RESEARCH ARTICLE

Application of population intelligence optimization algorithms to environmental monitoring problems in maize fields

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Problems in intelligent farming include soil erosion, pests, diseases, *etc*. Population intelligence optimization algorithms have a wide range of application prospects in farming environments. While in practical applications, there are problems such as vulnerability to disturbance, tendency to fall into local optimization, and lack of accuracy. Thus, in this study, the Moth Flame Optimization (MFO), Grey Wolf Algorithm (GWO), and Integrated Particle Algorithm (PSO) were combined with improved algorithms for optimization. The Sine Cosine Strategy (SCS) was used to promote the MFO algorithm and was adopted for the land erosion prediction problem based on the Kernel-Based Extreme Learning Machine (KELM) algorithm. The multi-strategy mechanism was used to improve the GWO as a basis for designing an accurate fertilization model. The traditional PSO algorithm was improved by applying elite augmentation and applied to the segmentation of maize disease images. The results showed that the improvement of SMFO-KELM for KELM effectively improved the prediction ability of soil erosion classification. In intelligent agriculture, the performance of multi-strategy GWO was distinctly better than other improved algorithms. In contrast to traditional PSO algorithm, the structure similarity index of the elite enhanced PSO algorithm was improved from 0.88 to 0.95, and the feature similarity index was improved from 0.72 to 0.86 and could obtain better segmentation accuracy than other similar algorithms in solving the overall effect of multi-threshold segmentation for maize rust spot disease. The accuracy of the population intelligence algorithm was improved, and the problem of interference was solved. The use of the population intelligence optimization algorithm realized real-time monitoring and intelligent management of the corn field environment, including the monitoring and regulation of soil moisture, temperature, nutrient status, and other parameters to promote the growth and development of maize and improve the yield and quality of maize, which helped to promote the development of intelligent agriculture and realize the refinement and intelligent management of the agricultural production process.

Keywords: population intelligence optimization algorithm; moth algorithm; grey wolf algorithm; particle swarm algorithm; intelligent agriculture.

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Introduction

In agroecosystems, the mainstay is crops, and maize is a widely grown crop worldwide [1]. With the development of computer information technology, smart agriculture has been widely used and the core technology of smart agriculture is information technology for modern agricultural production [2-4]. In the case of maize cultivation, for example, many issues need close attention during the growth of maize. Examples include monitoring the environment in silt fields to classify and predict land infestation, analyzing the amount of fertilizer applied to different plants, and monitoring and analyzing diseases in maize [5]. The Moth Flame Optimization (MFO) algorithm, first proposed by Mirjalili and inspired by learning the special positioning navigation mechanism of moths during flight, is a new population intelligence optimization algorithm proposed in 2015. The algorithms are optimized using intelligent technology to analyze and solve the problems faced by land environment monitoring. The main problems of land environment monitoring are the impact of soil erosion on maize plants, the deterioration of land conditions due to unregulated fertilizer use, and the impact of diseases and pests on maize yields [6, 7]. The existing population intelligence algorithms are not accurate enough to solve these problems and are susceptible to disturbances and tend to fall into local optimization [8]. To address specific challenges, the MFO algorithm is enhanced with the positive cosine strategy for improved performance in the health control of land environments using the Kernel-Based Extreme Learning Machine (KELM) algorithm. Additionally, a multi-strategy mechanism (SLE) is employed to enhance the Integrated Particle Algorithm (PSO) for maize disease image segmentation, resulting in the development of an elite enhanced PSO.

Currently, the main research method adopted is the intelligent optimization algorithm, and the research object is the sensor detection problem. With the development of the times, group intelligence algorithms have become more mature. Shaikh *et al*. used Grey Wolf Algorithm (GWO) to optimize the calculation of parameters for transmission lines during their research on power systems. This algorithm not only accurately found the optimal solution for the parameters, but also analyzed the influence of various styles of conductors on the transmission line. The results showed that this algorithm was more stable and converges faster [9]. Karaoglan addressed the problem that different extrusion processes had different degrees of impact on product quality by building a model based on the GWO algorithm, expecting this model to analyze the factors that caused inconsistent product quality to achieve cost control and improve product quality [10]. Abbassi *et al*. designed an economic evaluation system to optimize the size of a renewable energy system, combining the model with the moth flame algorithm. The results showed that this model could provide a detailed analysis of the scale problem, provide solutions, and achieve cost control [11]. Mortazavi *et al*. proposed an improvement to the knowledge-sharing structure that built upon the PSO approach. Their research method not only tracked the interaction domain but also incorporated the selection of the search domain. Validation experiments of the method showed that the structure of the research method was more comprehensive and competitive compared to traditional algorithms [12]. Sun *et al*. optimized the overall arrangement of the kitchen based on the PSO for the layout and cooking efficiency of the kitchen, expecting to make the kitchen layout more rational and bring better usage experience. The results showed that the research design approach effectively improved the space utilization of the kitchen, resulting in a more rational layout [13]. Zhao *et al*. optimized the sensitivity of the sensor based on a population intelligence algorithm and showed that the research method not only improved the sensitivity of the sensor by 0.55% but also automatically optimized it for use in all types of sensors [14]. Wang *et al*. proposed a new approach to sensor fault detection and automatic correction based on traditional sensors. The method utilized intelligent population optimization algorithms to enable local coupling between all intelligent nodes to assist in the monitoring and correction of sensor faults. The results showed that the research method raised the sensor detection accuracy and effectively detected faults and corrected them in time [15]. Cervantes-Castillo *et al*. put forward a novel manner to raise the computational power of the population intelligence algorithm by combining an improved brainstorming optimization algorithm with the constrained consistency method. This proposal computed the consistency vector by sequentially addressing the hardest constraint of the current infeasible solution, thus eliminating the need for mixing other feasible vectors. The study suggested that, when compared to state-of-the-art algorithms, adding special operators to enhance the abilities of population intelligence algorithms was feasible [16]. The problem of environmental monitoring has also received extensive scholarly control recently, and Alobaidi and Valyrakis designed a sensor for the problem of monitoring in the direction of environmental topography, ecology, and water resources in the expectation of effective monitoring of the environment. Firstly, micro-particles were designed and developed to be embedded in the micro-sensor. The sensor was then calibrated using physical methods to estimate the errors of the sensor. Then, physical evaluation experiments were designed to validate and evaluate the designed sensor. The results showed that the sensors had low errors and could sense and monitor small environmental changes accurately [17]. Stahl *et al*. discovered that satellite imagery could be leveraged to address data gaps in the field of environmental monitoring. The study made full use of image information to improve environmental monitoring models and found that effective use of imagery could make environmental monitoring models more sensitive and stable [18].

The population intelligence algorithms are relatively well-developed and have been used to varying degrees in various fields. Since less research has been carried out in the field of environmental monitoring, this study combined population intelligence optimization algorithms to investigate the environmental monitoring problem in maize fields and apply intelligent optimization algorithms to practical agricultural problems and more widely in the construction of intelligent agriculture.

Materials and Methods

The SCS Moth Flame Algorithm (SMFO) and its optimization algorithm model

SMFO is an enhanced algorithm that incorporates the Moth Flame algorithm to improve its performance by addressing issues such as a simple structure, susceptibility to interference from pool exploration problems, and the tendency to get stuck in local optimization encountered in the MFO algorithm. All experiments in this study were performed on a computer equipped with a 3.40 GHz Intel® Core i7 processor and 16 GB of memory, encoded using Matlab2018b. The SCA strategy was introduced into the MFO algorithm to provide a set of random solutions for the moth positions at update time, which would explore the region outside the space when the return values of the SCS were not in the region [-1, 1], and searched for the best position in the region when the return values were in the region [-1, 1]. The SCA algorithm, SCS, exhibited a range of adaptation from smoothing to exploitation with a high probability that the optimal solution laid in the vicinity of the previously obtained optimal solution. Therefore, the optimization process performed a focused search for the best region of space. The individual states were updated as shown in equation (1).

$$\vec{X}_i^{t+1} = \begin{cases} \vec{X}_i^t + r_1 \times \sin(r_2) \left| r_3 \vec{P}_i^t - \vec{X}_i^t \right|, r_4 < 0.5 \\ \vec{X}_i^t + r_1 \times \cos(r_2) \left| r_3 \vec{P}_i^t - \vec{X}_i^t \right|, r_4 \geq 0.5 \end{cases} \quad (1)$$

where $\vec{X}_i^t$ was the solution of the current solution in the t-th iteration in the i dimension. $\vec{P}_i^t$ was the destination of the optimal solution in the t-th iteration in the i dimension, and $| \, |$ was the absolute value. r_1 was determines whether the next position was explored within the destination and could enhance the global exploration capability of the MFO algorithm. r_2 defined the next unknown update step. r_3 was a random weight where the data range determined the ability of the target destination to influence the current solution. r_4 was the probability value for a random switch by the positive cosine mechanism. To balance the relationship between the exploration and being

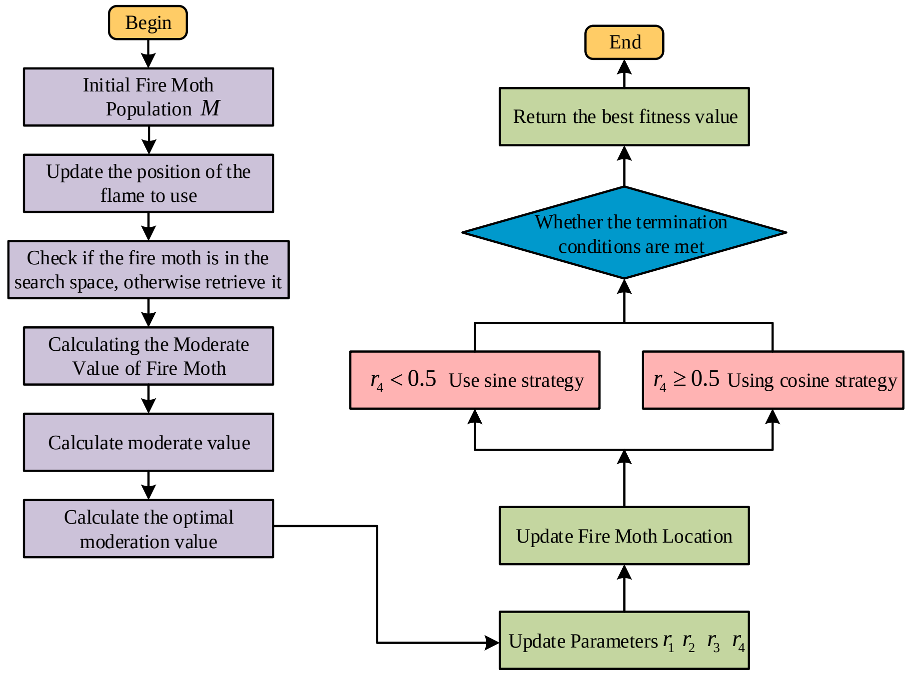

Figure 1. SMFO algorithm flowchart.

explored, the exploration converged gradually to the optimal solution with the expression shown in equation (2).

$$r_1 = a - t\frac{a}{T} \quad (2)$$

where t was current iteration and T was the max amount of iteration. a was a constant of 2. The SMFO algorithm, obtained by adding the SCA algorithm for improvement, raised the global exploration ability of MFO and ensured the local optimal solution's accuracy (Figure 1). The improved SMFO's time complexity was related to the number of iterations. The parallel optimization capability of the MFO algorithm was very strong. The MFO algorithm could search extensively for globally optimal regions in space. The flame in the MFO algorithm was the best position reached by the moth, which was placed in the matrix F and the fitness value of the flame was placed in the array OF. With the flame locus, the moth renewed its position as shown in equation (3).

$$\vec{M}_t = S(M_i, F_j) \quad (3)$$

where $\vec{M}_i$ was the i -th moth. $\vec{M}_t$ was the position that could fly in one or more dimensions of the allowed region. F_j was the j -th flame and S indicated the spiral function. The flight path was the range of solutions, and the coordinates of its position were the solutions that existed as shown in equation (4).

$$\vec{M}_t = \vec{D}_t \cdot e^{bt} \cdot \cos(2\pi t) + \vec{F}_j \quad (4)$$

where F_j was the j -th moth. b was the logarithmic spiral shape constant. t ranged from -1 to 1, and $\vec{D}_t$ was the length from the i -th moth to the j -th flame as expressed in equation (5).

$$\vec{D}_t = \left|\vec{F}_j - \vec{M}_t\right| \quad (5)$$

where t was the step size of the moth's defective flight. The moth position defined in equation (4) had limitations that could lead the MFO

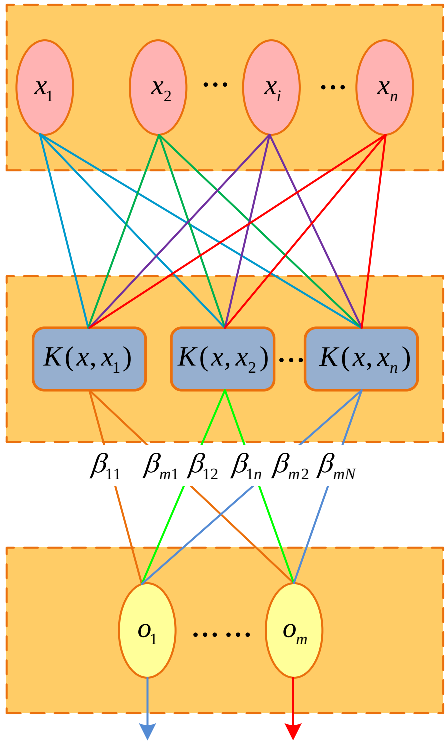

Figure 2. Schematic diagram of KELM structure.

algorithm to be involved in local optima. The flames were updated adaptively to solve this problem, and the quantity of flames was decreased incrementally to reduce the calculation time and improve operational efficiency. The flame update expression was shown in equation (6).

$$flame_{no} = round(N - k * \frac{N-1}{T}) \quad (6)$$

where N was the maximum number of flames. k and T represented the current and the maximum number of iterations, respectively. When iteration ended, the best moth position when the condition was satisfied was determined as the best return value obtained. The Extreme Learning Machine (ELM) algorithm, implemented as a kernel with the K function, was defined as a kernel limit learning machine, which was an improvement on the ELF algorithm to give it more stable performance and generalization capability. The structure of the KELM was shown in Figure 2. The K function mentioned in the study was a kernel function. For the output function was expressed in equation (7).

$$f(x) = \begin{bmatrix} K(x, x_1) \\ K(x, x_N) \end{bmatrix}^T (\frac{I}{C} + \Omega_{EML})^{-1} T \quad (7)$$

The kernel function for KELM was the Gaussian kernel function, which was shown in equation (8).

$$K(u, \upsilon) = -\exp(-\gamma \|u - \upsilon\|^2) \quad (8)$$

The KELM algorithm is a fast learner and has generalization ability [19, 20]. Therefore, it has been used extensively to solve parameter optimization and model prediction. In this study, the SNFO algorithm was combined with the KELM algorithm to address the problem of soil erosion classification prediction in maize fields and to improve its accuracy. The SMFO-KELMD soil erosion prediction model was shown in Figure 3. Faced with the problem of classifying and predicting soil erosion, the penalized, kernel

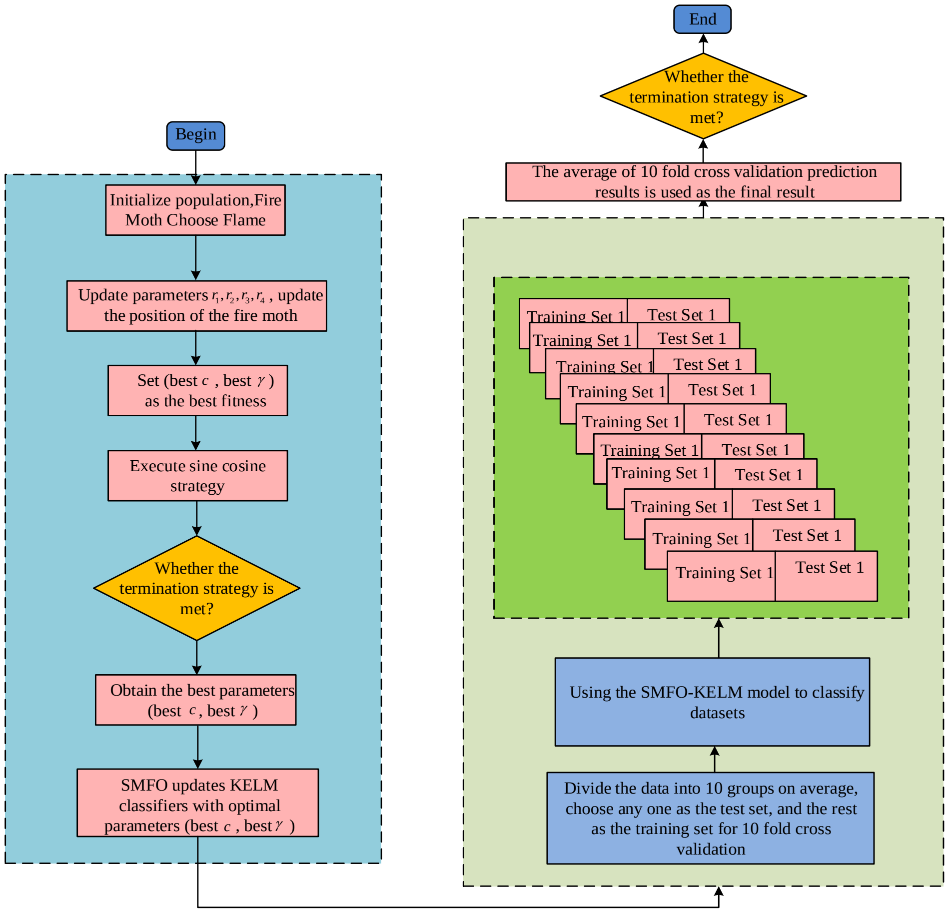

Figure 3. Flow chart of SMFO-KELMD based soil erosion prediction model.

parameters in SMFO-KELMD were used to accurately classify the soil erosion problem. In Figure 3, it acted on the model optimization and classification evaluation process. To obtain accurate and error-free results, the performance of the classifier was evaluated using the crossover method when validating the classification evaluation model by dividing the data into ten random groups. Nine of which were chosen to be training set and the rest one to be test set. The final evaluation metrics included accuracy, Mathew's correlation coefficient, sensitivity, and specificity. Because the samples were randomly selected, the ten cross-tests did not reflect whether the classification was correct or not. So, based on this, ten times ten cross-validations were performed for all methods, and the resulting values were finally selected and averaged for the final evaluation result.

Improved multi-strategy mechanism grey wolf algorithm (SLEGWO) precision fertilization model and elite enhanced integrated particle algorithm (GCLPSO)

SLEGWO was built on the foundation of the GWO, obtained by combining the SMA, LF, OBL, and GS strategies, which could be well applied to optimally solve the nutrient constant equation coefficients of the fertilizer effect equation and improve the model over-fitting effect of fertilizer application to predict the best fertilizer application ratio and maximum yield. The hierarchy of the GWO was shown in Figure 4. GWO was introduced in 2014 after studying the hierarchy and hunting strategies of wild grey wolves. Wolves were classified into four classes according to their strength including alpha (α), beta (β), delta (δ), omega (ω) and the best wolves were α, β, and δ, helping other wolves to explore a more favorable survival space. The behavior of wolves to identify prey to surround them corresponded to GWO as shown in equation (9).

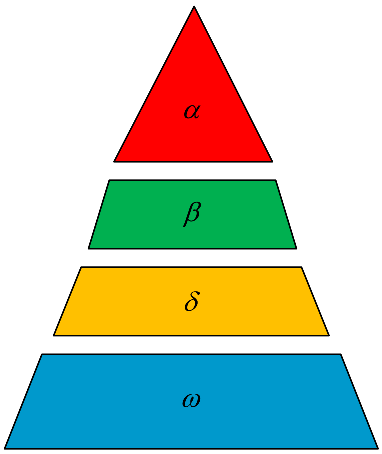

Figure 4. The hierarchical system of grey wolves.

$$\begin{cases} \vec{D} = \left|\vec{C} * \vec{X}_p(t) - \vec{X}(t)\right| \\ \vec{X}(t+1) = \vec{X}_p(t) - \vec{A} * \vec{D} \end{cases} \tag{9}$$

where $\vec{A}$ and $\vec{C}$ were the coefficient vectors. $\vec{X}_p$ was the prey position vector and $\vec{X}$ was the grey wolf position vector. The expressions for $\vec{A}$ and $\vec{C}$ were shown in equation (10).

$$\begin{cases} \vec{A} = 2\vec{a} * \vec{r}_1 - \vec{a} \\ \vec{C} = 2\vec{r}_2 \end{cases} \tag{10}$$

As the iteration continued to increase, $\vec{a}$ decreased from 2 to 0. $\vec{r}_1$ and $\vec{r}_2$ were in the interval [0, 1]. The hunt was led by α wolves, and the wolves were ranked from high to low as α, β, and δ played the role of assisting α to determine the location of the wolves, giving instructions to ω to implement the hunting action. The hunting process was described by the expression of equation (11).

$$\begin{cases} \vec{D}_a = \left|\vec{C}_1 * \vec{X}_a - \vec{X}\right| \\ \vec{D}_\beta = \left|\vec{C}_2 * \vec{X}_\beta - \vec{X}\right| \\ \vec{D}_\delta = \left|\vec{C}_3 * \vec{X}_\delta - \vec{X}\right| \end{cases} \tag{11}$$

$\vec{X}$ was calculated as shown in equation (12).

$$\begin{cases} \vec{X}_1 = \vec{X}_a - \vec{A}_1 * (\vec{D}_a) \\ \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 * (\vec{D}_\beta) \\ \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 * (\vec{D}_\delta) \end{cases} \tag{12}$$

The mean value of $\vec{X}(t+1)$ was shown in equation (13).

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{13}$$

The GWO algorithm is widely used in practical problems due to its advantages of simple parameters, fast convergence, and easy implementation. In the face of the gradual increase in spatial dimensionality, the convergence speed (CS) of the GWO has turned slower. To accelerate the CS and not drop into local optimum, the GWO is improved and optimized using a multi-strategy mechanism, which consists of the following strategies of reverse learning strategy, slime foraging strategy, Levi's flight strategy, and greedy selection strategy. The greedy selection strategy selected the optimal position from mucus foraging and Levi's flight strategy maintained the optimal solution of SLEGWO and removed other solutions. The expression for the greedy selection evaluation function was shown in equation (14).

$$\begin{cases} \vec{X}_{SMA}(t),\ f(\vec{X}_{SMA}(t)) < \vec{X}_{levy}(t) \\ \vec{X}_{levy}(t),\ f(\vec{X}_{levy}(t)) < \vec{X}_{SMA}(t) \end{cases} \tag{14}$$

Therefore, the improvement of GWO was SLEGWO, and the algorithm flow chart for SLEGWO was shown in Figure 5. The SLWGWO algorithm was applied to the problem of precision fertilization of maize fields, i.e.

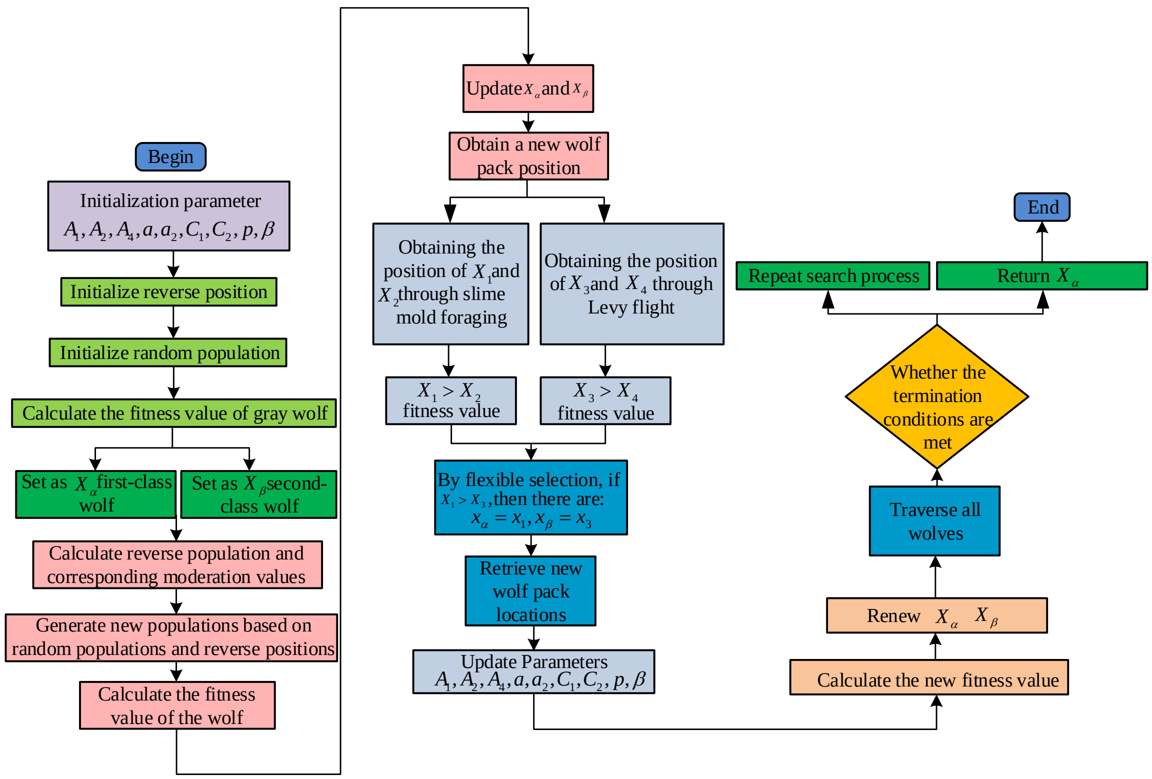

Figure 5. Algorithm flowchart of SLEGWO.

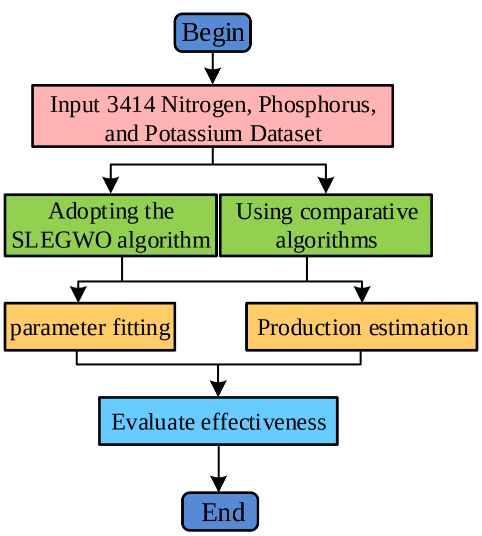

Figure 6. Flow Chart of SLEGEO-NPK precision fertilization method.

monitoring the soil environment and analyzing soil conditions for targeted fertilization. The SLWGWO precision fertilization model was fitted by the algorithm to the fertilizer effect function and the obtained function model was used to predict the fertilizer application rate and to estimate the maximum value of yield. The proposed SLWGWO algorithm IR was chosen to be fitted to other algorithms to obtain equation coefficients for the fertilizer effect ambiguity, and the SLWGWO algorithm for the NPK ternary fertilizer effect function precision fertilizer application route was shown in Figure 6.

In addition to fertilizer application, crop disease control is also critical, and the classification and diagnosis of crop diseases is an important need in the field of smart agriculture. Traditional identification of diseases mainly relies on manual identification, which is influenced by the instability of experience and is costly. With the development of computer images, the use of algorithms for real-time monitoring of maize and timely diagnosis of crops can raise the accuracy of judgment and reduce the cost of diagnosis and

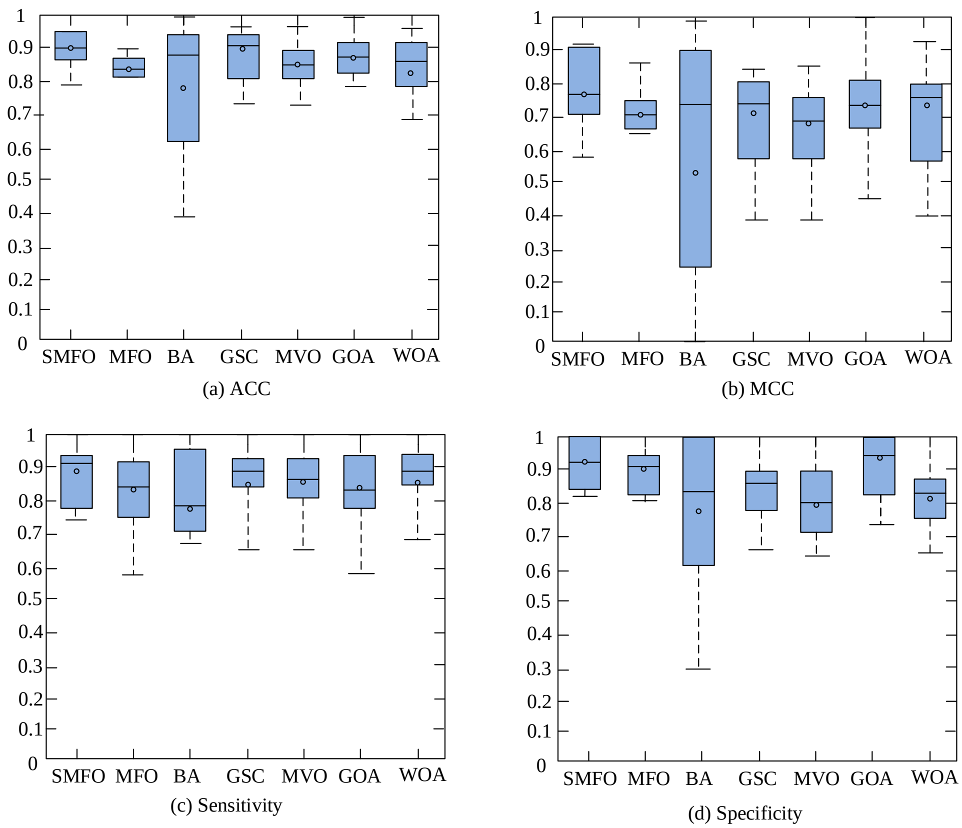

Figure 7. Box graph of KELM model combining SMFO-KELM with Original algorithm.

the economic loss of crops. It was performed for the velocity update term in the classical PSO, replacing its historical optimal term with a new integrated learning factor. If the number of stalls of a particle exceeded a threshold, another integrated learning factor needed to be generated for that particle in the past. The composite learning factor would select the better of the two random particles, and the best particle and the random learning probability were combined to obtain the composite learning factor, so the algorithm would still have a local optimal solution problem. Based on the CLPSO algorithm, the GWO was introduced to select the leading wolf strategy to obtain three locally optimal solutions, β, δ, for the alternative elite optimal solutions.

Results and discussion

Application of SMFO-KELM algorithm for land erosion classification and validation of the SLEGWO precision fertilizer application model

Taking the corn experimental field in Suihua City Heilongjiang Province, China as the experimental site for this study, the soil data used for the experiments came from a cornfield area where soil erosion was heavily influenced by heavy rainfall, so the area was used for the experiments in a more comparable way. The commonly used factors in agriculture to represent soil erosion included 10 influencing factors as EI30, slope degree, OC topsoil, pH topsoil, bulk density, topsoil porosity, soil fraction, clay fraction, sand fraction, and soil cover rate, and were named as X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8, X_9, and X_{10} with the average values of 135.27, 28.37, 1.93, 5.85, 1.40, 53.02, 35.07, 30.25, 36.33, and 53.66, respectively. To guarantee the fairness and validity of the experiments, comparisons among the algorithms were made under the

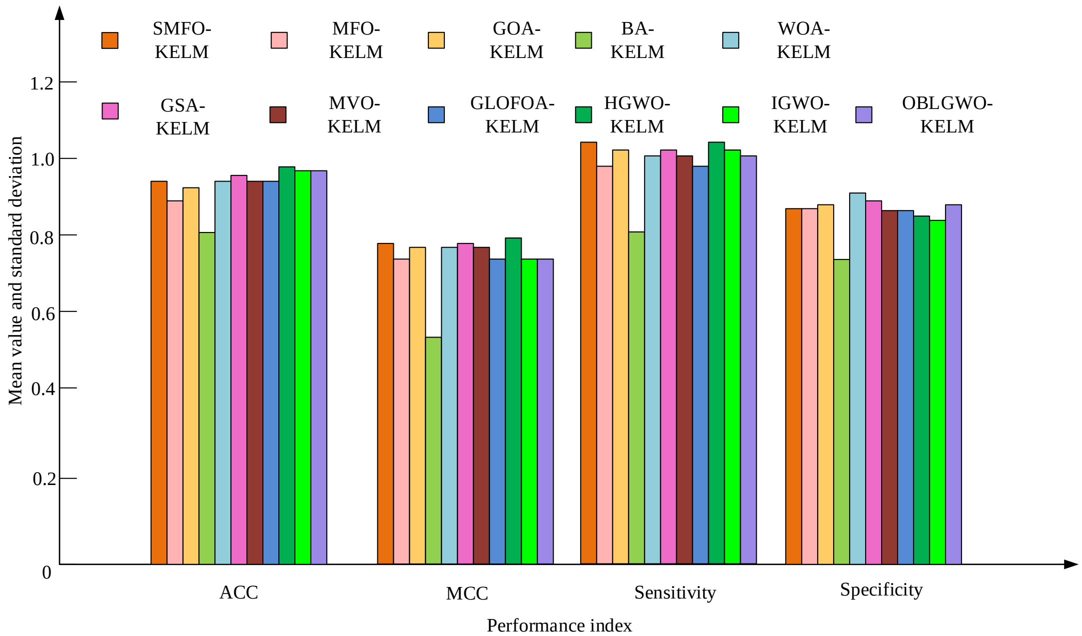

Figure 8. Histogram of SMFO-KELM model and comparison model.

same conditions. The effect of random conditions was decreased by testing all algorithms 30 times individually. Population size and maximum value were set to 20 and 100, respectively. SMFO-KELM was compared to the six classical original optimization algorithms including MVO-KELM, MFO-KELM, BA-KELM, GSA-KELM, WOA-KELM, and GOA-KELM in terms of 236 sets of 2 classifications consisting of 10 influencing factors. The results were expressed in ACC, MCC, sensitivity, and specificity (Figure 7), where ACC, MCC, sensitivity, and specificity showed the best behavior in SMFO-KELM, which indicated that SMFO-KELM was the best and most accurate algorithm among the five categories (Figure 8). SMFO-KELM generally outperformed the competing models compared to the traditional method due to the highest optimization capability of the SMFO optimizer used. One of the worst-performing models was BA-KELM. To test the reliability, statistical results, and robustness used in addressing the global optimality of the soil classification prediction problem significantly better than other algorithms, the study used the KELM with superb learning and generalization capabilities in combination with SMFO to predict the soil erosion classification problem. The results showed that the KELM classifier based on the SMFO algorithm outperformed other classifiers in four performance metrics and SMFO-KELM was an improvement on KELM that effectively improved the prediction of soil erosion classification.

SLEGWO was compared with 11 well-known optimizers competing algorithms including WOA, GWO, MFO, SCA, SSA, MVO, IGWO, RWGWO, MEGWO, CAGWO, and HGWO. The results were shown in Table 1. SLEGWO ranked first and best among the 11 compared algorithms with the Friedman test. The mean value represents the result of the mean fitness obtained from the Freidman test analysis. The smaller the mean value, the better the effectiveness, which was significantly better than other improved algorithms. In the SLEGWO precision fertilizer model validation experiment, SLEGWO was used to explore the maximum value of the above three fertilizer effect function models. The objective function was the residual of the fertilizer effect function with dimension 3. The maximum

Table 1. Mean and standard deviation.

Function	Rank	Mean	+/-/=
SLEGWO	1	2.3887	-
IGWO	5	6.2547	23/4/3
HGWO	9	6.9530	22/3/3
MEGWO	2	4.2105	23/6/3
CAGWO	6	6.3558	23/4/3
RWGWO	3	5.6002	25/4/0
GWO	7	6.7035	25/4/3
MVO	10	7.8023	24/4/3
WOA	4	5.6034	21/6/3
SCA	12	10.2350	27/1/1
SSA	8	6.7036	25/5/0
MFO	11	8.3805	27/2/1

Table 2. Mean and standard deviation.

kg / hm^2	SLEGWO	GWO	ABC	BA	SSA	PSO	WOA
Nitrogen	253.1575	233.774	234.2765	234.2635	234.2372	234.2578	234.5402
Phosphorus	107.2683	103.514	104.3582	103.5417	103.4510	103.4402	103.430
Potassium	108.3251	98.383	97.3255	98.0245	97.035	96.758	96.258
Maximum output	8995.853	8868.254	8878.351	8878.351	8878.351	8878.351	8878.351

number of iterations was 50,000 and the population size was 30. The minimum values of the maximum crop yield and the corresponding NPK fertilizer application with SLEGWO and other six algorithm models were shown in Table 2. The results obtained by other comparison methods were all around 8,868 – 8,995 kilograms per hectare. When the SLEGWO ratio of nitrogen / phosphorus / potassium in the fertilization expression was 253.1575 / 107.2683 / 108.3251 kg/hm^2, the estimated yield of the Nong'an corn experimental field was 8,995.853 kg/hm^2. The range of fertilization amount was within the range of reasonable fertilization, and the yield had increased by 127.599 kilograms per hectare compared to the second-ranked GWO algorithm. The results proved the superiority of the SLEGWO method over other comparative algorithm models in finding the fertilizer effect function.

The population intelligence optimization algorithm has the merits of having the internal constructs encapsulated and better portability in the maximum yield obtained compared to traditional methods. The put-forward algorithm GCLPSO was compared with 15 other comparative algorithms at CEC2017 with the function choice of unimodal function C1 and combined function C30 and the results were shown in Figure 9. The accuracy and CS of the GCLPSO function were higher than the other algorithms in the unimodal C1 function. In the C30 function, as the iterative process progressed, the CS in the early stages was slower than the other algorithms, and a significant improvement in accuracy occurred in the later stages. Thus, the outcomes obtained from the comparison of observations in Figure 9 showed that the GCLPSO algorithm achieved the best fitness values on most of the benchmark functions, and the GCLPSO algorithm had a clear advantage in C1 and C2. The study proposed GCLPSO with the elite incremental strategy, using GCL to raise the CS and accuracy of image segmentation. GCLPSO was built on the ground of PSO, and the integrated learning strategy was chosen to improve it.

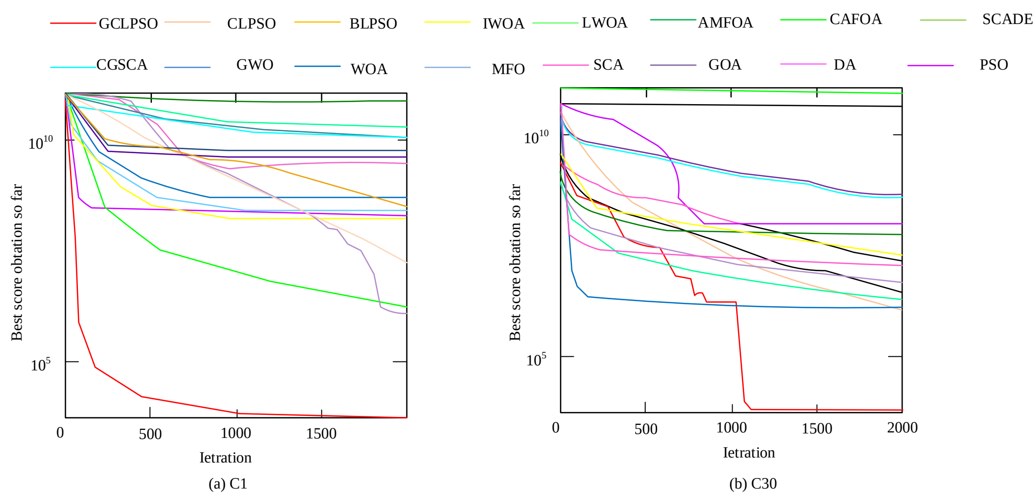

Figure 9. Comparison of convergence curves between GCLPSO and classical and other advanced algorithms.

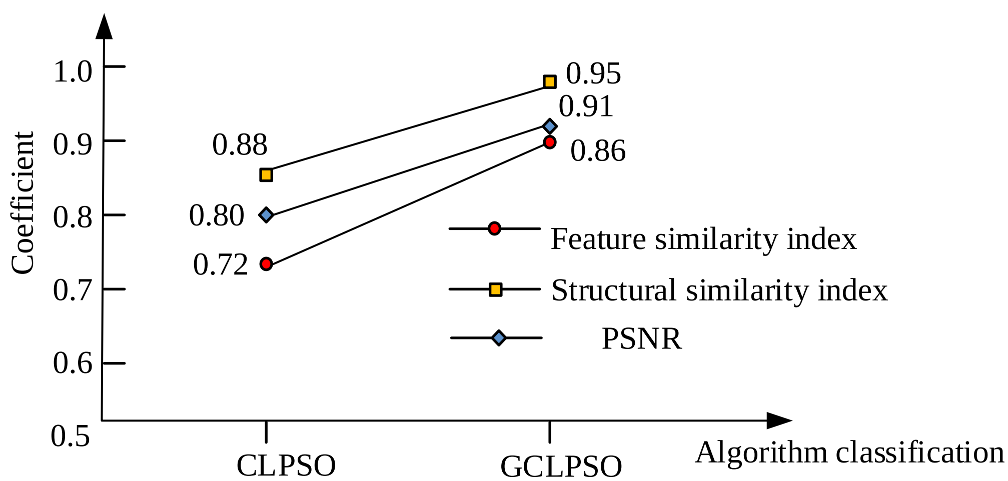

Figure 10. Comparison of performance between CLPSO algorithm and GCLPSO algorithm.

GCLPSO for disease image segmentation

In this study, GCLPSO was used for multi-threshold segmentation (MS) of maize disease. To verify the performance of GCLPSO on MS, it was compared with the original CLPSO and the improved GCLPSO algorithm, respectively. The segmented results were evaluated using the feature and structural similarity index and peak signal-to-noise ratio (PSNR) (Figure 10). The results demonstrated that the feature similarity index, PSNR, and structural similarity index were all obviously raised with the highest accuracy being the structural similarity index, which rose from 0.88 to 0.95. The feature similarity index and the PSNR also increased from 0.72 to 0.86 and 0.80 to 0.91, respectively. It was verified that the proposed GCLPSO algorithm was able to achieve better overall segmentation accuracy in solving the MS of maize rust than the previous algorithm. It was verified that the put-forward GCLPSO algorithm could realize better segmentation accuracy than the previous algorithm in solving the overall effect of MS of maize rust spot disease.

Conclusion

In the face of all the problems in intelligent agriculture, population intelligence optimization has a broad application foreground, while in practice there are problems such as susceptibility to interference, being easy to drop into local optimization, and insufficient accuracy. This research focused on enhancing and optimizing the MFO, GWO, and PSO algorithms. The MFO algorithm was improved using the positive cosine strategy to address land erosion prediction based on the ELF algorithm. The GWO algorithm was enhanced using SLE and utilized in designing an accurate fertilizer application model for intelligent agriculture. The PSO algorithm was improved using GCLP and applied to maize disease image segmentation. The results demonstrated that SMFO-KELM significantly improved the prediction ability of soil erosion classification. SLEGWO outperformed other improved algorithms, and GCLPSO achieved superior segmentation accuracy in addressing maize rust spot disease in MS. The application accuracy of these improved population intelligence algorithms was enhanced, overcoming vulnerability to interference. However, there are still shortcomings in the improved population intelligence optimization algorithm. As smart agriculture is complex and diverse, solving its problems requires the integration of multiple factors, for example, in the precision fertilizer model, analogous experiments can be carried out by increasing the type of fertilizer.

Acknowledgements

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