Identification of resilience characteristics of a regional agricultural water resources system based on index optimization and improved support vector machine

Dong Liu, Lei Xu, Qiang Fu, Mo Li and Muhammad Abrar Faiz

ABSTRACT

In order to solve the gap and accuracy in the analytical methods of the resilience of a regional agricultural water resources system, a suitable evaluation index system based on the optimal index model was introduced and applied to the 15 farms in the Jiansanjiang Administration of Heilongjiang Province of China. An improved support vector machine (SVM) was used to analyze the resilience level of each farm for the selected time period. The test results showed that the indicator optimization model had the advantage of eliminating redundant indicators and ensuring the maximum content of screening indicators. The indicator system reflected all original information by 34% of initial indicators. The results showed that the particle swarm optimization-support vector machine (PSO-SVM) model had higher accuracy for the evaluation of agricultural water resource resilience through the analysis of stability and reliability of each model. The spatial pattern of resilience over selected farms was generally characterized by 'low in the southwest and high in the northeast'. The research achievements may provide technical and theoretical support for solving problems of index optimization and analysis methods of system resilience, and have an important theoretical and practical significance for promoting the sustainable development of regional agricultural water resources systems.

Key words | improved support vector machine, indicator optimization, Jiansanjiang Administration, stability and reliability, water resource resilience

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INTRODUCTION

Agricultural water resources are an important part of agricultural production and a significant fundamental resource that supports the sustainable development of a region's economy (Liu *et al.* 2018). Due to human activities directly or indirectly (Liu *et al.* 2012) interfering with water resources used for agriculture, a series of ecological and environmental problems have occured. The gap between the supply and demand of agricultural water is increasingly prominent. Therefore, it is of great significance to carry out research on the resilience of regional agricultural water resources systems to ensure agricultural production.

Experts and scholars at national level and abroad have widely used the index optimization model in various fields. Yi *et al.* (2017) used the entropy method to screen the core indicators of an eco-city and establish the rationality of the indicators to measure the contribution rate of the indicators. Guan *et al.* (2016) used the trapezoidal fuzzy method to study the suitability evaluation index, constructed an evaluation index system for the comprehensive utilization efficiency of water resources, and applied this method to the Yellow River Basin in China. Huang *et al.* (2015) used the Comprehensive Method for Water Ecological Index

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Screening, which is based on principal component analysis (PCA) and Fidel's method, to screen ecological indicators of the main stream of the Liaohe River. The indicators can reflect actual ecological conditions. Zhu *et al.* (2015) established an initial evaluation index system, used factor analysis to optimize the initial evaluation index system, and verified it with a structural equation model. Liu *et al.* (2017) used PCA to analyze the assessment indicators of agricultural water resource resilience and applied the analytic hierarchy process (AHP) to test the reliability of the test results. Although the above methods are relatively reliable in terms of indicator optimization, there are still certain flaws. The PCA method and factor analysis method used in the above methods have excessive dependence on the indicator data, ignoring the true meaning of the indicator. The entropy method and trapezoidal fuzzy method rely solely on the meaning of indicators, and their subjectivity is strong.

Likewise, some researchers have also actively explored and developed some evaluation methods for resilience. Holling (1973) and Gunderson *et al.* (2006) constructed the theory of ecologically adaptive circulation and proposed the concept of resilience, and Kharrazi *et al.* (2016) used the ecological network analysis (ENA) method to evaluate the ecosystem service resilience of the Heihe River Basin and developed two hypothetical alternatives to improve the long-term health and resilience of the water system. Sun *et al.* (2011) used the Lower Liaohe Plain in Liaoning Province as an example to evaluate the resilience of a groundwater system by using AHP and geographic information system (GIS) technology. Gu *et al.* (2014) established a resilience evaluation model for the drought disaster system of Hebei Province based on variable fuzzy theory. Chen & Zhang (2016) used an assessment model for the recoverability of a quantified water environment, which was based on a combination of a variable fuzzy identification model and an improved AHP, to evaluate the recoverability of the water environment system in the middle and lower reaches of the Hanjiang River. Although the above methods of evaluating resilience have made some progress, they have certain deficiencies: the ENA method lacks the unified rules of system boundary division, and there is still the lack of a reasonable method to deal with non-stationary networks. The AHP is affected more by people. Variable fuzzy theory cannot consider the influence of correlation between indicators on evaluation results. The GIS technology evaluation process is too dependent on experience or simple formulas and there is no absolute best calculation basis.

In summary, the research on the methods of resilience diagnosis is still very weak, and the guiding effects of the resilience diagnosis results on practice need to be strengthened, to resolve the deficiencies of the above methods. The objectives of this study are as follows:

(1) Construct a suitable evaluation index system for agricultural water resources system resilience based on the optimal index model.
(2) Improve the support vector machine (SVM) evaluation model, and determine the level of agricultural water resources system resilience.
(3) Assess the stability and reliability of the evaluation model of agricultural water resources system resilience.

MATERIALS AND METHODOLOGY

Study area

The Jiansanjiang Administration (including 15 farms) is located in northeastern Heilongjiang Province, China. Its geographic coordinates are between 46° 49′–48° 12′ N and 132° 31′–134° 32′ E (Liu *et al.* 2018). The global terrain is low and flat; except for the mountains and hills in the northwest and southeast regions, most of the remaining areas are lowland marshes. The area is dominated by agricultural production, which is mostly planted with rice (Liu *et al.* 2017). Due to use of a high-intensity agricultural development model, a series of problems, such as the overexploitation of groundwater, decrease in soil fertility, and misallocation of soil and water resources, have occurred in some areas, affecting the sustained, healthy, and stable development of the local economy. Therefore, it is of great theoretical and practical significance to explore the identification of the characteristics of an agricultural water resources system. The 15 farms' locations in the Jiansanjiang Administration are presented in Figure 1.

Data sources

Data of 50 indicators from 2000 to 2015 were collected from the 'Statistical Yearbook of Heilongjiang' and 'Water

Conservancy Annual Report' of the Jiansanjiang Administration in Heilongjiang. Fifty indicators of the resilience of the water resource system of the Jiansanjiang Administration were evaluated based on the optimal index model. In addition, statistical data of hydro-meteorology and economic and social development of 15 farms established in the Jiansanjiang Administration in 2015 were extracted. This was used as the basic data of the four evaluation models. From the reference 'Groundwater Environment Quality Standards' (GBT14848-2017), eight water quality indicators, namely, pH, CODMn, NH3-N, NO3–N, Cl-, SO42-, Fe, and Mn were selected, and then the groundwater environmental quality index was calculated.

RESEARCH METHODS

The indicator optimization model based on the largest information content

Standardization: Standardize original indicator data to obtain a standardized matrix; the formula is as follows (Shi & Chi 2014).

Positive indicators:

$$g_{ij} = \left[O_{ij} - \min_{1\le j\le n}(O_{ij})\right] / \left[\max_{1\le j\le n}(O_{ij}) - \min_{1\le j\le n}(O_{ij})\right] \quad (1)$$

Negative indicators:

$$g_{ij} = \left[\max_{1\le j\le n}(O_{ij}) - O_{ij}\right] / \left[\min_{1\le j\le n}(O_{ij}) - \max_{1\le j\le n}(O_{ij})\right] \quad (2)$$

where g_{ij} is the normalized value of the ith index and jth year, O_{ij} is the jth year and the ith index value, and $\min_{1\le j\le n}(O_{ij})$ and $\max_{1\le j\le n}(O_{ij})$ are the minimum and maximum values for the jth year, respectively.

R-clustering: Eliminate redundant indicators by R-clustering and determine the final number of clusters (Das & Nag 2017); the formula is:

$$S_i = \sum_{j=1}^{n_i} (Y_i^{(j)} - \bar{Y}_i)'(Y_i^{(j)} - \bar{Y}_i) \quad (3)$$

$$S_i = \sum_{i=1}^{K}\sum_{j=1}^{n_i} (Y_i^{(j)} - \bar{Y}_i)'(Y_i^{(j)} - \bar{Y}_i) \quad (4)$$

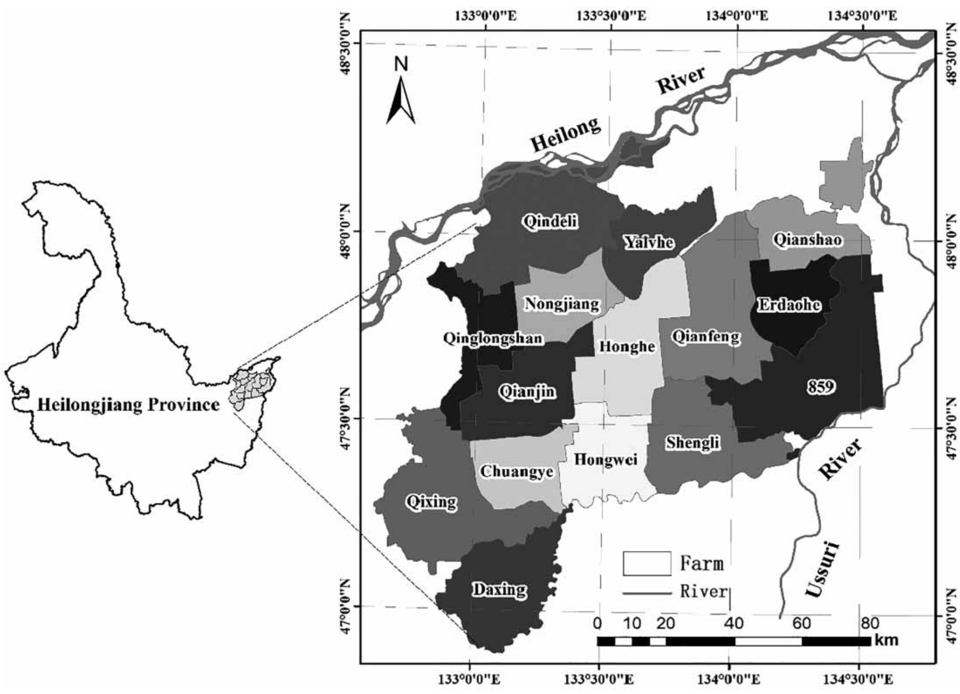

Figure 1 | The administrative division of the Jiansanjiang Administration.

where S_i is the sum of squared deviations of the evaluation indicators of the ith type ($i = 1,2,\ldots,m$), n_i is the number of evaluation indicators of the ith category, $Y_{i(j)}$ is the normalized sample value vector, and $\bar{Y}_i$ is the ith index sample mean vector.

Rationality test: non-parametric KW ANOVA is performed on each index after R-clustering. If the significance level of each index is $P > 0.05$, the number of clusters is reasonable.

The coefficient of variation: The larger the coefficient of variation of the indicator, the greater the information content (Das & Nag 2017). The formula is:

$$H_j = \sqrt{\left[\sum_{i=1}^{n} (h_{ij} - \bar{h}_j)^2\right]/n}/\bar{h}_{ij} \tag{5}$$

where H_j is the coefficient of variation of the jth index, n is the number of objects being evaluated, $\bar{h}_j$ is the average value of the data, and h_{ij} is the value of the jth year of the ith index.

Improved support vector machine

SVM is a machine learning theory based on statistical learning theory (Vapnik 1995; Liu *et al.* 2014). To solve a non-linear problem (Besalatpour *et al.* 2012), the optimal hyperplane is set up as follows:

$$D = \{(x_1, y_1), (x_2, y_2), \cdots (x_m, y_m)\} \tag{6}$$

where x_i is the m-dimensional coordinate and y_i is the value of x_i.

In order to ensure the maximization of the distance between the samples, a regression function f is defined as:

$$c(x, y, f(x)) = \max\{0, |y - f(x)| - \varepsilon\} \tag{7}$$

and the relaxation factors ξ_i and ξ_i^* are introduced; the constraints are as follows:

$$\begin{cases} y_i - \omega x_i + b \le \varepsilon + \xi_i \\ \omega x_i - b - y_i \le \varepsilon + \xi_i^* \end{cases} i = 1, 2, \cdots, m \tag{8}$$

Similar to the idea of the original problem, this is changed into an optimization problem as follows:

$$\text{Minimize } \Phi(W) = \|W\|^2/2 \tag{9}$$

Its dual problem by using the Lagrange function optimization method is:

$$L(w, a, b) = \|W\|^2/2 - \sum_{i=1}^{l} \alpha_i y_i (w^\circ x_i + b) + \sum_{i=1}^{l} \alpha_i,\ \alpha_i \ge 0,\ i = 1, 2, \cdots, l \tag{10}$$

where α_i is a Lagrange operator. The optimal conditions are as follows:

$$\text{Minimize } w(a) = \sum_{i=1}^{l} a_i - \sum_{i,j}^{l} a_i a_i y_i y_i x_i^\circ x_j/2 \tag{11}$$

$$s.t.,\ \sum_{i=1}^{l} \alpha_i y_i = 0,\ \alpha_i \ge 0,\ i = 1, 2, \cdots, l \tag{12}$$

After solving for α_i, the optimal hyperplane is determined.

However, in order to search the global optimal values of the two parameters C and g in a larger range, the particle swarm optimization (PSO) algorithm and global optimization are introduced (Shi *et al.* 2011). During each iteration the updated formula is:

$$V_{id,k+1} = \omega V_{id,k} + c_1 r_1 (P_{id,k} - W_{id,k}) + c_2 r_2 (P_{gd,k} - W_{gd,k}) \tag{13}$$

$$W_{id,k+1} = W_{id,k} + V_{id,k+1} \tag{14}$$

where ω is inertia weight, k is the current iteration, V_{id} is the speed of the particle, c_1 and c_2 are acceleration factor constants, and r_1 and r_2 are random numbers over [0,1].

The steps in the PSO-SVM model are as follows.

Step 1: Initialize algorithm parameters, which include setting global and local search capability parameters, maximum iterations ($I_{\max}$), maximum population ($N_{\max}$), and inertia weight (W).

Step 2: Determine the search scope of the optimal penalty factor C and kernel function parameter g in SVM, randomly generate the position P $(P_{i1}, P_{i2}, P_{i3},\ldots P_{in})^T$ and velocity V $(V_{i1}, V_{i2}, V_{i3} \ldots V_{in})^T$ of the particle, then obtain the initial fitness value.

Step 3: The fitness value is calculated by Equation (15). If the initialization parameters C and g satisfy the error requirements, the result is obtained. Otherwise, the position and velocity of the particle need to be updated by Equations (13) and (14).

$$\begin{cases} \min f(C,\ g) = \left[\sum_{i=1}^{n} (y_i - \hat{y})^2\right] / 2 \\ s.t. \quad C \in [C_{\min}, C_{\max}] \quad g \in [g_{\min}, g_{\max}] \end{cases} \tag{15}$$

Step 4: Determine the optimal penalty factor C and kernel function parameter g, then use the SVM model to predict the test sample. The flow chart of the improved SVM is shown in Figure 2.

Evaluation method of resilience measurement results

Spearman correlation coefficient (R): According to the theory of serial number summation (Lv 1996), the Spearman correlation coefficient is used to analyze the grade results. The formula is as follows:

$$R = 1 - \left(6 \sum C_i^2\right) / [n(n^2 - 1)] \tag{16}$$

where C_i represents the difference value between the ordering result and the reasonable ordering result of object i, and n is the total number of evaluation object i.

The theory of distinction degree (D): D is one of the effective methods to measure the reliability of evaluation methods (Zhou *et al.* 2016). D is defined as follows:

$$D = \sum_{i=1}^{m-1} \sqrt{(V_{i+1} - V_i)^2 + (M_{i+1} - M_i)^2} / \sqrt{(V_1 - V_m)^2 + (M_{i+1} - M_1)^2} \tag{17}$$

The formula after normalization is simplified as:

$$\begin{aligned} D &= \left[\sum_{i=1}^{m-1} \sqrt{(V_{i+1} - V_i)^2 + 1^2}\right] / \left[\sqrt{(m-0)^2 + (m+1)^2}\right] \\ &= \left[\sum_{i=1}^{m-1} \sqrt{(V_{i+1} - V_i)^2 + 1}\right] / \left(\sqrt{2m^2 - 2m + 1}\right) \end{aligned} \tag{18}$$

RESULTS AND ANALYSIS

Optimization of evaluation indicators

The principles of a specific indicator selection are characterized by the following standards: scientificness, representativeness, and comprehensiveness. The evaluation indicators are divided into three levels: the target layer, criteria layer, and indicator layer. The target layer is the evaluation of the water resource resilience of the Jiansanjiang Administration. The criteria layer is divided into the water resources system, agricultural system, ecological environment system, and social economic system (Liu *et al.* 2017). The indicator layer uses the R-clustering and variation coefficient optimization model to filter 50 standardized indicator data. After screening, 17 indicator data were retained. The direction of the data was also defined; the positive indicator ('+') and the negative indicator ('−'), as shown in Table 1.

The water resources system is clustered into five categories taken as an example to illustrate the clustering process. The original data were substituted into Equations (1) and (2) for standardization, and statistical software SPSS (Statistical Product and Service Solutions) (Sui & Cui 2016) was used to classify the criteria layer indicators into five categories. The clustering category results are listed in rows 1–15 of column 4 in Table 1. For example, per capita water resources, total amount of water resources, infiltration capacity, amount of surface water resources and amount of groundwater resources are clustered by SPSS. and its classification results meet the test standard of KW ANOVA: KW ANOVA is equal to 0.829, that is, the significance level satisfies $P > 0.05$, and the KW ANOVA results are listed in column 5 of Table 1. The variation coefficients were calculated using the above Equation (5) and are listed in rows 1–15 of column 6 in Table 1.

Determine the evaluation criteria

In view of the lack of a unified international standard for the grade standard of evaluating indicators for the resilience of agricultural water resources, we referred to previous studies and considered the local situation (Sun *et al.* 2011). The ArcGis natural breakpoint method (Bo & Ji 2014) based on the principle of maximum difference at each level was used

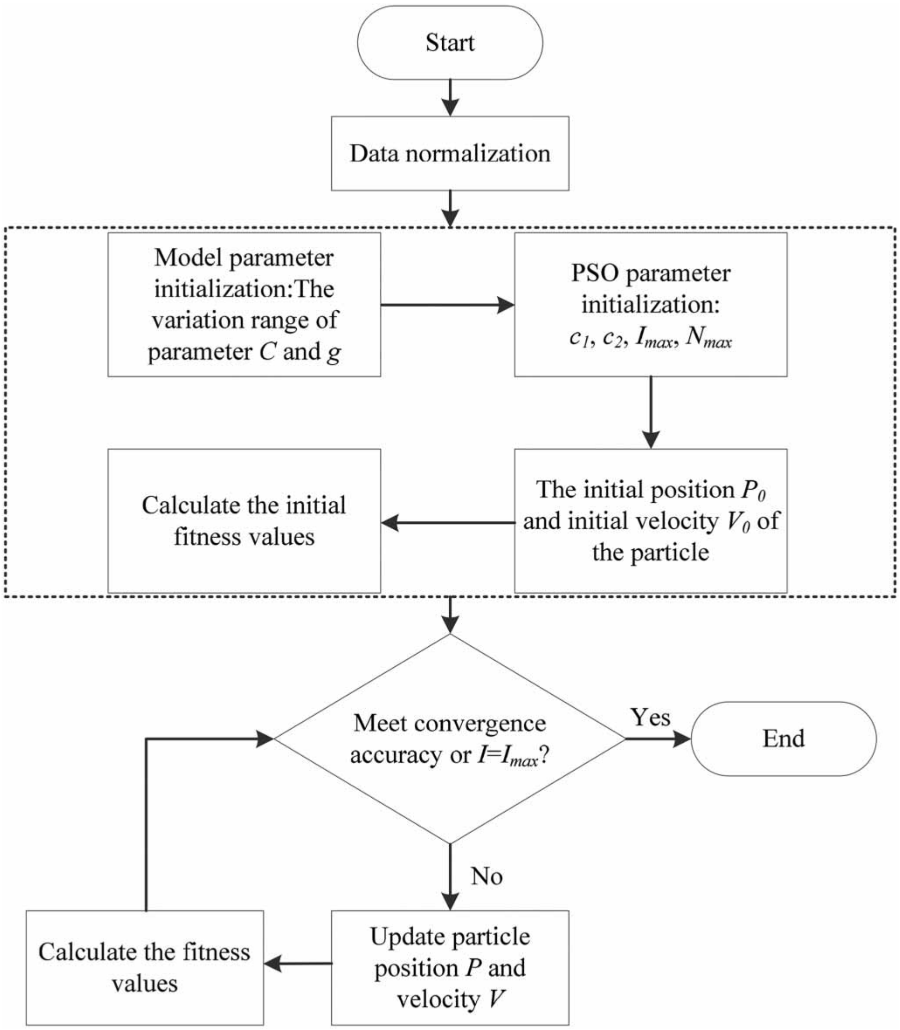

Figure 2 | Improved support vector machine.

to divide the evaluation index system reasonably. Resilience grades from low to high are categorized as Grade I: once destroyed, it will be difficult to restore balance. Grade II: it can be restored after being affected by external influences, but its speed is slow. Grade III: the regional water resources system is stable, and it can be restored after being affected by external influences. Grade IV: the regional water resources system is very stable and can quickly recover its balance after being affected. Grade standards are shown in Table 2.

Analysis of resilience evaluation

Using the improved SVM, the standard data in Table 2 were trained and the sample data were subjected to regression prediction. In the modified model, the range of penalty parameter C and kernel parameter g needed to be set as follows: C within [0.1, 100] and g within [0.01, 1000]. Iterative optimization is performed by updating the position P and velocity V of the particle, and the training results were: $bestC = 32$, $bestg = 2$. MATLAB2016R was used to write a program called *SVM-train* to train a random learning sample of libsvm toolbox, and substitute the optimal penalty parameter *bestC* and optimal kernel parameter *bestg* into the model.

The critical index values of each level in Table 2 were normalized, and the normalized data were substituted into the above-prepared PSO-SVM evaluation model to obtain simulation intervals at each grade. Simulation intervals of

Table 1 | R-clustering and variation coefficients for indicator screening

Target layer	Criteria layer	Indicator layer	Clustering category	KW ANOVA	Variation coefficients	Whether to keep	Direction
Evaluation of regional agricultural water resources system resilience	Water resources system	Water resources per capita (10^4 m^3/people)	1	0.829	0.649	Y	+
		Total amount of water resources (10^8 m^3)	1		0.555	N	+
		Infiltration capacity (10^4 m^3)	1		0.546	N	+
		Amount of surface water resources (10^8 m^3)	1		0.479	N	+
		Amount of groundwater resources (10^8 m^3)	1		0.425	N	+
		Groundwater environmental quality index (–)	2	0.138	0.782	Y	–
		Annual water supply for water conservancy projects (10^4 m^3)	2		0.725	N	+
		Exploitable modulus (10^4 m^3/km^2)	2		0.554	N	–
		Annual precipitation (mm)	3	0.258	0.825	Y	+
		Water producing coefficient (%)	3		0.618	N	+
		Recharge modulus (10^4 m^3/km^2)	3		0.573	N	+
		Total investment growth rate of water conservancy fund (%)	4	0.195	0.726	Y	+
		Water resource rate (%)	4		0.532	N	+
		Temperature (°C)	5	0.169	0.837	Y	+
		Penetration rate of tap water (%)	5		0.395	N	+
	Agricultural system	Amount of water resources per unit cultivated land (10^4 m^3/km^2)	1	0.317	1.021	Y	+
		Water consumption per unit area of farmland (10^4 m^3/km^2)	1		0.978	N	–
		Effective irrigated area rate (%)	2	0.053	0.698	Y	+
		Unilateral water grain output (kg/m^3)	2		0.513	N	+
		Application strength of chemical fertilizer (kg/hm^2)	2		0.635	N	–
		Area proportion of the paddy field (%)	2		0.678	N	+
		Irrigation rate (%)	3	0.138	1.254	Y	+
		Intact rate of water supply facilities (%)	3		0.835	N	+
		Agricultural power consumption (10^4 degrees)	3		0.674	N	–
		Cultivated land rate (%)	4	–	–	Y	–
		Unilateral output value of agricultural water supply (RMB/m^3)	5	0.071	0.881	Y	+
		Grain storage capacity (t)	5		0.625	N	+
		Vegetation coverage (%)	1	0.796	0.490	Y	+

(*continued*)

Table 1 | continued

Target layer	Criteria layer	Indicator layer	Clustering category	KW ANOVA	Variation coefficients	Whether to keep	Direction
	Ecological environment system	Control rate of water and soil erosion (%)	1		0.444	N	+
		Pesticide application intensity (kg/hm^2)	2	0.064	1.089	Y	−
		Ratio of waterlogging area to waterlogging area (%)	2		0.844	N	+
		Quota of urban green land (10^4 m^3/km^2)	2		0.832	N	+
		Water surface area ratio (%)	2		0.768	N	+
		Green area per capita (m^2)	3	0.166	0.931	Y	+
		Quantity of urban life sewage emissions (10^{4}t)	3		0.887	N	−
		Quantity of industrial wastewater discharge (10^{4}t)	3		0.806	N	−
		Forest cover rate (%)	3		0.657	N	+
	Social economic system	Natural population growth rate (%)	1	0.229	1.314	Y	−
		Emigration rate (%)	1		0.721	N	+
		Doctors per 10,000 people (people/10^4 people)	1		0.651	N	+
		GDP per capita (10^4 RMB)	2	0.582	0.935	Y	+
		Permanent population density (people/km^2)	2		0.831	N	−
		Farm family per capita net income (10^4 RMB)	2		0.893	N	+
		Unilateral water GDP (10^4 RMB)	2		0.925	N	+
		Ten thousand people have water professionals (people)	3	0.436	1.035	Y	+
		Primary school enrolment rate (%)	3		0.874	N	+
		Number of people with safe drinking water (10^4 people)	3		0.437	N	+
		Proportion of primary staff (%)	4	0.287	0.958	Y	−
		Public satisfaction (%)	4		0.768	N	+
		Domestic water quota (m^3/people)	4		0.455	N	−

Table 2 | The grade standards of agricultural water resource resilience

Index	I	II	III	IV
Per capita water resources (10^4 m^3/people)	<1.0	1.0–2.1	2.1–2.6	>2.6
Groundwater environmental quality index (-)	>5.2	5.2–4.8	4.2–4.8	<4.2
Annual precipitation (mm)	<520	520–600	600–670	>670
Temperature (°C)	<2.1	2.1–2.8	2.8–3.6	>3.6
Total investment growth rate of water conservancy fund (%)	<12	12–125	125–245	>245
Per capita green area (m^2)	<7	7–20	20–37	>37
Pesticide application intensity (kg/hm^2)	>6.0	3.5–6.0	2.5–3.5	<2.5
Vegetation coverage (%)	<13.5	13.5–17	17–21	>21
Amount of water resources per unit cultivated land (10^4 m^3/km^2)	<3,500	3,500–5,000	5,000–7,400	>7,400
The effective irrigated area rate (%)	<54	54–85	85–92	>92
Irrigation rate (%)	<4.5	4.5–12	12–20	>20
Cultivated land rate (%)	>60	43–60	33–43	<33
Unilateral output value of agricultural water supply (kg/m^3)	<4	4–6.6	6.6–8.4	>8.4
Natural population growth rate (%)	>4.4	3–4.4	0.5–3	<0.5
The proportion of primary staff (%)	>75	66–75	55–66	<55
Ten thousand people have water professionals (people)	<13	13–37	37–64	>64
Per capita GDP (10^4 RMB)	<20,000	20,000–45,000	45,000–70,000	>70,000

each grade of PSO-SVM assessment model are Grade I: [0.47278, 1.1257], Grade II: (1.1257, 1.9754], Grade III: (1.9754, 2.4940], Grade IV: (2.4940, 2.9783].

The values of the optimal evaluation indicators for the farms of Table 2 were normalized according to Equations (1) and (2), and the normalized data were brought into the constructed PSO-SVM evaluation model. The simulated values of the farms were obtained, as shown in Figure 3.

According to Figure 3, the spatial pattern of overall resilience is generally characterized by 'low in the southwest and high in the northeast'. The resilience grades of Farm Qixing, Farm Daxing, Farm Qinglongshan, Farm Qianjin, Farm Chuangye, Farm Hongwei, Farm Yalvhe, and Farm Erdaohe are categorized as II, accounting for 53.33% of all farms. The resilience simulation values of Farm Qixing and Farm Qinglongshan are 1.2202 and 1.3740, respectively, which are close to the lower limit of Grade II, indicating that the agricultural water resource resilience of the two farms tends to be transformed into Grade I, and once they suffer external influences, it will be difficult to restore the original state for a long period of time. According to the resilience simulation value, it can be seen that the order of recovery capacity of agricultural water resources is: Farm Qianshao < Farm Qianfeng < Farm Qindeli < Farm Shengli < Farm 859, and the resilience simulation values of Farm Qianshao and Farm Qianfeng are 1.9992 and 2.0296, respectively, which is close to the lower limit of Grade III, indicating that the agricultural water resource resilience of the two farms is deteriorating toward Grade II. The resilience grades of the agricultural water resources of Farm Honghe and Farm Nongjiang are Grade IV: the regional water resources system is very stable and can quickly recover its balance after being affected.

DISCUSSION

In order to assess the objective condition of water resource resilience, the four evaluation methods of the variable fuzzy set, the technique for order of preference by similarity to ideal solution (TOPSIS) model, SVM model, and PSO-SVM model were used for comparison, as shown in Table 3.

According to the evaluation results in Table 3, the evaluation results of the PSO-SVM model, SVM model, variable

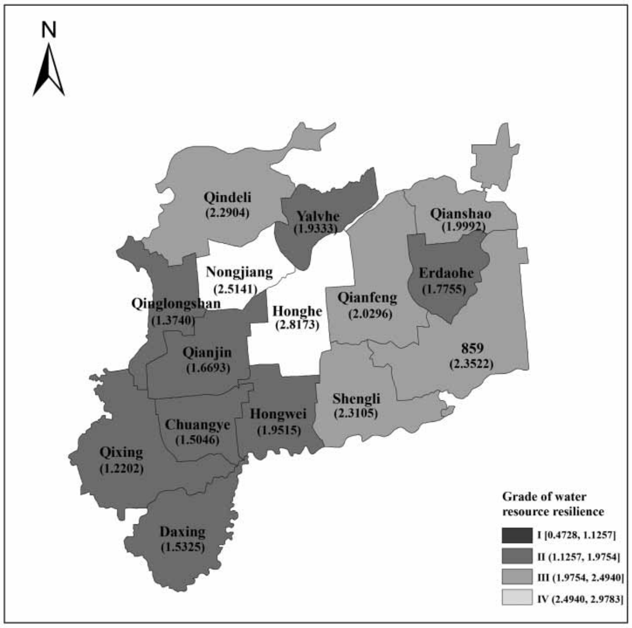

Figure 3 | Simulation values and grade of each farm.

fuzzy set, and TOPSIS were comprehensively compared. Nearly half of the evaluation results are consistent, including Shengli(III), Qixing(II), Qindeli(III), Qinglongshan(II), Hongwei(II), Honghe(IV) and Yalvhe(II). Moreover, the difference in the evaluation results of each farm differing by two grades only accounts for 6.67% of the total evaluation results, therefore, each evaluation model was relatively reasonable. In order to further evaluate the advantages and disadvantages of the four models, the stability and reliability of each model should be analyzed.

Stability analysis

The stability of each evaluation method, including the variable fuzzy set, TOPSIS model, SVM model and PSO-SVM model, was analyzed using the simulated values of resilience based on the theory of serial number summation., as shown in Table 4.

According to Equation (16), the Spearman coefficient between the ranking of each evaluation method and the relative rational ordering of different years was calculated, and the Spearman coefficients of each evaluation method were as follows: 0.8678 for the variable fuzzy set, 0.65 for TOPSIS, 0.9178 for the SVM model, and 0.9215 for the PSO-SVM model. It can be seen that the ranked results of stability were PSO-SVM model > SVM model > variable fuzzy set > TOPSIS.

Table 3 | Comparison of evaluation results of resilience under different models

Farm	Variable fuzzy set	TOPSIS	SVM model	PSO-SVM model
859	III	II	III	III
Shengli	III	III	III	III
Qixing	II	II	II	II
Qindeli	III	III	III	III
Daxing	I	I	II	II
Qinglongshan	II	II	II	II
Qianjin	I	II	II	II
Chuangye	I	II	II	II
Hongwei	II	II	II	II
Qianshao	III	II	III	III
Qianfeng	III	I	III	III
Honghe	IV	IV	IV	IV
Yalvhe	II	II	II	II
Erdaohe	III	III	II	II
Nongjiang	III	IV	III	IV

Table 4 | The reasonable ordering result and the ordering evaluation results of each evaluation method

Farm	Variable fuzzy set	TOPSIS	SVM	PSO-SVM	Relatively reasonable ordering
859	4	9	3	3	3
Shengli	7	4	4	4	4
Qixing	11	6	15	15	13
Qindeli	6	3	5	5	5
Daxing	15	14	13	12	15
Qinglongshan	12	7	14	14	12
Qianjin	14	10	11	11	11
Chuangye	13	12	12	13	14
Hongwei	10	8	9	8	8
Qianshao	2	13	7	7	7
Qianfeng	8	15	6	6	9
Honghe	1	2	1	1	1
Yalvhe	9	11	8	9	10
Erdaohe	3	5	10	10	6
Nongjiang	5	1	2	2	2

Reliability analysis

According to Equation (18), the distinction degree of each evaluation method was calculated as follows: variable fuzzy set (1.0237), TOPSIS (1.0646), SVM model (1.0589), PSO-SVM model (1.0687). The distinction degrees were close, and the ranked results of reliability based on the distinction degree were PSO-SVM model > TOPSIS > SVM model > variable fuzzy set.

CONCLUSIONS

(1) In this paper, the method of R-clustering and variation coefficients was used to solve the repeatability and randomness of primary indicators. From the 50 primary indicators, a total of 17 indicators were selected to establish an evaluation index system for the resilience.

(2) Using the improved SVM model to evaluate the water resource resilience, the water resource resilience grade of II accounts for 53.33% of the total number of farms. The spatial pattern of overall resilience is generally characterized by 'low in the southwest and high in the northeast'.

(3) According to the Spearman correlation coefficients, the ranked results of stability are PSO-SVM model > SVM model > variable fuzzy set > TOPSIS. According to the theory of distinction degree, the ranked results of reliability are PSO-SVM model > TOPSIS > SVM model > variable fuzzy set.

(4) The evolutionary trend of future resilience is an important basis for strengthening the restoration capacity of agricultural water resource systems. Hence, knowing the best method to use to reasonably filter the key drivers of resilience and then predict the resilience of an agricultural water resources system is valuable for further study.

CONFLICT OF INTEREST

The authors confirm that there are no known conflicts of interest associated with this publication.

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