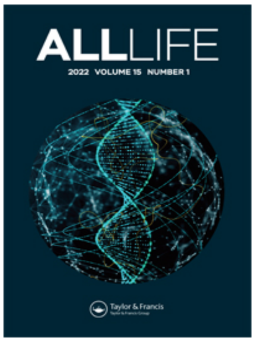

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The analysis and re-optimization of food systems by using intelligent optimization algorithms and machine learning

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ABSTRACT
Facing the serious concern of global food security, this study focuses on the feasibility of improvements to food systems and predicts future changes. This study proposes a coordination evaluation index incorporating diverse indicators of different food systems, analyzes the changes after modification, and predicts the equilibrium time and the critical point. In this regard, we pre-processed the data using the entropy method, variance contribution rate, and normalization. Instead of utilizing single-element linear forecasting and economic income and expenditure models, we innovatively developed a multivariate evaluation system for population, cultivated land, and food systems in three major directions. Meanwhile, after conducting a cross-sectional comparison of the prediction effects of various algorithms, we finally selected Gaussian process regression and a neural network to build a prediction model to develop food systems of different sizes. After establishing the evaluation index and development prediction model, we fitted the three-dimensional surface of the developmental change using thin-plate interpolation. We adopted the swarm intelligence optimization algorithm to search for the balance and critical points after the change. We also compared various swarm intelligence optimization algorithms, such as the particle swarm optimization algorithm, salp swarm algorithm, and whale optimization algorithm.

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KEYWORDS
Re-optimizing food systems; Multiple Regression Analysis; coupling degree evaluation model; swarm intelligence optimization algorithm; Neural Network

Introduction

The world's population has more than doubled in the past fifty years and is still growing rapidly. The world's population has now reached a staggering 7.6 billion and is expected to reach 8.18 billion by 2030 and 9 billion by 2050. It is no exaggeration to say that the COVID-19 pandemic sets back efforts to achieve Agenda 2030 (Food and Agriculture Organization 2021). According to the current development trend, we will face the massive crisis that the world's hungry population will exceed 840 million by 2030. The global food system appears to be an arduous task of several Sustainable Development Goals (SDGs) (United Nations 2015). It is difficult for us to achieve the grand vision of zero hunger by 2030 (United Nations World Food Programme 2019). Figure 1 shows the worldwide food insecurity index under moderate and severe conditions (Food and Agriculture Organization 2021).

However, people's understanding of the food system generally comes from qualitative understanding (Puma 2019). The complex changes of food system model are influenced by many factors, such as population growth (Godfray et al. 2010), changes in dietary structure (Barabási et al. 2020), changes in the development model of natural resources, and the corresponding changes in the climate and the environment (Battisti and Naylor 2009) and changes in the structure of economic and social resources. In the early part of the twentieth century, researchers gradually started to model and understand the global food system. (Christopher 2005) With the fast globalization of the world's economy, food insecurity in a certain country is not only due to the production shortage in that country independently but also closely linked to the international food market (Feng et al. 2010). Most of the existing food analysis models only take the natural factors of crop growth into account. It remains a challenge to handle complex models incorporating cultivated land, population, and economy simultaneously (Wu et al. 2011). The market equilibrium theory and trade balance models based on economic analysis, such as GTAP (Taheripour and Tyner 2011) and

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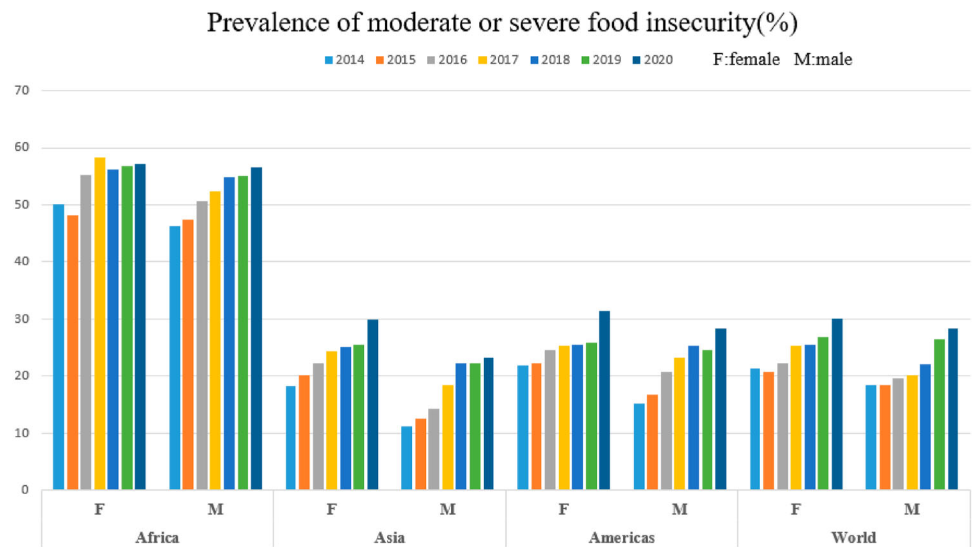

Figure 1. Prevalence of food insecurity on several continents and the whole world.

MPACT (Brown and Funk 2008), can respond well to the price fluctuations in the international agricultural market. However, it fails to take into account the use of land types and their varying patterns.

How to quantitatively understand the influence of the relevant factors in the food system and effectively build a multivariate food system evaluation model is an essential step for sustainable development. With the continuous progress of modern productivity, most parts of the world have achieved food self-sufficiency. However, there still exists substantial differences in local income, production capacity, population density, and related market policies among different regions (Dahl et al. (2014); ul Haq (2013); Godfray et al. (2010); Smith and Archer (2020); Rodriguez et al. (2021); Nuraliev (2017); Caswell (1997); Nuraliev (2019)). We need to store and classify food systems in different regions to realize internal-external scheduling optimization. In the early stages of food system modeling, researchers applied various predictive algorithms for changing systems. For example, in the early stage of data processing, the K-means clustering algorithm was chosen (Ran et al. 2021). In the covariance analysis of multivariate variables, methods widely used in the signal analysis were utilized (Cui et al. 2021). In the analysis and prediction process, multi-objective genetic algorithms and multivariate time series models were used and demonstrated satisfactory results (Zhang et al. 2021; Deng et al. 2022). In the search problem using swarm intelligence optimization algorithms, multiple intelligence optimization algorithms were attempted, such as Monarch Butterfly Optimization (MBO) (Wang et al. 2019) using evolutionary algorithms with population migration, Slime Mould Algorithm (SMA) (Li et al. 2020) based on slime mold oscillation to search for food, Moth Search Algorithm (MS) (Wang G 2018) based on moth phototropism, Hunger Games Search (HGS) (Yang et al. 2021) based on hunger competition, Harris hawks optimization (HHO) (Butcher 1976) based on Harris hawk encircling prey, and Colony Predation Algorithm (CPA) (Tu et al. 2021) based on group predation. The optimization for food systems is also inspired by algorithms such as the Runge Kutta method (RUN) (Ahmadianfar et al. 2022) and weIghted meaN oF vectOrs (INFO) (Heidari et al. 2019). All these algorithms have been compared in parallel and their advantages have been used to their full extent.

In this paper, we focus on establishing an effective evaluation model of the relationship among food production, population, and cultivated land, and proposing measures for improvement and the corresponding results in different environments. Compared with the early policy analysis and macroscopic qualitative understanding, we creatively introduced a large amount of data analysis. We used multiple linear regression analysis to construct a multivariate evaluation of coupled indicators including population, cultivated land, and food production.

Based on the grey prediction model, we also compared the performance of numerous algorithms and evaluation indexes, such as Gaussian Process Regression (GPR), Neural Network Prediction, Support Vector Machine (SVM), and Regression Tree along each direction of the population and other parameters of change (Wu et al. (2020); Elbakian et al. (2018); Liaposhchenko et al. (2019)). We also analyzed the indexes such as Root Mean Square Error (RMSE) of prediction validation and finally selected the appropriate models for different data conditions, respectively.

In addition, we divide the food supply process into three major stages: production, reserve processing, and distribution. And we innovatively adopted multivariate swarm intelligence optimization algorithms, such as the relatively classical particle swarm algorithm (PSO), as a reference. We adopted the trout sea squirt algorithm (SSA) and its subspecies and the whale optimization algorithm (WOA) in parallel for comparison. We searched for the time to change and the feasible domain needed to reach a good coupling in each region. Compared with the traditional search models, our proposed method has dramatically improved search efficiency. Calculation and optimization results provide classifications and corresponding adjustment suggestions for various countries.

Simulation

Assumptions

To simplify and better describe the food system, we made the following basic assumptions, each of which is appropriately justified.

Assumption 1: We assumed that the influence weights of the evaluation model of coordination degree among the population, cultivated land and grain (PCG) composite evaluation system on PCG index in different regions are similar, so we can calculate and compare them in a unified way

→ **Justification**: To make it convenient for us to reach the calculated values of food systems in different regions

Assumption 2: The influence of other extreme factors with a small probability on the food system is not considered

→ **Justification:** Ensure the stability and accuracy of the model and prediction results

Assumption 3: It is assumed that the collected data are reliable and consistent with the actual situation. At the same time, the data accord have relative stability

→ **Justification:** To facilitate our modeling and simplify the processing

Our approach

We want to establish a new food system, which is different from the purpose of only efficiency and profit, and is based on the careful consideration of environment-friendly sustainable development and ensuring the fairness of food security, and to predict the differences and results between this system and the current system, the implementation time, and to promote and verify the feasibility. In this regard, our work mainly includes:

(1) In this paper, we use the entropy method and variance contribution rate to pre-process all multivariate data, and we innovatively construct a new PCG index as an evaluation system for the parallel development of population, cultivated land, and food system compared with a single linear prediction and economic model.
(2) In the process of constructing the regression prediction model, we parallel comparison of various algorithms, selected Gaussian Process Regression (GPR), Neural Network as the main algorithm to process our required sample data., and the final test results also showed that the algorithm has a perfect fitting and generalization ability
(3) We adopted BP Neural Networks for learning and prediction regarding different country and region samples. Finally, we chose the Bayesian Regularization Processing method for model training in the tests, while further comparisons and improvements were trained for different sizes of food systems.
(4) In the problem of predicting the break-even point and time-critical point of income and expenditure, we standardized the data, established the related income and expenditure and balance analysis model, and constructed the three-dimensional surface of local changes of each variable by using thin-plate interpolation fitting.

In the general extreme value search on the surface, we compared the multivariate swarm intelligence optimization algorithm horizontally, and all of them showed better stability and convergence, and all of them were stable and fast to achieve the results we expected.

(5) Finally, after obtaining the corresponding models and training effects. We further generalize the situation for various country regions and give the feasibility analysis and related tests of the relevant policies.

Notations and data

Notations

Necessary notations used in this paper are listed in Table 1.

The data

The data we mainly used included population data for each country, the area of cultivated land, food production, and some measures of the development of the food system. The data sources are summarized in Table 2.

Table 1. Notations.

W	Index weight	\
x	A comprehensive index of population development	\
y	Change index of cultivated land resource utilization	\
z	The composite index of grain production	\
f(*p*)	Population development and change evaluation function	\
f(c)	Cultivated land resource utilization change evaluation function	\
f(g)	Comprehensive evaluation function of grain production	\
C	Coupling degree	\
D	Coupling degree of compatibility	\
μ, α	Uncertain parameters	\
$x^{(i)}(t)$	The data sequence	\
v_i	Particle velocity	\
C_1, C_2	Learning factor	\
ϖ	Inertia weight	\
$\mathbf{Q_1}$	Potential cost	$
α	Cost elasticity coefficient	\
τ	Value per unit time	$/
σ_j	The mean square deviation of the j-th index	s
$\mathbf{W_j}$	The weight coefficient of each index	\
$\mathbf{X_{ij}}$	The j index value of the system	\
$\mathbf{X_{j\,max}}$	The maximum value of the j index in the system	\
$\mathbf{X_{j\,min}}$	The minimum value of the j index in the system	\
$\mathbf{e_j}$	The direct value of index j	\
$\mathbf{g_i}$	The different index of index j	\
$\mathbf{w_i}$	The weight of index j	\
ub	Upper bounds of the search space	\
lb	Lower bounds of the search space	\

Table 2. Data source collection.

Database Names	Database Websites	Data Type
Worldometers	https://www.worldometers.info/cn/	Population
The World Bank	http://www.worldbank.org/	Economics
FAO	https://www.fao.org/statistics/zh/	Food Report
Google Scholar	https://scholar.google.com/	Academic paper
Ifpri	https://www.ifpri.org/	Food Report
CNKI	https://www.cnki.net/	Academic paper

Methodology

Establish food system evaluation model

Comparison with previous evaluation models

Previous food system review models prioritize efficiency and profitability, but we will build the models and prediction methods on the assumptions of efficient use of resources, equity, and maximization of sustainable development. The fundamental difference between the two is that the former is determined by market-economic spontaneity and the latter by macro regulation for sustainable development.

Definition and analysis of historical models

The evaluation model of coordination degree among the population, cultivated land and grain (PCG) refers to a complex system that takes the development and utilization of cultivated land resources as the basis, grain production, consumption, and circulation as the center, and meets human food demand as the ultimate goal within a certain geographical location (Amat et al. 2014).

It is not difficult to find: the quantity and quality of cultivated land determine the grain output; grain output and population determine the per capita amount of grain. In the course of human history, there are only two fundamental ways to ensure the overall food demand of human beings: one is to expand the area of grain cultivation. The other is to increase the grain output per unit area.

In this regard, some scholars use the fuzzy mathematics method to construct coordination relationships and identify the coordinated development relationship among regional population, cultivated land, and grain (Wei and Xinping 2017). Some scholars use the grey correlation model to predict and put forward suggestions (Yiqing et al. 2016).

Model building

We constructed a new set of indicator systems for the population to arable food composite system and an

Table 3. Evaluation index of coordination degree.

System	The weight	Indicators	The weight (%)	Effect
Population System (X_1)	0.3	Total population at year-end(X_{11},10,000)	0.066	−
		Proportion of non-agricultural population(X_{12},%)	0.068	−
		Population Density of Cultivated Land (X_{13}, person/mu)	0.068	−
		Natural Population Growth Rate (X_{14}, %)	0.047	−
		Farmers' per capita net income (X_{15}, yuan)	0.069	+
Cultivated land system (X_2)	0.4	Cultivated land area (X_{21}, ten thousand mu)	0.075	+
		Per capita cultivated land area (X_{22}, mu/person)	0.067	+
		Multiple cropping index (X_{23})	0.049	+
		Stable yield index (X_{24})	0.073	+
		Land reclamation index (X_{25})	0.071	+
		Land management probability (X_{26}, %)	0.071	+
Food System (X_3)	0.3	Total grain output (X_{31},10,000 hectares)	0.056	+
		Grain yield per unit area (X_{32} kg/mu)	0.066	+
		The sown area of grain crops (X_{33}, ten thousand mu)	0.053	+
		The growth rate of grain yield (X_{34},%)	0.055	+
		Total grain output per capita (X_{35},kg/person)	0.049	+

indicator system for sustainable development by drawing on the original system evaluation model, referred to as the PCG model system.

We present an analysis of the current food system situation in the world from different perspectives, using the extreme difference standardization method to standardize the raw data and the variance contribution ratio method to calculate the weight values of each indicator. We, therefore, calculate the PCG index for each region and, accordingly, serve as a basis for resource scheduling among regions. Moreover, we projected the time required for development trends and attainment of sound food systems for the next ten years of population coordination of cultivated land and food through grey prediction models.

This model has certain advantages for determining and improving the levels of grain coordination among the population, cultivated land, which can be used as a basis to evaluate the agricultural level variability among regions and thus maximize the allocation and efficient use of realized resources.

This paper constructs the population – cultivated land – grain compound system's evaluation index system based on the system theory. This index system includes three subsystems: population, cultivated land, and grain, as shown in Table 1. The positive (benefit type, where the more significant the index value is, the higher the coordination level of the population-cultivated land-grain system) and negative (cost type, where the more significant the index value is, the lower the coordination level of the system) are considered. In Table 3, '+' is a positive index, and '-' is a reverse index. Most indicators can be obtained directly from statistical data, while some must be calculated twice. (Amat et al. 2020).

To simplify the preliminary model and make it more representative, we first chose the most important influencing factors of population, cultivated land, and grain subsystems in the initial calculation. They are the total population at the end of the year(X_{11}) in the population system, the per capita cultivated land area (X_{21}) in the cultivated land system, and the total grain output (X_{31}) in the food system.

Model principle

(1) Data Processing

To understand the change of each index, we analyze the index of the PCG system and makes statistics on its attribute data

At the same time, in the stage of determining the weight, we discuss two calculation methods through variance contribution rate method and entropy method

(2) Calculate the Weight Value of Each Index by Variance Contribution Rate Method

Since multiple indicators are involved in the comprehensive evaluation process, and the dimensions and orders of magnitude of some indicators are different, to reduce the impact of dimensions and orders of magnitude, the range standardization is used to standardize the original data, and the variance contribution rate method is used to calculate the weight value of each indicator. The weights of each indicator and subsystem are shown in Table 3.

$$\begin{cases} (X_{ij} - X_{jmin})/(X_{imax} - X_{imin}) \quad (Benefit\_type) \\ (X_{imin} - X_{ij})/(X_{imax} - Xi_{min}) \quad (Cost\_type) \end{cases} \tag{1}$$

Where X_{ij} is the standardized value of the j index in the i system;

X_{ij} is the j index value of the i system;
$X_{ij\,\max}$ is the maximum value of the j index in the i system,
$X_{ij\,\min}$ is the minimum value of the j index in the i system.

When the index value is considerable, the system will play better. This kind of index becomes a benefit index.

The larger the index value, the worse the system performance. This kind of index is called the cost index.

This kind of transformation belongs to the normalized [0,1] transformation, which has more obvious consistency. It compresses the amplitude of the original data of each index after the shift to [0,1], and the characteristic number (standard deviation) measuring the degree of dispersion between data in each index is the smallest.

(3) Index Weight

The weight of each evaluation index is calculated according to the standardized index value.

Firstly, the mean square deviation of the j-th index is calculated

$$\sigma_j = \sqrt{\sum_{1}^{n} (X_{ij} - \bar{X}_j)^2} \tag{2}$$

Calculate the weight coefficient of each index

$$W_j = \sigma_j / \sum_{1}^{m} \sigma_j \tag{3}$$

m is the number of indicators under an evaluation element,

$$Obviously, \quad W_j \geqslant 0, \sum W_j = 1 \tag{4}$$

Based on data of standardization and index weight, the comprehensive index value of each subsystem is calculated by using the comprehensive evaluation function$f(p)$ of the population system, the evaluation function $f(c)$ of the cultivated land system, and the comprehensive evaluation function $f(g)$ of the grain system. The calculation formula is as follows:

$$\mathrm{C} = \mathrm{f(x)} \cdot \mathrm{g(y)} \cdot \mathrm{h(z)} \cdot \left[\frac{\mathrm{f(x)} + \mathrm{g(y)} + \mathrm{h(z)}}{3}\right]^{-3} \tag{5}$$

(4) Index Weight Determined by Evaluation Entropy Method

We choose the objective weighting method, which uses the direct value method to determine the weight. In the process of calculating with the direct value method, the extreme value and negative value can not be directly used for operation, so to make some practical changes to it, the standardized transformation method applied in this paper can change it to make the direct value method more flexible in the calculation process. The improved direct value method is used to determine the weight of the evaluation index, which is calculated as follows:

Comprehensively standardize the standardized value of the evaluation index, and calculate the proportion of the j-th index in the i-th year:

$$P = \begin{cases} (X_{ij} - X_{jmin})/(X_{imax} - X_{imin}) \\ (X_{imin} - X_{ij})/(X_{imax} - Xi_{min}) \end{cases} \tag{6}$$

$$\mathrm{Y_{ij}} = \frac{\mathrm{P_{ij}}}{\sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{P_{ij}}} \tag{7}$$

Where, $Y_i Y_{ij}$ is the value after comprehensive standardization, P_{ij} is the standardized value of the evaluation index, $i = 1, 2, \ldots, \mathrm{n}; j = 1, 2(\ldots)m$

Calculate the direct value of index j:

$$\mathrm{e_j} = -\mathrm{k} \sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{Y_{ij}} \ln \mathrm{Y_{ij}} \tag{8}$$

$$\mathrm{k} = \frac{1}{\mathrm{lnn}}, 0 \leq \mathrm{e_j} \leq 1 \tag{9}$$

Calculate the difference index of index j:

$$\mathrm{g_i} = 1 - \mathrm{e_j} \tag{10}$$

Calculate the weight of index j:

$$\mathrm{W_j} = \frac{\mathrm{g_i}}{\sum_{\mathrm{j=1}}^{\mathrm{m}} \mathrm{g_j}} \tag{11}$$

(5) Construction of Evaluation Model

This paper makes a quantitative analysis on the coordinated development relationship among the three factors of population, cultivated land and grain, and the corresponding coordinated development relationship between population and cultivated land, population and grain, cultivated land and grain. Let $\{x_1, x_2, \cdots, x_m\}$ describe the comprehensive index of population development change, $\{y_1, y_2, \cdots, y_n\}$

describe the index of cultivated land resource utilization change, and $\{z_1, z_2, \ldots, z_p\}$ describe the comprehensive index of grain production. The evaluation functions are:

$$f(x) = \sum_{i=1}^{m} w_i x_i, g(y) = \sum_{j=1}^{n} w_j y_j, h(z) = \sum_{k=1}^{p} w_k z_k \tag{12}$$

In the formula: W_i is the weight of the comprehensive index of population development and change, W_j is the weight of the index of cultivated land resource use change, W_k is the weight of the comprehensive index of grain production, W_i is the comprehensive index of population development and change, W_j is the change index of cultivated land resource utilization, Z_k is the standardized value of the comprehensive index of grain production. To achieve the coordinated development of population, cultivated land, and food security, the smaller the dispersion coefficient of $F(x), G(y), H(z)$, the necessary and sufficient condition for the smaller the dispersion coefficient is, the greater the C is, the better:

$$C = f(x) \cdot g(y) \cdot h(z) \cdot \left[\frac{f(x) + g(y) + h(z)}{3}\right]^{-3} \tag{13}$$

Where: $F\,(p), F\,(c), F\,(g)$ represent the comprehensive indexes of population system, the cultivated land system, and grain system respectively; P_{it}, G_{it}, C_{it} respectively refers to the dimensionless value of the i index of population system, cultivated land system, and grain system in year t, I represents the number of indicators, W_j means the index weight.

Get coordinated development degree

$$T = \alpha f(p) + \beta f(c) + \gamma f(g) \tag{14}$$

$$D = \sqrt{CT} \tag{15}$$

Where: D is the coupling co-scheduling, C is the coupling degree, $f\,(p)$, $f\,(c)$, $f\,(g)$ are comprehensive indexes of population, cultivated land, and grain, respectively, and α, β, γ are uncertain parameters.

Calculate the weight value of each system to determine its value. From Table 3, $\alpha = 0.3, \beta = 0.4, \gamma = 0.3$

The coupling coordination degree is a comprehensive index reflecting the coordinated development level of the system, which meets the positive correlation. It then uses the idea of fuzzy mathematics and the method of approximate distribution function to delimit the classification system and criteria.

Multiple regression prediction models

In the prediction process of the changes in the dataset and PCG index, we have used diverse regression learning models in parallel to the original grey prediction model for comparison and analysis, such as Gaussian Process Regression (GPR), Neural Network prediction, Support Vector Machine (SVM) and Regression Tree. And the best fitting effect and stability of the best Gaussian Regression Prediction (GRP) and Neural Network were selected for model training, and also obtained a better predictive analysis model, and we will discuss the results of the comparative analysis in the next chapter specifically.

Verify the coupling degree by using the grey prediction model

The primary task of the GM (1,1) model is to accumulate the original data series, fit and merge the collected data series with the exponential curve to establish a model, and then extrapolate according to time to predict. The grey prediction method is a method to predict the system with uncertain factors. The time response function of the grey prediction model is:

$$x^{(1)}(t+1) = \left[x^{o}(1) - \frac{\mu}{\alpha}\right] e^{-\alpha t} + \frac{\mu}{\alpha} \tag{16}$$

In equation (15), $x^{o}(1)$ is the original data sequence, μ and α are undetermined parameters, which are fitted by the least square method. Equation (15) is the basic formula for predicting the series. The predicted value $\hat{x}^{(1)}(t)$[16] of the series generated by one-time accumulation is obtained, and the reduced value function of the original number is:

$$\hat{x}^{(0)}(t) = \hat{x}^{(1)}(t) - \hat{x}^{(1)}(t-1) \tag{17}$$

The undetermined parameters are calculated by MATLAB software, and the values are $\alpha = -0.032 \mu = 0.48$ respectively. The prediction model established is

$$x^{(1)}(k+1) = 15.68e^{0.03k} - 15.2 \tag{18}$$

Fundamentals of Gaussian process regression

Gaussian process regression is a machine learning method mainly proposed by scholar Carl E. Rasmussen and scholar Christopher K. I. Williams in

1996. Compared to other algorithms that solve for Y given an input X. Gaussian regression is to obtain the distribution of the function $f(x)$. First, we calculate the joint probability distribution among the samples in the data set, and then we calculate the posterior probability distribution based on the prior probability distribution that needs to be predicted. (Rasmussen (2003); Seeger (2004); Johansen (1991)), The set of X_i to be predicted is defined as X^*, and the corresponding predicted value is f^*.

From the Bayesian formula, we have:

$$P(f^*|f) = \frac{P(f|f^*)P(f^*)}{P(f)} = \frac{P(f,f^*)}{P(f)} \tag{19}$$

We can find a suitable Kernel utilizing supervised learning, such as using the most widely used RBF Kernel:

$$\mathrm{k}(\mathrm{x},\mathrm{x}') = \alpha^2 \mathrm{e}^{\left(-\frac{1}{2l^2}\right)(\mathrm{x}-\mathrm{x}')^2} \tag{20}$$

We took a gradient descent approach to solve for the optimal value:

$$\frac{\partial \log p(Y|X)}{\theta} = \frac{1}{2} y^T K_y^{-1} \frac{\partial K_y}{\theta} K_y^{-1} y - \frac{1}{2} tr\left(K_y^{-1} \frac{\partial K_y}{\theta}\right) \tag{21}$$

As $f(\mathrm{x}) \sim (\mu,\mathrm{k})$ the first-check probability distribution is $f(x^*) \sim N(\mu^*, K(x^*, x^*))$

The prior distribution of its joint probability distribution can be calculated as:

$$\begin{pmatrix} \mathrm{f} \\ \mathrm{f}* \end{pmatrix} \sim \left(\begin{pmatrix} \mu \\ \mu* \end{pmatrix}, \begin{pmatrix} \mathrm{K} & \mathrm{K}* \\ \mathrm{K}*^{\mathrm{T}} & \mathrm{K}** \end{pmatrix} \right) \tag{22}$$

Among them, there are:

$$\mathrm{K}^{**} = \mathrm{k}(\mathrm{X}^*, \mathrm{X}^*), \mathrm{K}^* = \mathrm{k}(\mathrm{X}, \mathrm{X}^*) \tag{23}$$

The posterior probability was calculated as

$$p(f^*|f) = \frac{p(f|f^*)p(f^*)}{p(f)} = \frac{p(f,f^*)}{p(f)} \tag{24}$$

Thus, we get the information about the estimated value of f^*:

$$f^* \sim (\mu', K') \tag{25}$$

$$\mu' = K^T K^{-1} f \tag{26}$$

$$K' = K^{*T} K^{-1} K^* + K^{**} \tag{27}$$

Fundamentals of neural networks

A neural network (NN) is a nonlinear system composed of many simple computational neurons interconnected by a large number of neurons.

Each node represents a specific output function, called the activation function. Each connection between two nodes represents a weighted value for the signal passing through the connection, reached a weight. (Schmidhuber 2015; Aggarwal 2018)

BP network (Back Propagation Network), also known as a back-propagation neural network, is trained by sample data and continuously corrects the weights and thresholds so that the error decreases in the negative gradient's direction. Thus constantly changing approximating the desired output.

A BP network consists of an input layer, a hidden layer, and an output layer and usually uses Sigmoid differentiable functions and linear functions as the excitation functions of the network to normalize the output of the network to the range of $[-1, 1]$.

Fundamentals of support vector machines

Support vector machines (SVMs) are a binary classification model that aims to find a hyperplane to segment the samples to achieve segmentation and prediction.

What we call a linearly separable support vector machine corresponds to a straight line that divides the data correctly and at the maximum interval (Cherkassky and Ma 2004).

The interval γ is equal to the difference between two dissimilar support vectors of the projection on w, which is

$$\gamma = \frac{(\vec{\mathrm{x}}_+ - \vec{\mathrm{x}}_-) \cdot \mathrm{W}^T}{\|W\|} = \frac{\vec{\mathrm{x}}_+ \cdot \vec{\mathrm{W}}^T - \vec{\mathrm{x}}_- \cdot \vec{\mathrm{W}}^T}{\|W\|} \tag{28}$$

Where $\vec{\mathrm{x}}_+$ and $\vec{\mathrm{x}}_-$ denote the two positive and negative support vectors respectively

The following relationship equation is satisfied:

$$\begin{cases} (w^T x_+ + b) = 1, y_i = +1 \\ -(w^T x_- + b) = 1, y_i = -1 \end{cases} \tag{29}$$

Thus launching:

$$\begin{cases} \omega^T x_+ = 1 - b \\ \omega^T x_- = -1 - b \end{cases} \tag{30}$$

That gives:

$$\gamma = \frac{1 - \mathrm{b} + (1 + \mathrm{b})}{(w)} = \frac{2}{(w)} \tag{31}$$

The final minimum spacing equation obtained is as follows.

$$\min_{w,b} \frac{1}{2} w^2, s.t. y_i(w^T x_i + b) \geqslant 1 (i = 1,2,\ldots,m) \quad (32)$$

Fundamentals of regression trees

The regression tree is a way of dividing the space with hyperplanes, and each partition divides the current space in half. This method makes each leaf node a disjoint region in the space, and when making decisions, it will go down step by step according to the value of each dimensional feature of the input sample, finally making the sample fall into one of the N regions (assuming there are N leaf nodes).

If we have n features, each with a value of $S_j (j \in 1 \sim n)$, then we iterate through all the features, try all the values of the part, divide the space until we get the value s of feature j so that the loss function is minimized so that we get a division point. The equation describing the process is as follows.

$$\min_{js} \left[\min_{C_1} Loss(y_i, C_1) + \min_{C_2} Loss(y_i, C_2) \right] \quad (33)$$

The branching exhausts every threshold of every feature to find the optimal cut feature j and the optimal cut point s. The measure is the squared error minimization. Branching stops until a predefined termination condition (e.g. the upper limit of the number of leaves) is reached (Huang et al. 2011).

Using multiple swarm intelligence optimization algorithms to predict optimal solutions and equilibrium point time for food system changes

Based on the original classical particle swarm optimization algorithm (Clerc and Kennedy 2002), we utilized the more advanced trout Salp Swarm Algorithm (Mirjalili et al. 2017) and the whale optimization algorithm (WOA), considering that in order to be able to have a better fit and adaptability to the model (Mirjalili and Lewis 2016).

This type of algorithm draws on the laws of nature and uses inter-group motion and information-sharing methods, which have better probabilistic global optimization compared to the traditional idea of solving with a large number of calculations, and often have faster efficiency for obtaining the optimal global solution.

Basic principles of particle swarm optimization algorithm

PSO is initialized as a group of random particles (random solutions). The optimal solution is then found by iteration. In each iteration, particles update themselves by tracking two 'extremes' (pbest, gbest). After seeing these two optimal values, the particle updates its velocity and position using the following formula.

Position update formula

$$\mathrm{v_i} = \omega \mathrm{v_i} + \mathrm{c_1} \times \mathrm{rand()(pbest_i} - \mathrm{x_i}) + \mathrm{c_2} \times \mathrm{rand()(gbest_i} - \mathrm{x_i}) \quad (34)$$

Velocity update formula

$$\mathrm{x_i} = \mathrm{x_i} + \mathrm{v_i} \quad (35)$$

The update formula, $i = 1, 2, 3, 4, \ldots, N$, N is the total number of particles in this swarm. Rand () is used to produce random numbers between (0,1). C_1 and C_2 are learning factors. **pbest** and **gbest** denote the particle swarm's local and global optimal positions, respectively.

When $C_1 = 0$, then the particles have no more cognitive ability and become a social only model (social only)

$$\mathrm{v_i} = \omega \mathrm{v_i} + \mathrm{c_2} \times \mathrm{rand()} \times (\mathrm{gbest_i} - \mathrm{x_i}) \quad (36)$$

It calls the global PSO algorithm. The particles can extend the search space and have a faster convergence speed, but due to the lack of local search, it is easier to fall into local optimum than standard PSO for complex problems.

When $C_2 = 0$, there is no social information between particles, and the model becomes a cognition-only (cognition) model.

$$\mathrm{v_i} = \omega \mathrm{v_i} + \mathrm{c_1} \times \mathrm{rand()} \times (\mathrm{pbest_i} - \mathrm{x_i}) \quad (37)$$

It is called the local PSO algorithm. However, since there is no exchange of information between individuals, the whole population is equivalent to multiple particles performing a blind random search, and the convergence speed is slow; thus, the possibility of obtaining an optimal solution is slight.

In this problem, we use the social model of particles for the solution.

Basic principle of Salp Swarm Algorithm

The algorithm simulates the group behavior of a trout sea squirt chain and is a relatively novel swarm intelligence optimization algorithm. During each iteration, the leader guides the followers, in a chain-like behavior, to move toward the food. During the move, the leader performs global exploration while the followers perform local exploration, which significantly reduces the cases of getting stuck in a local optimum.

(1) Natural Principles

The Tarantula is a marine invertebrate with a barrel-shaped and almost completely transparent body that inhales and ejects seawater through the water. In the deep sea, Tar squirts are usually linked together as individuals, forming a 'chain' that follows each other in turn to move and feed. The chain is divided into a leader and a follower, with the leader moving toward food and guiding the follower's movement, making the chain highly capable of global exploration and local exploitation.

(2) Population Initialization

Let the search space by a $D * N$ Euclidean space, D is the spatial dimension, and N is the number of populations. Construct the matrix representation separately, where the position of the bottle sea squirt in the space is represented by X_n is denoted, the location of the food by F_n is indicated, and the upper and lower bounds of the search space are ub and lb, in that order

It can be known

$$X_{D*N} = rand(D,N)(ub(D,N) - lb(D,N)) + lb(D,N) \tag{38}$$

Where the leader uses X_d^1, the followers use X_d^i, $i = 2, 3, 4, \ldots, N$; $d = 1,\ 2,\ 3\ \ldots D$

(3) Leader Position Update

During the movement and foraging of the trout sea squirt chain, the leader position update is expressed as:

$$X_d^1 = \begin{cases} F_d + C_1((ub - lb)C_2 + lb), C_3 \geqslant 0.5 \\ F_d - C_1((ub - lb)C_2 + lb), C_3 < 0.5 \end{cases} \tag{39}$$

Where: X_d^1 and F_d are the positions of the first trout sea squirt (leader) and the food in the d-th dimension, respectively; ub and lb are the corresponding upper and lower bounds, respectively. Where C_1, C_2, C_3 are the control parameters.

Formula (39) shows that the leader's position update is only related to the position of the food. C_1 is the convergence factor in the optimization algorithm, which balances global exploration and local exploitation and is the most critical control parameter in SSA. The control parameters C_2, C_3 are random numbers of [0, 1], which are used to enhance the randomness and improve the global search and individual diversity of the chain population (Çelik et al. 2021).

(4) Follower Position Updating

In the process of moving and foraging for trout ascidian chains, followers move in a chain-like sequence by influencing each other between individuals in front and behind. Their displacement is under Newton's law of motion, and the followers' motion displacement is:

$$X = \frac{1}{2}at^2 + v_0 t \tag{40}$$

Fundamentals of the whale optimization algorithm

Humpback whale foraging behavior is known as the bubble-net feeding method, in which humpback whales can identify the location of their prey and surround it by spiraling upward. There are two main approaches to modeling the bubble-net behavior of humpback whales.

(1) Shrinkage bracketing mechanism: set the random value in the A vector between [−1,1], the new position of the search agent can be defined as any position between the original position of the agent and the current optimal agent position

(2) Spiral update position: this method first calculates the distance between the whale position and the prey position and then creates a spiral equation between the whale and the prey position to mimic the spiral movement of the humpback whale

Notably, the humpback whale swims around its prey in a shrinking circle while following a spiral path. To model this simultaneous behavior, assuming a 50% probability of choosing between the shrinking envelope mechanism and the spiral model to update the whale's position during the optimization process, the mathematical model is as follows:

$$\vec{D} = |\vec{C}\vec{X}^*(t) - \vec{X}(t)| \tag{41}$$

$$\vec{X}(t+1) = \vec{X}^*(t) - \vec{A} \cdot \vec{D} \tag{42}$$

$$\vec{X}(t+1) = \begin{cases} \vec{X}^*(t) - \vec{A} \cdot \vec{D} & \text{if } p < 0.5 \\ \overrightarrow{D'} \cdot e^{bl} \cdot cos\,(2\pi l) + \overrightarrow{X^*}(t) & \text{if } p \geq 0.5 \end{cases} \tag{43}$$

The WOA algorithm first randomly initializes a set of solutions, and in each iteration, updates their positions according to the randomly selected or optimal

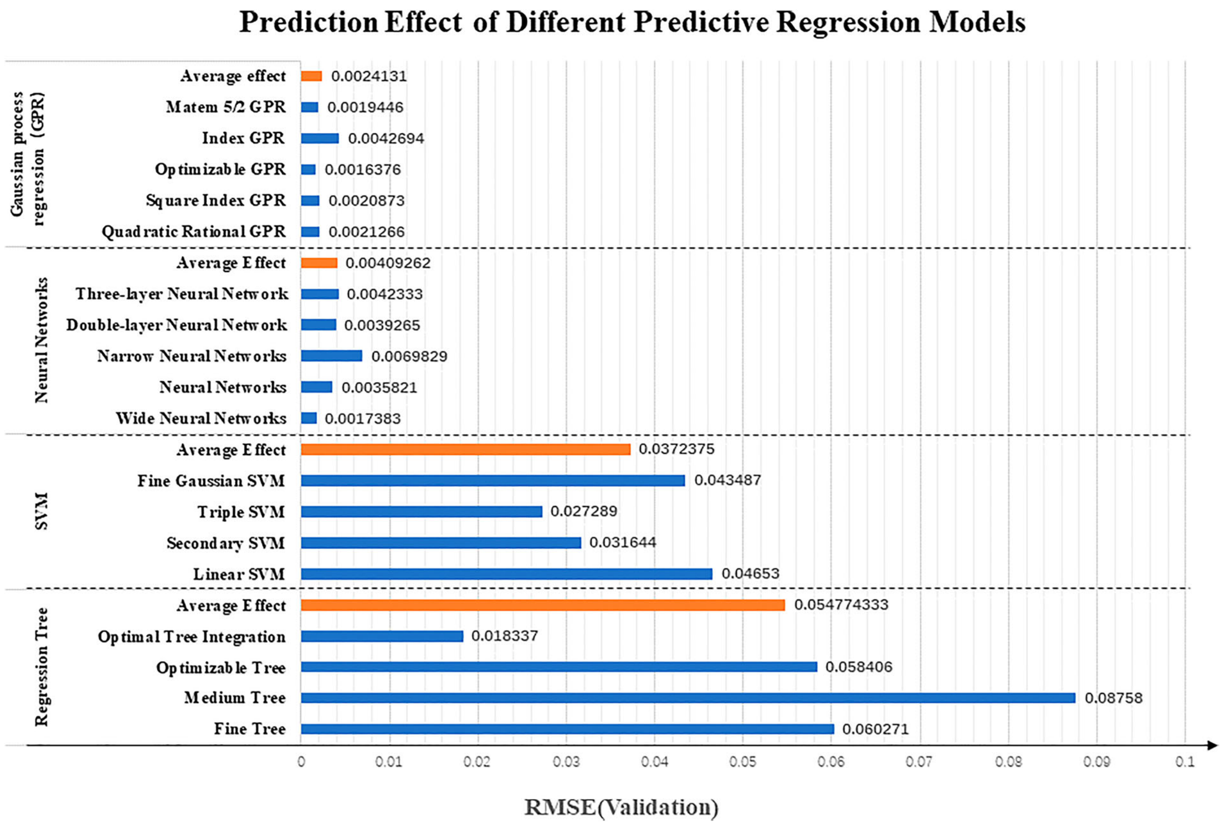

Figure 2. Prediction Effect of Different Predictive Regression Models.

solutions obtained so far. where t is the current iteration, $\vec{A}$ and $\vec{C}$ are the coefficient vectors, X^* is the position vector of the current optimal solution, and $\vec{X}$ is the position vector of the current solution.

The random search agent is selected when the A vector modulus grows larger than 1, and the optimal solution is chosen to update the search agent position when it is smaller than 1. Depending on the value of p, the switching between spiral and circular motions is performed. Finally, the WOA algorithm is terminated by satisfying the termination criterion

Results

Fitting and prediction analysis results of various multiple regression evaluation models

For the regression and prediction of the data set, we selected multivariate time series variables such as population, cultivated land, and food to analyze coupled evaluation indicators such as the PCG index. We used diverse regression learning models parallel to the original grey prediction model for comparison analysis, such as Gaussian Process Regression (GPR), Neural Network prediction, Support Vector Machine (SVM), and Regression Tree. We use these algorithms for comparison training and prediction. The specific analysis results and fitting effects are shown in Figure 2 below:

In the specific training and validation, we selected the variable root mean square error (RMSE) as the evaluation index of the fitting effect. The average impact of different models obtained in the training of multivariate data, in turn, is shown in above Figure 2.

We can easily find that neural network and Gaussian process regression have good performance in fitting the data set, and the prediction effect for the normalized data can. The regression of the Gaussian process using feedback optimization achieves a regression effect of 0.0016376. Considering the stability and interpretability of the model, we decided to use the serial regression and analysis models of neural network and Gaussian process regression in the following data.

Establishment of cultivated land evaluation mod for food population by Multiple Regression Analysis

Through the above evaluation model, we can calculate the PCG index of each region separately. Thus, the

Table 4. Coupling coordination degree system of PCG system and its criterion.

D	Type	Contrast relationship	Coupling evaluation type
0.80 ~ 1	Good coordination	f(p) > f(c) > f(g)	Population development **advanced** type, cultivated land, and grain coordination
		f(p) = f(c) = f(g)	Population, cultivated land, and grain coordination **synchronous** type
		f(c) > f(p) > f(g)	Cultivated land development **advanced** type, population, and grain coordination
		f(g) > f(c) > f(p)	Grain development **advanced** type, cultivated land, and population coordination
0.60 ~ 0.80	Moderate coordination	f(p) > f(c) > f(g)	Population development **advanced** type, cultivated land, and grain **basic** coordination
		f(p) = f(c) = f(g)	Population, cultivated land, and grain coordination **synchronous** type
		f(c) > f(p) > f(g)	Cultivated land development advanced type, population, and grain **basic** coordination
		f(g) > f(c) > f(p)	Grain development **advanced** type, cultivated land, and population **basic** coordination
0.40 ~ 0.60	Barely coordination	f(p) > f(c) > f(g)	Population development **lead** type, cultivated land, and grain **lag** type
		f(p) = f(c) = f(g)	Population, cultivated land, and grain coordination **synchronous** type
		f(c) > f(p) > f(g)	Cultivated land development **lead** type, population, and grain **lag** type
		f(g) > f(c) > f(p)	Grain development **lead** type, cultivated land, and population **lag** type
0.20 ~ 0.40	Moderate disorders	f(p) > f(c) > f(g)	Population development **lead** type, cultivated land, and grain **profit and loss type**
		f(p) = f(c) = f(g)	Population, cultivated land, and grain **co-loss** type
		f(c) > f(p) > f(g)	Cultivated land development advance type, population, and grain **profit and loss** type
		f(g) > f(c) > f(p)	Grain development advance type, cultivated land, and population **profit and loss** type
0 ~ 0.20	A serious imbalance between	f(p) > f(c) > f(g)	Population development **lead** type, cultivated land, and grain **profit and loss** type
		f(p) = f(c) = f(g)	Population, cultivated land, and grain **co-loss** type
		f(c) > f(p) > f(g)	Cultivated land development advance type, population and grain **profit, and loss** type
		f(g) > f(c) > f(p)	Grain development advance type, cultivated land, and population **profit and loss** type

index can quantitatively measure the degree of mutual coordination among the population, cultivated land, and food system of a part, and a food system and use it as the basis for resource dispatch between regions. We classify different coordination relationships into the following five criteria categories, and the specific evaluation criteria are shown in Table 4.

From this table, the coupling coordination indicator of 0.8–0.1 can be considered as good coordination, so we adopt the assumption of the minimum standard, we consider the coordination of a region acceptable when the coupling coordination indicator of the PCG system reaches 0.8.

We select a sample of model regions to test the established model appropriately: bring in the collected data of population, cultivated land, food of relevant countries and regions, for example, Pakistan's data from 2010 to 2019 are substituted into the PCG model for testing, and the specific test results are shown in Figure 3.

Coupling validation using the gray prediction model

The grey prediction method is a method to predict the system containing uncertainties. We predict by grey prediction model GM (1,1) model is to accumulate the original data series and exponential curve to fit and merge the data series generated by accumulation to build the model, and use the existing data in turn to backward prediction test of time parameters, and then extrapolate according to time.

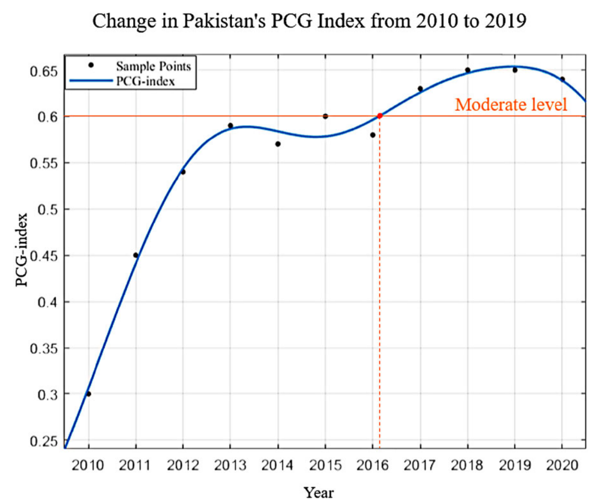

Figure 3. Change in Pakistan's PCG Index from 2010 to 2019.

Table 5. Coupling coordination degree prediction and types.

Year	2019	2020	2021	2022	2023	2024	2025	2026
Predictive value	0.66	0.67	0.68	0.71	0.73	0.77	0.79	0.81
Type	M	M	M	M	M	M	M	G

Ps: 1.M:Moderate coordination(0.60 ~ 0.80) 2:Good coordination (0.80 ~ 1.00).

We substituted the digital data of Pakistan from 2010 to 2019 into the prediction model and obtained the following results in Table 5.

Ultimately, we obtain a prediction based on the present model that Pakistan will achieve a good level of population, cultivated land, and food system interconnection by 2026 (five years from now). Similarly, the model can be used to predict the time to achieve sound food systems in different regions by substituting additional data

For the comparative analysis of benefit-cost differences between developing and developed countries

We collected data on total population P, cultivated land per capita C, and total annual food production G for several countries and regions for several decades in three broad directions and normalized each specific small point to bring in the action values according to the model. We selected representative countries in developing and developing countries to test the accuracy.

First, we selected developed countries such as the United States and Canada and developing countries such as China and Brazil by comparing the typical conditions of population and climate in some countries and regions.

Then, we calculated the PCG index (2010–2019) for each country over a decade using the data we collected. We analyzed the resulting data by using the formula obtained from the grey prediction model.

$$x^{(1)}(k+1) = 15.68e^{0.03k} - 15.2 \tag{44}$$

We predicted the subsequent trend of PCG changes and plotted the fitted curves as shown in Figure 4 below.

We use decades of complex coupled data to build the PCG index and thus the results after constant sampling and comparison by various means such as grey models, and test them in developed and developing countries, respectively, and the errors of the results

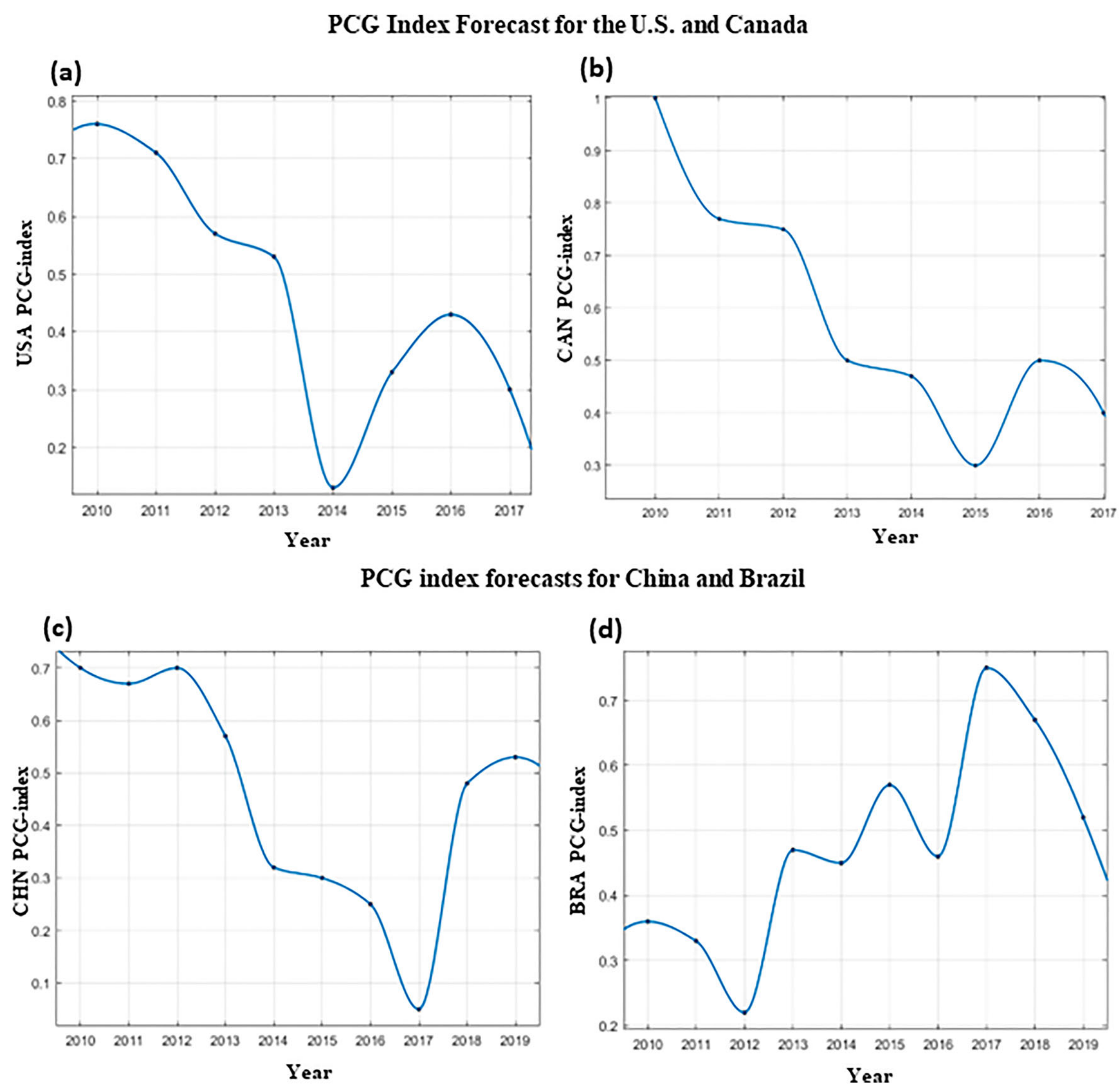

Figure 4. (a,b,c,d) PCG Index Forecast for the U.S., Canada, China and Brazil.

are within manageable limits. And the predicted trend of the basic data for the last decade is plotted as above. By comparing the above graph, we can find that the improved sustainable agriculture model has more obvious advantages for traditional developing countries.

Prediction results for food systems of different sizes

Construction of the prediction model with specific training effects

As seen from the above, we evaluated and predicted different types of multiple regression predictions and finally selected Gaussian regression models and neural networks for prediction analysis. The corresponding BP neural network prediction models were built and passed the model tests on the validation sets of other countries, and all of them showed good prediction and fitting effects.

Firstly, we selected Levenberg–Marquardt algorithm, Bayesian regularization, and scalar conjugate gradient. These three types of criteria are used as training methods.

We found that the Bayesian regularization algorithm has the best learning and generalization ability for relatively small datasets through several experiments. Therefore, we use Bayesian regularization as the main algorithm in all subsequent training. The model's specific learning and prediction results are shown in Figure 5.

It is not difficult to find that the model achieves the best training effect and the relative mean square deviation of 1.628E-4 when it has been trained for the 309th generation, and also basically achieves acceptable prediction and learning accuracy in the primary distribution graph of the error, and achieves convergence and gradient descent in the response of the output over time.

Prediction for large food systems

We selected the samples with the top 20% of all countries and regions in terms of population, food production capacity, and relative area of cultivated land for the classification of large food systems, such as the United States, China, Brazil, Russia, Indonesia, India, France, and Ukraine.

Among the above samples, we selected China and the United States as the training samples for the model in turn and obtained relative accuracies of 0.530 (actual 0.5305) and 0.2894 (actual 0.2890), respectively. For the trained prediction models, we constructed PCG evaluation indexes in turn and brought in other sample sizes for testing and correction, and finally, the relative error of the whole prediction training was controlled within 1%.

It is easy to see that the prediction model has substantial prediction accuracy and good stability for larger food systems. The relative errors are controlled within 1%. Thus reflecting the robust scalability and adaptability of our model and prediction method for larger food systems.

Prediction for smaller food systems

Our initial model achieved good predictions in relatively large countries and regions, and we began to wonder if it could be generalized to other medium or small food system models.

In this regard, we selected Korea as the initial sample for the test, and the main indicators of PCG changes in the last decade obtained from the calculations and predictions are shown in Figure 6 below.

Similarly, we used the model for prediction and calculated a value of 0.231 for the PCG indicator in Korea in 2020, but this has a significant error (relative error close to 30%) compared to the actual value of 0.3374 such a prediction result is not allowed. This result indicates that the prediction accuracy of our existing evaluation prediction model is not high for smaller food systems.

In this regard, we further analyzed the data relationships for Korea over the ten years from 2010 to 2019, as shown in Table 6

From the above data, it is easy to find that: the number of Korean population grows positively with time, and the amount of cultivated land per capita shows a decreasing trend with the increase in the number of people. However, the per capita cultivated land data in Korea are minimal and close to each other, so it is difficult to visualize the change in the model because the change is minimal in the calculation.

Instead, we standardized the data by deriving the following equation.

$$\begin{cases} (X_{ij} - X_{jmin})/(X_{imax} - X_{imin}) & (Benefit\_type) \\ (X_{imin} - X_{ij})/(X_{imax} - Xi_{min}) & (Cost\_type) \end{cases} \tag{45}$$

This equation means that during the calculation, the value of the third row of data in the table is calculated

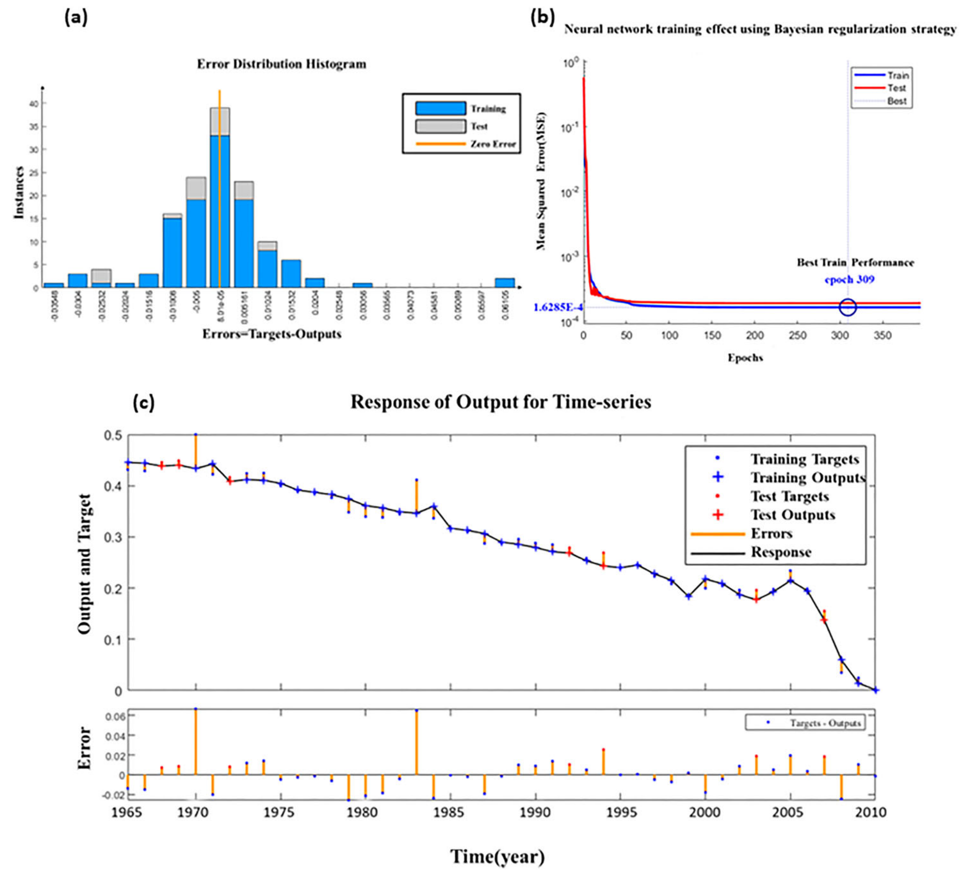

Figure 5. (a,b,c) The effect of Neural Network trained based on Bayesian Regularization.

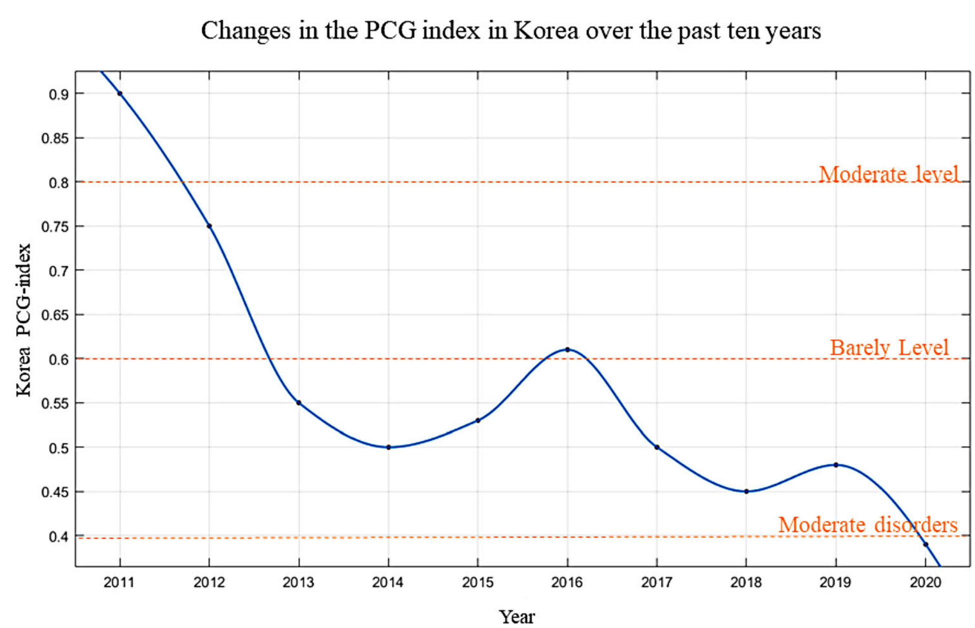

Figure 6. Changes in the PCG index in Korea over the past ten years.

Table 6. Statistics of South Korea from 2010 to 2019.

	2019	2018	2017	2016	2015	2014	2013	2012	2011	2010
Total population/10 million	5.16	5.14	5.12	5.10	5.07	5.04	5.02	4.99	4.96	4.93
Total grain output /million tons	6.759	7.525	6.354	7.082	7.860	7.500	7.458	7.131	7.675	7.617
Per capita cultivated land area/m^2	0.031	0.033	0.032	0.031	0.033	0.032	0.030	0.030	0.031	0.040

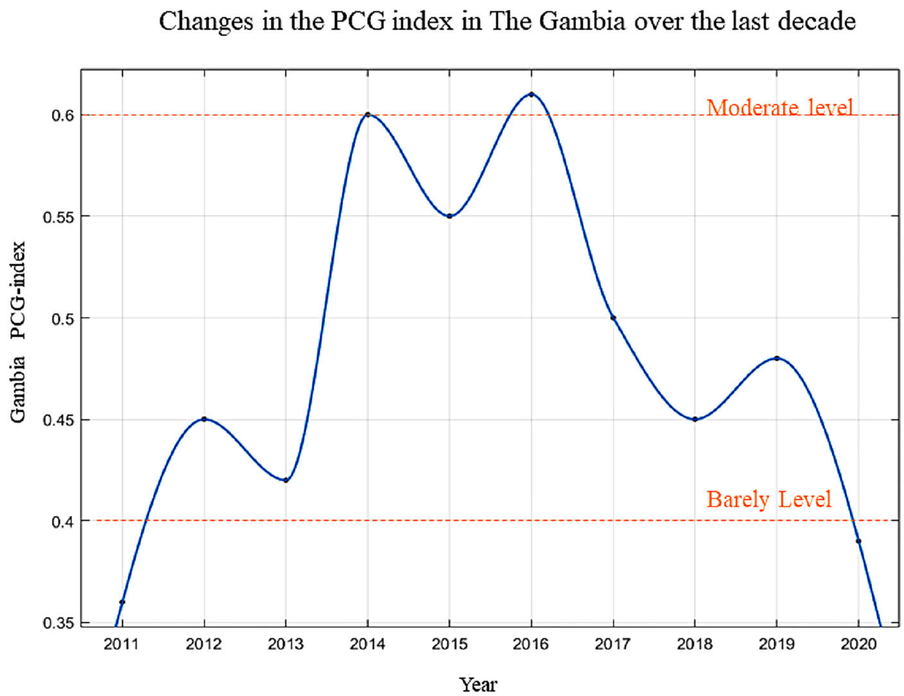

Figure 7. Changes in the PCG index in The Gambia over the last decade.

in a large amount, which affects the subsequent calculation process and makes the prediction and the actual situation has a significant error. This situation is where the biggest shortcoming of the present forecasting model.

At the same time, we assume that the model is relatively independent in the premise of the model establishment. In the model of population, cultivated land, food, food imports, and global environmental changes in the external factors are inevitable. Compared to the large volume of large countries, small countries in the food system under the high degree of external dependence, vulnerable to fluctuations and impact sex, which are undoubted to the forecast bring instability.

Not only that, compared to the relatively traditional self-sufficient underdeveloped regions, South Korea has a higher level of economy and a higher degree of external food imports, which leads to a low amount of cultivated land per capita in the calculation and a bias in the calculation results. In this regard, to test this conjecture, we also selected the Gambia, which has a relatively high degree of agricultural self-sufficiency, to bring into the test, and the calculation results are shown in Figure 7.

By repeating the above, we arrive at a PCG prediction for The Gambia of 0.402, which is only 0.5% relative error from the actual calculated value of 0.40 for 2020, indicating the likelihood of our assumptions and the essential stability of the model. In order to test the conjecture of the factors influencing the changes in external dependence and food system volatility, we selected Mexico, Egypt, Spain, the Netherlands, Korea, and Italy, which are small and medium-sized food systems with high external dependence, and Thailand, Argentina, Myanmar, Vietnam, Sweden, Uruguay, and the Czech Republic, which are relatively self-sufficient food systems, from the smaller sample of food systems.

We used samples from these country regions as basic controls influenced by external food systems, thus adjusting the correlation coefficient factor in the prediction model. Repeating the above steps, we basically verified the relevant conjecture. So we decided to select new samples, independent training samples for smaller food systems, and at the same time increase the

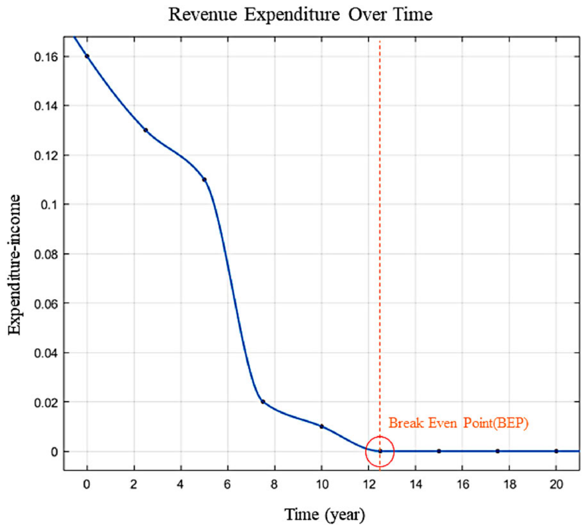

Figure 8. Revenue Expenditure over Time.

weight of several characteristics that are significant for fluctuating disturbances in external food systems and volatility of their changes.

Analysis of the pros and cons associated with a sustainable model of food systems

First, we define costs as including fixed and variable costs, Of which the total cost (TC) is as follows:

$$TC = cN = (c_0 + \lambda x)N \tag{46}$$

Among them, C_0 is the initial cost, λ is the coefficient of variation, and the parameters N are specified as follows, where A, E are fixed and variable cost parameters, respectively.

$$\mathrm{N} = \frac{\mathrm{k_1 a + k_2 e}}{\mathrm{A + E}}\mathrm{Q} \tag{47}$$

For the change in returns modeling the change in returns, we get

$$\mathrm{Q} = \mathrm{Q_1 e}^{-\alpha(\mathrm{P}+\tau \mathrm{t}+\mathrm{kt_d})} \tag{48}$$

Where Q_1 denotes the initial quantity. α is the elasticity coefficient, which indicates the percentage change in a given period. τ denotes the value per unit of time. The obtained return R is calculated as:

$$\mathrm{R} = \mathrm{PQ}\eta - \alpha\mathrm{N} \tag{49}$$

The relative cost variation over time is obtained, as shown in Figure 8:

It is easy to see: our model optimized based on sustainability will bring environmental improvements and efficiency gains at the same time, which may lead to a situation where its expenditures exceed its benefits for a certain period (Similar to the first curve before the break-even point), but will also change over time to a development where it breaks even, or its benefits exceed its expenditures.

Search and prediction of equilibrium critical point of PCG index using particle swarm iso-swarm intelligent optimization algorithm

Compared to the traditional cost and break-even models, such as GTAP (Taheripour and Tyner 2011) and IMPACT (Brown and Funk 2008). We selected various optimization models such as particle swarm in experiments; in the face of large complex multivariate data sets. The swarm intelligence optimization algorithm has many advantages of fitting efficiently and good global convergence. However, considering that all-natural algorithms have certain particular limitations, we selected different similar swarm intelligence optimization algorithms for comparison. However, the final results: all achieved good results and The same stable model solution.

First, we normalized the multivariate variables such as population, cultivated land, and food. To perform a local fit by thin-slab interpolation and obtain a local surface of change and an overall gradient downward trend. For example, the local coupling surface between the data on Pakistan with records 1961–2010 is shown in Figure 9 below.

Next, we fit the overall surface and establish the corresponding functional relationship model and sampling range. We sequentially choose Particle Swarm (PSO), Salp Swarm Algorithm (SSA), and Whale Optimization Algorithm (WOA) for the search iterations and continuously modify the adaptation values of the essential parameter elements.

The final partial best-fit and goodness-of-fit curves obtained are recorded as follows:

On the overall model for the critical point of multiple search experiments, we can complete the particular point's search and localization process. This method also fully reflects the feasibility and stability of the ideas of the swarm intelligence optimization algorithm in this model. After the basic correction for the parameters of each model and a small range of conditions, it is easy to see that all three types of algorithms have stable searchability and better convergence based on the

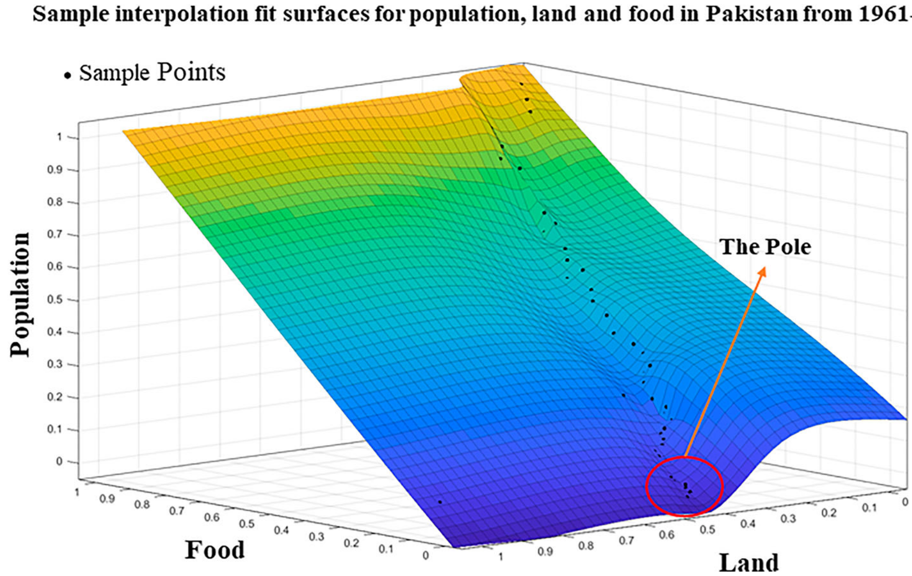

Figure 9. Sample interpolation fit surface for population, land, and food in Pakistan from 1961–2010.

correct search. The whale optimization algorithm has the highest adaptability and relative efficiency of search and has shown notable results in several subsequent experiments among them.

Conclusion

Conclude of the process

In the work of this paper, we pre-processed all multivariate data utilizing the entropy method and the variance contribution rate. In contrast to the single linear prediction and economic model, we innovatively constructed a new PCG index as an evaluation system for the parallel development of population, cultivated land, and food system. In constructing the regression prediction model, we selected Gaussian process regression and neural network as the main algorithms based on a cross-sectional comparison of various algorithms to process our required sample data. The final test results also showed that these algorithms have a perfect fitting and generalization capabilities.

Regarding different country and region samples, we took BP Neural Network for learning and prediction, and according to the results of several tests, we finally chose the Bayesian regularization processing method for model training. The obtained models affect positively impact the defined large food system prediction analysis. It has a good performance for the selected dozens of sample countries. In the face of the smaller existence of larger volatility and the later modification process after adding the perturbation of external food systems and their change factors, it was significantly improved.

After establishing the change of multivariate indicators and analyzing the evaluation criteria. The quantitative prediction of system changes and the balance of income and expenditure and time-critical points after the changes. Firstly, we standardized all the data, established the relevant income and expenditure and balance analysis model, and constructed the three-dimensional surface of local changes of each variable by using thin plate interpolation fitting. In the overall surface in the extreme value search, we compared the multivariate swarm intelligence optimization algorithms, such as Particle Swarm Optimization algorithm (PSO), Salp Swarm Algorithm (SSA), and Whale Optimization Algorithm (WOA), horizontally for many experiments. The whole optimization algorithm (WOA) performs best and achieves our expected results stably and quickly.

Research implications and future improvements

In this paper, we creatively establish a new evaluation system of the population, cultivated land, and food system changes, combining the original agricultural economics model with the quantitative idea of mathematics and computer means to perform the corresponding calculation, prediction, and solution for a large amount of data. This method is a new way

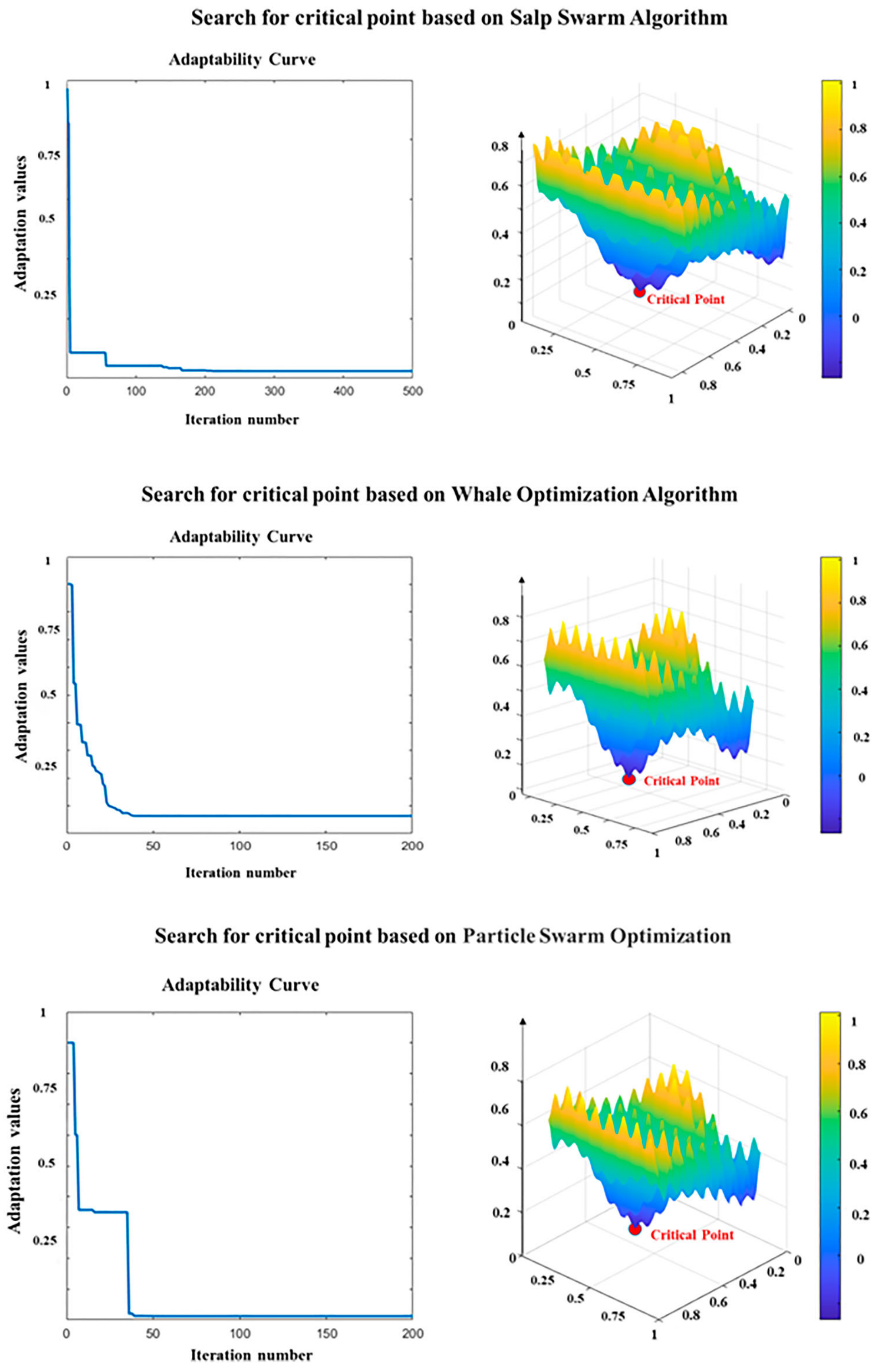

Figure 10. Effectiveness of search and adaptation curves on the swarm intelligence optimization algorithm.

of thinking and resolution to solve the existing food security and hunger problems.

Finally, the following improvements are given to address the decreasing accuracy of the model for smaller food systems.

To provide better accurate predictions for smaller food systems, we provide two solutions.

1. We can use more data sets, find fewer differences in data refinement, such as the proportion of crops in each country, production characteristics of further

Table 7. More complex measures.

System	The weight	Indicators	The weight(%)	Effect
Population System (X_1)	0.3	Total population at year-end(X_{11},10,000)	0.066	−
		Proportion of non-agricultural population(X_{12},%)	0.068	−
		Population Density of Cultivated Land(X_{13},person/mu)	0.068	−
		Natural Population Growth Rate(X_{14},%)	0.047	−
		Farmers' per capita net income(X_{15},yuan)	0.069	+
Cultivated land system (X_2)	0.4	Cultivated land area(X_{21},ten thousand mu)	0.075	+
		Per capita cultivated land area(X_{22}, mu/person)	0.067	+
		Multiple cropping index(X_{23})	0.049	+
		Stable yield index(X_{24})	0.073	+
		Land reclamation index(X_{25})	0.071	+
		Land management probability(X_{26},%)	0.071	+
Food System (X_3)	0.3	Total grain output(X_{31},10,000 hectares)	0.056	+
		Grain yield per unit area(X_{32}, kg/mu)	0.066	+
		The sown area of grain crops(X_{33}, ten thousand mu)	0.053	+
		The growth rate of grain yield(X_{34},%)	0.055	+
		Total grain output per capita(X_{35},kg/person)	0.049	+

subdivision, the use of more accurate estimates and calculations, as well as smaller time intervals, to reduce the relative fluctuations and instability of the amount of data, from the source to reduce the above error.

2. Incorporating more weighting factors and measures to multiply the PCG index for each region to avoid excessive interference of single data failure on the overall forecast, as shown in Table 7.

At the same time, we can select more types of indicators in those systems to which the data itself is smaller and less different and calculate the PCG index in an integrated manner to obtain more accurate calculation results.

After a series of practical tests, we found that: both of the above methods can effectively improve the accuracy and adaptability of this model, forecasting method.

Author contributions statement

The first author of this paper completed the following work: the conception and design, analysis and interpretation of the data; the drafting of the paper, revising it critically for intellectual content; and the final approval of the version to be published; and the author agree to be accountable for all aspects of the work.

Code Availability

All codes can be shared by contacting the author.

Data Availability

The data that support the findings of this study are available in 'Harvard Dataverse' in https://doi.org/10.7910/DVN/LJMWWL

Disclosure statement

No potential conflict of interest was reported by the author(s).

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