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Forecast model of agricultural circular economy development trend based on GP algorithm

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Abstract: To thoroughly and objectively analyze the developmental status of the agricultural circular economy and accurately forecast its future trends, we delved into a predictive model utilizing the GP algorithm. Building upon this foundation, we formulated an evaluation system for the agricultural circular economy's progression, taking into account economic and social development, resource reduction and investment, resource recycling, environmental impact, and population dynamics.

To streamline the evaluation process, we employed the kernel principal component analysis method to condense the indicator system's dimensions for agricultural circular economy development. The reduced dimensionality, representing the agricultural circular economy development index, served as input for the GP algorithm. Enhancements were made to the GP algorithm through a fixed structure, multipopulation, and coefficient climbing method.

Ultimately, we applied the refined GP algorithm to anticipate the developmental trajectory of the agricultural circular economy. The findings suggest that the model presented in this article successfully forecasts the agricultural circular economy, holding significant implications for advancing its further development.

Key words: GP algorithm, agricultural cycle, economic development trend, trend prediction model, index system, kernel principal component analysis

1. Introduction

The agricultural dilemma has perennially stood as a pivotal issue influencing China's national economic and social development. The conventional agricultural development model, as indicated by Leonardo et al. (2021), exhibits substantial drawbacks, inevitably leading to prolonged stagnation in agricultural economic development. In response, the emergence and development of the agricultural circular economy have delineated a contemporary path for agriculture, as noted by Jimenez et al. (2022).

The agricultural circular economy proffers a series of solutions to the problems in the process of agricultural development grounded in the principles of resource reduction, reuse, and recycling of agricultural resources, elucidated by Zhao and Guo (2023). Agricultural circular economy is a new economic development model (Ren and Wang, 2022) that unifies agricultural production, social benefits and economic gains. It encompasses the entire spectrum of agricultural resource input, production, consumption, and abandonment, and operates as a subsystem within the broader circular economy system.

This new model fosters a coordination between agricultural development and the ecological environment, adopting a feedback development process involving agricultural resources, products, and renewable resources (Kolling et al., 2022), marked by low exploitation, low emissions, and high utilization.

The development of human civilization, progressing through primitive, agricultural, and industrial stages, is presently transitioning from industrial civilization to ecological civilization. Ecology encompasses the relationships and existing dynamics between organisms as well as between organisms and their environment, also known as natural ecology. Agricultural ecological civilization pertains to the virtuous circle and harmonious symbiosis between natural and economic ecosystems in agricultural production. It serves as an agricultural development model characterized by the comprehensive and coordinated development of agricultural ecology, society, and economy (Ramirez et al., 2021). Central to this model is aligning agricultural production with ecological principles, enhancing the quality and ecological awareness of human civilization. It strives to ameliorate relationships

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among people, between people and nature, and between people and society by incorporating the principles of agricultural circular economy, encompassing agricultural environmental protection, a sustainable agricultural development model, and a scientific agricultural economy. Addressing the crucial concern of finding a sustainable model for agricultural economic development that conserves resources, minimizes pollution, and judiciously utilizes agricultural by-products is imperative for achieving the rapid and sustainable development of agriculture and increasing farmers' income without destroying the rural ecological environment. This challenge, highlighted by Echevarria et al. (2021), has garnered widespread attention in academic and theoretical circles and emerged as a focal point in recent years.

Within the comprehensive implementation of the agricultural sustainable development strategy, the agricultural circular economy assumes a pivotal role, intimately linked to the sustainable development of the entire social economy. Hence, the development of the agricultural circular economy and the construction of a distinctive agricultural circular economy development model emerge as pragmatic and effective strategies (Awasthi et al., 2022), underscoring the practical significance of researching agricultural circular economy.

As a variant of genetic algorithm, genetic programming (GP) algorithm can be used to realize the optimal design of the problem-solving program and automatic generation of program code owing to its direct and close combination with computer programs (Sheng et al., 2022), which has been paid more and more attention by researchers and applied to many engineering fields, such as artificial intelligence, machine learning, and symbol processing. The core of the GP algorithm lies in its adaptive evolutionary nature, continually adapting to objective data through processes such as copying, crossing, and mutating (Zhang et al., 2021). This adaptive approach automatically determines the suitable function form for specific problems. GP algorithm is an algorithm for the optimal design and automatic generation of computer programs, and its essence is to describe problems with generalized hierarchical computer programs. Through the random generation of the initial population, followed by natural selection, crossover, and mutation processes, the fittest individuals ultimately survive, leading to the automatic generation of a computer program with enhanced performance. GP algorithm has the characteristics of hierarchically describing problems and dynamically adjusting coding length (Bi et al., 2021), and the learning and evolution of the model population minimize the likelihood of "over-fitting" the model. There are few key parameters and little influence by user-set values, so a better model can be obtained by using default parameters. The principle of the algorithm is simple and easy to implement, and there is no need for input preprocessing or output postprocessing. It is precisely due to these distinctive characteristics that the GP algorithm has gained increasing attention from researchers and has been applied to various fields, including machine learning. It offers a novel approach to problem-solving: provide the necessary data samples for computers to undertake specific modeling tasks, and through the evolution facilitated by GP, computer programs can be developed to accomplish the tasks outlined by the provided samples.

Khan and Ali (2022) applied the circular bioeconomic method to the local agricultural sector. Simultaneously, they discussed technologies and supporting strategies for waste treatment to promote the development of the circular economy in China's agriculture. They proposed a hybrid ranking preference technology based on fuzzy strengths, weaknesses, opportunities, and threats, along with fuzzy ideal solution similarity. From the fuzzy analysis, composting and anaerobic digestion are considered the most sustainable technologies for agricultural waste.

Kumar et al. (2021) introduced interrelated new technologies and the concept of the circular economy. This provided the foundation for agricultural organizations to achieve sustainable development goals. On this basis, the integrated ISM-ANP method was employed to analyze the main obstacles to the development of the agricultural circular economy, and empirical testing was conducted on them.

Mahroof et al. (2021) conducted a study on the agricultural supply chain issues in the development of the agricultural circular economy. Based on the theory of the agricultural circular economy, they utilized the ISM method to model and analyze the agricultural supply chain, identifying challenges hindering its development in the agricultural circular economy. The analysis of agricultural disasters concluded that they have a significant impact on the development of the agricultural circular economy.

Bavi et al. (2023) investigated the economic relationship between DNA barcodes and the phylogenetic development of medicinal plants. DNA barcoding, a strategy employing short homologous genetic sequences and standard genomes, has the ability to specify species. This technology identifies crop developmental characteristics, distinguishes existing plant species, and ensures drug safety and efficacy. The economic benefits of medicinal plant species were evaluated through the similarity between sequences and their equivalents obtained in the NCBI database using this technology.

Sgroi (2022) explored the resilience and promoting effect of the circular economy on agricultural landscapes. This study investigated the protection and restoration strategies of farmers towards agricultural landscapes. Survey results indicated that, during the protection process, photovoltaic energy production technology combined with the opportunity cost method achieved clean energy production. Alongside agricultural activities, the company derived economic benefits, contributing to the protection of agricultural landscapes.

Through the above research, a comprehensive analysis was conducted on the development status of China's agricultural circular economy, accompanied by corresponding discussions. Based on this, strategies for developing a circular economy have been proposed. This project aims to predict the development trend of the agricultural circular economy using the GP algorithm, providing a valuable reference for planning and policy formulation in the agricultural circular economy development.

2. Agricultural circular economy development trend prediction model

2.1. Construction of agricultural circular economy development index system

The development index system for the agricultural circular economy needs to reflect the comprehensiveness of indicators and encompass all the characteristics inherent in the agricultural circular economy. The selection of indicators for the development of the agricultural circular economy involves two main stages: primary selection and subsequent refinement.

In the primary selection phase, the indicators are categorized, and those selected are further subdivided based on the measurement purpose. After subdivision, these indicators can be accurately described and operationalized through more specific statistical measures. Building on the distinct features of the agricultural circular economy, we propose an evaluation system for its development.

Within this framework, we introduce a three-level evaluation method encompassing evaluation objectives, evaluation standards, and evaluation indicators. The target level involves assessing the implementation of agricultural circular economy practices at different levels, while the criteria layer is subdivided into five indicator categories: economic and social development, resource reduction and investment, resource recycling, resource environment and safety, and population system. This structured approach to evaluation forms the foundation for the development index system of the agricultural circular economy, as illustrated in Table 1.

The index system for the development of agricultural circular economy primarily encompasses the following components:

(1) Economic and social development:

The social development index serves as a vital metric for gauging the potential and impetus of economic development. While acknowledging the pivotal role of resources and the environment in sustaining economic and societal progress, it is imperative to recognize that the level of agricultural economic and social development reciprocally influences the comprehensive utilization of agricultural resources, resource consumption, and environmental pollution. Four key indicators have been identified for this category: agricultural output value per unit area, per capita net income of farmers, total power of agricultural machinery, and grain yield.

(2) Reduced input of resources:

Reducing input involves minimizing agricultural waste discharge and curbing the utilization of agricultural resources and energy. Adhering to the "energy conservation and emission reduction" principle in agriculture, efforts begin at the source to curtail material and energy inputs detrimental to the environment and human health, thereby mitigating nonpoint source pollution in agriculture. Reduction, in this context, pertains to recycling waste resources through technological and managerial approaches in the agricultural production process, aiming to diminish emissions of pollutants. Five specific indicators underpin this aspect: agricultural energy consumption coefficient, fertilization intensity, pesticide usage, agricultural film usage, and water-saving irrigation coefficient.

(3) Recycling of resources:

Resource reuse in agriculture entails prolonging the lifespan of resources, thereby diminishing resource and energy consumption in agriculture and curtailing waste and pollutant discharge. Resource recycling involves the comprehensive repurposing of resources in agriculture by transforming waste into reusable resources. Two specific indicators encapsulate this dimension: fertilizer utilization rate and multiple cropping index.

(4) Resources, environment and safety:

The acute shortage of agricultural resources has emerged as a pivotal factor influencing agricultural economic development. Agricultural production and lifestyles must harmonize with the natural ecological environment and align with environmental carrying capacities. Key concerns currently include addressing cultivated land shortages, water scarcity, and forest conservation. Four specific indicators have been designated: per capita cultivated land, effective irrigation coefficient, forest coverage rate, and per capita water resources.

(5) Population system indicators:

Population factor is a problem impacting circular agriculture development. Improving population quality and optimizing resource allocation efficiency through technology (Chen et al., 2021)can reduce resource and energy wastage. On this foundation, novel ideas have been proposed to promote the development of a circular economy. Research findings highlight a significant

Table 1. Index system of agricultural circular economy development

Target layer	Criterion layer	Index level	Indicator interpretation
Agricultural circular economy development	Economic and social development	Agricultural output value per unit area	Total agricultural output value/ planted area of crops
		Annual per capita net income of farmers	Total income per capita of farmers - cost per capita
		Grain yield per unit area	Total grain output/grain sown area
		Total power of agricultural machinery	Agricultural and forestry machinery power + animal husbandry and fishery machinery power
	Resource reduction input	Fertilizer application intensity	Fertilizer application allowance/ crop sown area
		Agricultural energy dissipation coefficient	Agricultural diesel oil consumption/total agricultural output value
		Pesticide use level	Pesticide use/crop sown area
		Level of use of agricultural film	Agricultural plastic film usage/crop sown area
		Water-saving irrigation coefficient	Water saving irrigation area/arable area
	Resource recycling	Effective utilization coefficient of chemical fertilizer	Total agricultural output value/ conversion amount of fertilizer application
		Multiple cropping index	Total sown area/cultivated area of crops
	Resources, environment and security	Forest coverage rate	Forest area/total land area
		Effective irrigation coefficient	Available irrigated area/cultivated area
		Arable land per capita	Arable area/total population
		Per capita water resources	Total water resources/total population
	Population system index	Population density	Total land area
		The proportion of people employed in agriculture, forestry, animal husbandry and fishery in the rural population	People employed in agriculture, forestry, animal husbandry and fishery/total rural population
		Proportion of labor force population above junior high school	People employed in agriculture, forestry, animal husbandry and fishery/total rural population

relationship between the quality, structure, and quantity of agricultural production factors within a region and the overall agricultural production factors. Three specific indicators capture this aspect: population density, the proportion of the labor force with at least a junior high school education, and the proportion of employees engaged in agriculture, forestry, animal husbandry, and fisheries within rural populations.

2.2. Reducing the dimensionality of agricultural circular economy index based on kernel PCA method

Given the potential correlation among various indicators within the aforementioned agricultural circular economy development index system, we address the issue of data redundancy by employing the kernel principal component analysis method to reduce dimensionality.

Kernel principal component analysis (KPCA) serves as a bridge from linearity to nonlinearity, encompassing a series of sophisticated data processing technologies. The fundamental principle of the kernel function method involves mapping the input space of the agricultural circular economy development index to a high-dimensional space through a nonlinear function, thereby processing the data within the feature space (Roui et al., 2021). The crux lies in converting the inner product operation of the feature space postnonlinear transformation into kernel function calculation within the original space. This introduction of the kernel function simplifies the computational workload. The operational process is illustrated in Figure 1.

Let x_i and x_j represent the sample points in the data space of agricultural circular economy development index. The mapping function from data space to characteristic space is denoted as φ. The basis of kernel function is to achieve the inner product transformation of vectors:

$$(x_i, x_j) \rightarrow K(x_i, x_j) = \langle \varphi(x_i), \varphi(x_j) \rangle \quad (1)$$

Under the Mercer condition, the development index of agricultural circular economy with input space is set $x_i \in R$. For any symmetric continuous kernel function $K(x_i, x_j)$, there is a Hilbert space, and the mapping $\varphi: R^d \rightarrow H$, there are:

$$K(x_i, x_j) = \sum_{d=1} \varphi_d(x_i) \cdot \varphi(x_i) \quad (2)$$

In the formula (2), d is the spatial dimension of H. In fact, the kernel function of input space is equivalent

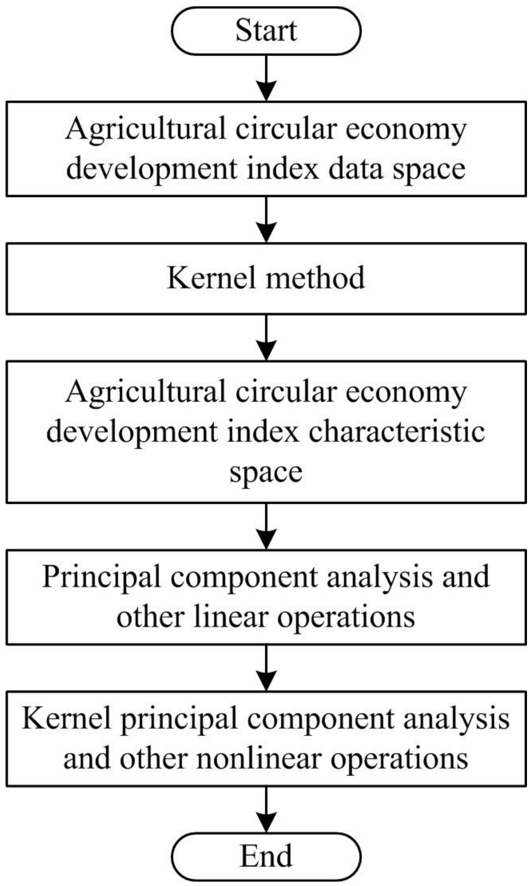

Figure 1. Core method structure diagram.

to the inner product of feature space, because in various practical applications of kernel principal component analysis, only the inner product of feature space needs to be applied (Ming et al., 2021) without knowing the specific mapping φ. When using the kernel principal component analysis method, we only need to consider how to select a suitable kernel function, without paying attention to the corresponding mapping φ whether there are complex expressions.

For the input space of agricultural circular economy development index M's k sample x_k, and $x_k \in R^N$, make $\sum_{k=1}^{M} x_k = 0$ the expression of covariance matrix C is as follows:

$$C = \frac{K(X_I,X_I)}{M} \sum_{J=1}^{M} x_j^2 \quad (3)$$

For the classical principal component analysis method, by solving the characteristic equation $\lambda v = C$, in this way, the eigenvalues with large contribution rate and the corresponding eigenvectors (Zhai et al., 2021) can be obtained, among which, λ is an eigenvalue of C,v is the corresponding feature vector. A nonlinear mapping function, denoted as φ, is introduced to input agricultural circular economy development indicators into the sample points in the space, transforming them into sample points in the characteristic space of agricultural circular economy development indicators, $\varphi(x_i)$. Suppose $\sum_{k=1}^{M} \varphi(x_k) = 0$, then, in the development index input space M, the covariance matrix is expressed as:

$$\bar{C} = \frac{C}{M} \sum_{j=1}^{M} \left[\varphi(x_i)\varphi(x_j)\right]^2 \quad (4)$$

Input space of agricultural circular economy development index M's eigenvalue and eigenvector are used to solve the equation as follows:

$$M = \frac{\varphi(x_k)}{\lambda(\varphi(x_k)\cdot v)} \quad (5)$$

The linear expression of proper vector v is:

$$v = \sum_{i=1}^{M} \alpha_i \varphi(x_i) \quad (6)$$

Among them, α_i represents the number of characteristic indicators. Based on the above formula, the projection of the test sample of agricultural circular economy development index on the spatial vector V^k is as follows:

$$V^k \varphi(x) = \lambda \sum_{i=1}^{M} \alpha_i [\varphi(x_k) \cdot \varphi(x_i)] + \bar{C} \sum_{i=1}^{M} \alpha_i^k K(x_i, x_j) \quad (7)$$

In the formula, K represents a kernel matrix. The nuclear PCA method is used to reduce the dimensionality of the agricultural circular economy index. The specific steps are:

(1) Obtain m data records from the data stream of agricultural circular economy development indicators, expressed as an m x n characteristic index matrix of dimension.

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix}$$

(2) Select appropriate kernel functions for the calculation of kernel matrix K. The article selects a kernel function of Gaussian radial basis and improves it, and its expression is as follows:

$$K = V^k \varphi(x) exp\left(-\frac{\|x-y\|^2}{\sigma^2}\right) \quad (8)$$

(3) Modify the kernel matrix K to get K_L.

(4) Calculate the eigenvalues λ_i and eigenvectors v_i of K_L.

(5) Arrange the characteristic values for agricultural circular economy development indicators in descending order (Gewers et al., 2021) and adjust the corresponding characteristic vectors.

(6) Use the Gram-Schmidt orthogonal method to unitize the feature vector.

(7) Calculate the cumulative contribution rate of the characteristic values of agricultural circular economy development indicators B_i .According to the given extraction efficiency p, if $B_t \geq p$, then extract t principal component.

(8) Calculate the corrected kernel matrix K_L's projection on the extracted characteristic vector of agricultural circular economy development index $Y = K_L \cdot a_{mn}$, the resulting projection Y, that is, the development index of agricultural circular economy is reduced by kernel principal component analysis.

2.3. Development trend prediction model based on the GP algorithm

Building on the preceding content, the dimensions of the agricultural circular economy development index have successfully undergone reduction. This accomplishment effectively tackles the issue of excessive and redundant indicators, minimizing the dimensionality of the original index space and extracting the essential features. Consequently, this reduction significantly streamlines computational complexity, enhancing the efficiency of model prediction.

The development index data for the agricultural circular economy, obtained after dimensionality reduction, serves as the input for the GP algorithm. The GP algorithm processes this input to generate forecasts for the development trend of the agricultural circular economy. In the GP algorithm, an individual chromosome comprises a combination of numerous computer programs, categorized into function sets according to the different expression meanings and combination position of the programs F and terminator set T, wherein the function set F includes operation symbols, mathematical functions, and conditional expressions. Terminator set T includes variables (such as input and state variables describing the system), constants, and nonparametric functions. Two critical conditions, sufficiency and closure, must be met by the function set and terminator set in GP algorithm. Sufficiency ensures that the combination space of the preestablished function set and terminator set encompasses the solution to the given problem. At the same time, the combination of function set and terminator set must be closed, and the parameters of any function and the types of any terminator must be consistent to ensure the the smooth operation of genetic transformations.

In the GP algorithm, the fitness value acts as a metric for individual quality. It determines whether a population will persist into the next generation or face elimination. Fitness represents the driving force behind population evolution, with the original fitness defined as an error. The agricultural circular economy development index, projected after dimensionality reduction through kernel principal component analysis, serves as the input for fitness calculations, guided by the following formula:

$$\phi = Y \sum_{j=1} |s(i,j) - c(j)| \quad (9)$$

In the formula, $s(i,j)$ represents an individual's return value in an instance under *i, j*, and $c(j)$ represents an instance's actual value of *j*. The fitness value of the development of agricultural circular economy should be as large as possible, which is converted by the following formula:

$$r(i,t) = E_{max} - \phi \quad (10)$$

In the formula, E_{max} is the maximum of the original fitness. The replication operation in genetic operations refers to selecting an individual with high fitness in a population and directly passing it on to the next generation without any processing, which is the continuation of the excellent genes of the parents. The proportional selection method is selected to carry out the genetic operation of the GP algorithm. This method imitates the principle of "survival of the fittest" in biology, favouring individuals with greater fitness for increased chances of being copied to the next generation. When copying into the GP algorithm, the probability calculation formula is:

$$P_i = {}^{f}\Big/_{\sum_{i=1}^{\varepsilon} f_i} \quad (11)$$

In the formula (11), f_i is the individual in the instance *i* under the fitness, ε is the population size of the genetic algorithm.

This article introduces a method for predicting the development trend of the agricultural circular economy using genetic programming. The process unfolds as follows:

(1) Define the individual expression mode and essential genetic parameters, encompassing the function set (F) and terminator set (T) in the genetic programming algorithm.

(2) Apply this method to predict the development of the agricultural circular economy.

(3) In predicting the development trend of the agricultural circular economy, the initial step involves calculating the fitness of each individual within the group.

(4) With the predefined genetic parameters, new individuals are generated through the following operations:

(a) Copying: Copying the existing exemplary individuals into new groups, eliminating inferior individuals accordingly.

(b) Crossing: Combining two selected individuals through crossing, and introducing the resulting two new individuals into a new population.

(c) Mutation: Randomly altering a segment of an individual and incorporating the new individual into a new population.

(5) Iteratively perform the aforementioned steps (3) and (4) until satisfactory results are obtained.

The workflow chart illustrating the application of the genetic programming algorithm to predict the development trend of the agricultural circular economy is depicted in Figure 2.

In Figure 2, G_n stands for genetic algebra. From the 0th generation, *R* initial individuals are generated form the initial population, and then the fitness of each individual is calculated to forecast the development trend of agricultural circular economy. Subsequently, operations such as replication, crossover, and mutation are performed in turn. Pictured P_r, P_c, and P_m represent the replication probability, crossover probability, and mutation probability respectively, and $P_i, P_i, P_i \in P_i$. In the context of genetic programming (GP) operations, replication, crossover, and mutation are sequentially executed by individuals in the next-generation population. This approach, involving some individuals with replication operations, others with crossover operations, and a few with mutation operations, increases the likelihood of retaining intact individuals. Predicting the development trend of the agricultural circular economy, the crossover operation of the GP algorithm entails randomly selecting two individuals, determining a crossover point, and allowing the length of subindividuals below the crossover point to vary. Given the dynamic variability in individual coding length, even identical individuals with the same crossover point will not remain the same after genetic operations. This dynamic aspect prevents the entire population from converging towards optimality. The dynamic coding length in the GP algorithm mitigates premature convergence, and the impact of mutation operations is consequently attenuated. To enhance the prediction accuracy of the agricultural circular economy's development trend, the GP algorithm undergoes optimization through the following steps: First, a fixed-length linear table is employed to describe

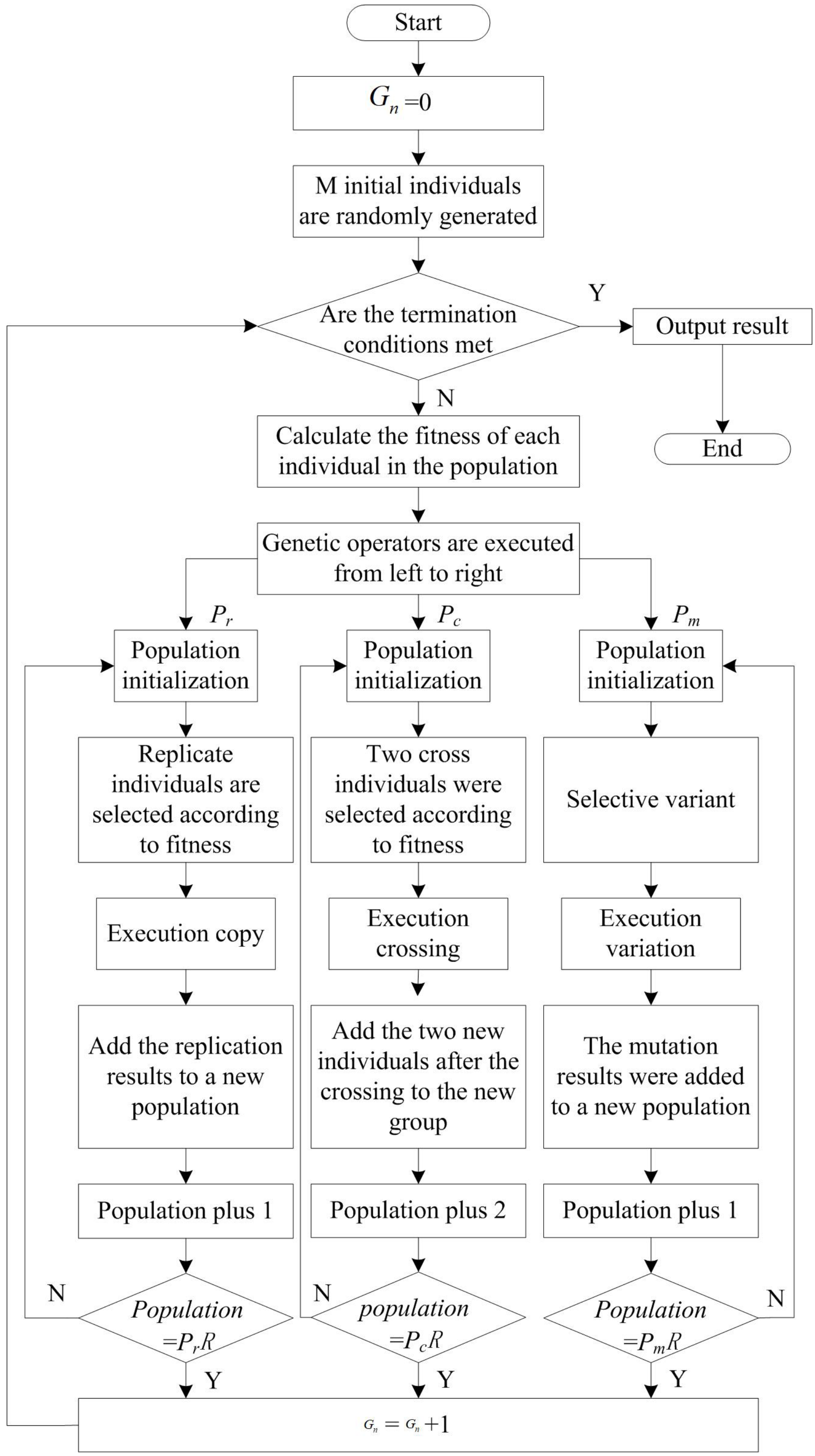

Figure 2. Workflow flowchart of the GP algorithm.

the problem, preventing the occurrence of the "scale explosion" phenomenon. Secondly, the algorithm adopts the concept of simultaneous evolution of multiple populations to enhance the global search capability in predicting the development trend of the agricultural circular economy, thereby increasing the diversity of solutions. Thirdly, leveraging the mountain climbing algorithm's local optimization concept, the coefficients are further optimized on the basis of structural optimization. This addresses the limitations of the traditional genetic programming algorithm, where structural optimization ability is robust, but coefficient optimization falls short. The result is a more objective model structure for predicting the development trend of the agricultural circular economy.

(1) Fixed structure optimization of GP algorithm

The GP classification algorithm's evolution might encounter an issue where the depth and breadth gradually increase, yet the corresponding fitness does not show a significant improvement. To address this, a solution is proposed by introducing a fixed-length linear table as an alternative to the traditional GP algorithm, effectively transforming it into a fixed-structure GP algorithm. The depth, represented by '*d*' expressions in a binary tree, can be expressed as $2^d - 1$. After this transformation, each classification model in the population is depicted as a chromosome within the fixed structure. By determining the gene's position in the linear table, the corresponding position in the expression binary tree is established. When forecasting the development trend of agricultural circular economy through the GP algorithm, the linear table is utilized to create a binary tree with a fixed depth, successfully mitigating the challenges associated with extensive trees and enhancing the algorithm's execution efficiency in predicting the agricultural circular economy's development trend.

(2) Multipopulation optimization of GP algorithm

The GP algorithm, a highly adaptive search algorithm widely applied in nonlinear prediction, encounters challenges with a single population genetic programming approach, often yielding to local optimal solutions and failing to achieve global optimality. During the initial evolutionary stage, individuals with superior fitness can dominate the entire selection process in predicting the development trend of agricultural circular economy, causing the algorithm to stagnate prematurely. To address this issue, this paper proposes a genetic algorithm featuring multiple populations for predicting agricultural circular economy trends.

In this multipopulation approach, various subpopulations can be assigned distinct crossover and mutation probabilities, and the evolution can occur in either a serial or parallel manner, with crossover operations taking place between subpopulations. Subpopulations continuously evolve, obtaining optimal solutions, and global optimal solutions are determined through comparison across all populations. This multipopulation genetic algorithm enhances diversity by exchanging individuals between populations, mitigating the premature convergence issue common in single-population evolution.

Building upon the concept of a parallel multipopulation structure, improvements are made to the fixed-structure genetic programming algorithm. Multiple populations replace the single population of the traditional algorithm, and each subpopulation evolves simultaneously according to different genetic strategies. In the process of evolution, crossover operations between subpopulations are carried out based on crossover probabilities, fostering increased population diversity. The flowchart of the parallel multigroup GP algorithm is illustrated in Figure 3. (3) The coefficient climbing optimization of GP algorithm.

In the fixed structure GP algorithm, each individual in the population is represented as a mathematical expression consisting of two parts: the fixed structure and the coefficient (i.e., the leaf nodes in the binary tree). In the evolution process of the traditional GP algorithm, effective local optimization of parameters is challenging, thereby reducing the algorithm's efficiency to some extent. Introducing the local optimization concept from the mountain climbing algorithm, we propose an optimization approach specifically targeting the coefficients of leaf nodes.

To ensure the effective application of this approach, it is essential, based on predicting the development trend of the agricultural circular economy, to define the value range and variation range of the leaf node coefficients. Importantly, the coefficient's variation range should be carefully determined, avoiding excessive values.

The mountain climbing algorithm functions as a local optimization method. Its principle involves systematically addressing and solving the study objectives, mirroring the step-by-step ascent to the mountain's summit. The journey from the initial step to the optimal solution takes a total of n steps, representing the number of steps required to ascend from the mountain's base to its peak. During the process of "climbing the mountain", each step involves a comparison with adjacent steps to determine whether to proceed.

To predict the trend of agricultural circular economy development, the value range of leaf node coefficient is specified as [−1,1], and the variation range is specified $\Delta \in [-0.5, 0.5]$. The detailed process of coefficient hill climbing optimization in the GP algorithm is as follows:

1) Calculate the fitness value of each individual in the population regarding the forecast of the agricultural circular economy development trend before any coefficient changes.

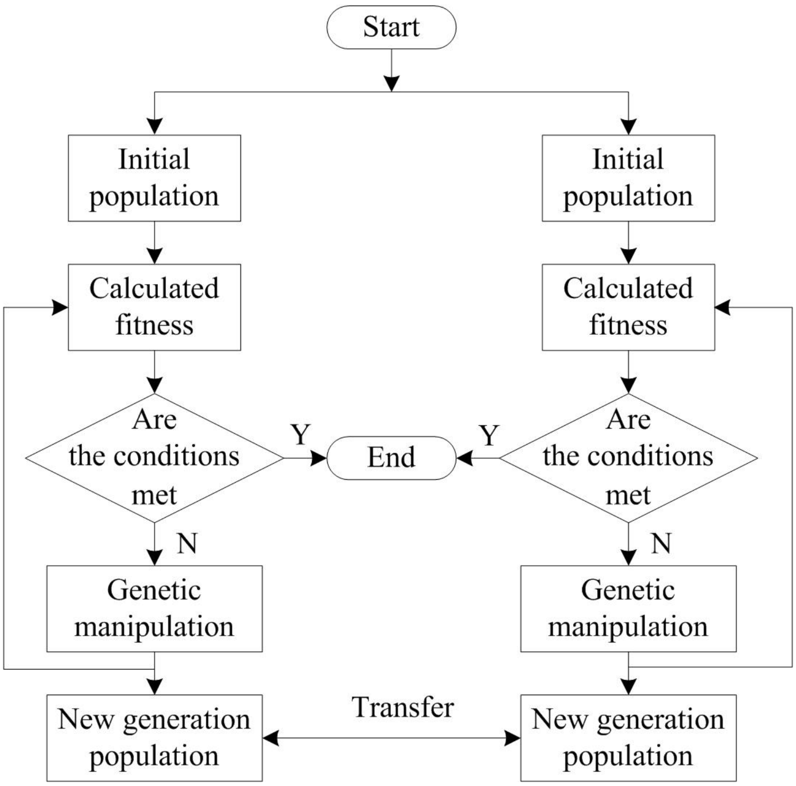

Figure 3. Paliurus flowchart of parallel multipopulation GP algorithm.

2) For all individuals in the population that require coefficient optimization, make slight adjustments to the coefficients of all leaf nodes within a specified range.

3) Based on the adjusted coefficients, predict the fitness of the new individuals.

4) Compare the new fitness value (ϕ) with the original fitness value. If the fitness improves, replace the original individual with the new one. If the fitness worsens, retain the original individual and discard the new one.

When applying the GP algorithm to predict the development trend of the agricultural circular economy, each time a new individual is generated in the population, it undergoes the optimization process to adjust its coefficients.

Building upon this, the GP algorithm is further optimized and applied to predict the development trend of the agricultural circular economy.

3. Results and analysis

This article focuses on predicting the development trend of the agricultural circular economy in a specific province and city. The data utilized for this research are sourced from various reliable databases, including historical statistical yearbooks, China agricultural statistical data compilations, China agricultural statistical yearbooks, China rural statistics, new China agricultural statistical data from the past 50 years, China statistical yearbooks, government reports, and environmental bulletins specific to the province and city over several years. Dimensionality reduction of the data is conducted using Python as the programming language and MATLAB as the simulation software. The testing system adopts Ubuntu 18.04, with an Intel Core i9-9900K CPU featuring 8 cores and 16 threads, a base frequency of 3.6GHz, a maximum frequency of 5.0GHz, and a 16MB cache. The GPU model is Nvidia GeForce RTX 2080Ti, equipped with 4352 CUDA cores, 11GB DDR6 memory, and a memory speed of 14Gbps. The GP algorithm is implemented using the EvolveGP software package, which encompasses various GP operations and functions such as crossover, mutation, and selection. The genetic programming method is configured with an overall size of 100, 50 iterations, and a crossover probability of 0.8. Experimental verification is conducted on the development index and trend data of the agricultural circular economy spanning from 2013 to 2022.

This study employs the kernel principal component analysis method to reduce the dimensionality of the agricultural circular economy development index system. The retained agricultural circular economy development indicators after dimension reduction are outlined in Table 2.

Table 2. Dimension reduction results of agricultural circular economy development index system.

Target layer	Criterion layer	Index level
Agricultural circular economy development	Economic and social development	Grain yield per unit area
		Total power of agricultural machinery
	Resource reduction input	Fertilizer application intensity
		Pesticide use level
		Water-saving irrigation coefficient
	Resource recycling	Effective utilization coefficient of chemical fertilizer
		Multiple cropping index
	Resources, environment, and security	Forest coverage rate
		Per capita water resources
	Population system index	Population density
		The proportion of people employed in agriculture, forestry, animal husbandry, and fishery in the rural population

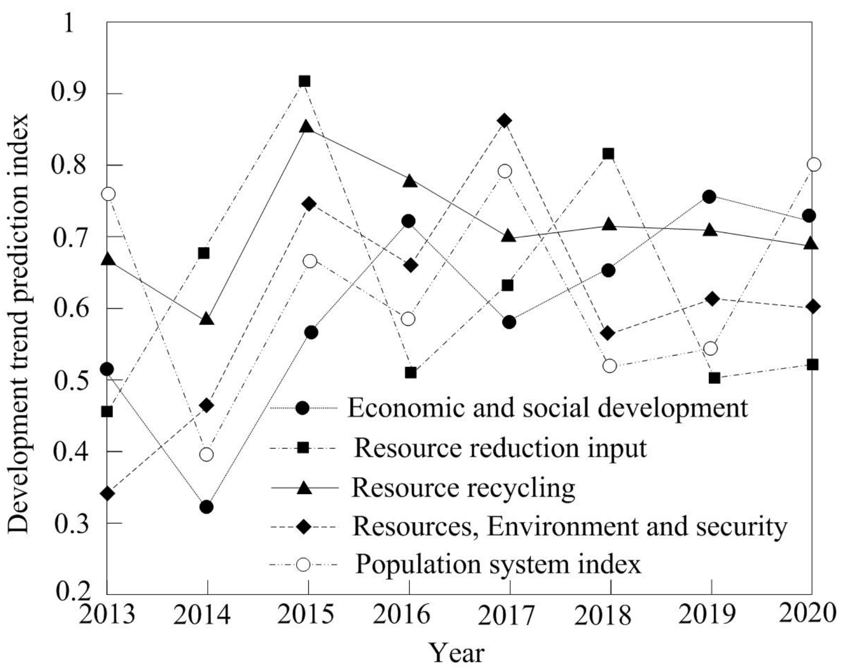

Figure 4. The prediction results of the development trend of regional criterion layer studied.

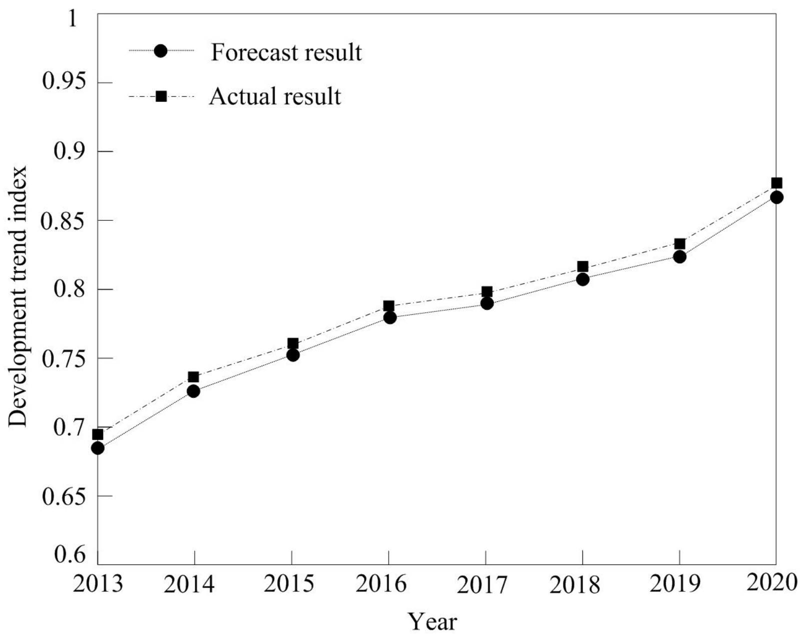

Figure 5. Forecast results of the development trend of agricultural circular economy.

3.1. Analysis of forecast results

Based on the indices derived from the dimension reduction of the agricultural circular economy development index system (Table 2), employed as inputs for the GP algorithm, the results of development trend predictions at the criterion layer within the research area are presented in Figure 4.

Analysing the experimental outcomes depicted in Figure 4, it is evident that the model proposed in this paper can effectively use the collected index data from the agricultural circular economy development index system.

This proficiency translates into accurate predictions of the development trend of the agricultural circular economy at the research regional criterion level. On this basis, by predicting the development trend of agricultural circular economy at the standard level in the research area, a comprehensive prediction value of the development trend of agricultural circular economy in the region was obtained and applied to practice, as shown in Figure 5.

From the experimental results in Figure 5, it is affirmed that this method can effectively predict the development of the agricultural circular economy in the region. Further analysis of the experimental outcomes in Figure 5 reveals a positive correlation between the predicted years and the increasing development index of rural circular economy.

This trend suggests that, with the ongoing progress of the agricultural circular economy in the study area, there is a consistent year-by-year augmentation in the development trend. Notably, the research area has demonstrated a heightened commitment to agricultural circular economy development, effectively enhancing agriculture through technologies like resource recycling.

The overall experimental findings affirm that this model can effectively predict the development trend of the agricultural circular economy in the study area, laying a solid foundation for similar developments in diverse regions.

3.2. Prediction accuracy analysis

To further verify the prediction accuracy of this model for the development trend of agricultural circular economy in the study area, by applying this model, conclusions can be drawn through statistical analysis of the root mean square error and relative error of the development trend of agricultural circular economy in the research area. The statistical results are shown in Figure 6.

Examining the experimental results in Figure 6, it is evident that the root mean square error of this method remains below 2%, while the relative error stays below 0.5. Through case analysis, it has been substantiated that the model possesses a robust predictive ability for the development trend of the agricultural circular economy in the region, providing a reliable foundation for decision-making in agricultural development across different regions. The high-precision development trend of the agricultural circular economy, as predicted by this model, aligns with the goals of implementing the Scientific Outlook on Development. This approach serves as a revolutionary means to alter the mode of agricultural economic growth, alleviate the pressure on agricultural resources and the environment, and address environmental pollution issues. Emphasizing the importance of various effective measures, it is crucial to promote the vigorous

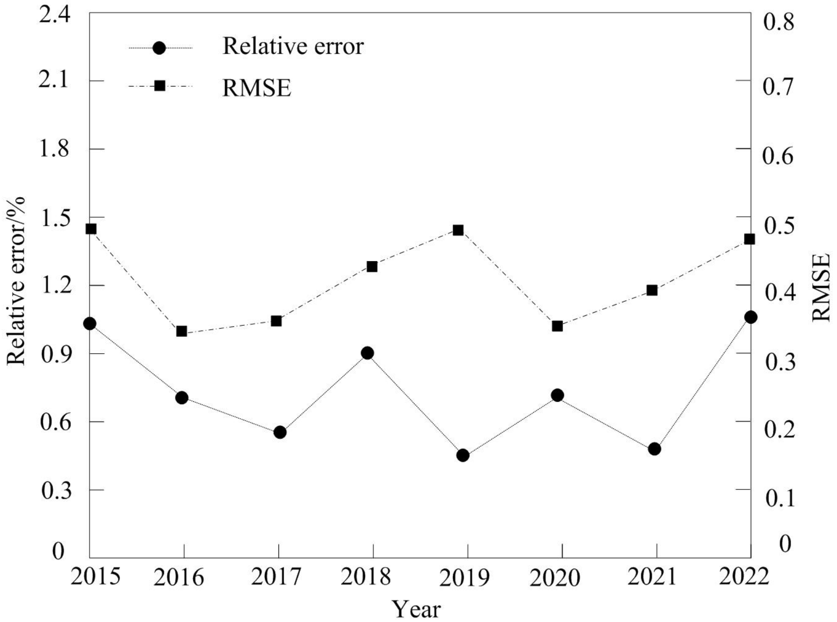

Figure 6. Prediction performance of the development trend of agricultural circular economy.

development of agricultural circular economy for the realization of sustainable agricultural development.

4. Conclusion

The agricultural circular economy stands as an inevitable trajectory for future agricultural development, representing the sole path to achieve economic progress, social harmony, and the enhancement of human settlements. Each region must engage in comprehensive planning for agricultural circular economy initiatives, selecting suitable development models based on local realities. This approach not only fosters increased agricultural production but also enhances farmers' income, improves the environment, and attains the objective of sustainable development.

To propel the continued advancement of the agricultural circular economy, an elaborate development index system was formulated. The application of kernel principal component analysis (KPCA) serves to streamline the index system by reducing its dimensionality. PCA, by substituting a few independent comprehensive indexes for the original multidimensional variables, mitigates information overlap, simplifies calculations, circumvents subjectivity and randomness, and renders prediction results more accurate, reasonable, and objective.

The dimensionality-reduced index system acts as input for the GP algorithm. Experiments employing the optimized GP algorithm to predict the development trend of the agricultural circular economy demonstrate that this method can scientifically and reliably forecast the trajectory of agricultural circular economy development.

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