

Received: 11 November 2022 Accepted: 15 March, 2023

DOI: <https://doi.org/10.33182/rr.v8i3.16>

The optimization path of rural land transfer based on ELM algorithm in the context of rural revitalization

Xin Liu*¹

Abstract

In the context of rural revitalization, rural land transfer is an important way to promote economic development in poor areas, and it is urgent to carry out an in-depth analysis related to rural land transfer in poor mountainous areas. This paper proposes to construct an LAFSA-ELM prediction model of rural land transfer based on ELM algorithm and LAFSA algorithm, and set evaluation indexes based on sample data. Based on the comparative analysis of the subjective reasons for willingness to transfer land, the highest percentage of the reasons for willingness to transfer is "V3 (high cost, hard work, low income)" (68.4%), while the highest percentage of the reasons for unwillingness to transfer is "M1 (need to secure food rations) The highest percentage of the reasons for not willing to transfer is "M1 (need to guarantee food rations)", which is 50.7%. This is a preliminary judgment that farmers' willingness to transfer land is closely related to their livelihood needs. To study the accuracy comparison results of LAFSA-ELM land transfer optimization prediction model, the accuracy rate of LAFSA-ELM algorithm for land transfer optimization prediction model stays in the range of 84%-92%, and in terms of accuracy above, LAFSA-ELM algorithm performs better compared to the two algorithms alone. This study is beneficial to the optimization of rural land transfer, thus promoting rural land transfer in poor mountainous areas and improving land use efficiency.

Keywords: Remittance, social development, human resource development, MMQR

Introduction

In the process of China's development, the land issue has been an important issue facing China, and many systems have been implemented around the land issue in China. For China's rural areas, the continuous reform and promotion of land policy is the most important part of the work related to China's rural areas (S. H., 2010).

With the implementation of land policy, it can help China to adjust the optimal layout of rural land resources between urban and rural areas, and the average income of farmers has increased.

China also points out that in the process of carrying out land policy promotion and implementation, the ownership issues involved in this process must be fully clarified, so as to

¹ School of Economics and Management, Zhengzhou Normal University, Zhengzhou, Henan, 450044, China

Corresponding author: Xin Liu (LXPY20160808@zznu.edu.cn)

ensure that the implementation of relevant policies can be smoother and also enhance the credibility of government departments (C., 2010; Nechaev & Zhavoronkova, 2013).

It is proposed to break the traditional thinking, strengthen innovation, and accelerate the development of rural and agricultural modernization; to promote the continuous development of rural areas with creative thinking and new methods to drive the work of "three rural areas", to continuously improve the efficiency of resource allocation in rural areas, and to avoid the waste of resources (W. H., 2011; Kong Q, 2013).

The relevant departments have further clarified the content of the "three rights" and pointed out that in the process of land policy reform, farmers' rights to land should be guaranteed, the relevant contracting rights should be stable and the management rights of land should be innovated, so that the reform and promotion of land policy can burst out with greater vitality (Liu, Lu, & Yan, 2016; Qi W, 2014).

Due to the large area of rural land in China and its fragmentation, rural land exists in all provinces and cities, and the lack of empirical analysis in the current study of rural land transfer makes the results of empirical analysis unconvincing (F., 2017; Yang X H, 2015).

Therefore, in this paper, the problem of rural land transfer is studied and analyzed by means of data analysis, and the final results are more convincing, so that the final countermeasure suggestions can be more scientific, which can further regulate the land transfer situation in rural areas of China and provide further guidance for the future land transfer work.

The solution of the rural land transfer problem will be beneficial to the development of China's rural areas and help China achieve the goal of rural revitalization (Chu C W, 2012; Wei-Qiu N I, 2011).

The literature (Xiaomei L I, 2019) elaborates the practical significance as well as legal problems of rural land transfer based on rural revitalization strategy from the perspective of rural economic construction and practical development, and ensures the practical solutions and legal regulations to solve the legal problems of rural land transfer in the perspective of rural revitalization strategy, so as to highlight the practical role of rural land transfer based on rural revitalization strategy.

Literature (Huang Y A, 2012) designed land transfer incentives to improve the stock of farmers' livelihood capital, optimize farmers' livelihood strategies, reduce farmers' livelihood risks, and improve farmers' sustainable livelihood development in response to the types of farmers' livelihood capital deficiency, so as to reduce farmers' dependence on various social security functions of land, promote rural land transfer, and ultimately realize large-scale land operation, farmers' income increase, and rural economic and social development.

The literature (X., 2012) has strengthened the support for rural land transfer through finance, which makes the transfer of rural land more and more reasonable and orderly.

However, at present, some rural areas still face difficulties in the process of land transfer, such as the credit support system is not sound enough, the insurance support system is not perfect enough and the supporting support system needs to be optimized.

In this regard, it is necessary to accelerate the sound credit support system, improve the insurance support system, and optimize the supporting support system.

In the literature (Xiao B, 2011), it is proposed that the rural land transfer process of "land outflow - intermediary service organization - land inflow" is formed through strict control of the transfer process, and agricultural cooperatives are encouraged to connect with formal financial institutions such as banks to cope with it.

In order to realize the orderly, standardized, and moderate scale of rural land transfer, and to realize the modernized agricultural business model with scale efficiency and the application of advanced agricultural technology, the government actively promotes the development of large-scale rural land transfer by stabilizing ten land property rights(L., 2012).

Promulgating corresponding laws and regulations, and improving the service mechanism of the transfer market. In this paper, the optimization path of rural land transfer using ELM algorithm is mainly studied and analyzed around IAFSA algorithm parameter improvement and ELM prediction algorithm.

The prediction of rural land flow optimization is calculated by inputting the data of influencing factors measured at a later stage into the constructed equations to obtain the prediction results. Since rural land flow optimization is a complex nonlinear system.

Ordinary mathematical regression equations are difficult to establish and the prediction results are poor.

To ensure the real feasibility of the study, 100 training tests were conducted on the sample data to study the accuracy comparison results of the IAFSA-ELM land transfer optimization prediction model.

IAFSA-ELM prediction model for rural land transfer

The mechanism of the factors influencing the willingness of rural land transfer in poor mountainous areas is consistent with the common sense judgment but also has some specificity, and the match between farmers' willingness to transfer land and their transfer behavior is poor, which is closely related to the relatively backward level of economic development in poor mountainous areas, the low literacy level of many farmers and their attachment to the land.

The AFS-ELM prediction model of rural land transfer is developed to improve the parameters of the artificial fish swarm algorithm, and coupling the improved artificial fish swarm algorithm with the extreme learning machine to solve the shortcomings of the extreme learning machine, so as to build the prediction model of rural land transfer.

IAFSA algorithm parameter improvement

IAFSA algorithm and improvement analysis

The artificial fish swarming algorithm is a bionic optimization algorithm proposed by Xiaolei Li, in which the artificial fish activities are visually simulated by the parameter "field of view", as shown in Figure 1. The core of the fish swarming algorithm is the four behaviors of individual artificial fish, i.e., feeding behavior, swarming behavior, tail-chasing behavior and random behavior.

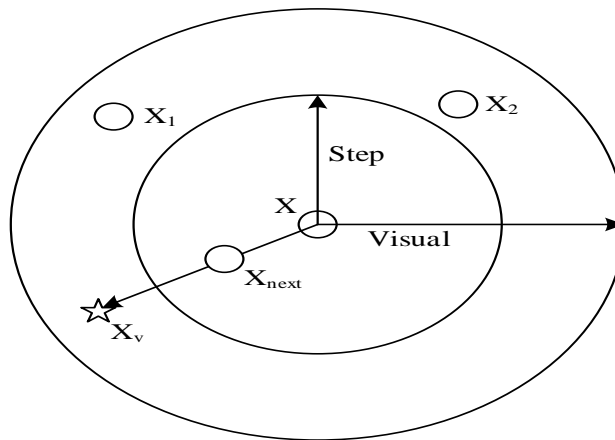


Figure 1: Visual simulation process of artificial fish

The meanings of the letter parameters involved in the four behaviors of the artificial fish swarming algorithm are shown in Table 1.

They are described briefly below. Foraging behavior is the artificial fish foraging process is to simulate the process of fish finding food and swimming to food, the state of artificial fish i is X_i and the new state X_j is:

$$X_j = X_i + Visual * Rand() \quad (1)$$

$Rand()$ in Equation (1) is a random number belonging to $(-1,1)$. If the new state X_j has a higher food concentration, then move one step towards the new state as shown in equation (2).

If the new state X_j is not better than the current state, then try to select the new X_j .

After the maximum number of attempts, if no new state is found, then move one step randomly.

$$X_i^{t+1} = X_i^t + \frac{X_t - X_i^t}{\|X_j - X_i^t\|} * step * Rand() \quad (2)$$

Table 1: List of parameter meanings

Name	Status	Food concentration	Step length	Maximum number of iterations
Symbols	X	Y	$step$	$max\ gen$
Name	Perspectives	Congestion factor	Maximum number of attempts	Population size
Symbols	$Visual$	δ	$trynumber$	N

The number of artificial fish in the current field of view ($d_{ij} < Visual$) is n_f and the average

state is $\frac{Y_c}{n_f}$. If $\frac{Y_c}{n_f} > \delta Y_i$, it means that the food concentration at the average state is higher, then move one step towards this state and perform the clustering behavior as shown in Equation (4), and if the food concentration at the average state does not meet the requirement, continue to act according to the foraging behavior.

$$X_c = \frac{\sum_{i=1}^{n_f} X_i}{n_f} \tag{3}$$

$$X_i^{t+1} = X_i^t + \frac{X_c - X_i^t}{\|X_c - X_i^t\|} * step * Rand() \tag{4}$$

Artificial fish within the current field of view ($d_{ij} < Visual$) looking for the individual in the best condition X_j , the food concentration at its state is Y_j . If $Y_j/n_f > \delta Y_i$, then it means that the food concentration at the individual in the best condition is higher, then the other artificial fish want to move one step for that individual, as shown in equation (5), if the food concentration of that individual does not meet the requirements, continue to act according to the foraging behavior.

$$X_i^{t+1} = X_i^t + \frac{X_j - X_i^t}{\|X_j - X_i^t\|} * step * Rand() \tag{5}$$

When the foraging behavior in foraging reaches $maxgen$ time, if the food concentration Y is not yet satisfied, then a state is randomly selected in the visual field and then moved one step in that direction, and the movement process is shown in Equation (6).

$$X_i^{t+1} = X_i^t + \text{Visual} * \text{Rand}(\quad) \quad (6)$$

Based on the above description of the fish swarm algorithm, the optimal search steps of the artificial fish swarm algorithm are shown in Figure 2. The artificial fish swarm algorithm has the characteristics of fast, sensitive, flexible and adaptive.

The artificial fish swarm algorithm has a very good optimization-seeking ability, but there are also problems due to its own characteristics, specifically its late convergence speed is slow and the accuracy of the optimal solution is not high.

This also affects the prediction accuracy and prediction efficiency of the whole prediction model.

In recent years, experts and scholars have conducted a lot of research on the improvement of the artificial fish swarm algorithm.

After reviewing a lot of literature, the improvement methods mainly include the following directions: the artificial fish swarm algorithm is improved from itself mainly in the following three aspects: improvement of the parameters of the artificial fish swarm algorithm, improvement of the four behaviors of the artificial fish swarm algorithm, and improvement of the neighborhood structure of the artificial fish swarm.

The parameters of the artificial fish swarming algorithm mainly exist in these four behaviors.

According to the list of parameter meanings and the analysis of these four behaviors, it is found that the parameters that affect the speed and result of the artificial fish swarming algorithm are mainly the visual field of view and the step length parameter, so the improvement of these two parameters can solve most of the problems.

Since the core of the artificial fish swarm algorithm lies in the four behavioral ways of the individual artificial fish, some scholars take the improvement of these behaviors as the solution, and some scholars also introduce some new behaviors to optimize the search performance.

Neighborhood structure is the key structure in various behavioral choices of fish swarm algorithm, and some scholars start from the neighborhood structure to improve the artificial fish swarm algorithm.

At present, different swarm intelligence algorithms have developed improvement methods suitable for their own characteristics, and all of them have their unique advantages. By mixing different swarm intelligence algorithms.

We can make different algorithms play their own advantages and make up for their own disadvantages, so that the performance of the algorithm can be improved.

Therefore, mixing artificial fish swarm algorithms with other algorithms is the second major direction of improvement, which mainly includes mixing with particle swarm algorithms, mixing

with genetic algorithms, mixing with ant colony algorithms, and mixing with other algorithms.

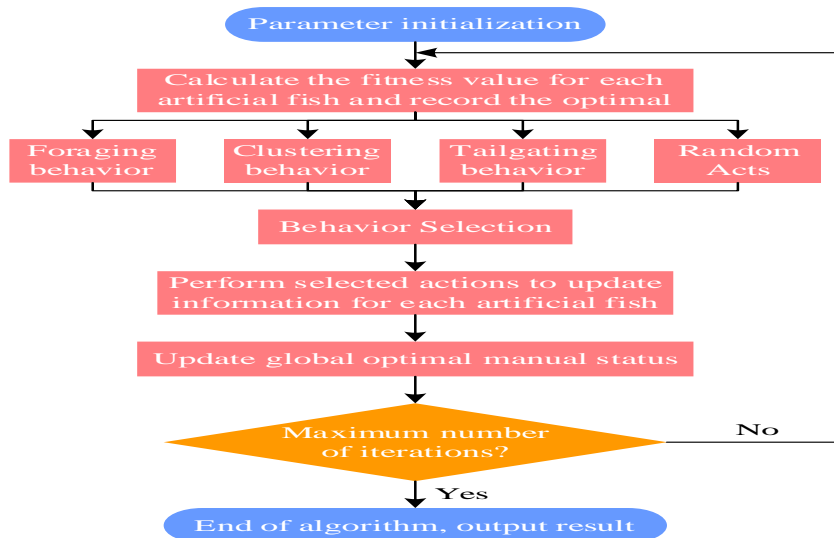


Figure 2: Optimization steps of basic artificial fish swarm algorithm

Lévy flight based IAFSA algorithm construction

According to the above improvement analysis, the parameters of the artificial fish swarm algorithm are chosen to be improved for the conditions of stable prediction and high prediction efficiency required by the optimal prediction of rural land transfer, which can meet the requirements and also be convenient and concise.

The fixed step length is the key to solve the shortcomings of the artificial fish swarm algorithm itself, because the step length is set to a fixed value, the moving step length of all four behaviors of the artificial fish is the same, when the step length is set to a relatively large value, the artificial fish will be faster when performing these four behavioral methods, but when the artificial fish all reach around the optimal value, the large moving step length will make the artificial fish cross the optimal value, thus repeatedly in the optimal value. When the step length is set to a smaller value, it takes more time for the artificial fish to reach the optimal value, and due to the randomness, the artificial fish may move to the wrong direction and reach the local extreme value, which will affect the final optimal search result. For the above reasons, this problem can be solved by turning the fixed step into a dynamic step.

A random walk model is found, i.e., the Lévy flight model satisfying the Lévy distribution, and the fixed step is replaced by this dynamic step to meet the demand of large step value in the early stage and small step value in the later stage. In the following, the Lévy flight model is introduced into the fixed step, and the fixed step of the artificial fish swarm algorithm is step, and the step parameter after the introduction of Lévy flight becomes:

$$Step' = step \otimes Levy(\beta) \tag{7}$$

In Equation (7): **step** denotes a fixed step, \otimes denotes a point-to-point multiplication, and Lévy (β)(β) denotes a Lévy random number that follows a Lévy-probability distribution.

$$Levy(\beta) \square \frac{\varphi \times \mu}{|v|^{1/\beta}} \tag{8}$$

Equation (8): u,v obeys the standard normal distribution, β is a constant (generally $0 < \beta < 2$), according to the iterative debugging algorithm, this algorithm takes $\beta=1.5$. The formula for calculating the value of φ is shown in Equation (9):

$$\varphi = \left\{ \frac{\Gamma(1+\beta) \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left[\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\frac{\beta-1}{2}}\right]} \right\}^{\frac{1}{\beta}} \tag{9}$$

Γ in Equation (9) is the standard Gamma function.

Extreme learning machine predictor and its parameter search optimization

ELM prediction algorithm

ELM is an algorithm proposed by Huang et al. Its fast learning speed and good generalizability can achieve near error-free construction of arbitrary function models for prediction or classification. Its network structure is shown in Figure 3. According to the principle of the algorithm, the following is a brief description of the prediction process of the extreme learning machine for the optimal prediction of rural land transfer. Let the influencing factor of rural land flow optimization prediction be x_i ($i=1,2,\dots,12$), then the training sample is represented as $[x_i, y_i]$ ($i=1,2,\dots,12$), the implied layer neurons are k , and the excitation function is $g(x)$. Then the prediction equation of the limit learning machine predictor can be expressed as:

$$y_i = \sum_{j=1}^k \beta_j g(a_j x_i + b_j) \tag{10}$$

Equation (10) β represents the output weights, a represents the input weights, and b represents the bias values. Can be expressed by the matrix as:

$$H\beta = Y \tag{11}$$

Among them:

$$H(a_1, \dots, a_k, b_1, \dots, b_k, x_1, \dots, x_{12}) = \begin{bmatrix} g(a_1 \cdot x_1 + b_1) & \dots & g(a_k \cdot x_1 + b_k) \\ \vdots & \dots & \vdots \\ g(a_1 \cdot x_{12} + b_1) & \dots & g(a_k \cdot x_{12} + b_k) \end{bmatrix}_{12 \times k}$$

$$\beta = [\beta_1^T, \beta_2^T, \dots, \beta_k^T], Y = [y_1^T, y_2^T, \dots, y_k^T] \quad (12)$$

During model training, a_j and b_j are also generated randomly without adjustment, and the least squares solution $\hat{\beta}$ is solved by Eq. (13):

$$\hat{\beta} = H^+ Y \quad (13)$$

H^+ in Equation (13) is the matrix obtained from the generalized inverse of matrix H . This is the process of training the ELM algorithm prediction and building the ELM prediction model.

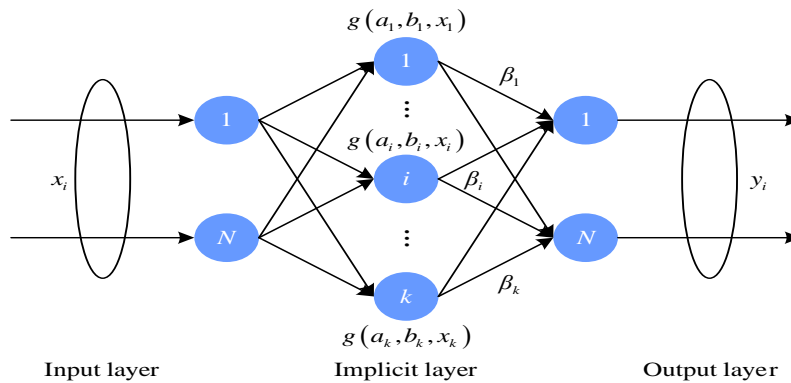


Figure 3: ELM structural model

IAFSA-ELM prediction algorithm

For the rural land transfer optimization prediction problem, this kind of time-sensitive neural network is needed to provide a good guarantee for the prediction effect. Through the above brief introduction of the prediction process of ELM, it can be known that a_j and b_j are generated randomly, that is to say, their connection weights and implied layer thresholds are generated by random initialization, which may result in different prediction values of its output for the same samples, and the performance of prediction cannot be guaranteed. The artificial fish swarm algorithm is improved based on the fast and efficient optimization-seeking capability of the Levy flight-based artificial fish swarm algorithm for the weights and thresholds of the extreme learning machine, so that they are no longer generated by random initialization. To solve this problem is to find the optimal weights and thresholds $W=(a,b,\beta)$ i.e., to solve the minimum cost function $E(W)$, which is expressed in the mathematical formula as:

$$\operatorname{argmin}_{W=(a,b,\beta)} E(W) = \operatorname{argmin} \|H(a_j, b_j) \cdot \beta - Y\|^2 \quad (14)$$

$$s.t. \sum_{j=1}^k \beta_j g(a_j \cdot x_i + b_j) - y_i = \varepsilon_i \quad i=1, \dots, 12 \tag{15}$$

Combining Equation (14) and Equation (15), the final objective function of IAFSA-ELM can be expressed by Equation (16).

$$Fitness(\hat{a}, \hat{b}, \hat{\beta}) = \arg \min_{w=(\hat{a}, \hat{b}, \hat{\beta})} E(W) = \arg \min_{w=(\hat{a}, \hat{b}, \hat{\beta})} \|H(\hat{a}_j, \hat{b}_j) \cdot \hat{\beta} - Y\|^2 \tag{16}$$

In Equation (16): $\hat{a}_j, \hat{b}_j, \hat{\beta}_j$ is the estimated value of the input weights, bias and output weights, respectively. The specific idea of the optimization search is as follows: for each fish individual, firstly, the output matrix H and output weights β of the limit learning machine are calculated according to Eq. (12) and Eq. (13), then the objective function value of the fish individual is calculated according to Eq. (14), and the optimal state and optimal value are obtained, then the location and bulletin board information are updated, and the objective function value is calculated again, and finally, whether the maximum number of iterations is reached is judged. If the stopping condition is reached, the optimal weights and thresholds $W(a,b,\beta)$ are saved as the algorithm parameters of the extreme learning machine predictor, after which the training and prediction of the model can be performed. According to the above optimization idea, the specific steps of preparing the algorithm coupling are shown in Figure 4:

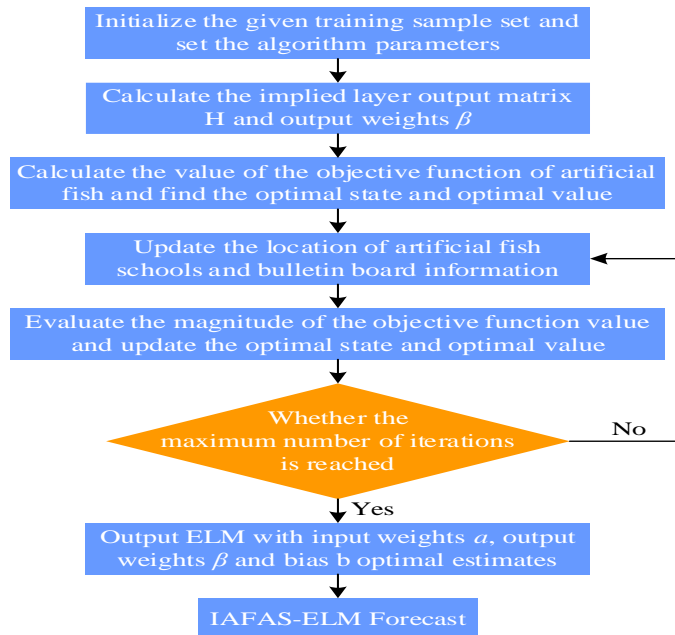


Figure 4: IAFSA-ELM Coupling Process Diagram

Construction of IAFSA-ELM prediction model for rural land transfer optimization

The prediction flow chart of the IAFSA-ELM-based prediction model for rural land transfer optimization is shown in Figure 5.

The prediction of rural land flow optimization is calculated by inputting the data of influencing factors measured at a later stage into the constructed equations to obtain the prediction results. Since rural land flow optimization is a complex nonlinear system.

Ordinary mathematical regression equation is difficult to establish and the prediction effect is not good, therefore, based on the prediction index system of rural land flow optimization determined in the early stage.

This paper combines the determined prediction model input variables and IAFSA-ELM prediction algorithm, combines the kernel principal component analysis, improved artificial fish swarm algorithm optimized limit learning machine, and constructs.

The optimized prediction model of land transfer based on IAFSA-ELM algorithm, and the mathematical expression of the prediction model is derived based on the algorithm formula and the prediction principle, as shown in Equation (17).

$$\left\{ \begin{aligned} F(x_i, y_i) &= K \cdot \alpha = [\Phi(b_1)\Phi(b_2)\cdots\Phi(b_{30})] \cdot a \\ F \text{ int ness}(\hat{a}, \hat{b}, \hat{\beta}) &= \arg \min_{W=(\hat{a}, \hat{b}, \hat{\beta})} E(W) = \arg \min_{W=(\hat{a}, \hat{b}, \hat{\beta})} \|H(\hat{a}_j, \hat{b}_j) \cdot \hat{\beta} - Y\|^2 \\ y_i &= \sum_{j=1}^k \hat{\beta}_j g(\hat{a}_j x_i + \hat{b}_j) \end{aligned} \right. \quad (17)$$

In the equation: $F(x_i, y_i)$ is the reduced-dimensional sample of kernel principal components, x_i is the input scalar, y_i is the prediction value.

K is the kernel matrix, α is the eigenvector of unit words, $b_1 \cdots b_{30}$ is the row matrix of 30 samples, $\hat{a}_l, \hat{b}_l, \hat{\beta}_l$ is the input weights and biased kernel output weights of IAFSA search, respectively, and $g(x)$ is the excitation function.

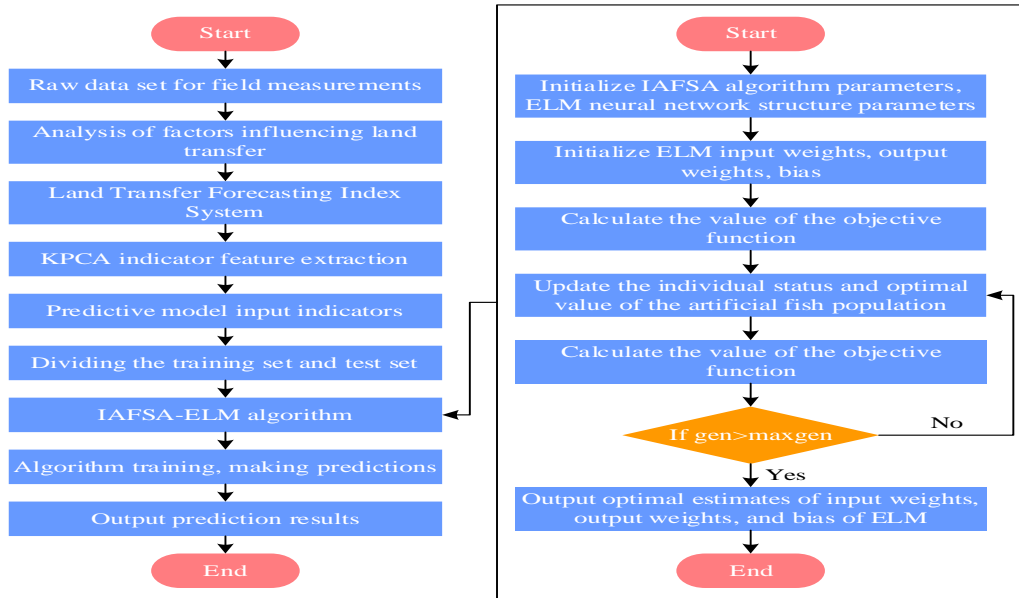


Figure 5: Flow Chart of Model Prediction

IAFSA-ELM model application and analysis

Data sources

The data used in this paper come from a special questionnaire survey conducted by the research group in August-October 2019 in poor areas of Guizhou Province, mainly in the form of questionnaires and interviews, from which questionnaires from poor mountainous areas were selected for research purposes, with a total sample of 461 and a valid sample of 457. The total number of samples was 461, and 457 samples were valid, with 99.13% validity rate. The scope of the research sample covers 19 poor mountainous counties within the jurisdiction of 6 prefecture-level cities in Guizhou Province as shown in Table 2. The research included four aspects, including farmers' own situation, farmers' family situation, farmers' village characteristics and farmers' knowledge of land policy, from which the main sample data were selected for descriptive statistical analysis in order to fully understand the characteristics of farmers in poor mountainous areas. The proportion of farmers in the age group of 31-50 years old was the largest, at 50.5%. From the perspective of farmers' education level, the largest proportion of farmers with junior high school education was 34.0%, followed by elementary school, and the proportion of farmers with high school education level or above was only 20%. Among the total income of farm households last year, the proportion of "10,000 to 30,000 yuan" was the majority, accounting for 38.2%, and the proportion of "30,000 yuan and above" was the smallest, accounting for only

13.2%, which reflects the relatively low overall income of poor mountain farm households. When asked the question "What is the income from farming in the family income", 48.5% of the farmers answered 30% or less, and only 12.9% answered 70% or more. The proportion of people working outside the village" was generated based on the variables of "how many people in your household" and "number of people working outside the village", and the largest number of people working outside the village was below 20%, accounting for 60.7%, while the total number of people working at 40% and above was less than 10.0%, which reflects that the number of people staying in the village in poor mountainous areas is relatively small. This reflects that there are relatively more farmers who stay in their villages and fewer farmers who go out to work. Farmers' knowledge of land policy directly affects their decision to transfer. According to the sample data, farmers chose the question "In your opinion, who owns the land you plant?" In the question "Who owns the land you plant?", more farmers chose "the state" and "yourself", with 38.9% and 34.0% respectively; in the question "What rights are determined by the land rights in your village now? In the question "What is the right of land ownership in your village?", the largest proportion of respondents chose "contracting right", 38.1%, while the proportions of respondents choosing "management right" and "unclear" were similar, 24.4% and 25.5% respectively. The proportion of those who chose "ownership" was 12.0%, and the proportion of those who chose "ownership" was 12.0%; among those who chose the question "Have you heard of the state policy that farmers' land rights remain unchanged for a long time? The proportion of "heard of it" is 38.8%, and the proportion of "not heard of it" is 61.2%. It can be seen that many poor mountain farmers do not know much about the land policy.

Table 2: Regional distribution of the survey sample

Researching the municipal area	Survey of the county
Kaili	Jianhe County, Congjiang County, Leishan County, Taijiang County
Bijie City	Dafang County, Hezhang County, Nayong County, Qianxi County
Anshun City	Puding County, Zhenning County, Guanling County, Ziyun County
liupanshui city	Shuicheng County
Zunyi City	Meitan County
Tongren	Dejiang County, Songtao County, Shiqian County, Sinan County

Table 3 shows the indicator system of the reasons for land transfer based on the model. The indicators of the reasons for willingness to transfer are set as $V = \{V1, V2, V3, V4, V5, V6, V7\}$, $V1$ for going out to work and having no time to take care of the land, $V2$ for the need of non-construction projects in the town or village, $V3$ for the high cost, hard work and low income of cultivation, $V4$ for the high income of transfer and

good value for money, $V5$ for no other reason than not willing to cultivate the land, $V6$ for following other people's practice, and $V7$ for others, please specify. The indicator of reasons for not transferring is set to $M = \{M1, M2, M3, M4, M5, M6, M7\}$, $M1$ indicates the need for food security, $M2$ indicates that there is no other employment channel.

$M3$ indicates that the contracted land is the main economic source of the family, $M4$ indicates that they are afraid of losing their land rights and interests after transferring, $M5$ indicates that they want to transfer the land but they are not willing or the price is too low, $M6$ indicates that they are worried that it is difficult to recover the land when they want to plant it, $M7$ indicates others, please specify.

Table 3 A system of indicators based on the causes of land transfer in the model

Reasons for willingness to circulate	Indicators	Reasons for reluctance to circulate	Indicators
Out of town for work, no time to take care of	V1	Safeguarding ration needs	M1
The need for non-fiddling construction projects in the town and village	V2	No other avenues of employment	M2
High cost, hard work and low income from farming yourself	V3	Landholding as the main source of household income	M3
High turnover income, good value for money	V4	Fear of losing land rights after transfer	M4
No other reason than unwillingness to work the land	V5	Wanted to transfer out but no willing or too low bid	M5
Follow the practice of others	V6	Worried that it will be difficult to get it back when you want to plant it yourself	M6
Other, please specify	V7	Other, please specify	M7

Data Analysis

Figure 6 shows the comparative analysis of the subjective reasons for willingness to transfer land based on the model ELM algorithm. The sample data show that the highest percentage of the reasons for farmers' willingness to transfer is "V3 (high cost, hard work, low income)", which is 68.4%, and the highest percentage of the reasons for not willing to transfer is "M1 (need to guarantee food rations)", which is 50.7%. This is a preliminary conclusion that farmers' willingness to transfer their land is closely related to their livelihood needs. Farmers' expectations

of land transfer mainly include the transfer rent and the transfer period, which are important factors influencing whether farmers are willing to transfer their land and whether land transfer will take place. According to the sample data, the majority of farmers chose "3-5 years" as the expected term of land transfer, accounting for 44.3%, while only 23.5% chose "10 years or more". 71.7% of the farmers chose the expected rent for land transfer. In the choice of the expected rent, the percentage of the choice of each expected rent range is not very different, but the percentage of "RMB 2,000 and above" is the highest, at 28.3%. This reflects that many farmers in poor mountainous areas have a short expectation of land transfer but a high expectation of rent.

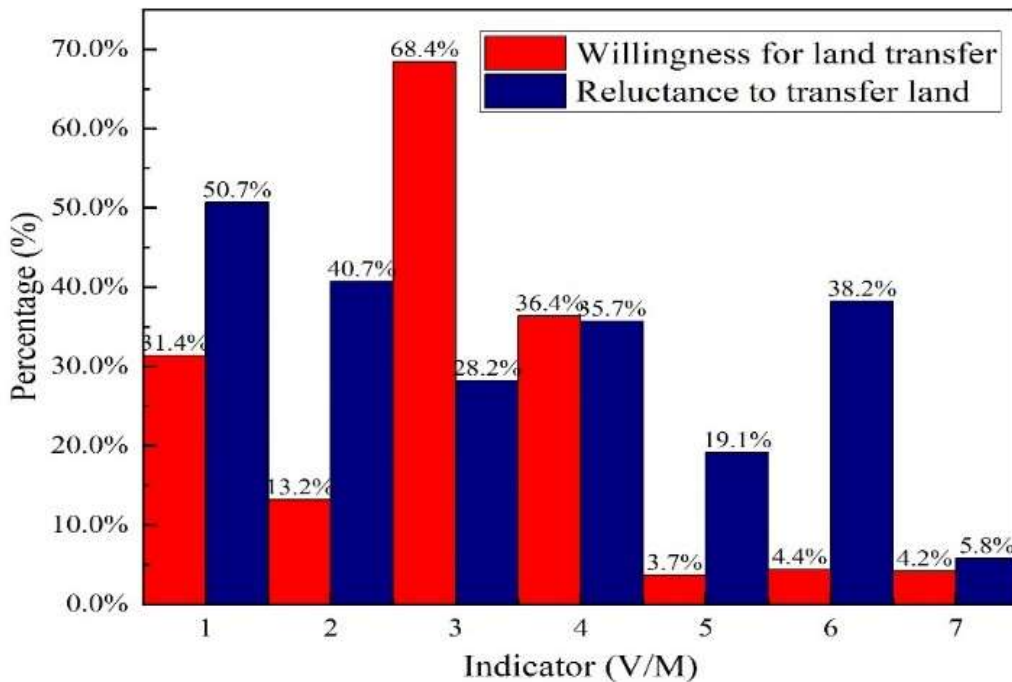


Figure 6: A comparative analysis of the subjective reasons for willingness to shift

The accuracy comparison results of the IAFSA-ELM land transfer optimization prediction model are shown in Figure 7. To ensure the real feasibility of the study, 100 training tests were conducted on the sample data.

It can be seen that the accuracy of the IAFSA-ELM algorithm for the land flow optimization prediction model stays in the range of 84%-92%, the accuracy of the IAFSA algorithm for the land flow optimization prediction model stays in the range of 72%-80%, and the accuracy of the ELM algorithm for the land flow optimization prediction model stays in the range of 63%-71%. Overall the IAFSA-ELM algorithm performs better than the two algorithms alone and is beneficial for rural land flow optimization research.

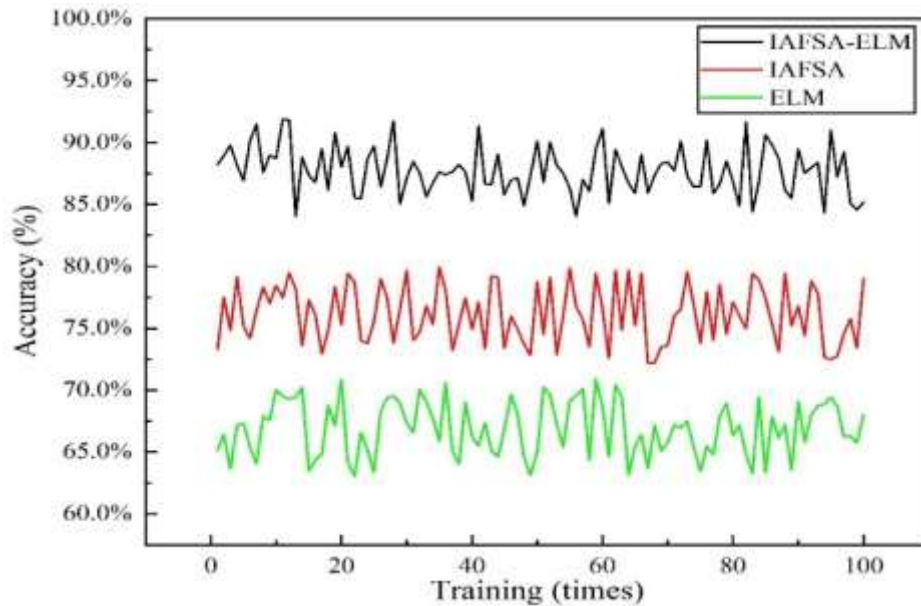


Figure 7: Accuracy comparison results of the IAFSA-ELM land transfer optimization prediction model

Conclusion

This paper proposes to study and analyze the optimization path of rural land transfer by ELM algorithm in the context of rural revitalization.

The rural transfer data are collected mainly based on research and analysis, and the IAFSA-ELM prediction model for rural land transfer optimization is constructed by combining the technical support of ELM algorithm and IAFSA algorithm. Based on the sample data, we constructed the index system of the reasons for land transfer in the model, and analyzed the subjective reasons for willingness to transfer land based on the ELM algorithm.

71.7% of the farmers chose the expected rent for land transfer, and the percentage of the choice of each expected rent range was not much different, so we can initially judge that the willingness of farmers to transfer land is closely related to the farmers' livelihood needs.

In order to ensure the real feasibility of the study, 100 training tests were conducted on the sample data to study the accuracy comparison of IAFSA-ELM land transfer optimization prediction model.

The accuracy rate of IAFSA-ELM algorithm kept in the range of 84%-92% compared to the performance of the two algorithms alone. This study provides reference and reference for promoting the smooth development of land transfer in poor mountainous areas and for relevant departments to formulate policies on land transfer and precise poverty alleviation.

Funding

This research was supported by the key project of the National Social Science Foundation in 2020 (20AJY013).

This research was supported by 2022 Research project of Henan Federation of Social Sciences and Economic and Trade Federation of Henan Province (SKL-2022-2458).

This research was supported by Zhengzhou 2022 Social Science Research Project (ZSLX20221185).



References

- C., Y. (2010). Research on the Circulation of Rural Homestead Use Right in the Process of Urban-rural Integration. *Issues in Agricultural Economy*.
- Chu C W, C.-Z. X. U. (2012). The Resolution of Rural Land Transfer Barriers——Taking Anhui Province as An Example to Exploring. *Journal of Chongqing University of Arts and Sciences(Social Sciences Edition)*, .
- F., Z. (2017). Why does free rent exist in rural land transfer: an empirical analysis from the perspective of rent type. *China Rural Survey*.
- H., S. (2010). The Predicaments of Collective Operation in China's Rural Areas and the New Choices. *Journal of Chongqing University(Social Science Edition)*.
- H., W. (2011). The Thinking on the Construction of Rural Credit System. *Journal of Jilin Financial Research*.
- Huang Y A, L. T. A., B F W. . (2012). A Study on Rural Labor Force Transfer in The Three-gorges Reservoir Area. *Journal of Chongqing University(Social Science Edition)*, .
- Kong Q, L. Z. (2013). Related Issues Discussed About How to Improve the Quality and Distribution of the Rural Land Consolidation Project. *Journal of Agriculture*.
- L., L. (2012). Research on Rural Land Institution Innovation from the Perspective of Income Gap between Urban and Rural. *East China Economic Management*.
- Liu, X., Lu, T., & Yan, S. (2016). Study on the Procedural Rights Guarantee and Farmers' Satisfaction in the Process of Land Acquisition: Based on the Investigation of 30 Villages, 6 Cities in Liaoning Province. *China Land Sciences*, 30, 21-28.
- Nechaev, N., & Zhavoronkova, N. (2013). Implementation of the rights of land ownership in terms of institutional change in agro-industrial complex. *Вестник аграрной науки*, 45(6), 49-53.
- Qi W, W. J. F. (2014). Basic Human Rights and Guarantee of the Land-Lost Farmers. *Journal of Hubei University of Education*.
- Wei-Qiu N I, B.-Y. Y. U. (2011). On the Transfer of Land-use Rights in Rural Areas of Heilongjiang Province under the Coordinative Development between Urban and Rural Areas. *Natural Resource Economics of China*.

- X., C. (2012). Condition, Framework and Countermeasures for Financial Development of Rural Land——Viewpoint Based on Chongqing Reform and Development. *West Forum*.
- Xiao B, W. D., Chen Y, et al. . (2011). MODES, PROBLEMS AND SUGGESTIONS FOR CHINA RURAL RESIDENTIAL LAND EXCHANGE. *Chinese Journal of Agricultural Resources and Regional Planning*.
- Xiaomei L I, U. S. S. (2019). Reflections on Rural Library Construction Based on the Strategy of Rural Revitalization. *The Journal of Shandong Agriculture and Engineering University*, .
- Yang X H, L. T., Zhao J L. (2015). Analysis of the standardization problem of rural land transfer. *Heilongjiang Animal Science and Veterinary Medicine*.