



# Optimization of China's pig production system to reduce environmental impacts based on a data envelopment and life cycle analysis model

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## ABSTRACT

Pig production system has significant impacts on global climate and environment; the greenhouse gas (GHG) annual emission from China's pig production system accounts for more than 4% of which from world's animal husbandry. This study applied DEA and LCA methods with statistics of China's pig production, compared the environmental impact in each stage before and after optimization, aimed to calculate the resource input and energy consumption in pig production system, and realize lower investment and higher efficiency. The results showed that the optimized method could reduce 55.69 MJ energy consumption from each pig; the environmental impact potential of global warming, environmental acidification and eutrophication decreased by 1.56%, 0.6% and 0.072%. Considering the Chinese pig breeding market in 2018 as an example, with a total of 693.824 million pigs sold, the optimized GHG emission reduction would be equivalent to the GHG emitted by producing  $1.92812 \times 10^5$  vehicles.

## 1. Introduction

Adequate protein intake is essential for health and development of human beings. Animal-derived proteins are of superior quality due to their amino acid patterns and good digestibility. For example, the nutritional value of pork protein is higher than that of most plant-derived food (such as protein in grain-derived food) (Murphy and Affen, 2003). The essential amino acid composition of pork is relatively similar to that of casein, which is considered the "ideal protein" for nutritional research (Cheng et al., 2005). Pork is easy to digest and has high nutritional value; therefore, it is a high-quality meat product. To meet the dietary protein intake requirements of adults recommended by the Chinese Nutrition Society, the average daily animal food intake per person should be 125–200 g, and livestock and poultry meat should account for 50–100 g (Zhu et al., 2005). Pork is the most widely produced and consumed meat globally (FAOSTAT, 2019). Over the past two decades, pork consumption has increased by 56.59% globally. In addition, according to the Organization for Economic Cooperation and Development (OECD), meat consumption is likely to increase by 40 Mt by 2028 due to increases in the global population and income (OECD,

2019).

China is the largest pork producer and consumer globally. In 2018, the pork output in China reached 54.03 Mt (USDA data), accounting for 47.80% of the global pork production. In the same year, China's pork consumption accounted for 49.60% of the total consumption worldwide (Han, 2019). Moreover, by 2028, China's pork production will reach 58.05 Mt (OECD, 2019). The pig production system in China provides more than a third of the global meat products (Zhu and Chen, 2018).

According to Food and Agriculture Organization (FAO), the impact of animal husbandry on the environment deserves profound reflection (FAO, 2006). Greenhouse gas (GHG) emission from livestock and its secondary products were estimated to be 51% of the total emission worldwide, much more than that estimated by FAO (Goodland and Anhang, 2009). According to Gerber et al. (2013), the annual GHG emission of global animal husbandry is 7.1 Gt CO<sub>2</sub> eq, equivalent to 14.50% of the global anthropogenic GHG emission. Based on the data from the World Resources Institute (WRI data), since 2018, agricultural production has become the second largest source of GHG emission worldwide, with animal husbandry accounting for more than 60% of emissions. Furthermore, animal husbandry continues to make a

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significant contribution to the global GHG emission (Burattini et al., 2017).

The total GHG emission of pig production systems in 2013 reached 6.68 Mt CO<sub>2</sub> eq (Gerber et al., 2013), which accounted for 9% of the GHG emission generated by animal husbandry. In addition, the pig production system is considered the main factor causing environmental acidification and eutrophication due to the significant nitrogen and phosphorus emission only during the storage and transportation of pig manure (Vries and Boer, 2010). Therefore, pig production has a major influence on global climate change and environmental problems. Although it is essential to ensure a stable increase in pig production to meet the needs of a growing global population, it is equally critical to monitor the associated resource and energy inputs, quantify the environmental impact of each production stage, and optimize the production systems. Furthermore, it is crucial to balance the economic benefits and environmental impacts of pig production, to achieve sustainable animal husbandry development. Optimizing China's pig breeding processes could effectively improve production efficiency, enhance resource utilization efficiency, and reduce GHG emissions, which correspond to SDG 12 (responsible consumption and production) and SDG 13 (climate action) (SDG Goals, 2015).

Data envelopment analysis (DEA) is generally accepted as a nonparametric method of estimating the relative efficiency of several homogeneous units. The method systematically calculates the resource input and energy consumption during a production process to achieve a quantitative optimization of the production process and considers the dynamic economic and environmental efficiency in production (Asmild and Hougaard, 2006; Liu et al., 2020; Wang et al., 2015).

In recent years, DEA and life cycle assessment (LCA) have been collectively used in research evaluating the environmental and economic performance of various agricultural production systems, such as planting, animal husbandry or fishery. Samuel-Pfister et al. (2012) and Diego et al. (2011) used to apply this method to separately evaluate the environmental impact of aquaculture and dairy farming. Ian et al. (2012) used this method to improve the environmental impact during grape planting. Lozano et al. (2009) and Mohammad et al. (2015) respectively applied this method to sheep production and rice production to improve operational and environmental efficiency and to boost economic performance.

LCA is a powerful tool for evaluating the environmental performance of complex systems and is widely used in assessing the impacts of pig production (Liu and Zhao, 2012; McClelland and Arndt, 2018; Robles and Sastafiana, 2018; Vries and Boer, 2010). Feed production is a hotspot and contributes to most of the impact across several environmental impact categories (Li et al., 2019). The raw materials, resources and energy required for feed production and the transportation of raw materials and finished products increase the impact of pig production on the environment (Hayo et al., 2005; Nguyen et al., 2012). Previous studies were mostly based on pig production data, wherein LCA was used to quantify various environmental impacts. The complexity of production restricts the evaluation of diverse environmental impacts, particularly the continuous optimization of resource input and energy consumption in production, which may affect the evaluation of environmental impacts. Moreover, an incomplete understanding of the process of resource input and energy consumption in pig production restricts our accurate evaluation of various environmental impacts of pig production.

Integrating DEA-LCA in pig production processes could facilitate the development of an optimized process with optimal resource and energy input and a reduced environmental footprint. The objective of the study was to assess the effects of optimization of resource input and energy consumption of pig production on the environmental impacts, calculated by DEA-LCA model on public data at various scales in different provinces in China. LCA calculations were also performed to quantify changes in various environmental impact categories before and after optimization of the pig production system. The results of the present

study could facilitate the formulation of supportive schemes for GHG and other environmental emission reductions of various relevant aspects of pig production in China and minimize global GHG emissions in animal husbandry.

## 2. Materials and methods

### 2.1. Data collection

The data of this study were obtained from the cost-income data of major grain products and pig production at different scales in China in 2018, included in "Compilation of National Agricultural Product Cost Income Data" released by the National Development and Reform Commission People's Republic of China (NDRCPRC, 2019), and "China Statistical Yearbook" (NBSPRC, 2019) and "China Animal Husbandry and Veterinary Yearbook" published in the same year by the China Bureau of Statistics (MARAPRC, 2018). Statistical observations revealed that 163 days was the average feeding time of different scales of pig production in China in 2018. The input of pig production mainly included piglets, concentrated feed, water, electricity power, coal, diesel and labor, with live pigs as output.

Previously, researchers have mostly used objective pig production data from a specific area in a certain year to study production efficiency. To reflect the production efficiency of pigs at different feeding scales in different areas, during data processing, in this study, we adopted the weighted average value of pig production data with different feeding scales in various regions of China. The specific process was as follows: the scale weight value was determined using the feeding quantity and number of households with different feeding scales, by comparing the scale quantity with the total feeding quantity. For example, for 1–49 heads, the feeding number was 25, and the number of households was 35,718,766. For 50–99 heads, the feeding quantity was 75, and the number of households was 1,209,265. For 100–499 heads, the feeding quantity was 250 and the number of households was 603,091. After the sum of the three products was compared with the total feeding quantity, the weight coefficient of the loose feeding scale (less than 500 heads per year) was finally determined to be 0.77. The weight coefficients of small scale (less than 3000 heads year<sup>-1</sup>), medium scale (less than 10,000 heads year<sup>-1</sup>), and large scale (more than 10,000 heads year<sup>-1</sup>) were also calculated by the same method, which were 0.1, 0.05 and 0.08, respectively. Subsequently, the weighted average input-output data of pig production in each region were substituted into a DEA model for optimization, and LCA was used to evaluate the change in environmental impact potential in different production stages.

### 2.2. DEA analysis

DEA method was used to measure the production efficiency of pig production in China, and the relationship between the input and output and production efficiency was explained theoretically. DEA method includes two models: constant return to scale (CRS) and variable return to scale (VRS) (Yusuf and Maflomo, 2007; Zhang et al., 2012). CRS is a model with constant returns to scale, which measures the technical and scale efficiencies, whereas VRS is a model with variable returns to scale, which measures pure technical efficiency. The underlying logic of these models is to compress the input to determine the output, which indicates that the input of inefficient decision-making units should be reduced, or the output should be expanded to determine the input.

Using DEA, three efficiencies were estimated: technical efficiency (TE), scale efficiency (SE) and pure technical efficiency (PTE). TE refers to the degree of production efficiency of technology during its stable use (Li et al., 2019). SE refers to the degree at which the scale economies attain a certain production point as compared to their scale efficiency point. PTE refers to the level of operational management and production technology of a certain production point compared to other technical efficiency points (Yan and Xu, 2012). Coelli (1996) in their study

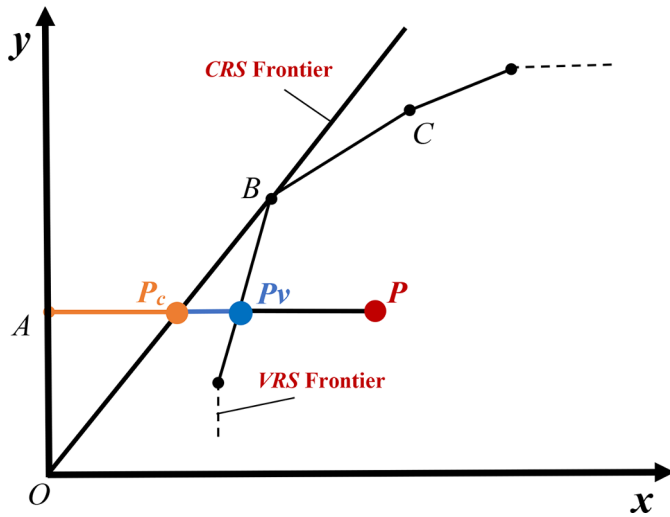


Fig. 1. Analysis of pig production efficiency (adapted from Coelli 1996).

established a DEA analysis model of pig production efficiency (Fig. 1) to explain the relationship between these three efficiencies.

In Fig. 1, under the CRS condition, the projective point of point P is  $P_c$ , the input-oriented TE of point P is  $TE_{CRS} = \frac{AP_c}{AP}$ . In the case of VRS, the projective point of point P is  $P_v$ , the TE is  $TE_{VRS} = \frac{AP_v}{AP}$ . The measurement difference of the aforementioned two TEs is  $SE = \frac{AP_c}{AP_v}$ , which is caused by scale inefficiency; hence, the scale efficiency can be expressed as  $SE = \frac{AP_c}{AP_v}$ . Considering the three efficiency formulas, it can be observed that the TE of CRS is divided into PTE and SE, that is,  $TE_{CRS} = TE_{VRS} \times SE$ .

To optimize the resource input of pig production, the energy-saving value of each input was initially calculated; thereafter, the reduced resource consumption of each input was obtained by dividing it by the energy equivalent corresponding to the input. The energy equivalents and references used in this study are listed in Table 1.

The actual energy input in the production process was used as the input of DEA model through Dwelling Energy Assessment Procedure (DEAP) software to identify the inefficient input. Based on the actual energy input of pig production, DEAP software can clarify the energy input redundancy of inefficient production by comparing different production efficiencies. The conserved energy was evaluated by subtracting the ideal value from the actual value of energy consumption, and it was further converted into a reduced resource input by dividing it

by the corresponding energy equivalent. Eventually, LCA method was used to estimate the environmental impact changes caused by the optimization of the resource input in a pig production system.

### 2.3. Life cycle assessment

LCA method provides a comprehensive quantitative assessment of the environmental impact and resource consumption of a product during the entire life cycle “from cradle to grave” (McCaulliffe et al., 2016). The assessment results can be used to improve the resource and environmental burdens throughout the life cycle (Cecilia et al., 2017). The main steps of LCA method include: purpose and scope determination, inventory analysis, environmental impact assessment, result interpretation, and improvement analysis (Jiang et al., 2019; Wang et al., 2015). This study applied LCA method to calculate the changes in energy consumption and environmental impact of pig production before and after improving DEA model.

#### 2.3.1. Purpose and scope determination

The first step of LCA is to define the purpose and scope of research, which includes analyzing the purpose of LCA, the boundary of the evaluated product system, the functional units, and other issues, which are crucial for evaluating the depth and breadth of LCA (ISO 14044, 2006b; ISO 14040, 2006a). In the present study, LCA method was used to calculate the changes in environmental impact of pig production before and after DEA model optimization. Agricultural resources production was considered as the initial phase, followed by crop cultivation & feed production stage and pig breeding stage; eventually, the environmental output pollutants generated from treatment of manure were defined (Fig. 2). The functional unit of this study is a fully-grown pig ready for slaughter. The average weight of finishing pigs is 122.55 kg.

Table 1

Energy equivalent value of pig production input unit: Megajoule per functional unit.

Input	Functional Unit	Energy equivalence	References
Piglet	kg	13.67	Shi et al. (2015)
Corn	kg	14.43	He et al. (2020)
Soybean Meal	kg	15.15	He et al. (2020)
Wheat Bran	kg	11.72	Zhang et al. (2012)
Electric power	kWh	10.71	Jia et al. (2010)
Coal	kg	29.31	Jia et al. (2010)
Diesel oil	kg	41.16	Liu et al. (2012)
Labor Force	d	19.61	Song et al. (2014)

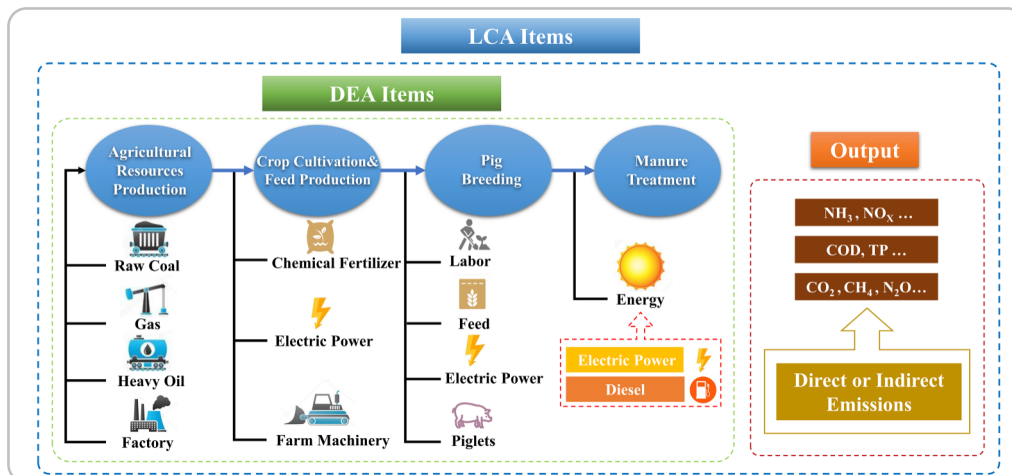


Fig. 2. Boundary of pig production system.

### 2.3.2. Inventory analysis

Divide the unit process and collect data according to the principles of continuity and functionality of production process and the main characteristics of pig production stage (Hufi et al., 2016). The present value input and ideal input of pig production is used as the data of LCA model to measure various environmental impact changes. The different stages take into consideration gas emissions and pollutant emissions generated by electric power consumption in the process of fertilizer production; resource consumption and pollutant emission of chemical fertilizer and the use of agricultural machines during crop cultivation and pig breeding, electric power consumption during feed production; resource consumption and pollutant emissions of feed, piglets, diesel, electric power and other inputs during pig breeding; and electric power consumption of manure treating equipment and resource consumption and pollutant discharge generated during the manure treatment.

Pig feeding mainly depends on the concentrate feed, which includes 70% corn, 9% soybean cake, 7% wheat bran, 4% rapeseed meal, 4% cottonseed meal, 2% fish meal and 4% other mineral components (Liu et al., 2012). As rapeseed meal, cottonseed meal and fish meal in the feed are present in minor components and the content in different feeds shows marked variation, this study mainly focuses on the corn, soybean cake and wheat bran in the feed. The feeding period of five pigs is 163 days, the average weight of piglets is 17.68 kg (approximately 50 days old), the average weight at slaughter is 122.55 kg, the average amount of feed is 1.99 kg per head d, and average manure excretion is 3.50 kg per head d. Manure is treated via aerobic and anaerobic fermentation. The electric power consumption of composting equipment in the process of aerobic composting is 3.00 kWt, and the converted electric power consumption of mixing equipment and biogas electric power generation equipment in the process of anaerobic fermentation is 1.63 kWt<sup>-1</sup> (Pefi, 2012).

### 2.3.3. Impact evaluation

The third step of LCA is to analyze and evaluate the environmental impacts of diverse production systems. In this study, the equivalent coefficient method was used to convert similar pollutants into the environmental impact potential of reference (Brentup et al., 2004), to evaluate the environmental impact of pig production. The characterization factors used in this study are all from Chinese Life Cycle Database (CLCD), and the characterization factor for eutrophication potential calculation are: 1 for PO<sub>4</sub><sup>3-</sup>, 3.06 for TP, 0.42 for NO<sub>3</sub><sup>-</sup>, 0.35 for NH<sub>3</sub>, 0.33 for NH<sub>4</sub><sup>+</sup> and 0.1 for COD. The characteristic factors of environmental acidification potential calculation are: 1 for SO<sub>2</sub>, 1.88 for NH<sub>3</sub>, 0.7 for NO<sub>x</sub>. The characteristic factors for the calculation of global warming potential are: 1 for CO<sub>2</sub>, 21 for CH<sub>4</sub>, 2 for CO and 310 for N<sub>2</sub>O. The results of the environmental impact assessments are presented in Table 5.

### 2.3.4. Sensitivity analysis

The sensitivity analysis of inventory data is also referred to contribution rate analysis, which refers to the sensitivity of inventory data to each index and the contribution rate under a linear relationship. If the inventory data, which is an input or an output in a unit process, changes by 1%, LCA index will also change by a certain percentage. The ratio of these two percentage changes is called inventory sensitivity. If an inventory dataset is sensitive to a characteristic index, it means that when we change the data of the process, it will have a greater impact on the results.

## 3. Results and discussion

### 3.1. Pig production efficiency

In this study, we calculated the TE, PTE and SE of pig production using CRS and VRS models. The results are summarized in Table 2.

**Table 2**

Efficiency of pig production in China.

Efficiency category	Minimum	Average	Maximum	Standard deviation
Technical Efficiency	0.68	0.97	1.00	0.07
Pure Technical Efficiency	0.80	0.98	1.00	0.05
Scale Efficiency	0.85	0.99	1.00	0.03

**Table 3**

Variation of functional unit energy input based on DEA method Unit: MJ head<sup>-1</sup>.

Input	Energy values		Energy Saving
	Now	After optimization	
Piglet	241.69	231.78	9.91
Concentrated feed	3987.88	3985.07	2.81
Labor force	98.24	90.09	8.14
Electric power	70.64	51.67	18.96
Coal	51.14	37.36	13.77
Diesel oil	7.86	5.76	2.10
Total	4457.45	4401.73	55.69

The average values of TE, PTE and SE of pig production in China were all lower than 1 (Table 2), which indicated the possibility of optimizing the energy and resource investment of pig production in China. At the same time, the standard deviation of TE was the highest (0.07), indicating greater variation compared with PTE and SE. Hence, attention should be directed to TE in the production process.

The backgrounds of different breeding provinces, breeding scales and breeding modes in China revealed a remarkable impact on TE (Li, 2019). Compared with northeast China, northwest China lacked feed supply and faced transportation issues. Owing to the more developed economy in north China, the labor and land costs increased, which affected technology improvement in breeding production and reduced the technical efficiency of pig production (Leng et al., 2018); therefore, the advantages of scale economy in pig production and advancement in breeding technology should be considered (Key and McBride, 2007). China should focus on improving the production based on pig breeding technology, optimizing production conditions, and enhancing management measures to fundamentally increase the survival rate and meat yield of pigs (Li and Xiong, 2019).

### 3.2. Energy consumption

Various energy inputs were reduced after optimizing the parameters of the pig production system, and each pig could reduce the energy input to 55.69 MJ (Table 3). Energy savings of electric power, coal, and diesel were 26.84%, 26.93% and 26.72%, respectively. For example, compared with a traditional piggy (the raw material for heating in the piggy is coal-fired heating, and the coal consumption and heat consumption of the heating in the piggy are positively related to its heat transfer coefficient. The wall of the heating piggy is made of 240 mm thick clay bricks, and the roof is generally made of colored steel tiles and asbestos tiles. The windows of the piggy are mainly plastic steel windows, and the doors of the piggy are generally iron doors.), the savings in terms of coal, heat, energy and water consumption in the fermentation bed model piggy is significantly higher (Hou et al., 2019). The input optimization of piglets could also reduce the energy consumption from 241.69 MJ head<sup>-1</sup> to 231.78 MJ head<sup>-1</sup>. The piglets in the relatively quiet environment (55–60 dB was stimulated with 75–77 dB noise. The respiratory rate decreased by 15% and then returned to a normal level after 1 h. The average daily weight gain of piglets under 60–63 dB sound management was 2.50% higher than that under 75–77 dB. The quiet rest environment reduced the respiratory rate of piglets, led to daily weight gain (Cheng et al., 2021) and enhanced nutrition (Jin et al., 2021). Addition of plant extracts (Jiang et al., 2021; Wang et al.,

**Table 4**

Variation of functional unit resource based on the DEA method Unit: MJ head<sup>-1</sup>.

Input / Output	Unit	Resource values Now	After optimization
<b>Input</b>			
Piglet	kg	17.68	16.96
Concentrated feed	kg	324.62	324.39
Water	m <sup>3</sup>	7.88	7.72
Electric power	kWh	6.59	4.82
Coal	kg	1.74	1.27
Diesel oil	kg	0.22	0.16
<b>Output</b>			
live pig	kg	122.55	122.55

2021) could also promote the growth performance of piglets, which is conducive to the health of piglets. The reinforcement of labor management could also reduce energy consumption from 98.24 to 90.09 MJ head<sup>-1</sup>. The situation of male dominance in agriculture and farm management changed gradually (Thingbafijam et al., 2019), which urged the producers to rely on technology to feed pigs and operate farms (Yang, 2015); however, in a certain period, it was almost impossible to optimize the feed input, which is the necessary nutrient source for pig breeding.

### 3.3. Resource use

The energy savings of each input in Table 3 were compared with the corresponding energy equivalent in Table 1 to obtain the reduced resource consumption of the pig production system. The current resource consumption and resource consumption after efficiency optimization were summarized in Table 4, which was used as the comparison data of environmental impact changes in LCA model.

### 3.4. Environment effects

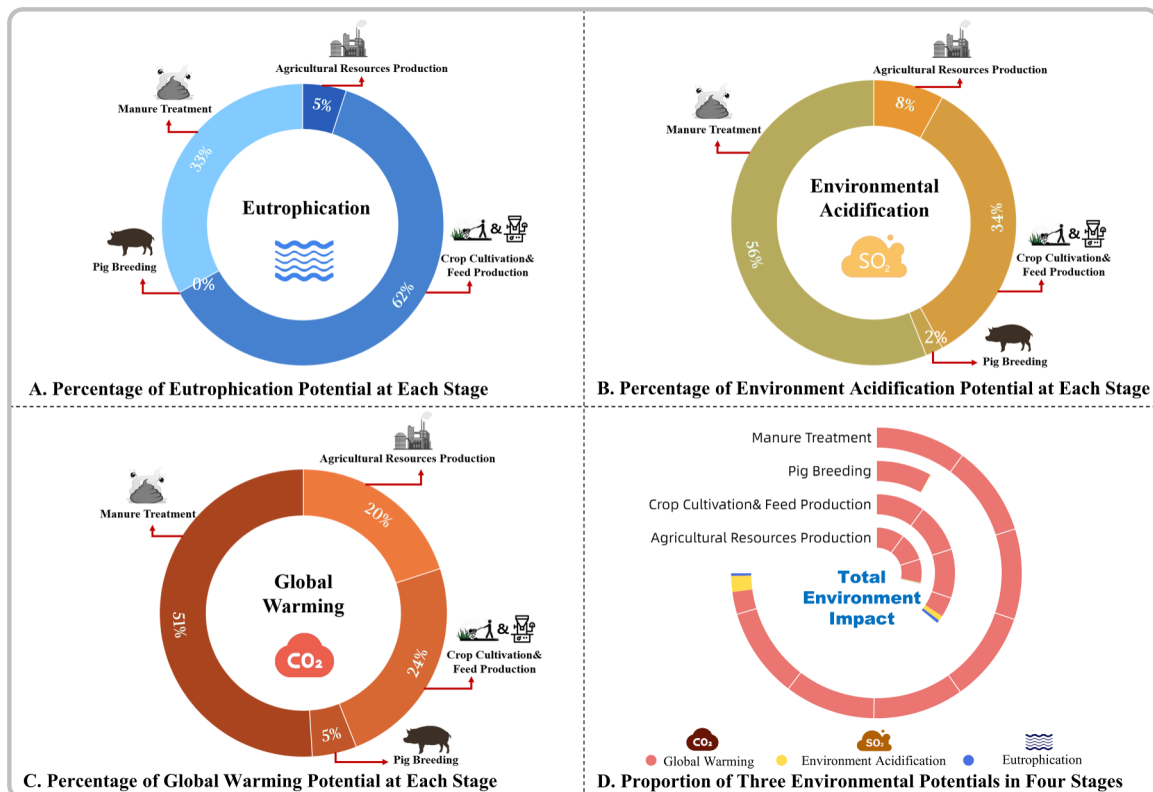
The environmental impact potential value of eutrophication, environmental acidification and global warming during pig production can be calculated according to formula (1). The environmental impact types were selected based on the material consumption and pollutant discharge in four stages of pig production, and the data used were obtained from the public data described in Section 2.1.

$$E_{P(x)} = \sum E_{P(x)i} = \sum [Q_{(x)i} \times E_{F(x)i}] \quad (1)$$

In the aforementioned formula,  $E_{P(x)}$  is the potential value of the environmental impact of the system;  $E_{P(x)i}$  is the potential value of the emission substance from the environmental impact;  $Q_{(x)i}$  is the emission value of emission substance  $i$ ;  $E_{F(x)i}$  is the equivalent coefficient of the emission substance from the environmental impact. The results of the environmental impact potential were illustrated in Fig. 3.

(1) The potential value of eutrophication caused by pig production was 0.97 kg PO<sub>4</sub><sup>3-</sup> eq head<sup>-1</sup>, which mainly occurred in the planting stage of the feed crops, accounting for 61.61% of the total impact. Excessive application of chemical nitrogen fertilizer and phosphorus fertilizer during the planting of feed crops led to numerous residues entering the water body (Zhang et al., 2021; Zhao et al., 2021), which intensified the degree of eutrophication. Corn productivity in China was 0.75, and the average input efficiency of chemical fertilizers was 0.45, which had a massive potential for decreasing fertilizer input (Zhang et al., 2018). The “Chemical Fertilizer and Pesticide Reduction” guidelines implemented by the state to achieve zero growth of chemical fertilizers and pesticides were well received and responded to by the agricultural producers, which was promising for reducing eutrophication (Deng, 2016).

(2) The potential value of environmental acidification caused by pig production was 3.16 kg SO<sub>2</sub> eq head<sup>-1</sup>, which mainly occurred during crop cultivation & feed production stage and manure treatment stage,


**Fig. 3.** Contributions of different stages of pig production to environmental impact.

accounting for 34.43% and 56.06% of the total emission of the process. The total amount of feed required to produce one pig emitted 1.09 kg SO<sub>2</sub> eq substances during the process of feed crop planting and feed production, which led to environmental acidification. This is mainly due to the application of nitrogen fertilizer, a large amount of nitrogen oxides and ammonia will be discharged in the feed plant production stage, and a large amount of ammonia will be discharged in the manure treatment stage. Safa et al. (2017) have clearly pointed out that nitrogen oxides, sulfur dioxide and ammonia are the main substances causing environmental acidification. Under natural conditions, soil environmental acidification should have been a relatively slow process; however, in recent years, the high input (mainly nitrogen fertilizer input in this study) and unbalanced fertilizer use has immensely enhanced soil acidification and nutrient consumption (Liebig et al., 2002), which was specifically reflected in the decreased soil pH value (Huang et al., 2004). Organic matter enhancers, such as green manure and crop straw returning, are widely recommended to improve the crop yield and soil quality (Shisanya et al., 2009).

In the manure treatment stage, one pig produced 1.77 kg SO<sub>2</sub> eq, with NH<sub>3</sub> gas discharged by the aerobic composting process as the main pollutant source. Aeration crucially affects the emission of NH<sub>3</sub> and other gas during the composting process. At present, there are mainly two methods to control nitrogen loss in the composting process. One is to change the process conditions, the other is to add additives in the composting process. The process conditions changed by the former mainly include appropriate temperature control, ventilation and increasing water content. The additives added by the latter mainly include the following categories of carbon rich substances, such as peat, straw, biochar, zeolite, bentonite, calcium superphosphate, etc. (Yang et al., 2005; Chowdhury et al., 2014).

(3) The global warming potential of pig production was 142.75 kg CO<sub>2</sub> eq head<sup>-1</sup>, which was mainly attributed to the agricultural resources production, crop cultivation, feed production and manure treatment. The data analysis revealed that the agricultural resources production stage emitted 28.29 kg CO<sub>2</sub> eq, and CH<sub>4</sub>, N<sub>2</sub>O and CO<sub>2</sub> emission from pig farms accounted for 12.68%, 44.04% and 43.28%, respectively (Zhang et al., 2019). The planting, farming and irrigation of feed need the input of chemical fertilizer, pesticide and energy; the feed processing needs energy; the production of chemical fertilizer, pesticide and energy needs the exploitation of coal, oil and natural gas. Large-scale enclosed industrialized pig farms require tremendous energy for lighting, heating, cooling, automatic feeding, water supply and maintaining air circulation (Wang et al., 2010), which consumes a large amount of fossil fuels during agricultural production. The government should further strengthen the pollution control of agricultural production industry and promote agricultural production enterprises, such as chemical fertilizer factories and energy providers, to reduce pollutant emissions via combination of punishment and incentives. They could further optimize the collection of drainage dues (Zhang and Zhang, 2016), and increase subsidies for environmental protection technology investment of agricultural production enterprises (Huang and Wang, 2011).

In general, 72.47 kg CO<sub>2</sub> eq could be emitted at the manure treatment stage, most of which included CO<sub>2</sub>, N<sub>2</sub>O, and CH<sub>4</sub> because anaerobic fermentation and aerobic composting would produce a large amount of GHG (Yang et al., 2016). Farms should enhance the treatment of manure waste, such as covering manure waste stored in open air. Surface mulching, particularly straw mulching can reduce methane emission from liquid manure by an average of 38% (Sommer et al., 2000). CH<sub>4</sub> is produced by anaerobic fermentation of organic matter in the manure. Therefore, dry cleaning of manure was advocated instead of soaking manure and flushing them with water (Zhu et al., 2006). Reducing the stacking time of manure (Ofesen et al., 2006) by incorporating an anaerobic digestion unit to recover biogas in the form of CH<sub>4</sub> would prove beneficial. A pig farm with an annual output of 10,000 pigs could receive an annual GHG reduction of 504 t CO<sub>2</sub> eq by implementing a biogas project.

**Table 5**

Environmental impact changes of functional unit pigs before and after DEA optimization.

Environmental Impact Types	Unit	Impact values		The impact of the reduction
		Now	After optimization	
Eutrophication	kg PO <sub>4</sub> <sup>3-</sup> eq head <sup>-1</sup>	0.97	0.97	0.00
Environmental acidification	kg SO <sub>2</sub> eq head <sup>-1</sup>	3.16	3.14	0.02
Global warming	kg CO <sub>2</sub> eq head <sup>-1</sup>	142.75	140.53	2.22

Moreover, 34.05 kg CO<sub>2</sub> eq could be emitted while planting feed crops. CO<sub>2</sub> and N<sub>2</sub>O were the main sources of pollutants, accounting for 43.78% and 55.93% of the GHG emission. The CO<sub>2</sub> emission mainly comes from the diesel consumption in the process of crop cultivation and the power consumption in the process of feed processing. The feed production process of food crops (wheat and corn) is an important emission source of N<sub>2</sub>O. Farmland management includes fertilization, irrigation, farming and straw management, in which reasonable nitrogen application is the most direct factor to reduce N<sub>2</sub>O production and emission (Li et al., 2020). At the same time, the application of agronomic measures such as crop rotation and tillage, irrigation, organic fertilizer and straw returning, phosphorus and potassium fertilizer and medium and trace element management can also effectively reduce N<sub>2</sub>O production and emission (Hoben et al., 2011; Maharjan et al., 2014). The development and application of urease inhibitor, nitrification inhibitor and release-controlled fertilizer also provide a way to reduce N<sub>2</sub>O emission from farmland (Zhu et al., 2019). Another effective means to reduce pollutant emission is to improve the productivity of planting feed crops. Studies have reported that by nutrient management, applying controlled-release fertilizers (Dora and See, 2021), farmyard fertilizer and N-P-K fertilizer (Mete et al., 2015), foliar fertilizer (Moreira et al., 2017), biochar (Affler et al., 2018), changed land farming system (no tillage, conservation tillage, etc.), and inter-cropping could remarkably increase the yield of crops such as soybean and corn (Ashworth et al., 2017; Zhan et al., 2020) and reduce soil erosion.

After calculating the environmental impact type and actual impact value of pig production, the ideal value after optimization was calculated via comparative analysis of DEA method. The reduced environmental impact value was obtained by determining the difference between the actual and ideal values. The results are presented in Table 5.

In the present study, the indicators of eutrophication, environmental acidification, and global warming potential of pigs were 0.97 kg PO<sub>4</sub><sup>3-</sup> eq head<sup>-1</sup>, 3.16 kg SO<sub>2</sub> eq head<sup>-1</sup>, and 142.75 kg CO<sub>2</sub> eq head<sup>-1</sup>, respectively, which were higher than those reported by Liu et al. (2012). This may be attributed to the data obtained from different scales of pig production in China, including numerous individual pig farmers. The input efficiency of individual pig farmers was low, which could presumably have profound impact on causing environmental pollution. After optimization based on the DEA method, the environmental impact values of various types were reduced, and the impact of global warming could be reduced by up to 2.22 kg CO<sub>2</sub> eq head<sup>-1</sup>.

Eventually, after comparing the current environmental impact values of eutrophication, environmental acidification and global warming produced by pigs with the values optimized by the DEA method (Fig. 4 and Table 5), the values of all environmental impact types were reduced. Through DEA model optimization, the three types of environmental impacts decreased to 99.93%, 99.40% and 98.44% of the current potential values. Among these, the decline in the environmental impact of global warming was the most obvious. Considering 693.824 million pigs produced in China in 2018 as an example, the potential global warming impact of the process could decrease by  $1.5425 \times 10^9$  kg CO<sub>2</sub> eq. According to the estimation of Lindsay (2014), the carbon emission per kilogram in the production and

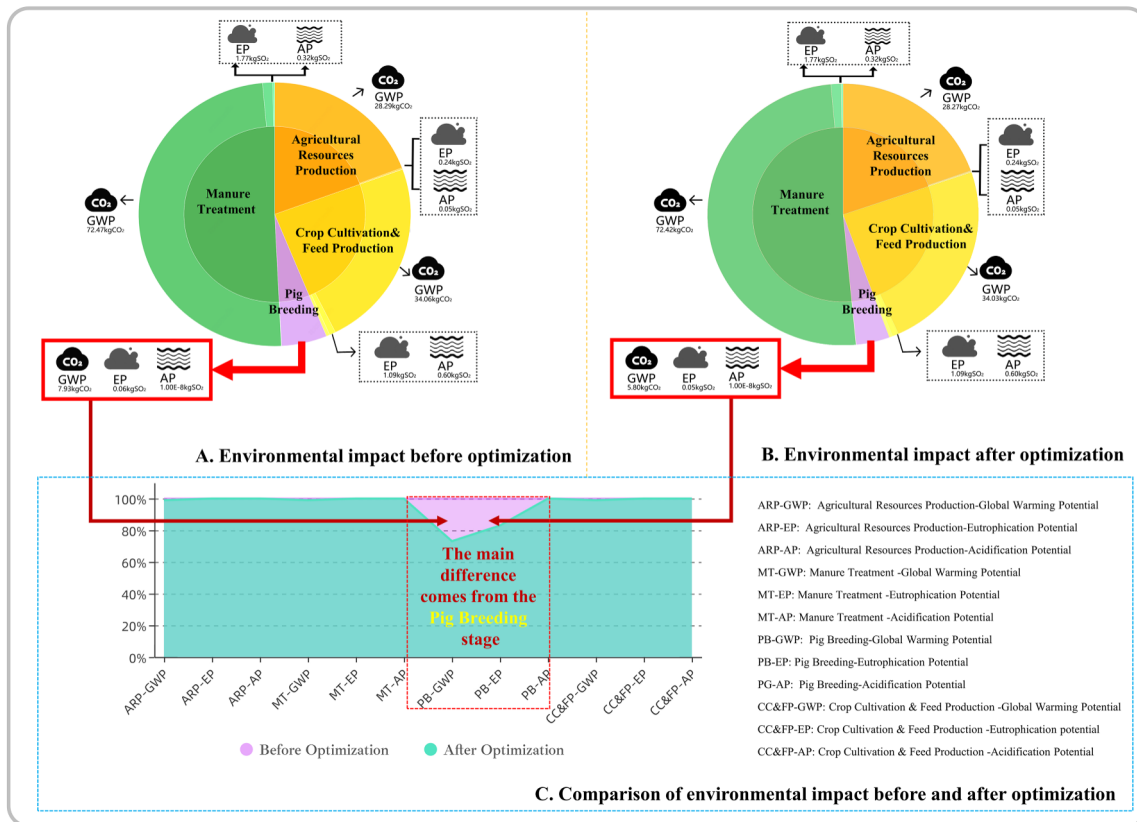


Fig. 4. Total environmental impact at each stage of pig production before and after optimization.

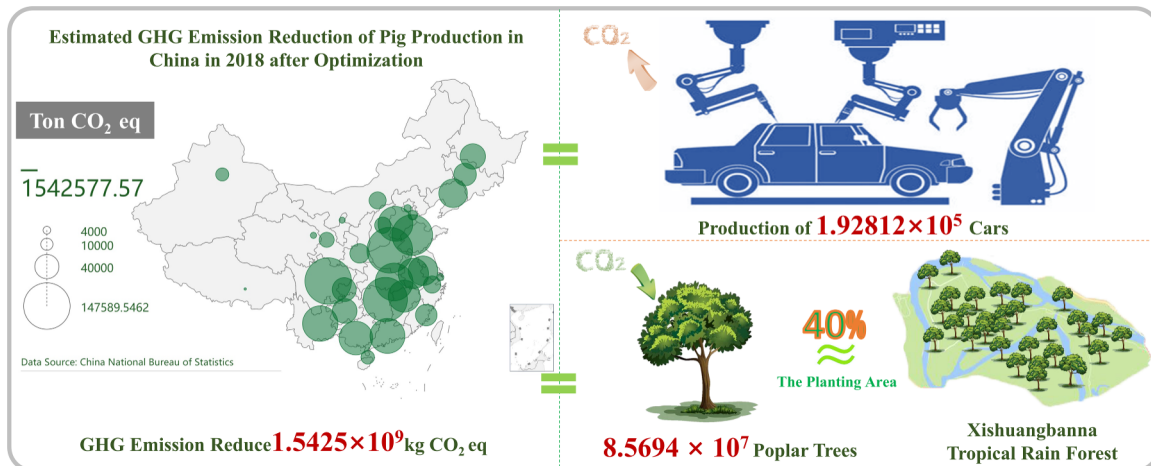


Fig. 5. Estimation of GHG emission reduction in Chinese pig production in 2018 after optimization.

manufacturing process of ordinary gasoline vehicles is approximately 4–7 kg CO<sub>2</sub> eq. Therefore, the carbon emissions associated with manufacturing an ordinary gasoline car is approximately 8 t CO<sub>2</sub> eq. Therefore, the optimized GHG emission reduction is relative to the GHG emitted by the production of  $1.92812 \times 10^5$  cars. Based on the results of studies by China's National Forestry and Grass Administration, a tree could fix 18 kg CO<sub>2</sub> year<sup>-1</sup>, and the decline in the potential environmental impact of global warming of China's pig industry through DEA model optimization was equivalent to fixing by approximately  $8.5694 \times 10^7$  trees. Considering the poplar used in calculating mature forestry carbon sequestration as an example (the canopy density of poplar planting was  $\geq 0.2$ , 900 trees could be planted per ha), the decline in the

global warming impact potential of China's pig industry could be equivalent to an increase of  $9.5216 \times 10^4$  ha of forest area (Fig. 5).

### 3.5. Results of sensitivity analysis

Sensitivity analysis was used to evaluate the sensitive parameters on environmental impacts. The sensitivity ratio (SR) is the ratio between the environmental impact change and parameter change, which indicates the change of overall environmental impact of the system after the change of a certain parameter (Huang et al., 2012). Combined with the previous environmental impact calculations, it is found that the environmental impact caused by pig producing process mainly comes

**Table 6**  
SR analysis results.

Adjustment content	AP	EP	GWP
Application rate of chemical fertilizer reduced by 10%	0.99	0.88	0.75
Electric power for pig raising reduced by 10%	1.02	0.71	0.84

from the crop cultivation process, in which the excessive use of chemical fertilizer is the main reason for the great environmental impact at this stage. At the same time, many stages of pig producing process involve the consumption of electric power. Therefore, in sensitivity analysis, the amount of chemical fertilizer application and the electric power consumption for pig producing were discussed as two analysis parameters. In the study, both chemical fertilizer application and the electric power consumption were reduced by 10% to calculate the SR value.

Following a reduction in chemical fertilizer application by 10%, the environmental impacts of eutrophication, acidification and global warming decreased by 9.90%, 8.80% and 7.50%, respectively (Table 6). It can be concluded that the strategy of "Reducing the application of chemical fertilizers" proposed by the Ministry of Agriculture and Rural Affairs People's Republic of China can well promote the cleaner production of China's pig industry and effectively reduce environmental pollution. However, to varying extent of implementation of this strategy in different regions of China, it also leads to the uncertainty of the environmental impact of pig breeding.

In addition, reduction of electric power consumption by 10% reduced the environmental impacts of eutrophication, acidification and global warming by 10.20%, 7.10% and 8.40%, respectively (Table 6). Therefore, the change of electric power consumption can significantly affect the environmental impact of pig producing. Improving the hardware facilities, the heat preservation and ventilation of the pig house, and applying the biological fermentation bed technology, are all effective ways to reduce heat consumption in the pig house, so as to further reduce the environmental impacts (Hou et al., 2019).

#### 4. Conclusion

The optimization of resource input and energy consumption in Chinese pig systems decrease global warming, acidification and eutrophication. The integration of data envelopment analysis and life cycle assessment can facilitate the optimization process. Optimizing China's pig production processes could effectively improve production efficiency, enhance resource utilization efficiency, and reduce greenhouse gases emissions, which correspond to SDG 12 (responsible consumption production) and SDG 13 (climate action). However, the reduction in use of chemical fertilizer and electric power are more effective ways to reduce greenhouse gas emissions than the optimization of resource input and energy consumption.

#### CRediT authorship contribution statement

**Ruoyu Sun:** Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Resources, Writing – original draft, Funding acquisition. **Xianjun Liu:** Resources, Writing – review & editing. **Dabing Li:** Investigation, Resources. **Jie Zhuang:** Formal analysis, Writing – review & editing. **Shengrui Qi:** Visualization. **Bo Meng:** Methodology, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Mingda Liu:** Conceptualization, Methodology, Formal analysis, Resources, Writing – original draft, Writing – review & editing, Supervision, Project administration, Funding acquisition.

#### Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence

the work reported in this paper.

#### Data Availability

Data will be made available on request.

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