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Evaluation and advancement of the integrated circular economy model of farming and stock raising

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A B S T R A C T

The integrated circular economy model of farming and stock raising (ICEMFSR) has attracted increased attention as an effective model for solving the current irrational allocation of agricultural resources and realizing the agricultural value-added industrial chain. This study uses emergy analysis to comprehensively examine and evaluate the economic benefits, environmental pressures, and sustainable development levels of ICEMFSR in Shucheng County, China. The results show that the ICEMFSR possesses the value of popularization with optimally allocated resources in the studied region, in which the emergy yield ratio (EYR), emergy loading ratio (ELR), and emergy sustainable index (ESI) in this model accounted for 3.59, 1.25, and 2.89, respectively. This result indicates a leading position in the national agricultural system. Hence, this study constructs a new model based on the coupling of emergy evaluation and multi-objective linear programming to study ICEMFSR. Consequently, the EYR, ELR, and ESI respectively varied by +24.23%, −10.40%, and +38.06% after replanning of ICEMFSR. This variation implies a significant improvement in the sustainable development level of the model. In addition, the optimized scenario design for key substances is proposed based on traceability and the reduce-reuse-recycle principle, including biogasification of crop straw and enhancement of crop scientific planting capacity.

1. Introduction

With rapidly developing agricultural technology, many countries face serious challenges such as reduced land resources and increased agricultural pollution. Therefore, the traditional agricultural model needs to undergo urgent transformation and upgrading to achieve sustainable development and intensive resource use (Hu et al., 2008; Lu et al., 2015). Due to different resource availability, countries have applied different methods to transform and upgrade agricultural development, including "biological agriculture" adopted by Western European countries, "precision agriculture" employed by the United States, and "organic agriculture" used by Japan (Qiao and Wang, 2019). Many studies on agricultural development have been conducted in China, and the practical focus has gradually shifted to the integrated circular economy model of farming and stock raising (ICEMFSR). ICEMFSR is a scientific, efficient, and organic form of planting and raising, developed to realize the following goals: (1) ensuring the cleanliness of the agricultural production process, (2) producing green and organic agricultural products, (3) recycling waste from agricultural activities, and (4) generating zero (minimum) emissions due to agricultural activities (Kapoor et al., 2020). The Chinese government has published a series of policies to develop ICEMFSR. Among these, rural revitalization has emerged as the national strategy, which indicates that developing ICEMFSR is critical for the structural reform of the agricultural supply (Li et al., 2019). Despite the positive benefits, the application of ICEMFSR is facing problems, such as dependence on government subsidies, defective industrial and theoretical systems, and secondary pollution caused by the biogas project (Liu et al., 2019a; Zhang and Xu, 2020). These problems have hindered the advancement of ICEMFSR. How to effectively using local resources and promoting large-scale implementation of the model while ensuring optimal resource allocation are challenges to the government. Therefore, constructing an assessment method for analysis, evaluation, and planning that advances ICEMFSR is necessary to overcome these challenges.

Several studies exist on the agricultural circular economy model. However, most of these focus on sustainable development evaluation, which adopts various methods, such as index evaluation, life cycle assessment, input–output, and emergy analysis (EMA). Wu (2008) used the index evaluation method to evaluate the development of agricultural circular economy in the Chaohu Lake Basin from 1990 to 2004. Xue et al. (2019) used life cycle assessment methods to compare differences between traditional and biogas-based circular economy models for pig farms and estimated the environmental and economic benefits of carbon

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trading. Sun et al. (2016) used the input–output method to evaluate the efficiency of circular agriculture in 17 regions in Hubei Province and proposed several countermeasures to improve efficiency. Wu et al. (2015) utilized EMA to examine the comprehensive agricultural model that comprises multiple subsystems (walnuts and grains, pigs and poultry, and biogas) in northwest China. Their results showed that the model improved environmental, economic, and sustainable benefits compared with the traditional model. Su et al. (2020) conducted an emergy and economic performance assessment of the "rice fish, rice duck" integrated agricultural model as well as single planting and non-food production systems. This assessment proved that integrated agriculture is a promising model for sustainability. As a mature theoretical and methodological system, EMA can integrate various indicators—such as emergy yield ratio (EYR), emergy loading ratio (ELR), and emergy sustainable index (ESI)—in economic, social, and environmental aspects to evaluate the sustainable development capability of ICEMFSR. EMA can also provide theoretical support for comparing planning and design effects, which has been recognized by scholars in the evaluation of the agricultural circular economy model. The existing EMA related researches provide a good theoretical foundation for this research.

Considering agricultural development model planning, the involved methods mainly include analytic hierarchy process (AHP) (Giri and Nejadhashemi, 2014), multi-objective linear programming (Liu et al., 2019b), geographic information system analysis methods (Feizizadeh and Blaschke, 2013; Parlato et al., 2020), and system dynamics models (Rich et al., 2018). Zhang et al. (2019) developed a framework based on the Nerlove and interval fuzzy credibility constraint bi-level programming models for planning agricultural production in arid and semi-arid regions. Sun et al. (2019) established a multi-objective evaluation model based on AHP and gray relation analysis and proposed an agricultural program that could meet the Xinjiang irrigation water demand and reduce agricultural non-point source pollution. Sapino et al. (2020) developed a multi-model integration framework containing five mathematical programming models and determined the relationship between rice and agricultural water pricing through experimental research on the Piedmont region of northwestern Italy. Drobnik et al. (2017) proposed a framework model that combined agent-based agricultural economic optimization and automaton-based settlement growth models to provide services for ecosystem trade-off decisions. Galán-Martin et al. (2015) introduced a multistage linear programming model to determine the optimal planting plan decision based on the latest Common Agricultural Policy, which promoted the widespread adoption of additional sustainable agricultural practices. The analysis of the aforementioned literature shows that under the condition of limited resources, multi-objective linear programming achieves sustainable development of a system through comprehensive design of multi-dimensional factors, including environment, economy, society, and policy. Hence, this method is suitable to plan and analyze the agricultural circular economy model system from the perspective of optimizing the allocation of agricultural resources.

The extant research and analysis results do not organically combine model evaluation and planning. In addition, a complete methodology system has not yet been formed despite some studies introducing optimization and design based on sustainability evaluation. This research innovatively couples EMA with multi-objective linear programming to fill this gap and establishes a methodology system from model evaluation to design and optimize. Therefore, a mathematical model is established based on EMA with emergy indicators combined with other indicators, and a multi-objective linear programming method is used to plan the limited resources in the study area reasonably. Through sensitivity analysis and key material identification, the key emergy flow and the corresponding key material that restricts the sustainable development of the model are found. Finally, an optimal design idea based on the "3R (reduce, reuse, recycle)" principle is proposed. The construction of this methodological system can provide a new perspective for research in similar fields, and the research conclusions can provide insights for decision-makers to promote ICEMFSR effectively.

2. Materials and methods

To examine and evaluate the economic benefits, environmental pressures, and sustainable development levels of ICEMFSR, the following steps are conducted to develop the research roadmap for this study. First, the material and energy flow of the input and output systems are converted into solar emergy, and a comprehensive emergy evaluation index system is built based on the conversion. Second, the economic benefits, environmental pressure, and sustainable development capacity are discussed using the calculation results of the evaluation index system. The emergy parameters and multi-objective linear programming are coupled to plan and analyze the system to produce the best strategy for optimal resource allocation. Third, the key substances, which restricted the systematic sustainable development level, are diagnosed and identified through sensitivity analysis. Finally, the study proposes an optimized design plan for source reduction, process reuse, and end resource utilization (3R) based on key substances position in the system. The specific research technical roadmap is shown in Fig. 1.

2.1. Study site

Anhui Province is an important Chinese agricultural production base, and its grain output in 2019 ranked fourth in China (40.54 million tons) (PRCNBS, 2020). Shucheng County belongs to Lu'an City, Anhui Province, and is located in the central part of Anhui Province. The geographical material of Shucheng County is shown in Table 1. It is a good area for planting tea, oil, rice and other agricultural products. Recently, the Shucheng County government has actively developed clean energy in rural areas to increase grain production and income for farmers and has established a demonstration site of the agricultural ecological model in the form of "pig (poultry)−marsh−rice (vegetables, fruits)." The government is continuously and vigorously developing modern agriculture and focusing on improving agricultural industrialization. Shucheng County has 15,000 households that use biogas and 60 biogas digesters. Five large-scale biogas projects have been built in the surrounding communities with 66 village-level biogas service outlets. The biogas project has reached millions of households in China, which provide a practical comprehensive utilization method for most breeding wastes. Therefore, the "pig (poultry)−marsh−rice (vegetable, fruit)" model in Shucheng County has become a typical agricultural circular economy model for the country, which has provided a good example.

2.2. Emergy model

Establishing a systematic index system for emergy evaluation is crucial. As the founder of emergy theory, Odum (1996) proposed a series of emergy indicators with good universality on a global scale. Since then, other scholars have suggested the improved emergy index system according to the context of their research. Reflecting structural, functional, economic, and environmental development of the system is imperative. Therefore, the emergy waste to output ratio (EWR), EYR, the emergy self-sufficiency ratio (ESR), the environmental loading ratio (ELR), and the emergy sustainability index (ESI) are enhanced in the emergy index system developed in this study. In this study, the goal is to evaluate the ICEMFSR comprehensively from economic and environmental aspects and includes three parts: livestock and poultry breeding, biogas power generation, and agricultural planting subsystems. Fig. 2 shows the emergy flow, which is transformed from systematic material and energy flow. This study used the research results of Odum (1983), Yang and Chen (2014), and Wang et al. (2019a), to determine the unit emergy value (UEV) of each substance in the system Considering the research results from Brown and Ulgiat (2016), 12.00×10^{24} sej/year is used as the standard emergy to define the UEV of each substance under different reference conditions, and various emergy flows are converted into solar

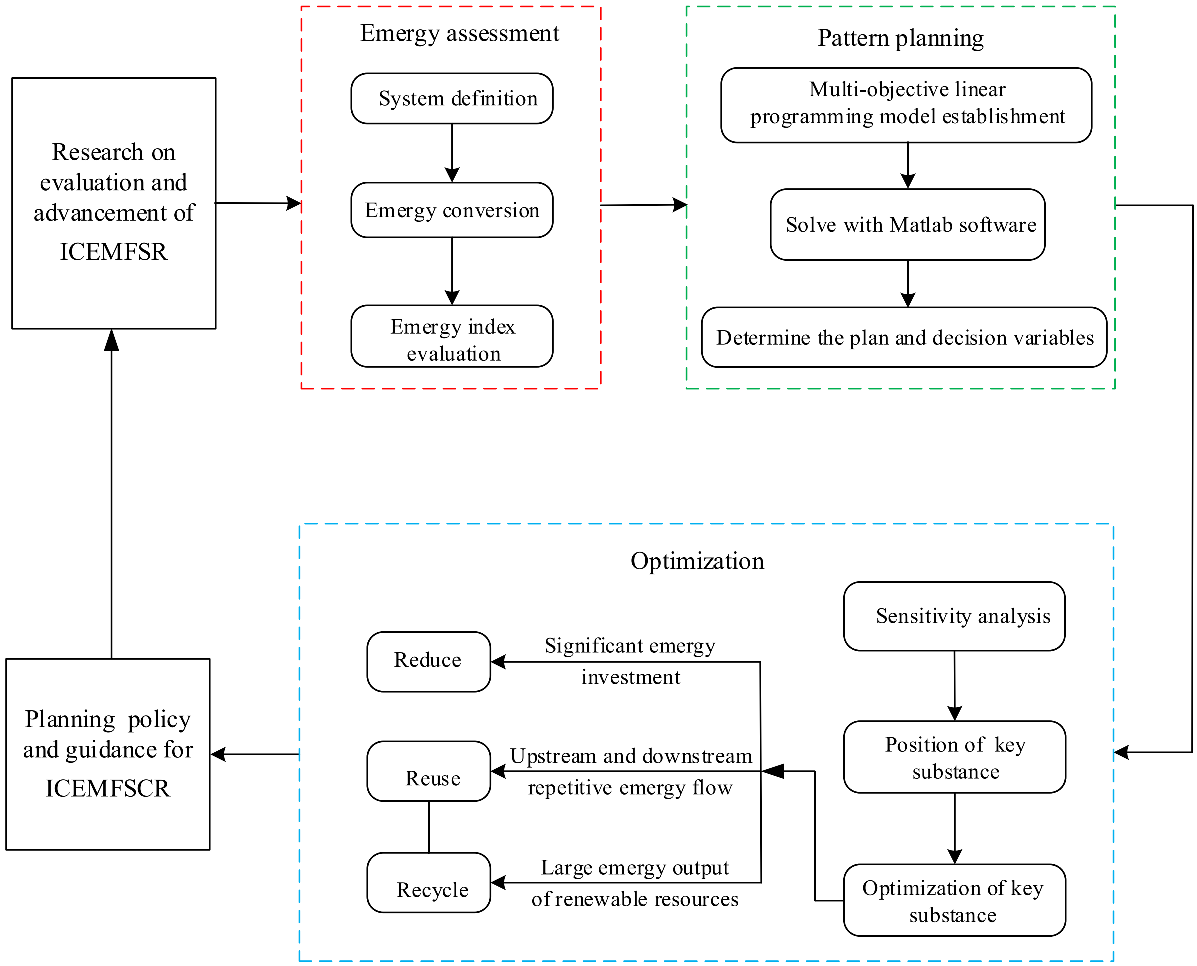

Fig. 1. Technical roadmap for ICEMFSR.

Table 1
Geographical material of Shucheng County.

Item	Amount	Unit
Solar rational intensity	17500.00	kj/m^2
Average wind speed	2.50	m/s
Air density	1.29	kg/m^3
Average elevation	75.00	m
Mean rainfall	1.10	m/y
Planting area	61874.00	ha
Annual sunshine duration	2145.00	h

emergy (Table 2). Therefore, this study built a set of comprehensive emergy evaluation index systems (Table 3).

2.3. Multi-objective linear programming model

Planning of the agricultural circular economy model aims to achieve the effective adjustment of the agricultural industry structure by optimizing the allocation of limited resources and reduce external industrial auxiliary emergy input to improve the sustainable development capacity of the system. The "pig (poultry)–marsh–rice (vegetable, fruit)" agriculture model in Shucheng County is taken as an example to conduct the research.

2.3.1. Mathematical model construction

The constraint Equation:

$$\sum_{j=1}^{n} a_i x_j > b_j \quad (b \gg 0,\ i = 1, 2, 3, \cdots, n; x \gg 0,\ j = 1, 2, 3, \cdots, m) \tag{1}$$

Objective function:

$$(Max / Min) f(x) = \sum_{j=1}^{n} c_j x_j \tag{2}$$

wherex_i is decision variables, a_i represents the coefficient of decision variable, b_j represents the resource limit,c_j is the variable coefficients in the objective function, and $f(x)$ is the decision goal.

The decision variablex_i represents the ith decision variable. The specific decision variables in Table 4 are determined.

2.3.2. Objective function

The objective function includes three aspects—economy, society, and environment—which are specifically expressed as total income index, grain output, crop fertilization, and crop water requirement.

The total income index is selected as the economic objective function, which is the income from crop farming and livestock breeding. Crop planting income is the product of the unit area net income of crops (RMB/ha) and the total area of crops planted (ha). The income of the livestock breeding industry is the product of the unit net income of livestock, poultry (RMB/head), and the total number of breeding. The specific expression is shown in Equation (3).

Total return objective function expression:

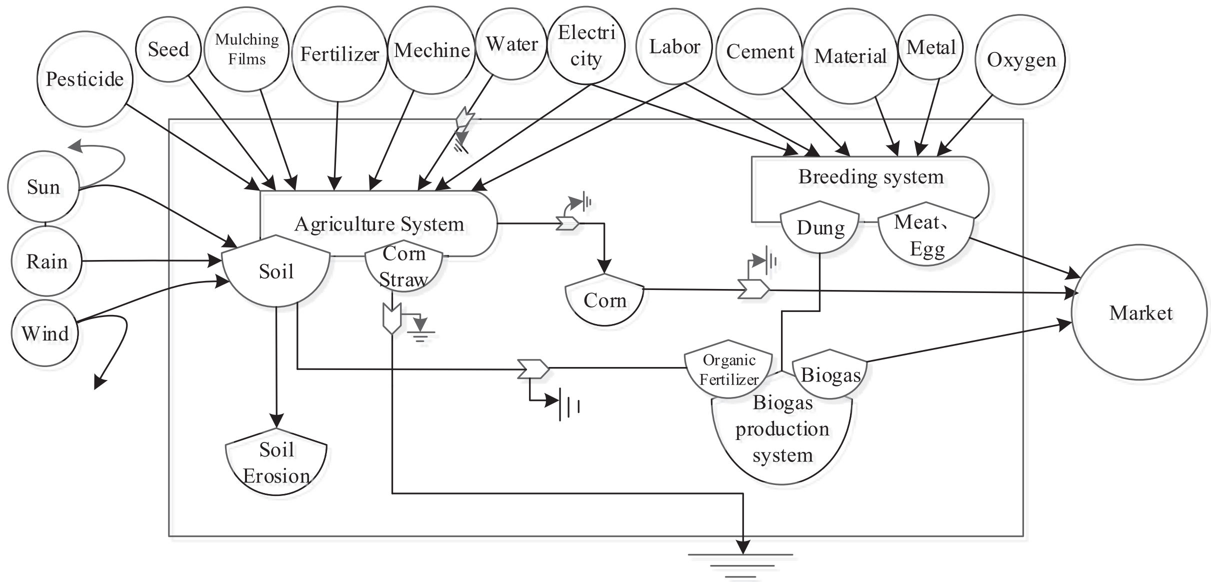

Fig. 2. Emergy system diagram of the agricultural system.

$$Maxf_1(x_i) = \sum_{i=1}^{7} a_i x_i \tag{3}$$

wheref_1 is the total revenue, anda_i is the net income coefficient of crops per unit area or per unit of livestock.

The parameters of the economic objective function are determined (Tables 5 and 6) through field investigation combined with relevant data of the local statistical yearbook (LSB, 2018).

The total grain output is selected as the social objective function, which is expressed by the output per unit area of the grain crops and the area of the grain crops in the planting industry.

Grain output expression:

$$Maxf_2(x_i) = \sum_{i=1}^{3} b_i x_i \tag{4}$$

where $f_2$is the total grain output, and b_i represents the output per unit area of the grain crops.

The main food crops in Shucheng County are rice, wheat, and corn. Therefore, these food crops are selected as calculation parameters.

The environmental objective function comprises the total fertilization and the total water requirement. The former is the total amount of chemical fertilizers applied during the planting stage, and the latter is the total irrigation water required during the planting stage.

Total fertilization:

$$Minf_3(x_i) = \sum_{i=1}^{5} c_i x_i \tag{5}$$

where f_3 represents total fertilization, and c_i represents the amount of fertilizer applied per area (Table 7).

Total water requirement:

$$Minf_4(x_i) = \sum_{i=1}^{5} d_i x_i \tag{6}$$

where f_4 represents the total water requirement, and d_i represents the water requirement of crops per planting area during the entire growth period (Table 8).

The total objective function is obtained from Equations (3)–(6) and shown as Equation (7).

$$\begin{cases} Maxf_1(x_i) = 8904.83x_1 + 7134.75x_2 + 6551.79x_3 + 15585.86x_4 \\ +7468.35x_5 + 523.18x_6 + 1290x_7 \\ Maxf_2(x_i) = x_1 + x_2 + x_3 \\ Minf_3(x_i) = 975x_1 + 337.5x_2 + 375x_3 + 46x_4 + 187.5x_5 \\ Minf_4(x_i) = 7249.5x_1 + 3800x_2 + 4880x_3 + 4050x_4 + 4000x_5 \end{cases} \tag{7}$$

2.3.3. *Constraints*

This study selects the total planting area, local labor, and non-renewable industrial auxiliary emergy input as constraints.

The agricultural sown area should not exceed 94,413 ha because the agricultural planting area of Shucheng County is 94,413 ha (LSB, 2018). The mathematical form is shown in Equation (8):

$$\sum_{i=1}^{5} x_i \le 94413 \tag{8}$$

The number of agricultural employees in Shucheng County in 2017 was 201,459 (LSB, 2018). The annual agricultural working time of farmer was eight months (240 days); therefore, the available local agricultural labor force was 48,350,160 days. The details are shown in Table 9.

Non-renewable industrial auxiliary emergy input constraints:

$$\sum_{i=1}^{7} h_i x_i \le 7.79 \times 10^{20} \tag{9}$$

whereh_i represents the non-renewable industrial auxiliary emergy input of crops per unit area or livestock per unit number.

The non-renewable industrial auxiliary emergy input of crops per unit area and livestock per unit number (Table 10) is calculated in accordance with the emergy flow list.

The overall constraints are calculated using area, labor, and non-renewable auxiliary emergy constraints, as shown in Equation (10):

$$\begin{cases} x_1 + x_2 + x_3 + x_4 + x_5 \le 94413 \\ 82.7x_1 + 83.7x_2 + 78.9x_3 + 100.7x_4 + 525x_5 + 6.0x_6 + 12.7x_7 \le 48350160 \\ 1.02 \times 10^{16}x_1 + 2.50 \times 10^{15}x_2 + 3.55 \times 10^{14}x_3 + 2.71 \times 10^{15}x_4 \\ +7.36 \times 10^{16}x_5 + 8.88 \times 10^{12}x_6 + 1.63 \times 10^{12}x_7 \le 7.79 \times 10^{20} \end{cases} \tag{10}$$

2.3.4. *Total objective function*

The difference in importance of the three aspects of objective function— economy, society, and environment—will cause remarkable

Table 2
Emergy analysis table for ICEMFSR.

Item	Raw data	unit	UEV (sej/unit)	Reference	Solar emergy (sej)
Input Local renewable resources(R)					
Sunlight	7.54×10^{18}	J	1	Odum and Odum (1983)	7.54×10^{18}
Wind	6.23×10^{14}	J	1.91×10^{3}	Odum and Odum (1983)	1.19×10^{18}
Rain, chemical	6.55×10^{14}	J	2.31×10^{4}	Odum and Odum (1983)	1.28×10^{19}
Rain, potential energy	8.26×10^{15}	J	1.27×10^{4}	Brown and Ulgiat (2016)	1.05×10^{20}
Earth cycle	1.02×10^{15}	J	4.32×10^{4}	Odum and Odum (1983)	4.41×10^{19}
Subtotal	2.86×10^{16}	J			1.71×10^{20}
Local non-renewable resources(N)					
Topsoil loss	3.25×10^{15}	J	9.41×10^{4}	Odum (1996)	3.06×10^{20}
Subtotal	3.25×10^{15}	J			3.06×10^{20}
Non-renewable industrial auxiliary input(F)					
Electricity	5.74×10^{14}	J	5.07×10^{4}	Wu et al. (2014)	1.25×10^{19}
Mechanical power	1.07×10^{12}	J	7.50×10^{7}	Wang et al. (2019a)	8.05×10^{19}
Pesticide	4.88×10^{9}	g	1.10×10^{10}	Asgharipour et al. (2020)	5.37×10^{19}
Nitrogen fertilizer	8.21×10^{10}	g	4.83×10^{9}	Wang et al. (2019b)	3.97×10^{20}
Phosphate fertilizer	1.90×10^{10}	g	4.96×10^{9}	Wang et al. (2019b)	9.42×10^{19}
Potash fertilizer	1.80×10^{10}	g	1.40×10^{9}	Wang et al. (2019b)	2.52×10^{19}
Compound fertilizer	2.51×10^{10}	g	3.56×10^{9}	Asgharipour et al. (2020)	8.92×10^{19}
Plastic sheeting	1.01×10^{10}	g	2.88×10^{8}	Wang et al. (2019a)	2.90×10^{18}
Construction and maintenance of biogas digesters	814.6965	US$	1.75×10^{12}	Wu et al. (2014)	1.43×10^{15}
Pigsty construction	1.83×10^{6}	US$	1.75×10^{12}	Wu et al. (2014)	3.21×10^{18}
Potions	4.90×10^{8}	g	1.27×10^{9}	Wu et al. (2014)	6.23×10^{17}
Fossil fuels	1.62×10^{14}	J	2.24×10^{4}	Wang et al. (2019b)	3.63×10^{18}
Subtotal	7.37×10^{14}				7.79×10^{20}
Renewable organic energy input (T)					
Seed	1.51×10^{15}	J	8.39×10^{4}	Wang et al. (2019a)	1.26×10^{20}
Labor	3.13×10^{14}	J	4.83×10^{5}	Wang et al. (2019a)	1.51×10^{20}
Feed	4.29×10^{15}	J	8.04×10^{4}	Wu et al. (2014)	3.45×10^{20}
Piglets	9.37×10^{13}	J	7.41×10^{5}	Wu et al. (2014)	6.94×10^{19}
Young poultry	3.46×10^{12}	J	2.60×10^{6}	Wang et al. (2019a)	8.99×10^{18}
Subtotal	6.20×10^{15}	J			7.01×10^{20}
Output(Y)					
Rice	5.93×10^{15}	J	1.91×10^{5}	Xu et al. (2019)	1.13×10^{21}
Wheat	7.79×10^{14}	J	6.80×10^{4}	Wang et al. (2019a)	5.30×10^{19}
Corn	2.10×10^{14}	J	2.70×10^{4}	Wang et al. (2019a)	5.67×10^{18}
Oil crops	7.43×10^{14}	J	8.60×10^{4}	Wang et al. (2019a)	6.39×10^{19}
Vegetable	7.10×10^{14}	J	2.70×10^{4}	Asgharipour et al. (2020)	1.92×10^{19}
Pig	2.76×10^{15}	J	1.70×10^{6}	Wang et al. (2019a)	4.69×10^{21}
Poultry meat	1.04×10^{14}	J	3.00×10^{6}	Xu et al. (2019)	3.11×10^{20}
Poultry eggs	1.76×10^{14}	J	2.57×10^{6}	Xu et al. (2019)	4.51×10^{20}
Biogas	7.35×10^{14}	J	4.17×10^{5}	Wu et al. (2014)	3.07×10^{20}
Straw	1.65×10^{16}	J	4.96×10^{4}	Wang et al. (2019a)	8.16×10^{20}
Subtotal	2.86×10^{16}	J			7.85×10^{21}

Source: Field research and Lu'an City Statistical Yearbook (LSB, 2018).

Table 3
Emergy indicators system of ICEMFSR.

Indicator	Expression	Data	Unit
R	/	1.71×10^{20}	sej/yr
N	/	3.06×10^{20}	sej/yr
F	/	7.79×10^{20}	sej/yr
T	/	7.01×10^{20}	sej/yr
U	/	1.96×10^{21}	sej/yr
E	/	7.03×10^{21}	sej/yr
W	/	8.16×10^{20}	sej/yr
Y	/	7.85×10^{21}	Sej/yr
Percentage of non-renewable resources	(N + F)/U	55.50%	/
External energy input ratio	(N + F + T)/U	75.60%	/
Energy output per capita	Y/population	3.90×10^{16}	sej/R
Emergy land density	Y/area	7.69×10^{12}	sej/m²
Emergy abandonment rate	W/Y	41.63%	/
Emergy waste to output ratio (EWR)	W/E	0.10	/
EYR	(F + T)/Y	3.59	/
ESR	(R + N)/Y	0.24	/
ELR	N/R	1.25	/
ESI	EYR/ELR	2.89	/

Table 4
Decision variables of ICEMFSR.

Crop type	Sown area	Poultry type	Number of breeding
Rice	x_1	Pig	x_6
Wheat	x_2	Poultry	x_7
Corn	x_3		
Oil crops	x_4		
Vegetable	x_5		

uncertainty in the result. The difference in importance of the three aspects will cause remarkable uncertainty in the result. The study uses fuzzy AHP to determine weights to reduce the influence of subjective factors on the uncertainty of the research results. The specific steps are as follows.

The original data are standardized, and the obtained index value range is indefinite and has negative numbers. Therefore, further linearization processing is required to obtain data with the same comparison scale, which can be added and compared. The linearization method of the standard index with a benchmark of 50 and a standard deviation of 10 is shown in Equation (11).

$$A = 50 + A_i * 10 \tag{11}$$

Let $F = \{f_1, \ldots, f_n\}$ be a set of evaluation indicators under a certain criterion.

(1) Detailed information related to the evaluation system is sent to the selected P experts, and the experts are informed of the conditions that the importance matrix should meet. The experts are then

Table 5
Input and output benefits of crops per unit planting area.

Type	Item	Rice	Wheat	Corn	Oil crops	Vegetable
Output	Unit output	6343.18	4622.00	6365.50	2147.92	26,641.62
	Total output value	17,488.15	10,777.58	10,459.79	10,945.70	53,906.25
Input	Seed	918.00	1059.90	831.60	307.20	3035.10
	Fertilizer	1848.75	2106.45	1935.15	1288.95	6314.55
	Pesticide	795.60	334.65	250.35	246.00	2541.00
	Mechanical operation fee	3161.10	2494.65	2085.75	1280.10	2984.85
	Labor cost	1077.45	207.75	353.10	221.85	17,284.05
	Land cost	892.05	438.30	397.65	193.65	2082.90
	Transportation	74.40	12.30	7.35	18.90	2152.35
	Total investment	8701.35	6654.00	5860.95	3556.65	36,394.80
Benefit	Annual income per hectare	8786.80	4123.58	4598.84	7389.05	17,511.45

Note: Except when the unit of yield is kg/ha, all are RMB/ha. The data are from field research and Lu'an City Statistical Yearbook (LSB, 2018).

Table 6
Unit input and output benefits of livestock and poultry.

Type	Item	Pig	Poultry
Output	Unit output	120.72	298.87
	Gross output value	1826.77	7735.68
Input	Breeding stock	588.90	1426.36
	Feed	831.81	5312.42
	Epidemic prevention fee	28.17	124.35
	Labor cost	0.34	/
	Other inputs	8.33	61.25
	Total investment	1457.55	6924.38
Benefit	Annual income per hectare	369.22	811.30

Note: Unit of production is kg/head (pig), kg/100 heads (poultry), and the other units are RMB/head (pig) and RMB/100 heads (poultry). The data come from the Lu'an City Statistical Yearbook (LSB, 2018), and the compilation of national agricultural product cost and income data (NDRCPD, 2018). Due to the small size of poultry, one unit is 100 heads.

Table 7
Fertilizer application for each crop per unit planting area.

Item	Rice	Wheat	Corn	Oil crops	Vegetable
Fertilizer application	340.20	415.05	373.20	242.25	860.85

Note: Unit is kg/ha. The data are from the compilation of national agricultural product cost benefit (NDRCPD, 2018).

Table 8
Water requirement for crops per planting area during growing period.

Item	Rice	Wheat	Corn	Oil crops	Vegetable
Crop water requirement	7249.50	3800.02	4880.02	4050.00	4000.02

Note: Unit is m^3/ha. The data are from field research.

Table 9
Laborers per unit area of crops or livestock.

Crop/Poultry type	Number of work (days)	Crop/poultry type	Number of work (days)
Rice	82.65	Vegetable	525.00
Wheat	83.70	Pig	5.98
Corn	78.90	Poultry	12.72
Oil crops	100.65		

Source: Compilation of national agricultural product cost benefit data (NDRCPD, 2018).

asked to give estimates of the importance of the indicators. This process is conducted independently by experts.

Table 10
Non-renewable industrial auxiliary emergy input per unit.

Crop/Poultry type	Non-renewable industrial auxiliary energy value input (sej)
Rice	1.02×10^{16}
Wheat	2.50×10^{15}
Corn	3.55×10^{14}
Oil crops	2.71×10^{15}
Vegetable	7.36×10^{16}
Pig	8.88×10^{12}
Poultry	1.63×10^{12}

Assuming that the ith expert gives the estimated value for the first time to construct the matrix, Equation (12) is obtained.

$$X_1^k = \begin{pmatrix} x_{11}^{k1} & L & x_{1n}^{k1} \\ L & L & L \\ x_{n1}^{k1} & L & x_{nn}^{k1} \end{pmatrix} \tag{12}$$

Calculate the mean: $\overline{x_{ij}^1} = \frac{1}{p}\sum_{k=1}^{p} x_{ij}^{k1}$

Deviation: $\sigma_{ij}^1 = \frac{1}{p}\sum_{k=1}^{p}\left|x_{ij}^{k1} - \overline{x_{ij}^1}\right|$

(2) All data are sent to the experts anonymously, and further supplementary materials are attached. Each expert is asked to give a new estimate after examining the data.
(3) Steps (1) and (2) can be repeated several times until the deviation value is less than or equal to the predetermined standard $\varepsilon > 0$. For example, $d_{ij}^k \le \varepsilon$ is first reached at step K (take $\varepsilon = 0.1$), and d_{ij}^k is the deviation of step K.
(4) The $\overline{x_{ij}^k}$ and d_{ij}^k obtained in step K are passed on to the experts to help them make a final judgment and give an estimate. In addition, experts are asked to give their respective "degrees of freedom" e_{ij}^k for their estimated values. The e_{ij}^k represents the degree of certainty of the K^th^ expert's own estimate of x_{ij}^k. The value of e_{ij}^k is specified to be in the range of [0,1] to obtain matrix Y, as shown in Equation (13).

$$Y = \begin{pmatrix} x_{ij}^1 & x_{ij}^2 & L & x_{ij}^p \\ e_{ij}^1 & e_{ij}^2 & L & e_{ij}^p \end{pmatrix} \tag{13}$$

(5) Process matrix Y.

Let λ be a predetermined standard, $0 < \lambda < 1$ (take $\lambda = 0.8$).

Let $M_{ij}^{\lambda}=\left\{k: e_{ij}^{k}\geq\lambda,\ k=1,2,\cdots p\right\}$

Then $X_{ij}=\frac{1}{\left|M_{ij}^{\lambda}\right|}\sum_{k\in M_{ij}^{\lambda}}x_{ij}^{k}$

where $\left|M_{ij}^{\lambda}\right|$ represents the number of elements in the set $\left|M_{ij}^{\lambda}\right|$.

Thus, the importance matrix X is obtained, as shown in Equation (14).

$$X=\begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \cdots & \cdots & \cdots \\ x_{n1} & \cdots & x_{nn} \end{pmatrix} \tag{14}$$

The calculation method of its weight vector $W=(w_1,\cdots,w_n)$ is Equation (15).

$$W_i=\frac{1}{n}-\frac{1}{2\alpha}+\frac{1}{n\alpha}\sum_{i=1}^{n}X_{ik}\ \alpha=\frac{n-1}{2} \tag{15}$$

The calculated weighting results are as follows: total revenue, output, chemical fertilizer, and crop water consumption accounted for 35.1%, 19.8%, 30.2%, and 14.9%, respectively.

The optimal value of each objective function ($f_i^*=Max[Min]f_i$) is determined in the feasible domain according to Equation (16), and the extreme result of each objective function is shown in Equation (17).

$$MaxF(x_i)=w_1\times\frac{f_1}{f_1^*}+w_2\times\frac{f_2}{f_2^*}+w_3\times\frac{f_3}{f_3^*}+w_4\times\frac{f_4}{f_4^*} \tag{16}$$

$$\begin{cases} f_1^*=3.42\times10^9 \\ f_2^*=94413 \\ f_3^*=8.05\times10^7 \\ f_4^*=6.84\times10^8 \end{cases} \tag{17}$$

The final total objective function is calculated from Equations (16) and (17), as shown in Equation (18).

$$\begin{aligned} f=&5.88\times10^{-6}x_1+4.98\times10^{-6}x_2+5.05\times10^{-6}x_3+2.55\times10^{-6}x_4 \\ &+5.91\times10^{-6}x_5+3.78\times10^{-8}x_6+8.31\times10^{-8}x_7 \end{aligned} \tag{18}$$

3. Results

3.1. Emergy evaluation

The analysis in Table 3 reveals that, the EYR of this agricultural circular economy model is 3.59, which is considerably higher than the crop planting system of large or small farms (1.35, 1.37) in the North China Plain region from 2015 to 2017 (Yang et al., 2019). The result indicates that the system has a high emergy output. The ESR is 0.244, which is lower than the national animal husbandry system in 2015 (0.56) (Zhai et al., 2017). This result indicates that the resources required by the current agricultural circular economy model rely on industrial auxiliary input. The ELR is 1.25, which is lower than the lowest level of the national agricultural system in 2015 (Liu et al., 2019c). Thus, the system has minimal pressure on the surrounding environment and has good environmental benefits. In addition, the ESI is 2.89, which is higher than that of the Anhui agricultural eco-economic system from 2013 to 2016 (Ma and Wu, 2019). This result shows the good potential for sustainable development. Therefore, ICEMFSR has a higher emergy output and better economic benefits than other agricultural ecosystems and has certain advantages in the aspect of sustainable development.

Moreover, the ESR is at a low level, implying that the system relies on external emergy input. This finding is due to the high demand for chemical fertilizers and the excessive use of machinery and equipment during the agricultural planting process. While ICEMFSR still has potential for optimization, the focus of optimization is the input reduction of non-renewable industrial auxiliary emergy through the rational allocation of limited resources.

3.2. Multi-objective linear programming model

The Matlab software is applied to program and solve the total objective function. The optimal plan for the resource allocation of agricultural circular economy model in Shucheng County is obtained (Table 11).

The analysis in Table 12 shows that through reasonable planning and design (optimized allocation of resources), the ESI increased from 2.89 to 3.99, which is an increase of 38.06%. The growth in ESI can be attributed to two reasons. First, the total resource input is 1.69×10^{21}sej (with a 13.78% reduction) after changing. The reduction is from external purchase emergy input, which is non-renewal auxiliary emergy inputs, causing the fall of ELR from 1.25 to 1.12. Second, the system net emergy output, EYR, and ESR are substantially improved by 7.40%, 24.23% and 15.57%, respectively. Without changing the total amount of natural resources input, reasonable resource allocation considerably improves the economic and environmental benefits of the system and promotes the sustainable development of the region. Therefore, sensible planning and design have important practical significance for the effective promotion of ICEMFSR.

4. Discussion

4.1. Sensitivity analysis

Table 12 shows that the proportion of non-renewable resource inputs before and after planning accounted for 55.50% and 52.80%, respectively, which exceeded 50%. Thus, significant non-renewable resource inputs are found in the agricultural planting and the poultry breeding subsystems, indicating heavy reliance on non-renewable resources. Considering resource input, some optimization potential in this model remains. Optimization should identify and analyze non-renewable resources with a considerable impact on various systematic indicators. The non-renewable resources are the key substances that must be reduced by the system.

Referring to ISO (2006a,b), sensitivity analysis is conducted to diagnose and identify key substances. The sensitivity coefficient calculation formula is shown in Equation (19).

$$SC=\left|\frac{(EE_2-EE_1)/EE_1}{(C-C_1)/C_1}\right| \tag{19}$$

where SC represents the sensitivity coefficient; EE_1 and EE_2 are the corresponding influences on indicators before and after the main parameter change, respectively; and $C_1$and C_2 are the corresponding parameter change amount before and after the change, respectively. SC >1 means indicators change more than the parameter change; SC $=1$ is proportional change; and SC <1 is a smaller change in indicators than in the parameter. The results are shown in Fig. 3.

Fig 3a. Main emergy flows increasing 10%.

Figure 3b. Main emergy flows decreasing 10%.

Fig. 3 shows that the main indicators of ICEMFSR have different

Table 11
Multi-objective linear programming decision plan.

Crop/Poultry type	Proposal	Crop/Poultry type	Proposal
Rice (ha)	11,500	Vegetable (ha)	55,482
Wheat (ha)	9875	Pig (head)	229,286
Corn (ha)	6523	Poultry (hundred)	1,140,000
Oil crops (ha)	11,036		

Table 12
Comparison of emergy index before and after model optimization.

Index	Before planning	After planning	After scenario optimization	Unit
Total investment	1.96×10^{21}	1.69×10^{21}	1.62×10^{21}	sej
Percentage of renewable resource investment	44.50%	47.20%	50.20%	/
Proportion of non-renewable resource investment	55.50%	52.80%	49.80%	/
External energy input ratio	75.60%	71.80%	70.60%	/
Net energy output	7.03×10^{21}	7.55×10^{21}	7.06×10^{21}	sej
EYR	3.59	4.46	4.36	/
ESR	0.244	0.282	0.29	/
ELR	1.25	1.12	0.99	/
ESI	2.89	3.99	4.40	/

degrees of sensitivity to five kinds of purchasing emergy. The change in fertilizer emergy flow has the most significant impact on the main emergy indicators. With 10% growth, EYR decreased by 2.79%, EIR increased by 4.19%, ELR increased by 4.81%, and ESI decreased by 8.30%. The increase in the emergy input of fertilizer reduces the systematic economic benefits and increases the systematic environmental load, which is harmful to the sustainable development of the system. When the emergy flow of fertilizers decreased by 10%, EYR increased by 3.33%, EIR decreased by 3.87%, ELR decreased by 5.60%, and ESI increased by 9.34%. The reduction in the emergy flow of fertilizers can significantly improve the sustainable level of ICEMFSR. According to the sensitivity of the main emergy indicators to the changes in the five types of purchased emergy input flows, the influence degree of each parameter on the sustainable level of ICEMFSR is as follows: fertilizers > technical services > raw materials and equipment > energy > building materials.

As shown in Fig. 4, with a 26.82% proportion in ICEMFSR, nitrogen fertilizer has the highest proportion in chemical fertilizer emergy input flow, whose sensitivity is also the highest in the entire system. When the nitrogen fertilizer emergy input flow increased by 10%, EYR decreased

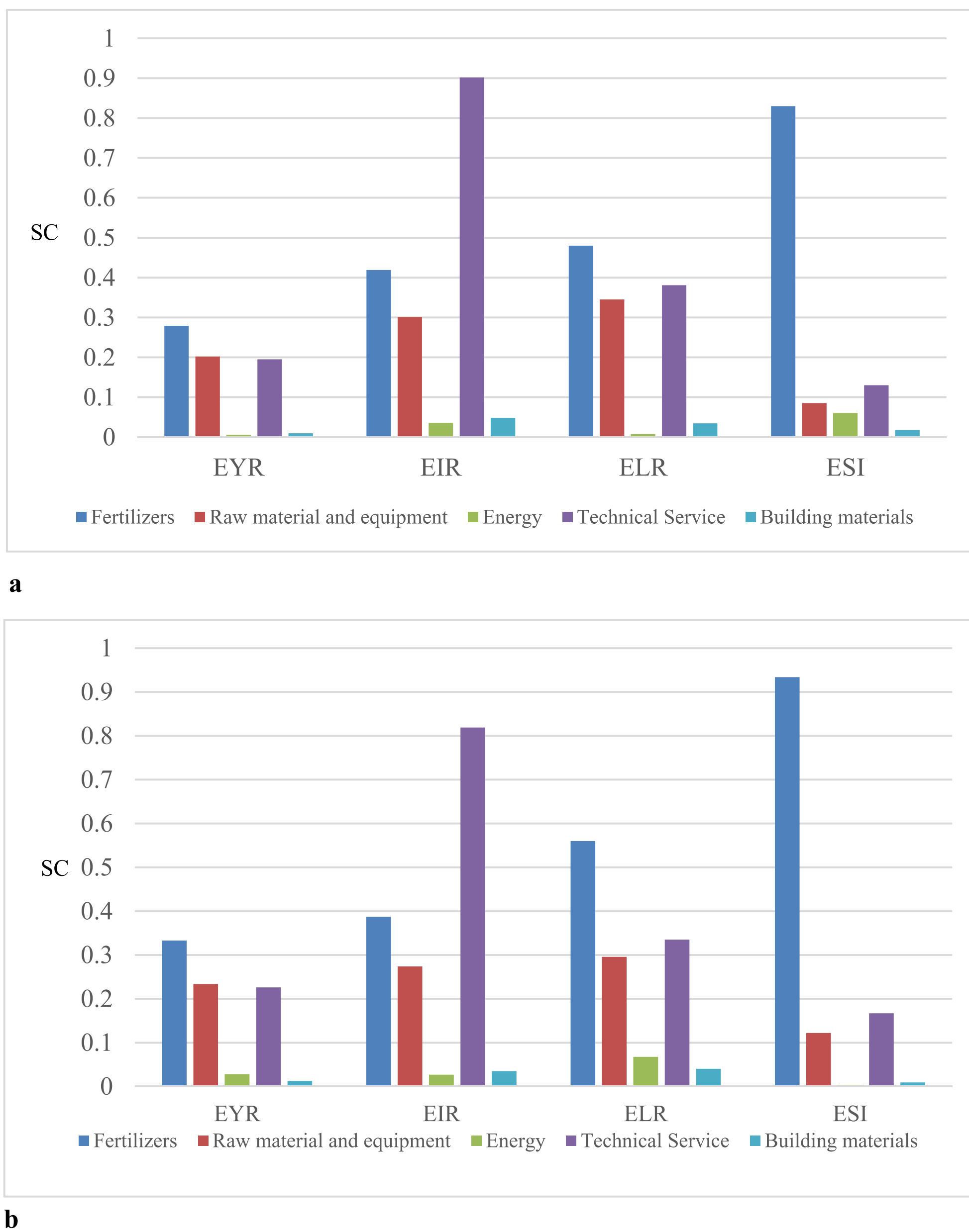

Fig. 3. Sensitivity analysis of the main emergy flows.

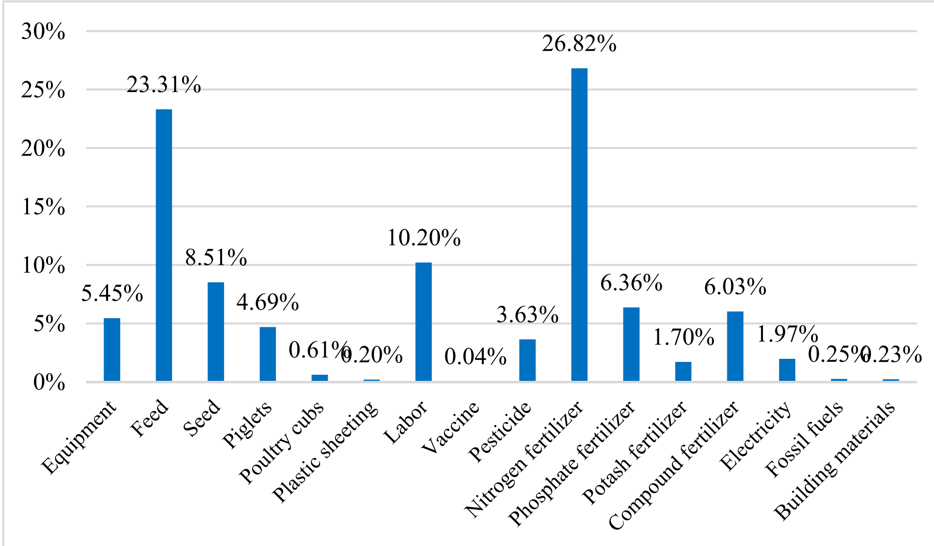

Fig. 4. Proportion of internal components purchased for emergy input.

by 1.88%, EIR increased by 2.82%, ELR increased by 3.27%, and ESI decreased by 5.57%. The results indicate that nitrogen fertilizer is the key substance with the highest level that affects the sustainable development of the system. Similarly, labor force is the key substance for technical services, and the key substances in raw materials and equipment are feed, seeds, and mechanical equipment. The focus of the next optimization design is to increase the use of organic fertilizer and improve the capacity of scientific planting production to further reduce the number and impact of key substances.

4.2. Optimization of scenario design

According to the position of key substances in the agricultural system, three optimization scenarios are designed following the ideals of “source reducing, process reusing, and end recycling”.

Scenario 1: The current integration of farming and raising is aimed at waste in the breeding industry. Small quantities of biogas slurry and residue are produced from the breeding waste biogasification, which can replace chemical fertilizers. Wang et al. (2019) researched biogas emergy and determined that the straws of various crops in the planting industry could be used in the biogas industry to produce biogas slurry and residue. The 2017 data revealed that the annual output of corn straws is 6.93×10^{14}J. Considering the research results of Yang and Chen (2014) and Houshyar et al. (2018), 60% of corn straws are mixed with breeding waste for biogasification, and the comprehensive utilization rate of biogas slurry and residue is 90%. A total of 30% of this rate is returned to the field, and 70% is used in the production of organic fertilizer. Thus, 60% of traditional nitrogen fertilizer and 20% of compound fertilizer will be replaced. This replacement can markedly reduce the use of agricultural fertilizer and further decrease its damage to land fertility and environmental surroundings. The above research indicates that the environmental load of the system has been significantly reduced.

Scenario 2: Effectively reducing the systematic non-renewable industrial auxiliary emergy input and improving systematic sustainability is possible by increasing crop output and reducing feed emergy input. Referring to Hong et al. (2019), Wang et al. (2020a), and Wang et al. (2020b), instead of corn monocropping, the corn oil crop and corn wheat intercropping can increase the output of wheat and oil crops and further decrease the feed emergy input. Assuming that 30% of the corn planting area is intercropped with oil crops and wheat, the wheat and oil crop outputs are expected to increase by 60% and 21%, respectively. Therefore, 50% of the corn and wheat can be mixed with externally purchased fodder. Approximately 17% of feed emergy input will be reduced to achieve a compressive agricultural cycle.

Scenario 3: The agricultural irrigation methods in this region are mostly single-family flood irrigation. In addition to causing water waste, this method requires additional power from machines and consumes considerable energy. Based on the international advanced water-saving irrigation techniques (Abadia et al., 2012), a small low-pressure irrigation network is established to transform the agricultural irrigation into an efficient water distribution network and a low-power irrigation system because of the wide area of crops and concentration of species. Referring to Wang et al. (2014) and García et al. (2017) and combined with actual local conditions, the regional low-pressure energy-saving irrigation technology is assumed to be implemented in the irrigation area, which is expected to reduce the power of irrigation equipment by 22% and decrease regional irrigation electricity consumption by 18%. The economic benefits and sustainable development capabilities of the system have been significantly improved.

If these three optimization scenarios are realized, then the calculated optimization results are shown in Table 12. The total resource input is 1.62×10^{21} sej after scenario optimization, which is 4.14% lower than that after multi-objective planning; EYR and ELR are 4.36 and 0.992, which are respectively 2.24% and 11.43% lower than those after multi-objective planning. Meanwhile, ESI is 4.40, which is 10.28% higher than that after multi-objective planning. The level of systematic sustainable development has been further improved. This improvement could be attributed to the design of the optimized scenario, which reduces the use of key substances and subsequently reduces the non-renewable resources invested. For example, Scenario 1 uses straw biogasification, and the produced biogas slurry and residue are adopted to replace chemical fertilizers. Scenarios 2 and 3 reduced the input of feed and the use of mechanical power, respectively, by improving the capacity of scientific planting production.

5. Conclusions

The study innovatively constructs a multi-objective linear programming model coupled with emergy indicators. Based on this model, the environmental benefits, economic performance, and sustainable development capability of the system are comprehensively evaluated, and the local resource is reasonably optimized and designed. Therefore, the planning proposal determined that the planting area of rice, wheat, corn, and oil crops are 11,500 ha, 9875 ha, 6523 ha, and 11,036 ha, respectively, in the planting industry, and the raising amounts of pig and poultry are 229,286 and 1.14×10^8 in the breeding industry.

After planning, the EYR, ESR, and ESI of ICEMFSR increased by 24.23%, 15.57%, and 38.06% respectively. Considering the maintenance of the total input of natural resources, the planning proposal achieves significant improvement in economic and environmental benefits through reasonable resource allocation. The planning of resources is effective in improving sustainable systematic development. The key substances were diagnosed and identified through sensitivity analysis to further improve the sustainability of the system. Moreover, the research ideas of traceability and the "3R" principle were adopted to propose several optimized scenario designs, such as biogasification of crop straws and improvement of the scientific planting capacity of crops.

The study examined sustainable developmental evaluation, resource planning configuration scheme, and optimized scenario design of ICEMFSR from the theoretical perspective. However, some issues still need to be examined in the future research. For example, volunteer farmers could influence the replacement of planted crops, and market price fluctuations could negatively impact the systematic economic benefits. The main contribution of this study is a method constructed for the advancement of ICEMFSR. This study focused on the construction and application of the coupling of emergy evaluation and multi-objective linear programming models, which provides a new research perspective for studies in similar fields. Therefore, experts and scholars should consider this research method and further improve its effectiveness.

Disclosure statement

No potential conflict of interest was reported by the authors.

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