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Factors limiting the sustainable implementation of the rice-crayfish system in Hubei Province, China

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Abstract

CONTEXT: As the most popular model of rice-fish system (RFS) in China, the rice-crayfish system (RCS) has been shown to theoretically increase economic output and improve the ecological integrity of farmlands. Despite its importance, there are some issues to address. Many studies have been done based on the field experiments; however, present work was a comprehensive multistage survey which covered larger areas. Estimating the environmental efficiency (EE) of farmers' RCS and analyzing its limiting factors deserves more attention as farmers' behavior plays a key role in this respect.

OBJECTIVES: This study aimed to: (1) estimate EE, (2) determine the causes of differences in EE, and (3) analyze the factors restricting farmers' optimal application of the RCS.

METHODS: In total, 199 rice-crayfish farmers' field survey data collected across two cities of Hubei Province were applied to estimate the EE and determine its limiting factors.

The EE of the RCS was calculated using the slack-based measure (SBM). The limiting factors were analyzed using the combined least absolute deviation model.

RESULTS AND CONCLUSIONS: The average land productivity and net profit of our sampled farmers were US$ 10,119 and 4,364 per ha, respectively, with a rice yield of 7,832 kg/ha and a crayfish yield of 1,748 kg/ha, and EE value on average was 0.618. Overall, the large-scale (> 2 ha) farmers performed best in terms of profit and EE value. The SBM results showed that the input, desirable output and undesirable output inefficiencies were 0.311, 0.201 and 0.214, respectively. Redundant inputs such as drugs, feed and labor with redundancy ratios of 50%, 44% and 35%, respectively, resulted in the overall difference in EE performance. Enhancing farmers' education level, technical training, and organic fertilizer application and decreasing their part-time employment can improve the EE of RCS.

SIGNIFICANCE: The findings are expected to facilitate an improvement in production practices that target green agricultural development. Moreover, these results should act as a reference for the government and farmers in the formulation of relevant policies and to guide the implementation of RCS, respectively.

JEL Codes: Q10, Q56, O13

Keywords: rice-crayfish system; land productivity; environmental efficiency; green agricultural development; farm household; field survey

1. Introduction

Reducing carbon emissions is now a significant policy agenda for greening agricultural development globally (Ou et al., 2024; Shen et al., 2024). For the last six decades, agricultural development strategies in most countries have focused on intensification by increasing external inputs such as fertilizers, concentrates, and energy (Khatri-Chhetri et al., 2023). Although this has enhanced yields, the widespread adoption of intensive production practices has also increased greenhouse gas (GHG) emissions. For example, the Institute for Global Decarbonization Progress reported that nearly 14% of China's total GHG emissions, or 1.65 billion tons CO_2eq, were emitted by the agri-food system, of which agricultural production was the largest source of emissions (Chen et al., 2023). Agricultural growth, which primarily depends on the intensive input of production factors, inevitably causes severe resource wastage and carbon emissions, threatening green agricultural development (Luan et al., 2013; Qiu et al., 2014).

Integrated rice-fish system (RFS) was originally introduced into agricultural production practices as viable strategy for promoting green and efficient agriculture (Cao and Sang, 2020; Chen and Tang, 2013). The RFS facilitates the development of a diverse eco-economic system by combining rice cultivation and aquaculture. Through inter-species reciprocity and complementary utilization of resources, this strategy is expected to conserve land, increase economic outputs, and improve the overall ecological integrity of farmlands (Chen and Tang, 2013); these trends should allow for the attainment of objectives outlined in "dual uses of one water, double harvests in one field" (*yishui liangyong*, *yitian shuangshou* in Chinese) (Cao et al., 2017). The RFS has expanded rapidly and reached over 1.06 million ha according to *the 2019 Report on the Development of Rice-fishery Integrated Farming Industry in China*.

Compared with rice-fish, rice-crab, rice-duck, etc., the rice-crayfish system (RCS) is the most widely used RFS and rapidly developed, accounting for more than nearly 50% of the national RFS in 2019. Moreover, RCS has been greatly promoted in governmental documents. For example, from 2016 to 2018, the Chinese central government's No. 1 Document consecutively highlight the urgent need to promote the implementation of RCS; these documents also highlight the important role RCS could play in stabilizing grain production, driving further development of the fishery industry, and enhancing agricultural production quality and efficiency. Simultaneously, some local governments such as Hubei, Zhejiang, and Jiangsu have strengthened their promotion of RCS by formulating a series of policies. However, owing to the high investment and technical requirements in agricultural practices, some rice-crayfish farmers often struggle to achieve the expected returns (Lian et al., 2018). According to Hubei Provincial Center of Aquatic Technology Extension, among the more than 2,000 rice-crayfish farmers in 2018, only one-third made a profit (Zhu et al., 2019). In practice, some farmers invested in large quantities of materials to gain economic benefits, leading to severe resource wastage and environmental pollution (Chen et al., 2020). Therefore, regardless of the promotion and popularity of RCS, its performance remains to be thoroughly interrogated.

Current studies on the effects of RCS either primarily focus on its ecological impact (Shen et al., 2010; Yu et al., 2014; Lin and Zhou, 2012) and economic benefits (Ahmed et al., 2011; Chen, 2018; Li et al., 2014; Wang and Tan, 2020). However, an environmental or economic perspective is not sufficient to illuminate the role of RCS in greening agricultural development. Additionally, the data that underlies most studies on RCS were obtained primarily through field experiments. For example, by testing field plots nationwide, Chen et al. (2019) compared net income per unit area of RCS with rice monocropping and found that the former was about 45% higher than the latter. Based on field experiments, Xiang et al. (2006) found that RFS increased the farmers' economic benefits and reduces CH_4 emissions from paddy fields. Considering the key role of farmers in technology selection and production decision, this study applies farm-level micro-survey data to estimate the ecological impacts of RCS and to analyze its limiting factors. Environmental efficiency (EE), namely the ratio of economic value added to the observed side effects on the environment under desirable outputs and conventional inputs (Tyteca, 1996; Kortelainen, 2008), is used as an indicator to evaluate the performance of RCS (Aldanondo-Ochoa et al., 2014). EE emphasizes the integration of economic benefits and environmental protection and is thus referred to be a better assessment indicator of agricultural practices. The study is expected to provide suggestions for promoting eco-economic effects at farm household level, thereby improving carbon emission reduction and agricultural green development.

2. Understanding the RCS in the study areas

2.1 The eco-economic principle of RCS

Due to symbiosis within the system, the RCS can derive maximum benefits from the internal energy cycle, which provides a basis for achieving resource recycling, reducing carbon emissions, and boosting eco-friendly economic growth. Specifically, the functioning of RCS is rooted in the corporation of multiple organisms; therefore, its implementation improves the ecological richness of rice ecosystems (Zhen et al., 2019). Compared to the rice monoculture model, RCS makes better use of the shallow water environment and idle period of winter and spring in paddy fields (Tan et al., 2021). This allows one field to harvest rice and crayfish, thus increasing the economic outputs. In the monoculture model, many resources such as rice flowers, paddy weeds, benthic creatures, and plankton are lost in the water and weeds are uprooted, as shown in Fig.1 (dotted part). This results in significant energy losses and insufficient utilization of the biological productivity in paddy field system. However, in the RCS, the rice-crayfish symbiotic cycle converts the materials wasted in the monoculture model into energy recycling. Crayfish help weeding, control pests, and loosen soil for rice (Li et al., 2023). In turn, rice provides shade, improves water quality, and optimizes the living environment for crayfish. This decreases the use of pesticides and fertilizers, thereby reducing environmental pollution and saving agricultural inputs. In summary, RCS is expected to improve the economic outputs, reduce agricultural inputs and carbon emissions, and enhance ecological benefits, thus achieving "dual uses of one water, double harvests in one field."

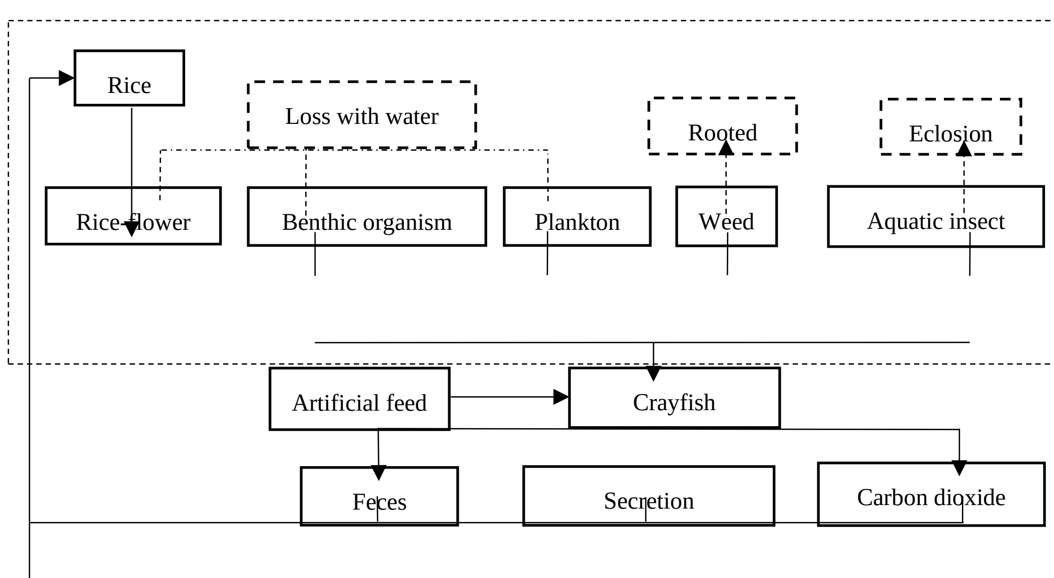
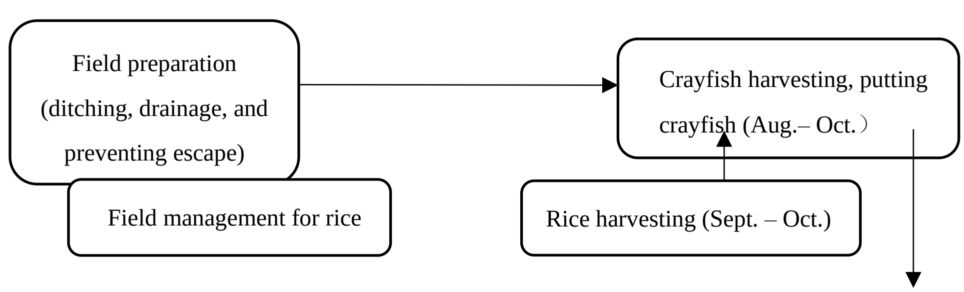


Fig. 1. Ecological principle of rice-crayfish farming. Source: Adapted from Xi and Zhou (2016).

Rice-crayfish coculture refers to planting one season of rice and breeding two seasons of crayfish each year (Chen, 2018). Cao et al. (2017) mapped the process of RCS according to the chronological sequence of events, as shown in Fig. 2. In the field renovation, a breeding ditch approximately 4 m wide and 1.5 m deep is dug; other remolding work, such as sterilizing crayfish ditches, planting water plants, improving drainage systems, and constructing escape prevention facilities then follows. Parental crayfish should be introduced before the rice harvest in August–September, or the young crayfish should be introduced after rice harvest in September-October. The density of released crayfish is approximately 375 kg per ha. In practice, this translates to approximately 7,000 or 8,000 parents and juvenile crayfish. During the four-to-six-month growth cycle, farmers need to frequently inspect the water quality and crayfish's feeding status, as well as clean the aquaculture environment. Adult crayfish are harvested in March–June of the following year, but some of them should be retained in fields for breeding. A crayfish purchasing station is set up in the village for farmers to sell their crayfish during the harvest season. The prices of crayfish vary greatly; they are primarily determined by crayfish size and partly by weather and market rules. At the end of May or the beginning of June, the field should be prepared for transplantation. Crayfish crawls out of rice paddies and into crawfish ditches. Before plowing, farmers need to remove standing water and expose the fields to sunlight for 10-15 days to remove residual pathogens from the soil (Si et al., 2017). When rice is transplanted, and the rice fields are filled with water, rice and crayfish will coexist in one field. The second batch of crayfish will be harvested in August–September. This process will go back and forth alternately.



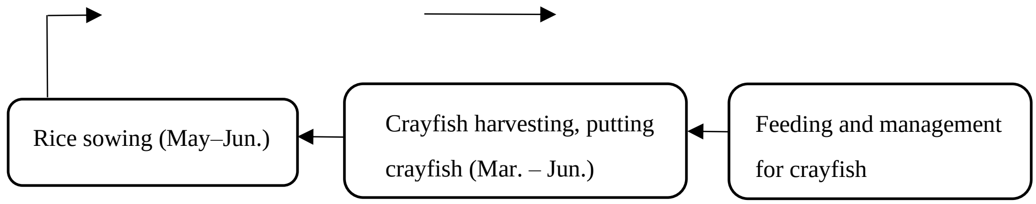


Fig. 2. Diagram for the rice-crayfish coculture system. Source: Adapted from Cao et al. (2017).

2.2 The RCS in the study area

Hubei Province is the birthplace and main production area of RCS. Based on *the 2019 Report on the Development of Rice-fishery Integrated Farming Industry in China*, Hubei has the largest RFS and RCS areas compared to the other four main-producing provinces, namely, Hunan, Anhui, Jiangsu, and Jiangxi. Table 1 summarizes the farming areas and their proportion in the context of the use of RFS and RCS in 2018. The total RFS area reached approximately 2.13 million ha, of which RCS accounted for 50%. Among the provinces, Hubei has the largest farming area for RCS accounting for 36% of the total. It has noteworthy inherent advantages such as sunshine, temperature, water, and soil. The rice planting area in Hubei is more than 2 million ha, of which approximately 1 million ha is suitable for rice-fish coculture. In 2018, there was 0.39 million ha of RFS in Hubei, of which RCS accounted for nearly 97%. This suggests that there is a great potential for Hubei to lead the development of RCS.

Two cities, Jingzhou and Qianjiang Cities, are selected as the study areas. Jingzhou City has the largest area of RCS in Hubei. According to Hubei Statistical Yearbook 2019, its total crayfish production reached approximately 337,100 tons. Qianjiang City is the birthplace of RCS in China. The area of the RCS in Qianjiang was approximately 36,000 ha, and crayfish production reached 92,200 tons in 2018. Technical regulations for RCS developed by Qianjiang have been released as a national standard. Moreover, Qianjiang is adjacent to Jingzhou, making it convenient for us to conduct surveys (See Fig. 3).

Table 1

The farming area of RFS and RCS in 2018

Region	RFS		RCS		RCS/RFS (%)
	Area (ha)	Proportion (%)	Area (ha)	Proportion (%)	

Total in China	2,133,333	100	1,059,627	100	50
Hubei	393,167	18	380,667	36	97
Hunan	300,147	14	197,938	19	66
Anhui	150,633	7	148,136	14	98
Jiangsu	241,060	11	74,916	7	31
Jiangxi	66,993	3	59,021	6	88
Other provinces	981,333	46	60,823	19	6

Notes: The proportion is based on the total farming area of RFS or RCS in China.

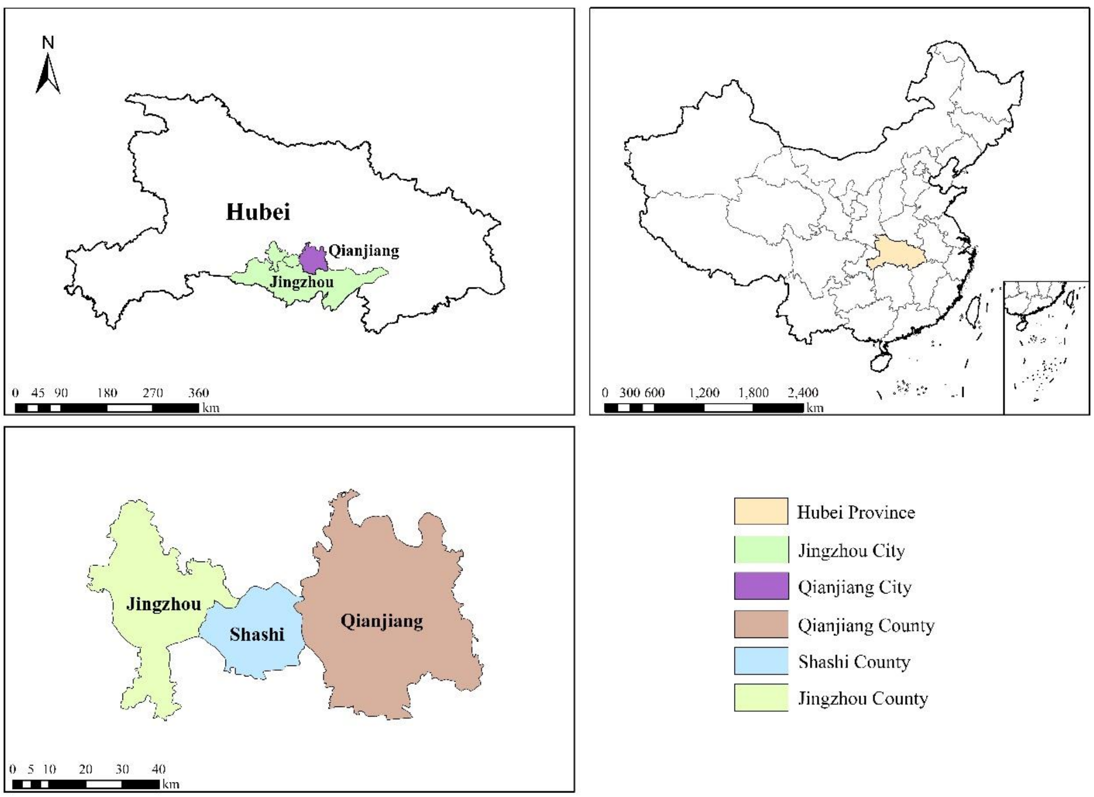


Fig.3. The maps of the study areas.

3. Research methodology

3.1 Sampling and data collection

The data used for the subsequent analyses were collected from field surveys conducted in Qianjiang and Jingzhou cities of Hubei Province from 2018–2019. Four field surveys were conducted (see Table

2). The first two surveys, held between June and July 2018, aimed to illuminate the socio-economic and bio-physical circumstances of the study areas. These findings drove the creation of the questionnaire. Based on those surveys, three counties from the two cities were selected to conduct the third survey in August 2019. This survey collected data on inputs, outputs, their farming practices, and routine management. Specifically, we collected their 2018 rice and crayfish revenue, respectively, as well as various costs (e.g., the cost of seeds, fertilizer, and pesticides, crayfish feed and drugs, etc.). Data on land, labor, and machinery were collected jointly.

We randomly selected approximately 60–80 RCS households from each county in the third survey, resulting in 229 in-person interviewed samples. However, field abandonment was observed in some areas in which rice-crayfish cocultures were implemented. We therefore made a supplementary survey in October 2019 to see whether such trends were present in our samples. Based on this survey, we excluded 10 samples with abandoned coculture fields and 10 samples with missed important indicators, resulting in 199 valid samples. The samples and their distributions are presented in Table 3.

Table 2

The description of the surveys

	Time	Type	Objective
I.	2018.07	Pre-survey	To get more understanding of the study areas and their RCS and decide how to sample
II.	2018.08	Pre-survey	
III.	2019.08	Large-scale formal survey	To collect the data on production inputs, and outputs, and field management, etc.
IV.	2019.10	Supplement survey	To confirm whether the sampled households abandoned their coculture fields

Table 3

Samples and distribution

City	County	The number of farm households	Percentage of sampled farm households (%)
Jingzhou	Jingzhou	59	30
	Shashi	82	41
Qianjiang	Qianjiang	58	29
Total		199	100

Notes: Jingzhou is a prefecture-level city. Qianjiang is a county-level city directly governed by Hubei province.

3.2 Calculation of RCS productivity and profit

The possibility boundary was constructed by considering the rice-crayfish farmer as the decision-making unit (DMU). Using published studies (Ahmed et al., 2011; Tan et al., 2021), we selected seven factors, namely land, labor force, machinery, seeds, fertilizer, feed, and some chemicals, as input indicators. Land inputs were expressed in terms of total operational areas, including contracted land and leased land. The labor force included both family and employed labor. According to our exploratory fieldwork, most farmers used their family labor force for rice-crayfish production activities, and some farmers employed short-term workers during the harvest season. Family labor was estimated as working man days (8 hours a day) multiplied by the local wage, typically $12 per day[1]. Machinery primarily included plowing and harvesting inputs during rice production and ditching and dredging inputs during farmland rehabilitation. Seed inputs included rice and crayfish seeds. The fertilizer inputs primarily included compounds, nitrogen, phosphate, potash, and organic fertilizers. Feed refers to the total feed cost incurred in crayfish farming, including purchased feed and farmer-planted feed, such as corn, wheat, and soybean. The cost of farmer-planted feed was calculated as the market price. Chemicals were primarily used to manage ulcers, ciliates, viral diseases in crayfish and control pests and diseases in rice. To unify the measurements, we estimated the chemical inputs in monetary terms.

Productivity in this study refers to land productivity, namely physical or economic output per unit area, and the net profit of RCS implies total revenue per unit area minus total cost. As the coculture fields produce both rice and crayfish by applying fertilizers, seeds, and labor force, etc. as inputs, it is difficult to aggregate the two outputs physically. Therefore, we used economic output to measure land productivity. The equations of land productivity and net profit of RCS can be specified as follows:

$$Productivity = \frac{Reve_1 + Reve_2}{Tota} \tag{1}$$

$$Profit = \frac{Reve_1 + Reve_2 - \sum_{k=1} Input_k \times Price_k}{Tota} \quad (k = 1, \ldots, 9) \tag{2}$$

where $Reve_1$ and $Reve_2$ denote the total revenues of crayfish and rice in 2018, respectively; $Tota$ refers to the total operation area of the sampled household, including the contracted land and leased

[1] In this study, $ refers to U.S. dollars.

land; $Input_k$ denotes the kth input, representing rice and crayfish seeds, machinery, labor, fertilizer, pesticide, feed, drug, and leased land, respectively; and $Price_k$ is the corresponding price per unit land area.

3.3 The slack-based measure (SBM) model to estimate the eco-efficiency

EE was estimated using the SBM. The rice-crayfish practice produces the expected output as well as discharges undesirable outputs (environmental pollution) (Färe and Grosskopf, 2009). The expected output from the RCS can be divided into rice production and crayfish production. We use the revenues of rice and crayfish to denote the desirable outputs. The undesirable output primarily includes water pollutes such as excessive nitrogen and phosphorus, as well as carbon emissions. It can be distinguished into non-point source pollution (TN and TP) and carbon emissions from fertilizer overflow in this study.[2]

The water pollute emissions were estimated based on the method of Lai et al. (2004). Specifically, we calculated the amount of non-point source pollution (TN and TP) produced by the RCS using equation (3):

$$E_m = \sum E_{ij} = \sum C_{ij} * \mu_{ij} = \sum T_i * \rho_{ij} * \mu_{ij} \tag{3}$$

where E_m is the total pollutant emissions from non-point sources of fertilizer; E_{ij} is the emission of the *j*th pollutant in each DMU i; C_{ij} is the production amount of the *j*th pollutant in unit i; T_i is the statistics of unit i; and ρ_{ij} and μ_{ij} are production pollution coefficient and fertilizer loss rate, respectively. Because potash fertilizer does not directly cause non-point source pollution, pollution is primarily driven by nitrogen, phosphate, and compound fertilizers. According to the chemical composition of fertilizer, TN and TP of nitrogen fertilizer have a pollution coefficient of 1, and TN and TP of compound fertilizer have a pollution coefficient of 0.33 and 0.15, respectively. In Hubei Province, the nitrogen and phosphate fertilizer loss rates were 20% and 7%, respectively (Lai et al., 2004). The determining factors for pollutant emissions are the amount of N and P fertilizer inputs. Compared to the mono-rice planting system, RCS might affect the pollution coefficient and fertilizer loss rates. However, our research aims to compare the differences in EE among farmers and further analyze limiting factors

[2] Because the chemicals are very complex and most of them are inorganic, their effects on the non-point source pollution and carbon emission of RCS are not considered in this paper.

that underlie EE, so that the formula (3) can be used for this study.

Using a method proposed by Li et al. (2011), the indirect carbon emissions of fertilizers were calculated using equation (4):

$$C_i = F_i * \xi \tag{4}$$

where C_i is the carbon emission of fertilizer in the production activities of the ith farmer; F_i is the amount of fertilizer used; and ξ is the carbon emission coefficient of fertilizer, which is approximately 0.8956 kg/kg.

Although Data Envelopment Analysis (DEA) is an effective method for evaluating the relative efficiency of DMUs, it does not account for unexpected outputs. Tone (2001) proposed a SBM of efficiency, which considers both the input excesses and output shortfalls of each DMU concerned. This measure uses a non-radial and non-angular approach to estimate EE values and explore factor redundancy. Therefore, the SBM based on undesirable output was used in this paper. Undesirable production is measured by non-point source pollution and carbon emissions caused by farmers' overuse of chemicals. When considering environmental pollution, the definition matrix of the undesirable output vector, that is, $y^b \in R$^(s_2), is $Y^b = \left[\left(y_1^b, y_2^b, \cdots y_n^b\right)\right] \in R^{s_2 \times n}$. Under the variable returns to scale settings, that is, $\sum_{j=1}^{n} \lambda_j = 1, \lambda_j \geq 0,\ j = 1,2,\cdots n$, the SBM with undesirable output can be expressed as equation (5):

$$\rho^* = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}}{1 + \frac{1}{s_1 + s_2}\left(\sum_{r=1}^{s_1}\frac{s_r^g}{y_{r0}^g} + \sum_{r=1}^{s_2}\frac{s_r^b}{y_{r0}^b}\right)}$$

$$s.t.\begin{cases} x_0 = X\lambda + s^- \\ y_0^g = Y^g\lambda - s^g \\ y_0^b = Y^b\lambda + s^b \\ s^- \geq 0,\ s^g \geq 0, s^b \geq 0 \end{cases} \tag{5}$$

where $s^-, s^g,$ and s^b are slack variables; s^- represents the redundancy of the inputs; s^g is the shortage of desirable outputs; and s^b is the excess of undesirable outputs. P* represents the EE value with respect to diminishing $s^-, s^g,$ and s^b. In the SBM, the efficiency of each DMU is computed by minimizing the slack variables. If $\rho^* = 1$ and $s^- = s^g = s^b = 0$, the function has an optimal solution, and the DMU is completely efficient. When $\rho^* < 1$ and at least one of s^-, s^g, s^b is not equal to zero, there is efficiency loss in the DMU (environmental inefficiency), indicating the necessity of improving the input-output situation. Cooper et al. (2007) decomposed environmental inefficiency into input inefficiency (IE_x), desirable output inefficiency (IE_g), and undesirable output inefficiency (IE_b), expressed as equation (6):

$$IE_x = \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}}, (i = 1, \cdots m)$$

$$IE_g = \frac{1}{s_1}\sum_{i=1}^{s_1}\frac{s_r^g}{y_{r0}^g}, (r = 1, \cdots, s_1)$$

$$IE_b = \frac{1}{s_2}\sum_{i=1}^{s_2}\frac{s_r^b}{y_{r0}^b}, (r = 1, \cdots s_2) \quad (6)$$

Then, we probed deeper into how land productivity, profit, and EE vary across different farming scales. According to China's Ministry of Agriculture and Rural Affairs, nearly 96% of the total farms in China had operating scale less than 2 ha, among which farms less than 0.667 ha and having 0.667-2 ha accounted for 43% and 57% in 2020, respectively. We therefore categorized the total samples into small-scale (<0.667 ha), medium-scale (0.667–2 ha) and large-scale (>2 ha) groups. This categorization was based on the operational RCS land area of the farms, including their contracted and leased land. Each group has 50, 96, and 53 households, accounting for 25%, 48% and 27% of the total samples, respectively.

3.4 The combined least absolute deviation (CLAD) model to analyze factors influencing EE

Production practices of farmers usually influence agri-EE. Farmers who adopt eco-friendly technologies or make protective inputs can effectively reduce environmental pollution (Alauddin and Quiggin, 2008), whereas irrational production behaviors may increase environmental pollution (Hu, 1997). This section identifies the factors that influence EE based on farm household characteristics and external environmental factors. The expected effects on EE of all variables, including the household head's individual characteristics, household livelihood strategies, production behaviors, and production conditions, are summarized in Table 4.

Table 4

Potential factors influencing the EE and their expected effects

Variables	Explanation	Unit	Expected effects
Individual characteristics			
Age	Age of the household head	year	+/-
Education	Education level of the household head	year	+
Livelihood strategies			
Part-time farming	The share of off-farm income	%	-
Production behaviors			
Technical training	Does the household head participate in any technical training? yes=1, otherwise=0		+
Organic fertilizer application	The amount of organic fertilizer application	kg/ha	+
Informal lending	Does the head borrow informally for production? yes=1, otherwise=0		+/-
Production conditions			
Land fragmentation	The average area of plots	ha	-
Policy promotion	Does the local government promote RCS related policies? yes=1, otherwise=0		+

The **age of the household head** is an essential factor affecting agri-EE. However, their effects remain uncertain. Age-related experiences enable farmers to apply productive inputs in more environmentally efficient ways (Ma, 2009; Yang et al., 2015). In contrast, older farmers tend to be risk-averse and less receptive to pro-environmental technologies than younger farmers (Liang et al., 2016). **Educational level** may positively affect EE, as higher education levels may enhance the ability of farmers to acquire more scientific knowledge on rice-crayfish production inputs (e.g., pesticides, fertilizers, and machinery). This helps to reduce the possibility of environmental inefficiency (Chang and Meyerhoefer, 2016). Livelihood strategies refer to farmers' means of making a living, that is, whether the household relies on pure agriculture, part-time farming, or off-farm employment for their livelihood. Some studies argue that **part-time farming** reduces farmers' incentives to invest in land conservation and sustainability (Yang et al., 2015) while switching to environmentally unfavorable practices to ensure their economic benefits (He and Wei, 2003; Lyu et al., 2018). We expected an increase in the share of off-farm income to negatively affect EE.

Technical training helps guide farmers' production management and increases their awareness of pro-environmental agricultural techniques. We expected that participation in technical training would lead to higher levels of agri-EE. **Organic fertilizer application** generally reduces agro-environmental pollution. However, bio-organic fertilizers applied in rice-crayfish farming are more expensive and require higher labor costs than compound fertilizers. Therefore, their effects on EE are mixed. **Informal lending** is a critical way to meet farmers' investment demands. In the early stages of production, rice-crayfish coculture requires digging trenches, purchasing feeding tools, and inputting shrimp seeds, which require high investment capital. Although informal lending may increase farmers' incomes by meeting input demand, it still has the potential to reduce agri-EE. When farmers face financial constraints, the desire for increased income is preferred to ecological capital inputs. Thus, the effects of informal lending are mixed. **Land fragmentation** is the state of several spatially separate plots of land farming as single units (Tan et al., 2006; Gomes et al., 2019). This results in poor efficiency owing to the inefficient use of inputs (Manjunatha et al., 2013) and creates a barrier to agricultural development (Hartvigsen, 2014). Some studies argued that farmers with highly fragmented land tended to invest more in fertilizers (Nkamleu and Adesina, 2000). Therefore, we expected land fragmentation to decrease the EE of rice-crayfish production. Agricultural policy refers to a specialized policy that addresses problems in agricultural development. Rice-fish coculture is still in the development stage; thus, **policy promotion** is significant for achieving efficient and sustainable agricultural production.

We considered that the EE calculated by the SBM is a variable with a non-negative truncated feature. The Ordinary Least Squares method often yields biased estimation results for restricted dependent variables. Therefore, we considered the Tobit or CLAD model to identify the limiting factors. The Tobit model makes strict assumptions, namely normal distribution and homoscedasticity, in terms of the distributional characteristics of the target variables. Therefore, we employed CLAD if the prerequisite assumptions were not met. The Conditional Moment (CM) and Lagrange Multiplier (LM) tests were used to verify whether normality and homoscedasticity were satisfied.

CM test is expressed as equation (7):

$$\frac{1}{N}\sum_{i=1}^{N} w_i \hat{\eta}_i \underset{p}{\rightarrow} \lim_{N\to\infty}\frac{1}{N}\sum_{i=1}^{N}E[w_i u_i] \tag{7}$$

where $\hat{\eta}_i = I_i\left(y_i^* - x_i'\beta\right) - (1-I_i)\hat{\sigma}\hat{\lambda}_i$, $\lambda_i = \varphi(z_i)/(1-\psi(z_i))$, and $z_i = x_i'\beta/\sigma$ denotes the density and cumulative distribution functions of the standard normal distribution, respectively, and w_i is a representative potential exclusion variable.

LM statistics is stated as equation (8):

$$\mathrm{LM} = \left(\sum_{i=1}^{n}\hat{s}_i'\right)\left(\sum_{i=1}^{n}\hat{s}_i\hat{s}_i'\right)^{-1}\left(\sum_{i=1}^{n}\hat{s}_i\right) = 1's\left(s's\right)^{-1}s'1 \tag{8}$$

The constructed auxiliary regression is equation (9):

$$1 \xrightarrow{ols} \hat{s}_i'\gamma + \vartheta_i$$

$$R_{uc}^2 = \frac{1's\left(s's\right)^{-1}s'1}{1'1} = \frac{LM}{n}, \quad LM = nR_{uc}^2 \tag{9}$$

where $\hat{s}_i = s_i(\widehat{\beta_R})$ is the value at p of the contribution of the ith observation to the score function, and R_{uc}^2 is the non-center R^2.

When the Tobit model was not applicable, the CLAD model was employed to obtain more robust results. This method only requires the perturbation terms to follow identically independent distributions. The CLAD model can be constructed as equation (10):

$$y_i = \max\left(0, x_i'\beta + \varepsilon_i\right) \tag{10}$$

If $x_i'\beta + \varepsilon_i \geq 0$, then $y_i = x_i'\beta + \varepsilon$, otherwise $y_i = 0$. The objective function is the sum of the absolute values of the deviations in equation (11):

$$\min_{\beta}\sum_{i=1}^{n}\left|y_i - \max\left(0, x_i'\beta\right)\right| \tag{11}$$

4 Results

4.1 Descriptive statistics

Descriptive statistics of the analyzed variables are presented in Table 5. The heads of the surveyed households were, on average, 55 years old, with the oldest being 77. The education level was moderate, with an average of 7 years, and several farmers were uneducated. The degree of part-time farming differed considerably from household to household, with the share ranging from 0% to 99%. Notably, the share of organic fertilizer application was relatively low, with an average of 64±56 kg/ha. The minimum was 3.5 kg/ha, and the highest was 361 kg/ha. Land fragmentation represented by the average plot size varied from 0.02 to 11.4 ha with an average size of 1.1±1.3 ha. The other indicators also showed substantial variations.

To calculate the EE of the RCS, we adopted three types of indicators–production inputs, desirable outputs, and undesirable outputs–all of which were calculated per ha. The summary statistics of the inputs and outputs are presented in Table 6. Each of these indicators varied considerably. In terms of inputs, the cost of crayfish seeds averaged $1,512±1,342, which was the highest among all the inputs. Desirable outputs include crayfish and rice revenues, with an average of $9,048±4,627 for crayfish and $3,264±847 for rice, but the gaps between the DMUs was relatively large. In Hubei Province, rice and crayfish prices faced by farmers were relatively stable and similar in 2017. Therefore, the revenue difference between farmers was primarily caused by their crayfish yield. In terms of the undesirable outputs, the average of non-point source pollution and carbon emissions were approximately 77±30 and 639±270 kg, respectively. The maximum carbon emissions were 2,280 kg.

Table 5

Descriptive statistics of the variables used in the analysis

Variables	Mean	S.D.	Min	Max
Individual characteristics				
Age (*years*)	55	9.45	25	77
Education (*years*)	7	3.1	0	15
Livelihood strategies				
Part-time farming (%)	27	29	0	99
Production behaviors				
Technical training	0.4	0.5	0	1
Organic fertilizer application (*kg/ha*)	64	56	3.5	361

Informal lending (yes=1, otherwise=0)	0.3	0.5	0	1
Production conditions				
Land fragmentation (*ha*)	1.1	1.3	0.02	11.4
Policy promotion (yes =1, otherwise =0)	0.3	0.5	0	1

Source: Calculated from the survey data.

Table 6

Summary statistics of inputs and outputs (per *ha*)

Indicators	Mean	S.D.	Max	Min
Production inputs				
Rice seed (*$*)	238	178	1,133	34
Crayfish seed (*$*)	1,512	1,342	5,803	9
Machinery (*$*)	437	187	1,813	26
Labor (*$*)	19	16	120	4
Fertilizer (*$*)	290	138	1,074	39
Pesticide (*$*)	200	131	839	21
Feed (*$*)	884	784	6,528	43
Medicine (*$*)	707	884	3,781	14
Desirable outputs				
Crayfish production (*kg/ha*)	1,748	1,116	6,872	119
Crayfish revenue (*$/ha*)	9,048	4,627	19,041	329
Rice production (*kg/ha*)	7,832	2,306	21,429	1,500
Rice revenue (*$/ha*)	3,264	847	7,688	455
Undesirable outputs				
Non-point source pollution (*kg*)	77	30	201	19
Carbon emission (*kg*)	639	270	2,280	114

4.2 Productivity, profitability, and EE

Table 7 presents the results of productivity, profitability, and EE. On average, the land productivity and net profit were 10,119 and 4,364 \$/ha, respectively. Land productivity of the small-, medium-, and large- scale group averaged 10,730, 9,741, and 9,887 \$/ha, respectively. The small-scale farmers had the highest revenue. However, when considering the production costs, their profit was lower than that of their medium- and large-scale counterparts, specifically, 2,930 vs. to 4,626 and 5,537 \$/ha, respectively. Obviously, small-scale farmers bear much higher costs.

Table 7

Productivity, profit, and environmental efficiency (EE) distribution

	Total samples	Small-scale	Medium-scale	Large-scale
Productivity (\$/ha)	10,119	10,730	9,741	9,887
Profit (\$/ha)	4,364	2,930	4,626	5,537
EE	0.618	0.532	0.620	0.701

Notes: The results in the table are the average values of the variables.

The SBM was used to estimate the EE of the surveyed households. The average EE of all the studied households was 0.618. Specifically, the EE values of the small-, medium-, and large-scale groups were 0.532, 0.620, and 0.701, respectively. This suggests that the EE values of the RCS increase with production scale. To comprehensively elucidate the dynamics of EE, we divided these households into nine groups based on their EE values and farming areas. Table 8 provides a snapshot of the distribution of EE across all the sampled households. Using lateral efficiency groups, we distinguished the farmers into three groups: high-efficiency group ($EE\ value = 1$), medium-efficiency group ($0.5 \leq EE\ value < 1$), and low-efficiency group ($EE\ value < 0.5$). Farmers in the high-efficiency group accounted for approximately one-third (33%) of the total sample with an EE value of 1. These farmers performed excellently on the frontier surface. Farmers in the medium-efficiency group accounted for 16% of the sample; the EE values ranged from 0.5–1, which can be improved through reasonable allocation of production factors and technical management. Notably, more than half (51%) of the total sample in the low-efficiency group had relatively low EE values (less than 0.5). Overall, large-scale farms performed best in terms of profit and EE value.

Table 8

Environmental efficiency distribution

Total farmers	EE values	Total		Small-scale		Medium-scale		Large-scale	
		Hhs	Pct (%)	Hhs	Pct (%)	Hhs	Pct (%)	Hhs	Pct (%)
High-efficiency	1	66	33	14	23	25	31	27	46
Medium-efficiency	0.5-1	31	16	7	12	18	23	6	10
Low-efficiency	< 0.5	102	51	39	65	37	41	26	44

Notes: Hhs indicates the number of each household group; Pct refers to percentage.

4.3 EE performance

The SBM results revealed that EE varies greatly among farmers. Differences in EE performance can be elucidated through a study of input, desirable output, and undesirable output, according to Cooper et al. (2007). The input, desirable output, and undesirable output inefficiencies of the surveyed farmers were 0.311, 0.201, and 0.214, respectively, indicating that input redundancy has a greatest negative impact on EE.

In rice-crayfish coculture practices, farmers need to invest in fertilizers, pesticides, and seeds during rice planting, and use drugs, feed, and crayfish seeds during crayfish farming. Except for 66 DMUs ($EE\ value = 1$), the inputs of the other DMUs were excessive in some cases. The redundancy ratio of each factor input was equal to the slack variable S^- of each input divided by the corresponding input variable. We found that the input redundancy ratios of each production factor were drugs (50%), feed (44%), labor (35%), crayfish seeds (33%), rice seeds (31%), pesticides (23%), fertilizers (17%), and machinery (16%). Higher redundancy rates indicate greater overuse of inputs and a major contributor to environmental inefficiency. Specifically, farmers overused drugs and feeds in crayfish production and failed to appropriately allocate the labor force. Excessive drugs and feeds, etc., were used in crayfish disease control, feeding, harvesting and routine management, thus increasing undesired outputs and carbon emissions.

4.4 Factors limiting EE

To determine the factors limiting EE performance, we first test the CM and LM statistics to examine whether the error term satisfies the prerequisite assumptions, that is, normal distribution and homoscedasticity. The CM statistic was 112.03 (Table 9), rejecting the null hypothesis that the error term follows a normal distribution. Similarly, the auxiliary regression LM statistic was 25.33 with a p-value of 0.000, indicating that the error term does not satisfy homoscedasticity. The use of a Tobit model led to biased estimates. Therefore, we adopted the CLAD model to analyze the factors restricting farmers' performance of the RCS by referring to the method by Zhang et al. (2017). This model only requires the error term to be identically distributed. A consistent estimator can be obtained under truncated data, which follow an abnormal distribution and show heteroscedasticity. The results are presented in Table 10.

Table 9

Test results for the distribution of the perturbation term

CM Test			LM Test	
CM		112.03	nR_{uc}^2	25.33
	10%	12.03	p-value	0.000
Critical values	5%	15.42		
	1%	39.92		

All variables were significant except for informal lending and land fragmentation. Farmers' characteristics, namely age and education level, positively impacted EE, implying that an increase in age does not constrain farmers from enhancing production efficiency. In contrast, older producers have more experience in fertilizer and pesticide application, which can effectively improve the efficiency of input factors. Moreover, the estimated coefficient of education was 0.007, indicating that when the average years of education of farmers increase by 10 years, EE increases by approximately 7%. Farmers with higher education levels have more extensive knowledge of applied technology and management methods, contributing to efficiency improvements.

Among the livelihood characteristics of farmers, part-time farming significantly negatively impacted EE, which is consistent with our expectations. Farmers' part-time behavior makes them reduce resource inputs in agricultural production, and several arable lands are more likely to be underutilized, resulting in rough agrarian management and a low-efficiency level.

Regarding production behaviors, the estimated coefficients of technical training and organic fertilizer application were significantly positive. Farmers participating in technical training acquire more advanced farming techniques and scientific production methods. This reduces the risk of excessive inputs and unnecessary losses in production practices. Organic fertilizer application reduces environmental pollution by partly replacing chemicals and increasing the sustainable utilization of resources. Regarding informal lending, the estimated coefficient was insignificant. Although informal loans exert financial constraints on farmers, these constraints are more elastic than formal lending. The high returns from rice-crayfish coculture increase expected returns, and then the impact on farmers' short-term production behavior is insignificant.

In production conditions, policy promotion was significant at 1%. Policy promotion has a positive impact on the EE of RCS. The policy relative to rice-crayfish farming can enhance farmers’ knowledge of RCS and provide a policy safeguard for production and operation.

Table 10

The results of the determinants of environmental efficiency

Variables	Coefficient	S.E.	Variables	Coefficient	S.E.

Individual characteristics			Informal lending	-0.001	0.007
Age (years)	0.002***	0.000	*Production conditions*		
Education level (years)	0.007***	0.001	Land fragmentation (*ha*)	0.000	0.000
Livelihood strategies			Policy promotion	0.047***	0.009
Part-time farming (%)	-0.058***	0.012	Constant	-0.120***	0.031
Production behaviors			Pseudo R^2	0.373	
Technical training	0.015*	0.008	Number of observations	199	
Organic fertilizer application	0.78***	0.001			

5 Discussion

5.1 How different farmers performed?

This study revealed that RCS partly fulfills the principles outlined in "dual uses of one water, double harvests in one field." Although RCS has higher revenue than monocropping model (Wang and Tan, 2020), the EE of RCS still had notable potential for improvement. To understand factors driving the difficulty of optimizing RCS in practice, we divided the total sample into three farm-size groups. We found that the small-scale farmers had the highest revenue but lowest profit and EE values. This finding is consistent with that of Tu et al. (2021). This trend is most likely rooted in the fact that small-scale farmers tend to bear the highest production costs and undesired outputs than their large-scale counterparts. For example, Ju et al. (2016) argued that fertilizer use per ha sharply increased with a decrease in farm size. To guarantee profitability, small-scale farmers have to adopt an intensive approach to farming. However, this approach, in the context of the required production inputs, is more expensive and it also generates a high amount of carbon emissions. Another possible reason is that small-scale farms are not conducive to adopting innovative eco-friendly techniques, such as new rice-crayfish fertilizer and other chemical-saving technology (Vidogbéna et al., 2016). Specifically, in the context of small-scale farms, the use of new techniques does not bring significant benefits in the short term and even entails high fixed costs. In the long term, however, they can considerably reduce carbon emissions and improve the ecological status of the soil. As such, the small farms are difficult to promote their profit and EE performance.

According to the Technical procedure of "crayfish-rice synchronous + crayfish-rice rotation" complex model of planting and breeding (2023), a suitable unit area for RCS is 1.33–3.33 ha. In our study, the average unit sizes of the small- (<0.667 ha), medium- (0.667–2 ha) and large-scale (> 2 ha) households were 0.8, 1.2 and 2.4 ha, respectively. Obviously, the large-scale farms meet the recommended requirement of size, and had the highest profit and best EE performance. As introduced in Section 3.3, the above three farm groups were classified based on China's Ministry of Agriculture and Rural Affairs, which is inconsistent with the recommended size (1.33–3.33 ha) in Technical Procedure. To be noted that among the large-scale group with total 53 farms, only 9 samples having size more than 3.33 ha, of which both the largest one with 11.4 ha and the second largest one with 8 ha had negative profits. This partially supported the Technical Procedure with regard to the suitable size. Unfortunately, nearly 54% of the sample farmers had a total operating area less than 1.33 ha. If these farms can be enlarged appropriately, they are expected to be more profitable and efficient. This suggests that it is necessary to take supervision, rewards, and punishment measures to guide small farmers rationally into the rice-fish coculture model.

5.2 What caused differences in EE performance?

We found that although one-third of farmers were effective, almost more than half were ineffective ($EE\ value < 0.5$). Some studies have argued that the RCS can achieve greater ecological and economic benefits than rice monocropping (Ahmed et al., 2011; Wang and Tan, 2020; Yu et al., 2014). However, when considering integrated eco-economic effects, the EE of RCS varies for various reasons. The results of SBM showed that input redundancy might explain the difference in EE performance. Specifically, the redundancy rate of each factor of production was drug (50%), > feed (44%), > labor (35%), > crayfish seeds (33%), > rice seeds (31%), > pesticide (23%), > fertilizer (17%) and > machinery (16%). This showed that the drugs and feed invested in crayfish farming were not used sustainably, and that the labor force was not appropriately allocated. Owing to the high investment cost required for RCS, producers should allocate input factors reasonably and grasp scientific management methods, if not, their operations will be subjected to a great amount of risk (Chen et al., 2019). In practice, 64% of the surveyed farmers considered that the crayfish disease risk was very high, 16% responded that the disease risk was considerable but manageable, and only 20% held that the risk was not high.[3]

Labor redundancy is also an important contributor to the variation in EE among farmers. Compared to large farms, the small-scale farmers are not conducive to using labor-saving machinery, especially for rice cultivation, such as those for plowing, transplanting, and harvesting. This produces large labor inputs, increasing the odds of small-scale farms drifting toward labor redundancy. Additionally, the rearing and harvesting of crayfish rely on the producer's routine maintenance. Farmers with weaker technical and managerial skills tend to hire workers unreasonably, resulting in redundant labor input. Therefore, improving the management practices of farmers and promoting the efficiency of labor utilization are important ways to enhance EE.

The results of CLAD model indicated that age and education level of the household head, and technical training had positive impacts on EE. An increase in age and education level can increase farmers' experience and improve their production and management capacities. Farmers who participate in technical training can implement insights gained from scientific guides, thereby achieving a higher efficiency. Therefore, it is necessary to strengthen farmers' technical training and increase their knowledge of modern production.

Part-time farming negatively impacts EE. Although previous studies have divergent views on the relationship between part-time employment and the farm sector, the consensus is that this relationship is influenced by rural labor market circumstances (Mutyasira et al., 2018). Due to the coherence and intensity of rice-crayfish farming, the greater the part-time extent, the lower the labor input, and the less efficient the land utilization. Organic fertilizer application has a positive

[3] Source: Calculated from the survey data.

impact on EE. According to our survey, farmers normally use organic fertilizer as a carrier, add functional bacteria to improve the water environment, and add shrimp fertilizer with trace elements required for the growth of crayfish. This help reduce environmental pollution and promote green agriculture by partly replacing chemicals.

It should be noted that there exist some limitations in the current study. Due to the existing limited research, we used the estimation methods of water pollute and carbon emissions based on Lai et al. (2004) and Li et al. (2011), respectively, which were conducted in mono-rice planting systems. We primarily estimated carbon emissions stemming from the application of fertilizer, as is one of the main sources of carbon emissions. Compared to mono-rice planting systems, RCS might reduce the water pollution and carbon emissions (Berg, 2002), and the emission factors and rates might be different (Yuan et al., 2022; Jiang and Cao, 2021). To a certain extent, we might underestimate the EE of the RCS. However, this study was centered on the differences in EE among farms that have implemented RCS, instead of comparing EE trends between RCS and mono-rice planting systems, thus, the estimation methods might not affect our results and the conclusions. Meanwhile, as this research was based on farmer survey, it was too difficult to measure or estimate the direct carbon emission RCS, such as CH_4 emission (Hu et al., 2016). Therefore, it is necessary to estimate the EE based on RCS field experiments, especially carbon emission such as CH_4 emission in the future study. Additionally, factors affecting farmers' profitability we primarily considered their farming experience and may have neglected market regulation. Future research will add some macro data to calculate farmers' profitability.

6 Conclusion

This study demonstrated factors affecting the EE of RCS by employing 199 rice-crayfish household’s data collected from two cities of Hubei province, China. This study showed that the average land productivity and net profit of our sampled farmers were US$ 10,119 and 4,364 per ha, respectively, with a rice yield of 7,832 kg/ha and a crayfish yield of 1,748 kg/ha. The average EE of RCS was 0.618, with notable variations in EE values among different-scale farmers.

Compared with their small- and medium-scale counterparts, the large-scale farmers performed best in terms of profits and EE values. Additionally, the input, desirable output and undesirable output inefficiencies were 0.311, 0.201 and 0.214, respectively. Redundant inputs such as drugs, feed and labor with redundancy ratios of 50%, 44% and 35%, respectively, resulted in the overall difference in EE performance. To better realize “dual uses of one water, double harvests in one field,” farmers need to reduce unnecessary inputs to improve EE as much as possible. Enhancing farmers’ education level, technical training, and organic fertilizer application, and decreasing their part-time employment will further optimize EE performance of RCS.

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Declaration of competing interest

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