coefficient of Livestock and Poultry Industry* (FNCP, IEDA, and NIES 2009)[1]. These data came from the research of the pollution conditions of the livestock and poultry industry in China as measured by the Ministry of Agriculture of China, the Chinese Academy of Agricultural Science, and the Ministry of Environmental Protection of China. The respondents of this research consisted of specialized households (more than 50 hogs), scaled farms (more than 500 hogs), and raising zones (without definition in breeding scale) in the north, northeast, east, south-central, southwest, and northwest of China (The northern region includes Beijing, Tianjin, Hebei, Shanxi, and Inner Mongolia; the northeastern region includes Liaoning, Jilin, and Heilongjiang; the eastern region includes Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, and Shandong; the south-central region includes Henan, Hubei, Hunan, Guangdong, Guangxi, and Hainan; the southwestern region includes Chongqing, Sichuan, Guizhou, Yunnan, and Tibet; and the northwestern region includes Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang). These data included the chemical oxygen demand (COD), total nitrogen (TN), total phosphorus (TP), copper (Cu), and zinc (Zn) per hog per day. Other data were from the *China Statistical Yearbook* (NBSC 2005–2020), which is collected by the National Bureau of Statistics and published annually.

The input variables are four conventional input variables: (1) Feeding input: This includes the cost of concentrated feed and the cost of green roughage. We used the feed price index to deflate the depreciation data. (2) Labor input: Tian et al. (2015) used person-days spent on hog production. However, this cannot reflect the changes for labor prices and, thus, cannot properly describe the actual labor costs. Therefore, we used the cost of labor, which includes the conversion cost of family labor and the cost of hired labor. In particular, we deflated the depreciation data using the resident consumption index. (3) Fixed capital input: This includes the depreciation of fixed assets, tool and material costs, repair and maintenance costs, and feed processing costs (Li and Cao 2017). We used the fixed capital price index to deflate the depreciation data. (4) Other inputs: These refer to all material and service costs except the piglet cost, the depreciation of fixed assets, and feeding input. As there are different types of expenses included in "other inputs", we deflated the depreciation data using the agricultural production material price index. Thus far, almost all the costs of hog production have been included in our input indicators.

In this paper, the desired output variable is the net value of slaughtered fattened hogs for each province. The net value equals the total value (including the value of the main product and the by-products) minus the cost of each piglet. We used the production price deflator of hogs to calculate the real price of the net value, as the production price index measures the trend and degree of changes in the ex-factory price of products. The undesired output was measured by the total amount of the substances that are harmful to the environment in hog manure. We considered the hog manure emissions with different clean methods, including the dry clean manure and water flush manure. Zhang et.al (2005) considered the ratio of dry clean manure and water flush manure as 8:2. In the present study, we are concerned with the aggregate undesired output of every hog; hence, we propose the following equation:

$$QP = \sum AD \times (0.8PD_{a1} + 0.2PD_{a2}) \times (W/W_0), \quad a = 1,2,\cdots 5 \tag{8}$$

where QP is the undesired output; AD is the average raising days where raising days are the number of days the hog is fattened until reaching slaughter weight; PD_{a1} and PD_{a2} are the pollutant discharge coefficients of the ath pollutant in the dry manure and water flush manure, respectively; W denotes the actual weight of hogs; and W_0 presents the reference weight. Previous literature usually related the small-scale, medium-scale, and large-scale farms in CAPCBC (NDRC 2005–2019) to the specialized households, scaled farms, and raising zones, respectively in IEDA and NIES (2009) (Du and Wang 2020).

Thus, in this paper, we utilized the mean value for input and output factors of different scales, and we discuss the eco-efficiency across 30 provinces in China. In addition, all price data are deflated to 2003 constant prices by the price index. Finally, a total of 1239 samples were obtained. We used the MaxDEA pro software to solve the SE-SBM model and obtain the annual eco-efficiency in each province. The description of variables is reported in Table 1.

Table 1 Summary statistics of variables (per hog).

	Unit	Small-Scale		Medium-Scale		Large-Scale		Total	
		Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Total feeding cost	CNY	425.726	74.085	434.507	70.592	412.494	63.41	424.2086	69.931
Labor cost	CNY	123.811	66.577	85.266	48.132	58.092	34.432	88.185	57.532
Fixed capital cost	CNY	15.392	5.502	15.453	5.172	17.305	7.8	16.07	6.345
Other inputs	CNY	27.741	30.617	29.746	5.022	39.132	20.381	32.194	22.146
desired output	CNY	651.755	97.196	646.151	90.579	606.17	97.19	634.277	97.063
undesired output	kg	20.247	5.211	19.746	5.022	26.674	12.584	22.27	9.023

CNY, China Yuan.

[1] IEDA (Institute of Environment and Sustainable Development in Agriculture, Chinese Academy of Agricultural Sciences), NIES (Nanjing Institute of Environmental Science, Ministry of Environmental Protection of China). 2009. The First Census of Pollution: Manual of Discharge Coefficient of Livestock and Poultry Industry. Unpublished.

As Table 1 shows, for all types of inputs, except for the total feeding cost, the mean value of each input at the small-scale was higher than in other scales, reflecting that the average cost can be reduced through large-scale production. The undesired output level was not significantly different among different farming scales, and the medium scale was the lowest. The standard deviation of the desired output was large, indicating that there were great differences across provinces. Among all scales of farms, the small-scale farms had the highest desired output, which can be explained by the large input. The desired output at the medium-scale was higher than that at the large-scale, while the cost of inputs was less than that at the large-scale except for the total feeding cost and labor cost. This shows that the return to scale is not fixed, and, to a certain extent, this reflects the validity of the model in this paper.

Changes in Hog Production Areas

The changes in the distribution of pork production in China's 30 provinces in 2004 and 2018 are shown in Fig 1. From 2004 to 2018, China's hog production was mainly concentrated in south-central China, with a further trend of concentration and agglomeration. In 2018, the eight main hog producing provinces in China were Henan, Hubei, Hunan, and Guangdong in south-central China; Sichuan and Yunnan in southwest China, Hebei in North China; and Shandong in east China.

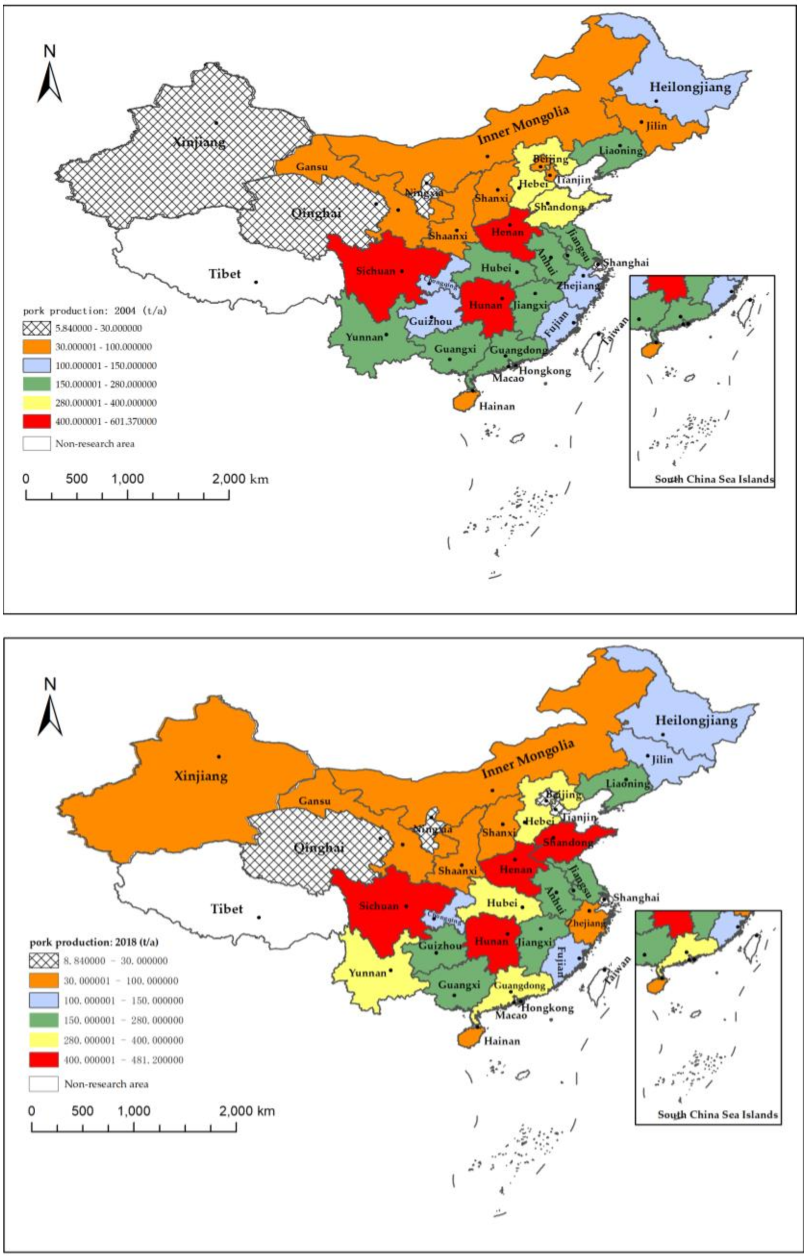

Fig. 1 The spatial distribution of pork production across China's provinces in 2004 and 2018 (ArcGIS 10.2).

Compared with 2004, the proportion of pork production in north, east, and southwest China out of the country's pork production declined by 18.81%, 0.24%, and 8.35%, respectively (the total national production is the total value including Tibet). Pork production in south-central China accounted for 34.24% of the country's total output (31.1% in 2004), and this demonstrated a 10.07% increase over 2004, while the proportion in the north decreased by 28.81%. This indicates that there was a shift of hog production from the north to the northeast, south-central, and northwest of China as well as a spread to the surrounding areas with the south-central as the primary production area.

In terms of the growth rate, hog production in Shanghai, Guangxi, Xinjiang, and Jiangxi developed rapidly, and increased by 93.49%, 63.16%, 55%, and 50.88%, respectively. However, while Shanghai's pork production increased a great deal, its gross production was relatively small with 113,000 tons in 2018. Pork production in Beijing, Zhejiang, and Tianjin dropped significantly, reaching 57.57%, 41.5%, and 35.85%, respectively. Only Heilongjiang essentially maintained the previous production (with a growth rate of 0.27%).

Hog production in China demonstrated a shift from the north to the south (especially to the South Central of China) from 2004 to 2018. This is inconsistent with the conclusion of Hu et al. (2005) regarding the shift of pork production from the south to north in China from 1980 to 2002. The classification of provinces in the regional division is slightly different; thus, in the present study, we only analyzed the significant trend. This different result can be explained by the change of the advantage of feed production in north China and the industrial function of provinces. Before 2002, the southwest (25.68%) and north (24.31%) of China were the main producing areas, and the growth rate of North China ranked first in the country. However, with the improvement of transportation convenience, the decrease in transportation cost weakened the advantage of the feed producing areas in North China. In 2018, due to the sharp decline in the production of Beijing and Tianjin, the proportion of pork production in north China dropped significantly. As the administrative capital and surrounding areas, environmental regulation in Beijing and Tianjin are more stringent, and the rapid cost growth of land, labor, and other inputs lead to a shift in pork production to other regions. Thus, compared with the trend of hog production from the south to the north before 2002, this trend reversed after 2004. In addition, on the basis of 2002, the main hog production provinces added Yunnan and Hubei in 2018.

Empirical Results

Eco-Efficiency Estimates

The scores of eco-efficiency based on the SE-SBM model are reported in Table 2. In most regions, the eco-efficiency was significantly lower than the TFP; however, the eco-efficiency of east and south-central China rose, which may be attributable to regional differences in the average level of the undesired output. The negative externalities of eco-efficiency were strengthened by the increase in undesired output, and the higher the impact of undesired output, the stronger the negative impact of eco-efficiency. We tested the impact of the undesired output on the eco-efficiency by using the proportion of undesired output/desired output to measure the differences of the undesired output across provinces (the results are reported at Figure A1 in the Appendix A). As Figure A1 shows, the average undesired output in east and south-central China was the lowest and much lower than the national level, while other regions were higher than the national level. This implies that a higher undesired output leads to the decrease in eco-efficiency relative to the TFP, and a lower undesired output below the average level leads to the increase in eco-efficiency relative to the TFP.

From the perspective of provinces, the eco-efficiency fluctuated and the environmental performance was improved. Among the eight main hog production provinces in 2018, only Hunan's eco-efficiency ranked the top in the whole country (as No. 3). According to the regional production, the possible reason is that the hog production in the other seven provinces was far beyond the optimal scale, which leads to a decrease in eco-efficiency.

Table 2 Eco-efficiency/total factor productivity (TFP) scores from SE-SBM model across regions, 2004–2018.

	2004	2006	2008	2010	2012	2014	2016	2018
Areas in china								
North	0.891/0.945	0.79/0.839	1.004/1.032	0.925/0.96	0.874/0.914	0.978/0.993	0.937/0.996	0.861/0.903
Northeast	0.754/0.792	0.834/0.792	0.815/0.909	0.674/0.899	0.703/0.77	0.799/0.747	0.751/0.827	0.701/0.762
East	1.117/0.995	1.085/0.992	1.059/0.961	1.052/0.892	1.077/0.926	1.038/0.912	1.052/0.874	1.087/1.01
South Central	0.941/0.877	0.843/0.839	0.839/0.817	0.903/0.841	0.899/0.853	1.026/0.961	0.904/0.878	0.983/0.977
Southwest	0.79/0.846	1.043/1.039	0.933/0.915	1.036/1.025	1.044/1.057	1.032/1.039	1.024/1.033	1.048/1.058
Northwest	0.974/0.993	1.145/1.172	0.919/0.933	0.841/0.829	0.873/0.869	0.766/0.738	0.883/0.868	0.89/0.896
Average	0.908/0.9	0.927/0.929	0.93/0.92	0.905/0.874	0.918/0.887	0.943/0.903	0.927/0.889	0.937/0.936
Main hog breeding production provinces in China (2018)								
Henan	0.802/0.732	0.712/0.719	0.665/0.659	0.827/0.673	0.791/0.619	1.021/0.8	0.709/0.677	0.809/0.813
Hubei	0.672/0.607	0.696/0.734	0.719/0.762	0.842/0.81	0.786/0.776	0.852/0.801	0.85/0.845	0.843/0.8
Hunan	1.249/1.247	0.918/0.919	0.94/0.979	0.906/0.931	1.038/1.066	1.222/1.249	1.142/1.186	1.136/1.192
Guangdong	0.911/0.772	0.868/0.872	0.811/0.835	0.758/0.752	0.785/0.747	0.908/0.824	0.74/0.701	0.926/0.898
Sichuan	0.896/0.865	1.055/1.032	1.07/1.06	1.101/1.07	1.064/1.061	0.963/0.966	0.951/0.976	1.03/1.025
Yunnan	0.804/0.885	0.955/0.98	0.788/0.822	0.997/1.017	1.066/1.09	0.986/0.99	0.98/0.997	0.997/0.999
Hebei	0.836/0.885	0.793/0.852	1.054/1.053	1.075/1.077	1.049/1.048	1.044/1.044	0.968/1	1.03/1.03
Shandong	0.904/0.843	1.026/0.981	1.152/0.941	1.079/0.813	1.124/0.863	1.115/0.816	1.194/1.016	1.339/1.028

Complete provincial data are shown in Table A1 of the Appendix.

Decomposition of Eco-Efficiency Growth

From 2004 to 2018, the eco-efficiency of hog production in China showed a slight upward trend, and the increase in technical efficiency was the main reason for the increase in eco-efficiency. As Table 3 shows, the average growth rate of the eco-efficiency was about 0.1%, while the TFP increased about 0.3% in average. The average technical efficiency index (MLEFFCH) of eco-efficiency and TFP were 0.018 and 0.019 higher than the technological frontier, respectively, and the average technical progress index (MLTECH) were 0.002 and 0.003 lower than the technological frontier, respectively.

Combined with the dynamic changes over years, this can be explained by the increased investment in hog production in certain provinces, including the increase in labor costs due to wage increases, the production input for expanding the production scale, etc. However, although the increase in input can improve the efficiency of the output to an extent, the inputs cannot translate into revenue completely, which increases the total cost accordingly and restricts the improvement of the efficiency of technological progress. In addition, another important factor contributing to the increase in investment in hog farming is the cyclical change in farmer decision behavior around market price changes. As shown in Table A2 of the Appendix, the price of pork had a positive effect on the technical efficiency (MLEFFCH) that was statistically significant at the 1% significance level. When the price of pork went up, the profit of breeding was increased, farmers tended to increase their investment in order to obtain more profit, and the technical efficiency was improved. However, the increased input cost cannot fully translate into the current income return, which restricted the current technical progress to a certain extent (the regression coefficient was negative but not statistically significant).

Table 3 Decomposition of the eco-efficiency and TFP Growth, 2004–2018.

Year	Eco-Efficiency			TFP		
	ML	MLEFFCH	MLTECH	Malmquist	MLEFFCH	MLTECH
2004–2005	0.861	0.938	0.942	0.887	0.943	0.964
2005–2006	1.195	1.153	1.082	1.166	1.167	1.042
2006–2007	1.084	1.010	1.088	1.074	1.001	1.082
2007–2008	0.740	1.054	0.719	0.736	1.046	0.718
2008–2009	0.990	0.969	1.049	0.995	0.961	1.055
2009–2010	1.207	1.051	1.161	1.213	1.026	1.192
2010–2011	1.038	0.993	1.053	1.038	1.012	1.032
2011–2012	0.831	1.031	0.810	0.833	1.016	0.823
2012–2013	1.058	0.999	1.064	1.048	0.989	1.065
2013–2014	1.007	1.045	0.972	1.006	1.041	0.971
2014–2015	1.126	0.978	1.156	1.152	0.999	1.157
2015–2016	0.909	1.005	0.910	0.914	0.984	0.938
2016–2017	0.951	1.035	0.925	0.934	1.073	0.882
2017–2018	1.150	1.006	1.161	1.178	1.020	1.171
Average	1.001	1.018	0.998	1.003	1.019	0.997

ML is an acronym for Malmquist–Luenberger Index.

Dynamic Rank of Eco-Efficiency across Provinces

Based on the results of Table A1 in the Appendix, we compared the eco-efficiency changes across provinces with respect to three types of scale in 2004, 2011, and 2018. As shown in Table 4: (1) Small-scale: the ranking of Liaoning and Guangdong remained unchanged; 14 provinces rose in the rankings, with Shandong (+11), Chongqing (+15), Sichuan (+17), Guizhou (+17), and Gansu (+17) with the largest increases; and 8 provinces fell in the rankings, including Inner Mongolia (−19), Anhui (−10), and Qinghai (−9) with the largest decreases. (2) Medium-scale: the ranking of Guizhou remained unchanged; 7 provinces rose in the rankings, with Beijing (+13), Shandong (+12), Yunnan (+13), and Qinghai (+9) showing a large increase; and 18 provinces fell in the rankings, with Tianjin (−13), Inner Mongolia (−9), Zhejiang (−9), Hainan (−18), and Xinjiang (−9) as the five provinces with the largest decreases. (3) Large-scale: the ranking of Jiangsu and Henan remained unchanged; 11 provinces rose in the rankings, among them, Jiangxi (+12), Shandong (+10), Hubei (+9), Hunan (+24), Guangxi (+19), Chongqing (+19), Guizhou (+22), and Xinjiang (+10) with a significant increase; while 16 provinces fell in the rankings, and Tianjin (−20), Shanxi (−10), Jilin (−10), Heilongjiang (−13), Sichuan (−14), and Qinghai (−23) had the largest declines.

Table 4 The ranking and dynamic changes of eco-efficiency in hog production across provinces.

	Small-Scale				Medium-Scale				Larger-Scale			
	2004	2011	2018	Ranking Changes	2004	2011	2018	Ranking Changes	2004	2011	2018	Ranking Changes
Beijing	11	-	-	—	25	27	12	(+13)	24	29	29	(−5)
Tianjin	-	-	-	—	6	17	19	(−13)	7	22	27	(−20)
Hebei	15	8	9	(+6)	16	1	20	(−4)	15	4	9	(+6)

Shanxi	19	16	15	(+4)	20	23	26	(−6)	12	24	22	(−10)
Inner Mongolia	6	3	25	(−19)	9	8	18	(−9)	3	21	7	(−4)
North	**3**	**2**	**5**	**(−2)**	**5**	**4**	**5**	**0**	**1**	**5**	**4**	**(−3)**
Liaoning	24	24	24	0	23	29	29	(−6)	21	25	28	(−7)
Jilin	26	25	23	(+3)	24	28	28	(−4)	16	23	26	(−10)
Heilongjiang	20	23	16	(+4)	10	25	13	(−3)	5	19	18	(−13)
Northeast	**6**	**6**	**6**	**0**	**6**	**6**	**6**	**0**	**3**	**6**	**6**	**(−3)**
Shanghai	-	-	-	—	-	-	-	—	2	1	10	(−8)
Jiangsu	1	10	2	(−1)	1	4	6	(−5)	4	14	4	0
Zhejiang	4	4	1	(+3)	7	11	16	(−9)	8	16	14	(−6)
Anhui	10	21	20	(−10)	12	21	15	(−3)	19	11	23	(−4)
Fujian	3	-	-	—	-	2	1	—	18	18	15	(+3)
Jiangxi	-	13	19	—	-	9	9	—	25	5	13	(+12)
Shandong	14	11	3	(+11)	15	5	3	(+12)	11	3	1	(+10)
East	**1**	**3**	**2**	**(−1)**	**1**	**1**	**2**	**(−1)**	**2**	**1**	**2**	**0**
Henan	17	26	21	(−4)	19	26	27	(−8)	17	27	17	0
Hubei	25	17	22	(+3)	22	18	25	(−3)	20	12	11	(+9)
Hunan	2	7	8	(−6)	2	15	7	(−5)	26	7	2	(+24)
Guangdong	13	15	13	0	18	24	22	(−4)	9	20	12	(−3)
Guangxi	7	6	5	(+2)	8	10	2	(+6)	22	8	3	(+19)
Hainan	8	19	12	(−4)	3	22	21	(−18)	13	17	5	(+8)
South-Central	**2**	**5**	**3**	**(−1)**	**2**	**5**	**4**	**(−2)**	**6**	**3**	**1**	**(+5)**
Chongqing	22	2	7	(+15)	-	7	10	—	27	10	8	(+19)
Sichuan	23	9	6	(+17)	13	3	11	(+2)	6	6	20	(−14)
Guizhou	21	5	4	(+17)	4	12	4	0	28	15	6	(+22)
Yunnan	16	14	11	(+5)	21	13	8	(+13)	10	9	16	(−6)
Southwest	**5**	**1**	**1**	**(+4)**	**3**	**2**	**1**	**(+2)**	**5**	**2**	**3**	**(+2)**
Shaanxi	18	12	17	(+1)	11	6	17	(−6)	14	13	21	(−7)
Gansu	27	20	10	(+17)	26	20	24	(+2)	23	26	25	(−2)
Qinghai	9	1	18	(−9)	14	14	5	(+9)	1	2	24	(−23)
Ningxia	12	22	14	(−2)	17	19	23	(−6)	-	-	-	—
Xinjiang	5	18	-	—	5	16	14	(−9)	29	28	19	(+10)
Northwest	**4**	**4**	**4**	**0**	**4**	**3**	**3**	**(−1)**	**4**	**4**	**5**	**(−1)**

"—" indicates no data. The absence of statistical data in some provinces results in the absence of efficiency values.

From a regional perspective, the eco-efficiency ranking of North China dropped significantly, and except for the medium-scale ranking, both the small-scale (−2) and the large-scale (−3) ranking dropped, and the large-scale eco-efficiency ranking dropped from first in 2004 to fourth in 2018. At the same time, the eco-efficiency rankings of south-central China and southwest China rose sharply. Among them, although the eco-efficiency ranking of small-scale (−1) and medium-scale (−2) farms in south-central China declined, the large-scale (+5) eco-efficiency ranking rose sharply, from sixth in 2004 to first in 2018. The eco-efficiency of small-scale (+4), medium-scale (+2), and large-scale (+2) farms in southwest China all increased. In Southwest China, the eco-efficiency of small-scale farms increased from fifth in 2004 to first in 2018, and the medium-scale farms in 2018 also ranked first. Thus, from 2004 to 2018, there was not only a shift in hog production from north to south but also an increasing trend of breeding eco-efficiency from north to south.

The common explanation for the above-mentioned situation can be explained as follows: due to overall strategic positioning adjustments, increased production costs and changes in resource endowments, the total production of hogs was reduced in north China. The decrease in total production mainly came from the decrease in large-scale production, in the case of the large amount of fixed investment, the reduction of production led to the insufficiency of scale benefits and the decrease in productivity. At the same time, the total production of hogs in south-central and southwest China increased significantly (as shown in Figure 1 above). The increase in large-scale breeding improved the scale benefit of breeding and promoted the eco-efficiency.

Determinants of eco-efficiency

To further find out the determinants for the variance of hog farm's eco-efficiency, we also conduct a Tobit function to analyze the effects of different determinants of eco-efficiency in three dimensions as environmental regulation factors, development of hog industry factors and regional development factors.

Environmental regulation factors: *The forbidden policy* (FP) is a dummy variable, according to the forbidden policy for livestock cultivation in certain areas, when province i completely implements the forbidden breeding policy at year t, then the FP equals 1, and, before year t, the FP equals 0. *Government's investment in environmental control* (GIEC) is measured by the ratio of the government's total investment in environmental pollution control to regional GDP.

Development of hog industry factors: *Structure of the hog production industry* (SHI) is measured by the proportion of hog production value to the total output value of agriculture, forestry, animal husbandry, and fishery. We deflated the "hog production value" and "the total output value of agriculture, forestry, animal husbandry and fishery" using the "total output value index of animal husbandry" and "total output value index of agriculture, forestry, animal husbandry, and fishery", respectively. *Density of slaughtered fattened hogs* (DSFG) is measured by the ratio of the slaughtered fattened hog quantity amount to the area of province. *Conditions of local feed supply* (CLFS) is expressed by the corn yield of each province. *Prices of hog* (PRICE). We calculated the average annual price of slaughtered hogs and its lagging price for one period based on the monthly price data collected from the CAAA (2021). Price fluctuations will affect the behavior choice of farmers (Zhou et al. 2018). According to the long-term characteristics of the hog cycle, the previous price will affect the current production behavior. The price of slaughtered hogs is the market price that farmers are concerned about. *Market advantage index* (MAI) can measure the degree of specialization and concentration of an industry in the whole market. We used the formulae as follows to calculate this: MAI = (hog production value of provincial i/animal husbandry production value of province i)/(national hog production value/national animal husbandry production value). The MAI value greater than 1 show that, compared with the whole country, the hog production in province i was more concentrated and had more market advantages, and a MAI value less than 1 was the opposite.

Regional development factors: *Rural economic development* (RED) is measured by the per capita net income of rural households. Rural economic development is ultimately reflected in the increase in the income of rural households, benefit to the adoption of advanced breeding technology, and the rational use of resources. *Urbanization rate* (UR) is measured by the proportion of urban population to the total population. The urbanization promotes the transformation of agricultural population into urban population, which affects the structure and quantity of the rural labor force and then affects the labor inputs of hog breeding. *Transportation conditions* (TC) are expressed for each province per square kilometer of road and railway geometric mean value. The better the transportation conditions, the more conducive to the decrease in transport costs (Wu 2008; Yuan 2016). *Rural human capital* (RHC) is measured by the average educational level in rural areas, and we used the following formula to calculate it: RHC = $(\sum_{i=1}^{5} w_i edu_i)/$ rural population over six years old, where edu_i denotes the educational level, and w_i is the corresponding weight, with I = 1, 2…5. When i equals 1, 2, 3, 4, and 5 this indicates not attending school, primary school education, junior middle school education, high school education, and junior college education and above education, respectively, with w_i equal to 1, 6, 9, 12, and 16 correspondingly. Hence, the Tobit regression equation is constructed as follows:

$$ML_{it} = \beta_0 + \sum_{n=1}^{12} \beta_n X_{nit} + \gamma_{it} \quad (9)$$

where ML_{it} is the eco-efficiency; X_{nit} denotes the influence factors (the density of slaughtered fattened hogs, prices of hogs, rural economic development, and transportation conditions are all expressed in logarithmic form, and all the price indexes are expressed in 2003 constant prices); β_n is a coefficient; and γ_{it} is the random error. In particular, we used the consumer price index (CPI) to deflate all the price indicators. The results are reported in Table 5.

Table 5 Regression results of factors affecting the eco-efficiency based on a Tobit model.

	Variables	(1) ML	(2) Large-Scale	(3) Medium-Scale	(4) Small-Scale
Environment regulation factors	FP	−0.008 (0.0369)	−0.0966* (0.0537)	−0.0228 (0.0494)	−0.0373 (0.0534)
	GIEC	1.3235 (1.9234)	0.2274 (2.92)	4.2643* (2.547)	0.9884 (2.7278)
Development of hog industry factors	SHI	−0.4848* (0.2888)	−0.5382 (0.4171)	−0.6495* (0.3844)	−0.2004 (0.4389)
	DSFG	−0.0648*** (0.0231)	−0.0725** (0.0339)	−0.056* (0.0309)	−0.0659** (0.0312)
	CLFS	0.0111(0.0074)	0.0109 (0.0112)	0.0124 (0.0101)	0.0145 (0.0107)
	PRICE	−0.0239*** (0.0059)	−0.0291*** (0.0089)	−0.0342*** (0.008)	−0.0144* (0.0083)
	L1. PRICE	−0.0338*** (0.0056)	−0.0158* (0.0084)	−0.027*** (0.0075)	−0.0192** (0.0077)
	MAI	0.2307*** (0.0582)	0.1789** (0.0887)	0.3015*** (0.077)	0.2531*** (0.0824)
Regional development factors	RED	0.0616** (0.0261)	0.0437 (0.0374)	0.0716** (0.0343)	0.0664* (0.0345)
	UR	−0.0294 (0.1417)	−0.1432 (0.2076)	0.0623 (0.1923)	0.0701 (0.2066)
	TC	0.0696* (0.0398)	0.1172* (0.061)	0.0362 (0.0531)	0.0431 (0.0551)
	RHC	0.0012 (0.0239)	0.0024 (0.0369)	0.0108 (0.0324)	−0.0011 (0.0335)
	constant	0.6733*** (0.2427)	0.5543 (0.3608)	0.6238* (0.3276)	0.4722 (0.3349)

*Indicates significance at the 10% level
** Indicates significance at the 5% level
***Indicates significance at the 10% level
All regressions control fixed effects. Standard errors are clustered at the region level and appear in parentheses.
The statistic description of influence factors is shown in Table A3 of the Appendix.

The regression results provide evidence for different correlations of eco-efficiency and influencing factors. In environment regulation factors, the forbidden policy for livestock cultivation in certain areas was correlated only with the large-scale eco-efficiency, and the coefficient was −0.0966 and was statistically significant at the 10% significance level. This indicates that the policy decreased the large-scale eco-efficiency by 0.0966. After the implementation of the forbidden policy for livestock cultivation, the farms in the forbidden breeding areas were closed down, and there was a limit on the scale of the farms in the restricted breeding areas, which, to a certain extent, reduced the scale benefit of the farms and, therefore, had a negative effect on large-scale farms. The government's investment in environmental control was correlated only with the medium-scale eco-efficiency, and the coefficient was 4.2643 and was statistically significant at the 10% significance level. Improving the environmental control investment, therefore, remains an important measure to improve the eco-efficiency of the China's livestock sector.

The development of hog industry factors also had different impacts on the eco-efficiency. The structure of the hog-breeding industry and density of slaughtered fattened hogs had a statistically significant negative effect on the eco-efficiency. According to the regression results, a larger proportion of the hog industry and density of hog production led to an increase in the undesired output, which inhibited the eco-efficiency. Due to the cross-regional feed procurement, the effect of the local feed supply conditions on the eco-efficiency was not significant. Each additional 1% of hog prices decreased the eco-efficiency of large-, medium-, and small-scale farms by −0.0291, −0.0342, and −0.0144, respectively. The negative effect of the previous price on the average co-efficiency was greater. The stable market price of agricultural products is an important factor to promote the growth of production efficiency. Hog production in high market advantage regions had greater eco-efficiency.

In regional development factors, the development of the rural economy promoted technical progress and environment improvements, especially in medium- and small-scale farms. The eco-efficiency of hog production in regions with food transportation conditions was slightly higher than in those with lower traffic conditions. Neither the urbanization rate nor rural human capital had a significant effect on any scale of farms' eco-efficiency.

Conclusions and Implications

In this paper, we utilized an analytical framework taking environmentally detrimental emissions as the undesired output and using data from IEDA and NIES (2009), NDRC (2005–2019), NBSC (2005–2020), and CAAA (2021). We conducted an empirical analysis of the environmental efficiency of hog production for 30 provinces (excluding Tibet) in China from 2004 to 2018. The empirical results showed that the eco-efficiency increased, and the increase was mainly by the improvement of the technical efficiency. Compared with the shift of hog production from the south to north before 2002, the main production areas gradually shifted from north to south in 2018. More specifically, the medium- and small-scale predominant production areas were transferred from eastern China to southwestern China, and the large-scale predominant areas transferred from northern China to south-central China. In addition, we found that only Hunan's eco-efficiency ranked in the top five of the eight main production areas, which reflects that there may be excessive scale in the main production areas.

We analyzed the influence factors for eco-efficiency using a Tobit model and found that the government's investment in environmental control, the rural economic development, the market advantage index, and the transportation conditions had positive effects on the eco-efficiency, while the forbidden breeding policy, the structure of the hog-breeding industry, the density of slaughtered fattened hogs, and the prices of hogs had negative effects on the eco-efficiency.

Based on the above findings, three suggestions are proposed: First, although the eco-efficiency of hog production in China demonstrated an increasing trend, the government should pay increased attention to the excessively expanding hog farm scales and encourage farmers to adopt technology and equipment for the recycling and harm reduction treatment of livestock and poultry manure, and to control the farm scales to a suitable range. Second, the government should support small- and medium-scale farms in advanced technologies to enhance the productivity and the ability of sewage disposal; and guide commercial capital to participate in the operation of large-scale farms, while improving the transport conditions for large-scale farms. Third, the government should advocate for ecological cycles in hog production and promote the integration of agriculture and animal husbandry.

Declarations

Ethics Approval and Consent to Participate： Not applicable.

Consent for Publication： Not applicable.

Availability of data and materials： All data generated or analysed during this study are included in this published article [and its supplementary information files].

Competing Interests: The authors declare that they have no competing interests in this paper.

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Appendix A

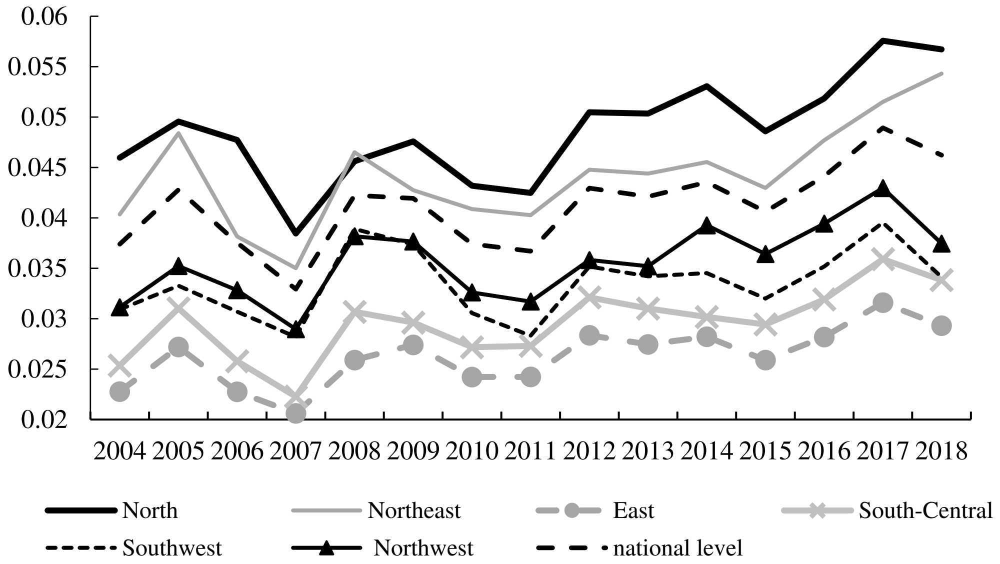

Figure A1. The undesired output/desired output in six regions of China.

Table A1 The eco-efficiency/TFP scores from the SBM model across 30 provinces in China, 2004–2018.

Province/Year	2004	2006	2008	2010	2012	2014	2016	2018	Ranks
Beijing	0.657/0.69	0.525/0.595	0.901/0.924	0.499/0.572	0.615/0.64	0.775/0.776	0.748/0.734	0.793/0.836	26/27
Tianjin	1.059/1.071	0.933/0.979	1.236/1.248	1.111/1.111	0.878/0.925	1.045/1.043	0.867/0.865	0.838/0.871	10/7
Hebei	0.836/0.885	0.793/0.852	1.054/1.053	1.075/1.077	1.049/1.048	1.044/1.044	0.968/1	1.03/1.03	20/17
Shanxi	0.79/0.825	0.914/0.931	0.866/0.938	0.872/0.891	0.798/0.897	0.973/0.996	0.953/0.98	0.781/0.836	23/21
Inner Mongolia	1.112/1.256	0.783/0.841	0.961/0.995	1.068/1.147	1.029/1.06	1.05/1.107	1.149/1.403	0.863/0.941	6/2
Liaoning	0.634/0.73	0.816/0.871	0.883/0.986	0.665/0.78	0.69/0.726	0.681/0.747	0.592/0.628	0.557/0.618	27/24
Jilin	0.706/0.693	0.842/0.928	0.761/0.842	0.653/0.76	0.695/0.785	0.711/0.801	0.649/0.715	0.627/0.658	24/26
Heilongjiang	0.921/0.952	0.844/0.929	0.8/0.869	0.705/0.77	0.723/0.73	1.004/0.931	1.011/0.942	0.935/0.981	13/11
Shanghai	1.355/1.138	1.206/0.877	1.222/1.058	1.34/1.052	1.206/0.869	1.164/1.055	1.209/0.719	1.079/1.002	2/4
Jiangsu	1.311/1.075	1.257/1.148	1.123/0.919	1.069/0.848	1.112/1.019	1.036/0.951	1.05/0.982	1.166/1.132	3/6
Zhejiang	1.078/0.954	0.845/0.782	1.039/0.952	0.935/0.737	1.021/0.841	1.036/0.913	1.102/0.961	1.068/1.012	8/10
Anhui	0.971/0.93	0.967/0.893	0.878/0.885	0.751/0.719	0.874/0.788	0.928/0.765	0.902/0.701	0.831/0.822	11/13
Fujian	1.081/1.031	1.155/1.136	0.984/1.038	1.088/0.957	0.996/0.952	0.971/0.884	1/0.919	1.176/1.185	7/9
Jiangxi	—	1.142/1.128	1.014/0.93	1.105/1.117	1.208/1.151	1.013/1.002	0.905/0.818	0.946/0.891	30/30
Shandong	0.904/0.843	1.026/0.981	1.152/0.941	1.079/0.813	1.124/0.863	1.115/0.816	1.194/1.016	1.339/1.028	16/20
Henan	0.802/0.732	0.712/0.719	0.665/0.659	0.827/0.673	0.791/0.619	1.021/0.8	0.709/0.677	0.809/0.813	22/23
Hubei	0.672/0.607	0.696/0.734	0.719/0.762	0.842/0.81	0.786/0.776	0.852/0.801	0.85/0.845	0.843/0.8	25/28
Hunan	1.249/1.247	0.918/0.919	0.94/0.979	0.906/0.931	1.038/1.066	1.222/1.249	1.142/1.186	1.136/1.192	4/3
Guangdong	0.911/0.772	0.868/0.872	0.811/0.835	0.758/0.752	0.785/0.747	0.908/0.824	0.74/0.701	0.926/0.898	14/22
Guangxi	0.937/0.844	0.928/0.837	0.878/0.844	1.018/0.949	0.986/0.936	1.091/1.022	1.112/1.074	1.19/1.16	12/19
Hainan	1.077/1.058	0.939/0.955	1.019/0.821	1.067/0.931	1.011/0.976	1.063/1.069	0.87/0.788	0.991/1.001	9/8
Chongqing	0.599/0.711	—	1.024/0.932	0.987/0.942	0.994/1.006	1.075/1.076	1.062/1.062	1.053/1.045	28/25
Sichuan	0.896/0.865	1.055/1.032	1.07/1.06	1.101/1.07	1.064/1.061	0.963/0.966	0.951/0.976	1.03/1.025	18/18
Guizhou	0.859/0.924	1.118/1.105	0.851/0.845	1.058/1.07	1.054/1.069	1.103/1.124	1.104/1.095	1.114/1.163	19/14
Yunnan	0.804/0.885	0.955/0.98	0.788/0.822	0.997/1.017	1.066/1.09	0.986/0.99	0.98/0.997	0.997/0.999	21/16
Shaanxi	0.905/0.915	0.945/0.991	0.951/0.964	1.026/1.041	0.781/0.811	0.786/0.806	0.935/0.933	0.862/0.891	15/15
Gansu	0.538/0.597	0.602/0.637	0.767/0.814	0.653/0.67	0.729/0.733	0.712/0.67	0.727/0.716	0.86/0.879	29/29
Qinghai	1.409/1.412	2.448/2.448	1.128/1.128	1.037/0.984	0.965/0.959	0.89/0.859	1.091/1.015	0.87/0.848	1/1
Ningxia	0.901/0.932	0.877/0.887	0.874/0.851	0.771/0.76	0.825/0.736	0.779/0.739	0.844/0.859	0.843/0.854	17/12
Xinjiang	1.115/1.107	0.875/0.895	0.876/0.911	0.716/0.691	1.066/1.107	0.663/0.615	0.815/0.815	1.017/1.007	5/5
Average	0.908/0.9	0.927/0.929	0.93/0.92	0.905/0.874	0.918/0.887	0.943/0.903	0.927/0.889	0.937/0.936	

"—" means no data.

The absence of statistical data in some provinces results in the absence of efficiency values.

There is a great variation in eco-efficiency across provinces, ranging from 0.557 to 1.19 with a mean value of 0.937 in 2018. And the overall average eco-efficiency increased from 2004 to 2018.

Table A2 Regression analysis on the price, technical efficiency, and technical progress index of hog production.

	ML	MLEFFCH	MLTECH
PRICE	0.007(0.022)	0.02***(0.006)	−0.008(0.021)
R^2	0.01	0.54	0.02

***Indicates significance at the 1% levels.

The standard error is shown in parentheses.
The “PRICE” adopts the annual price of pork market, and we deflated it using the price index of the pork market.
In accordance with this study, the price indexes were expressed in 2003 constant prices.
The sample period was 2005–2016 because the “PRICE” index only counts up to 2016.

Table A3 Summary statistics of variables in the Tobit regression.

	Variable	Obs.	Mean	S.D.	Min	Max
	ML	414	1.024235	0.221187	0.446094	1.878281
	Large-scale	392	1.045169	0.29708	0.356202	2.528874
	Medium-scale	392	1.041269	0.275553	0.447445	2.298067
	Small-scale	359	1.037703	0.26321	0.470719	1.934931
Environment regulation factors	FP	420	0.161905	0.368803	0	1
	GIEC	390	0.013439	0.006668	0.002991	0.042314
Development of hog industry factors	SHI	420	0.14338	0.06121	0.016118	0.365597
	DSFG	420	4.501904	1.403546	0.296976	6.090496
	CLFS	413	5.423296	1.870877	0.262364	8.28959
	PRICE	420	10.71826	5.167272	5.920777	97.10138
	L1. PRICE	420	10.84826	6.009947	5.920777	97.10138
	MAI	420	0.973057	0.360437	0.154708	1.691747
Regional development factors	RED	420	8.5748	0.624079	6.316107	9.947689
	UR	420	0.534867	0.139157	0.2687	0.896
	TC	420	6.964019	0.77028	4.369525	8.275311
	RHC	420	7.59258	0.643933	5.458665	9.837992

Reference

AHVYEBC (China Animal Husbandry and Veterinary Yearbook Editorial Board). 2018. China Animal Husbandry and Veterinary Yearbook. China Agriculture Press, Beijing, China. (In Chinese)

Banker RD, Charnes A, Cooper WW (1984) Some models for estimating technical and scale inefficiencies in data envelopment analysis. Manag Sci 30(9):1078-1092. https://doi.org/10.1287/mnsc.30.9.1078

CAAA (China Animal Agricultural Association) (2021) 2000-2020 Regional price trend of livestock products. From http://www.caaa.cn/market/trend/local/df.php?province=25. Accessed 23 Feb 2021

Caves DW, Christensen LR, Diewert WE (1982) The economic theory of index numbers and the measurement of input, output, and productivity. Econ 50(11):1393-1414. https://doi.org/10.2307/1913388

Charnes A, Cooper WW, Rhodes E (1979) Measuring the efficiency of decision making units. Eur J Oper Res 2(6):429-444. https://doi.org/10.1016/0377-2217(78)90138-8

Chung YH, Färe R, Grosskopf S (1997) Productivity and undesirable outputs: a directional distance function approach. J Environ Manag 51(3):229–240. https://doi.org/10.1006/jema.1997.0146

CSC (China State Council, Government of China) (2013) The No. 1 Central Document. From http://www.gov.cn/zhengce/zhengceku/2013-02/16/content_2738.htm. Accessed 5 Mar 2021

CSC (China State Council, Government of China) (2015) The Action Plan for the Prevention and Control of Water Pollution. From http://www.gov.cn/zhengce/zhengceku/2015-04/16/content_9613.htm. Accessed 7 Mar 2021

Du HM, Wang MC (2020) Environmental efficiency evaluation of hog scale production in superior districts of China: based on non-radical and non-oriented SE-SBM model. Econ Geogr 40(9):176–183. (In Chinese)

Färe R, Norris GM (1997) Productivity growth, technical progress, and efficiency change in industrialized countries. Am Econ Rev 87(5):1040-1043. https://doi.org/10.2307/2951341

Färe R, Grosskopf S, Pasurka CA (2007) Environmental production functions and environmental directional distance functions. Energy 32(7):1055–1066. https://doi.org/10.1016/j.energy.2006.09.005

Geng N, Li BL (2013) Analysis on influencing factor of technical efficiency of China’s meet sheep production and its regional difference: based on stochastic frontier analysis method. Technol Econ 32(12):25–32. (In Chinese)

Han Z, Yang C, Zhao XX (2019) Analysis of total factor productivity of mutton sheep breeding in pastoral areas under ecological compensation and reward mechanism. J Agrotech Econ 11:116–126. (In Chinese)

Heederik D, Torben S, Thorne PS, Kline JN, Rachel A, Bønløkke JH, Dosman JA, Caroline D, Kirkhorn SR (2007) Health Effects of Airborne Exposures from Concentrated Animal Feeding Operations. Environ. Health Perspect 115(2):298–302. https://doi.org/10.1289/ehp.8835

Hu H, Ying RY, Liu J (2005) An economic analysis of the movement of pig producing areas in China -- from natural distribution to economic distribution. Chin Rural Econ 12:46–52+60. (In Chinese)

Huang JH, Yang XG, Cheng G, Wang SY (2014) A comprehensive eco-efficiency model and dynamics of regional eco-efficiency in China. J Clean Prod 67:228–238. https://doi.org/10.1016/j.jclepro.2013.12.003

Li GC (2014) The green productivity revolution of agriculture in China from 1978 to 2008. China Econ Q 13(2):537–558. (In Chinese)

Li CX, Cao YN (2017) Calculation and analysis of environmental efficiency of dairy cattle breeding in China. Issues Agric Econ 38(3):80–88+111–112. (In Chinese)

Malmquist S (1953) Index numbers and indifference surfaces. Trabajos De Estadistica 4(2):209-242. https://doi.org/10.1007/BF03006863

Meng XH, Zhou HC, Du LY, Sheng GY (2019) The change of agricultural environmental technology efficiency and green total factor productivity growth in China: re-examination based on the perspective of combination of planting and breeding. Issues Agric Econ 6:9–22. (In Chinese)

NBSC (National Bureau of Statistics of China). 2005-2020. China Statistical Yearbooks. China's Statistical Press, Beijing, China. (In Chinese)

NDRC (National Development and Reform Commission, China). 2005-2019. China Agricultural Product Cost-Benefit Complication. China's Statistical Press, Beijing, China. (In Chinese)

Ni JQ, Heber AJ, Diehl CA, Lim TT, Duggirala RK, Haymore BL (1999) Burst releases of hydrogen sulfide in mechanically ventilated swine buildings. Proc of the Water Environ Federation 2000(3):564-574. https://doi.org/10.2175/193864700785302971

Pittman RW (1983) Multilateral productivity comparisons with undesirable output. Econ J 93(372): 883-891. doi:10.2307/2232753

Qiao F, Huang J, Dan W, Liu H, Lohmar B (2016) China's hog production: from backyard to large-scale. China Econ Rev 38(38):199-208. https://doi.org/10.1016/j.chieco.2016.02.003

Ramanathan R (2005) An analysis of energy consumption and carbon dioxide emissions in countries of the Middle East and North Africa. Energy 30(15):2831–2842. https://doi.org/10.1016/j.energy.2005.01.010

Reinhard S, Lovell CAK, Thijssen G (1999) Econometric Estimation of Technical and Environmental Efficiency: An Application to Dutch Dairy Farms. Am J Agric Econ 81(1):44–60. https://doi.org/10.2307/1244449

Schiffman SS, William C (2005) Science of odor as a potential health issue. J Environ Qual 34(1):129–138. https://doi.org/10.2134/jeq2005.0129

Tone K (2001) A slacks-based measure of-efficiency in data envelopment analysis. Eur J Oper Res 130(3):498-509. https://doi.org/10.1016/S0377-2217(99)00407-5

Tone K (2002) A slacks-based measure of super-efficiency in data envelopment analysis. Eur J Oper Res 143(1):32–41. https://doi.org/10.1016/S0377-2217(01)00324-1

Wang DX, Zheng YC, Li GC, Huang K (2015) Assessment and analysis of scale hog production efficiency in China under the constraint of environmental regulations and the discussion of the moderate scale management of hog production. Res Agric Mod 36(5):818–825. (In Chinese)

Weiss RA, Mcmichael AJ (2004) Social and environmental risk factors in the emergence of infectious diseases. Nature Medicine 10(12): S70-6. https://doi.org/10.1038/nm1150

Wu YR (2008) The role of productivity in China's growth: new estimates. China Econ Q 7(3):827–842. (In Chinese)

Wu XB, Qiao J, Li GC (2013) Study on productivity growth and decomposition of scale pig breeding in China under environmental regulation. Stat Decis 293(20):118–120. (In Chinese)

Yang CC, Hsiao CK, Yu MM (2008) Technical efficiency and impact of environmental regulations in farrow-to-finish swine production in Taiwan. Agric Econ 39(1):51-61. https://doi.org/10.1111/j.1574-0862.2008.00314.x

Yang CC (2009) Productive efficiency, environmental efficiency and their determinants in farrow-to-finish pig farming in Taiwan. Livestock Sci 126(1-3):195-205. https://doi.org/10.1016/j.livsci.2009.06.020

Yuan YJ, Xie RH (2016) Environmental regulation and the "green" productivity growth of China's industry: based on the re-examination of the "strong-version of Porter hypothesis". China Soft Sci 7:144–154. (In Chinese)

Zhang XH, Zhou YH, Zhang P (2015) Estimation of environmental efficiency of pig breeding in China: base on the study of nitrogen surplus in manure. J Agrotech Econ 5:92–102. (In Chinese)

Zhao LG, Lin J, Zhu JM (2015) Green total factor productivity of hog breeding in china: application of SE-SBM model and grey relation matrix. Pol J Environ Stud 24(1):403-412. https://doi.org/10.3724/SP.J.1105.2010.09178

Zheng J, Liu X, Bigsten A (1998) Ownership structure and determinants of technical efficiency: an application of data envelopment analysis to Chinese enterprises (1986–1990). J Comp Econ 26(3):465–484. https://doi.org/10.1006/jcec.1998.1540

Zhou YH, Zhang XH, Tian X, Geng XH, Zhang P, Yan BJ (2015) Technical and environmental efficiency of hog production in China—A stochastic frontier production function analysis. J Integr Agric 14(6):1069–1080. https://doi.org/10.1016/S2095-3119(14)60990-4

Zhou JJ, Tan Y, Hu HT (2018) The influences of environmental regulations on hog production distribution and industry movement in China. Res Agric Mod 39(3):440–450. (In Chinese)

Zuo YY, Peng Y, Feng YG (2016) Study on the total factor productivity of scale pig breeding under environmental con straints. Rural Econ 9:37–43. (In Chinese)

Zuo YY, Feng LG (2017) The total factor productivity's spatial-temporal variation and its convergence of scale pig breeding in China: under the view of environmental constraints. Econ Geogr 37(7):166–174+215. (In Chinese)

Figures

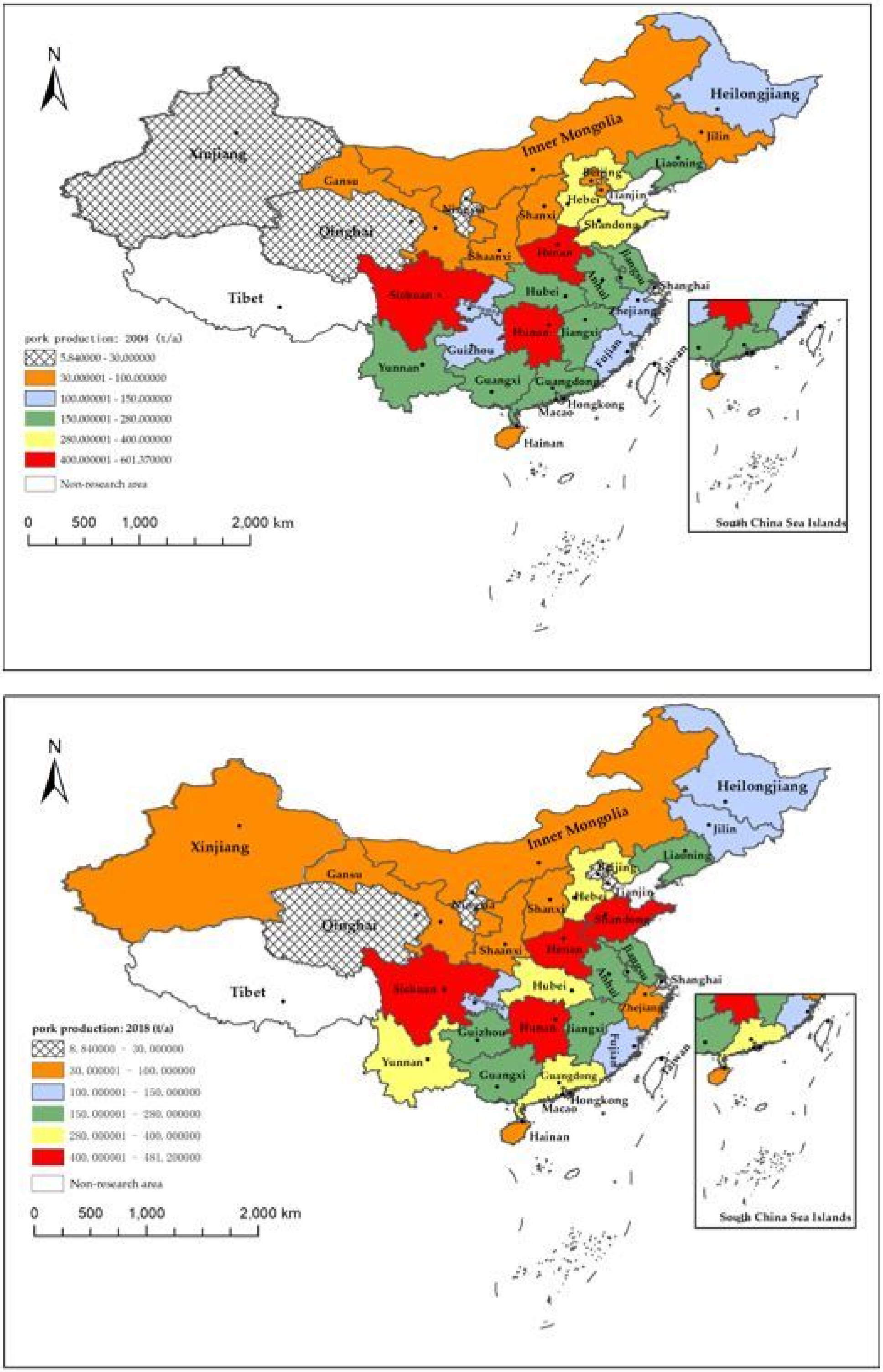

Figure 1

The spatial distribution of pork production across China's provinces in 2004 and 2018 (ArcGIS 10.2). Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

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