Indicator system optimization model for evaluating resilience of regional agricultural soil–water resource composite system

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ABSTRACT

Resilience is an important indicator for measuring regional sustainable development capacity. The construction of a suitable evaluation indicator system is the premise of evaluating regional sustainable development. In this study, taking the Jiansanjiang Administration of Heilongjiang Province in China as an example, a preliminary selection library of the evaluation indicator system for the resilience of a regional agricultural soil–water resource composite system covering seven subsystems and 59 indicators was established. Selection criteria such as the Dale indicator criteria, subjective and objective combination weighting and principal component analysis were introduced to construct an optimization model for the resilience evaluation indicator system for the ASWRS. First, 14 indicators that were incomplete or incapable were removed. Then, the Dale indicator selection criteria were used to ensure that 14 indicators were selected. The binary fuzzy comparison method and criteria importance through interference correlation method were used to calculate the combination weight. Finally, an indicator system optimization model was established. The indicator system was optimized from 59 to 35 indicators, and the completeness of the indicator system reached 85.75%. The proposed method had obvious advantages in terms of indicator identification and elimination, and it may truly achieve the goal of indicator optimization.

Key words | agricultural soil-water resource composite system resilience, BFCM-CRITIC, combination weight, Dale criterion, indicator optimization

HIGHLIGHTS

- Resilience has become a research hotspot of agricultural soil–water engineering.
- According to the Dale criteria construct a suitable evaluation indicator system.
- Construction of a suitable indicator system is the key premise for measuring resilience.
- Verify the rationality of the indicator system based on the combination weighting.
- The model can be used as the basis to select the evaluation indicator resilience.

INTRODUCTION

In ecosystems, soil and water resources are among the most widely affected resources, but water and land resources are not inexhaustible. Under the combined actions of the lithosphere, biosphere, atmosphere, hydrosphere, exosphere and humanity, the ecological environment is becoming severely damaged (Faiz et al. 2020). The uncertainty in regional agricultural soil and water resource systems has become increasingly clear, and the contradiction between supply...
and demand is becoming increasingly acute. Today, given the deteriorating ecological environment, the study of resilience is particularly important (Maleksaeidi et al. 2015). The establishment of a resilience evaluation indicator system has become an urgent need to maintain sustainable agricultural development. Therefore, it is very important to conduct research on the resilience of the agricultural soil–water resource composite system (ASWRS) to understand its status, predict its future development trends and achieve green environmental sustainability for its rational use (Selenica et al. 2011).

Resilience originated from the Latin word ‘resilio’, and is annotated in Webster’s dictionary as ‘the ability to recover its original shape and size after being subjected to a contraction deformation when subjected to pressure’ (Merriam-Webster 1998). Holling (1973) introduced resilience to the study of ecosystem stability in 1973, and the establishment of the Resilience Alliance, a famous international academic organization led by Holling, in 1999 marked the initial formation of the resilience research paradigm. However, there have been few studies on the resilience of ASWRS, and there is no uniform definition. Referring to the concept of a water resource system (Yu 2007) and ecosystem resilience (Ge et al. 2010) and on the basis of summarizing the definition of and research on resilience from other fields (Thompson et al. 2009), the resilience of ASWRS can be understood as a system of agricultural soil-water resources undergoing significant changes in structure and function when subjected to external stress. After the removal of the external stress and the return to conditions similar to those in the original state, the combined effects of its own forces and external forces enable the system to restore its original structure, function, and capabilities. That is, the system can absorb the disturbance by adjusting the influencing factor in the system while its own structure remains unchanged.

International scholars have actively researched a resilience indicator system and produced useful results. Mihunov et al. (2017) used the resiliency inference model to evaluate the drought resilience of the central and southern regions of the United States. Through a K-average pair analysis and regression analysis, the four major factors of society, economy, agriculture, and health were selected as the main resilience indicators. Liu et al. (2019a) selected 43 primary indicators from four criteria to describe the natural environment, culture, society, economic development and flood control technologies. The R clustering factor analysis method was used to determine 15 optimal indexes, including the annual average temperature, forest coverage rate, and paddy field coverage ratio. The improved PP model based on the WDO algorithm (WDO-PP) was used to evaluate the flood disaster resilience of 12 farms under the Hongxinglong Administration in Heilongjiang Province. Kotzee & Reyers (2016) focused on three flood-affected cities in South Africa and selected 24 flood-recovery-related indicators. They used principal component analysis (PCA) to convert these indicators into four major components: society, ecology, infrastructure, and the economy. Their results showed that the areas with the lowest resilience to floods had the lowest social, economic and ecological resilience. Liu et al. (2019b) selected 45 indicators, which they divided into five dimensions: the natural dimension, ecological environment dimension, social dimension, economic dimension, and technical management dimension. They used information substitutability to select 12 indicators for evaluating resilience. An MTS-GRA-TOPSIS model was used to evaluate the resilience rating of a combined regional agricultural water and soil resource system.

These studies show that current research on resilience focuses primarily on river basins or administrative districts; few studies have focused on core areas of grain production. There have been many studies on soil resources or water resources and related disasters. However, there have been few research projects on agricultural soil–water resource composite systems. Furthermore, a reasonable, complete and fixed indicator evaluation system has not been established. However, the lack of a strong principle for selection impacts the identification of resilience factors (Mnisi & Dlamini 2012). It is still necessary to construct a stronger and more complete model for the selection of resilience indicators (Valenti et al. 2018). Dale’s proposed criteria (Dale & Beyeler 2001) for inclusion offer a comprehensive, professional and mature ecological indicator selection principle. The criteria have universal applicability and provide reliable theoretical support for the indicator optimization model (Kuriqi & Ardiçlioğlu 2018). Considering weight calculation, methods are divided into subjective weighting methods and objective weighting methods. With
subjective empowerment methods, evaluators artificially empower people based on the importance of each indicator. The binary fuzzy comparison method (BFCM) is a relatively mature method for determining the weight of indicators, and this method has a good ability to eliminate the differences in values reported by different researchers (Luo 2012). The BFCM allows quantification through the matrix transformation of interconnected and differentiated indicators, extracts and summarizes information, and finds the fuzzy scale of linear changes so that comparisons can be made at a glance for complex systems (Zhang 2011). The objective weighting methods determine the weight from actual data and use objective information reflected by the indicator value. The CRITIC method considers the influence of differences in the indicators on the weight and considers conflict between the indicators. Among the various objective weighting methods, the CRITIC method is considered to be a calculation method that can reflect the objective weight of the indicators (Wang & Song 2003). The combination of subjective and objective weights reflects not only the preference of policymakers but also the objective attributes of the indicators themselves. Combining weights not only incorporates the advantages of the two weighting methods but also avoids their inadequacies to determine the final combined weight.

The Jiansanjiang Administration is an important commodity grain production base in China. It is mainly planted with rice and has a reputation as ‘the hometown of green rice in China’. In this area, due to the excessive pursuit of economic growth in recent years, the long-term, large-scale, inappropriate reclamation of marsh wetlands, woodlands, and grasslands in the reclamation area has resulted in the long-term, excessive and unreasonable use of chemical fertilizers and pesticides by local farmers in pursuit of higher yields (Zhang et al. 2020). Unsustainable agricultural development models and resource allocation models have generally resulted in effects such as declines in groundwater levels, increased soil erosion, aggravation of agricultural pollution, depletion of soil, shrinkage of wetland areas, and inadequate defence capabilities against agricultural floods and droughts. Therefore, it is particularly important to study the resilience evaluation indicator for the ASWRS in this area. Based on the above research, an agricultural soil resource system and water resource system are considered an organic composite environmental system. The primary selection pool of indicators affecting resilience was chosen according to the characteristics and definition of resilience for the ASWRS in the study area. Next, the indicators were screened to identify the decisive indicators, the indicator system framework was designed, and the indicator selection model was constructed. In this process, the Dale indicator inclusion criteria were introduced to provide theoretical support for the optimization model. When combining the BFCM and CRITIC in the indicator optimization model, the use of the main and objective weight calculation method alone is not sufficient or useful. The criterion defining indicator completeness as a cumulative contribution rate of ≥85% determined with the PCA method was selected as a constraint, and the evaluation indicators were selected and optimized. Finally, a relatively complete assessment indicator system was constructed for the resilience of the ASWRS.

The main objectives of this paper are as follows:

1. explore the connotation for the resilience of ASWRS, build a preliminary selection database of evaluation indicators, and determine the evaluation indicator levels;
2. determine the framework structure of the evaluation indicator system according to the logical relationship between each system and indicator. To ensure the completeness of the indicators, optimize the number of indicators and establish an indicator system optimization model; and
3. establish an indicator system optimization model based on different weight calculation methods, seek the most appropriate weight optimization method, and discuss the rationality of the evaluation indicator system for resilience.

**MATERIALS AND METHODS**

**Study area**

The Jiansanjiang Administration is in the hinterland of the Sanjiang Plain on the northern border of China, and the area is adjacent to Fujin, Tongjiang, Ruyuan and Raohe and two counties. It is part of the confluence zone of the Heilongjiang River, the Ussuri River and the Songhua River. The geographic coordinates are between 132°31′26″ ~ 134°22′26″E and 46°49′42″ ~ 48°13′58″N,
and the annual average temperature is 1–2 °C. With a total area of 12,400 km², 15 farms are located within the jurisdiction, accounting for 22% of the total area of the entire Heilongjiang reclamation area. With fertile land, flat terrain and abundant resources, this area with abundant rainfall, heat, and hours of sunshine is a highly productive zone in which rice, beans, and other cash crops grow. It is famous for producing high-quality green rice, and its annual grain production capacity exceeds 150 billion kg, with a commodity grain rate as high as 80%. It is also the core area of grain production in Heilongjiang Province (Liu et al. 2016). The specific location of the study area is shown in Figure 1.

**Data sources**

The Statistical Yearbook of Heilongjiang State Farms (1997–2016), the Statistical Yearbook of the Jiansanjiang Administration (1997–2016) and the Annual Report of Jiansanjiang Administration and Water Conservancy (1997–2016) were collected from the China Knowledge Network and the Agricultural Bureau of Heilongjiang Farms and Land Reclamation Administration. Based on a field sampling test in 2016, the water environmental quality composite index, soil environmental quality composite index and cultivated land environmental quality composite index were calculated using the improved Nemerow indicator method. Multiple linear regression analysis was used to extend the soil and water quality time series data in the study area.

**Methods**

**Data extension**

The explanatory variable data set was determined according to the definitions, influencing factors, and factors related to three interpreted variables: surface water environmental quality, groundwater quality, and soil quality. The data for each explanatory variable were collected in 2016 and used to calculate the water environmental quality comprehensive index and soil environmental quality index. SPSS software was used to perform multiple linear regression analysis (He 2015) on the above data to obtain multiple regression

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**Figure 1 | Location of the study area.**
equations for the water environmental quality composite index and soil environmental quality composite index. The 1997–2016 data were organized according to the explanatory variables in the multiple regression equations in order to extend the water and soil environmental quality composite index time series (Ke et al. 2013). The relationships between the variables are shown in Table 1.

Weight determination methods

*Binary fuzzy comparison method.* The basic concept of the BFCM is to sort the indicators according to importance and to determine the relative membership degree of each indicator by combining the fuzzy scale of the fuzzy tone operator to describe the concept of the importance degree (Wang et al. 2016). The relative membership degree vector is normalized to obtain the weight vector of each indicator. Chen (2009) proposed ten tone-level tone operators and assigned each tone operator a fuzzy scale value. The relationships between the tone operators and fuzzy scale values are shown in Table 2.

The calculation steps are as follows:

1. Determine the qualitative ordering matrix \( F \) of each indicator about importance.

2. According to the ordering of importance of matrix \( F \) and establishing a binary comparison matrix on the degree of importance,

\[
F = \begin{bmatrix}
  f_{11} & f_{12} & \cdots & f_{1m} \\
  f_{21} & f_{22} & \cdots & f_{2m} \\
  \vdots & \vdots & \ddots & \vdots \\
  f_{m1} & f_{m2} & \cdots & f_{mm}
\end{bmatrix} = (f_{kl})
\] (1)

If the condition \( \{ 0 \leq f_{kl} \leq 1, k \neq l \} \) is satisfied, the matrix \( F \) is called an ordered binary comparison matrix about importance, where \( f_{kl} \) is the importance fuzzy scale of indicator \( k \) on \( l \).

3. Determine the value of \( f_{kl} \) by using the relationship between the tone operator and the fuzzy scale. The non-normalized weight vector of the indicator is represented by the sum of the fuzzy scale value \( f_{kl} \) of each row of the square matrix \( F \), and the weight vector of the indicator is:

\[
w = (w_1, w_2, \cdots w_m)^T
\] (2)

4. Normalize the above equation for \( w \) to obtain the normalized weight vector \( w_{B} \), which is the indicator weight value calculated by the BFCM.

CRITIC. The CRITIC method determines the objective weight of the indicator to evaluate the contrast strength and conflict of the indicator, and the contrast intensity is reflected in the standard deviation (Diakoulaki et al. 1995). The formula for calculating the amount of information \( G_j \)

| Table 1 | The relationships between the explained and explanatory variables |
|---|---|
| Explained variable | Explanatory variables |
| Surface water environmental quality | Inland water area proportion, Soil and water loss rate, Amount of fertilizer applied per unit area, Per capita domestic water consumption, Applied amount of nitrogen fertilizer per unit area |
| Groundwater quality | Per capita domestic water consumption, Inland water area proportion, Applied amount of pesticide per unit area, Gross social output value, GDP energy consumption, Soil and water loss rate, Applied amount of nitrogen fertilizer per unit area |
| Soil quality | Precipitation, Soil and water loss rate, Applied amount of phosphate fertilizer per unit area, Applied amount of potash fertilizer per unit area, Gross social output value |

| Table 2 | The relationships between tone operators and fuzzy scale values |
|---|---|
| Tone operator | Fuzzy scale | Tone operator | Fuzzy scale |
| Same | 0.5 | Fully | 0.8 |
| A little | 0.55 | Very much | 0.85 |
| Slightly | 0.6 | Extremely | 0.9 |
| More | 0.65 | Nearly | 0.95 |
| Obvious | 0.7 | Unmatched | 1 |
| Significant | 0.75 |
contained in the \( j \)th indicator is as follows:

\[
G_j = S_j \sum_{i=1}^{m} (1 - X_{ij})
\]

where \( S_j \) represents the standard deviation of the \( j \)th indicator; \( X_{ij} \) is the correlation coefficient between indicator \( i \) and indicator \( j \); and \( \sum_{i=1}^{m} (1 - X_{ij}) \) is a quantitative indicator of the conflict between the \( j \)th indicator and the other indicators. A larger \( G_j \) value indicates a greater amount of information contained in the \( j \)th evaluation indicator and the greater relative importance of the indicator; thus, the objective weight \( w \) of the \( j \)th indicator is:

\[
w = \frac{G_j}{\sum_{j=1}^{n} G_j}
\]

Computed weights determine the weight coefficients. The weight combination method combines the respective advantages of the subjective weights and objective weights and improves the reliability of the weight selection. The calculation method is as follows:

\[
W_{yi} = w_B \cdot w_C
\]

where \( W_{yi} \) is the combined weight; \( w_B \) is the weight of the BFCM; and \( w_C \) is the weight calculated by the CRITIC method.

Analytic hierarchy process. The aim of the analytic hierarchy process (AHP) is to decompose the elements related to decision-making into goals, criteria, and programmes; this process is used for qualitative and quantitative analyses in decision-making (Gao & Su 2017).

The calculation steps are as follows:

① Analyse the relationships between various factors in the system. Compare the importance of the elements at the same level with respect to a criterion at the previous level. Construct the judgement matrix for the pairwise comparison.

② The relative weight of the elements compared with the criterion is calculated by decision matrix \( A \). The calculation should satisfy:

\[
A_W = \lambda_{\text{max}} \times W
\]

where \( \lambda_{\text{max}} \) is the maximum characteristic root of judgement matrix \( A \); and \( W \) is the normalized eigenvector corresponding to \( \lambda_{\text{max}} \). The component \( W_i \) of \( W \) is the weighted value of the corresponding single-order element.

③ Conduct a consistency test of the judgement matrix. The specific calculation process is as follows:

\[
CI = \sum_{i=1}^{m} W_{ai}CI_i
\]

\[
RI = \sum_{i=1}^{m} W_{ai}RI_i
\]

\[
CR = \frac{CI}{RI}
\]

where \( CI \) represents the consistency indicator of the total hierarchical ordering; \( W_{ai} \) represents the total rank weight of element \( A_i \) at the \( A \) level; \( CI_i \) refers to the consistency indicator of the judgement matrix at the next level corresponding to \( A_i \); \( RI \) represents the random consistency indicator of the total hierarchical ordering; \( RI_i \) represents the random consistency indicator of the judgement matrix at the next level corresponding to \( A_i \); and \( CR \) represents the random consistency ratio of the total hierarchical ordering.

If \( CR < 0.1 \), the total rank consistency test is considered to have been passed. Otherwise, it is necessary to adjust the judgement matrix of this level so that the total order of the level has satisfactory consistency.

④ Calculate the total ranking weights of the systems for each level and sort them.

Indicator system optimization model

The principle of selecting individual indicators. Because of the complexity of the indicator system, it is more difficult to select a single indicator. A set of indicator selection criteria is needed to provide reliable support and to effectively guarantee the indicator selection process. Therefore, the selection of individual indicators is based on the eight principles determined by Dale; these principles include measurable (M), vulnerable (V), predictable (P),
typical (T), integrative (I), controllable (C), responsive (R), and stable (S) (Dale & Beyeler 2001).

**Structuring the relationship matrix** $Z_{(i,j)}$. The relationship matrix $Z$ is constructed according to the hierarchical framework of the evaluation indicator system. It is used to determine the interaction between layers. $Z$ represents the relationship between the $n$th layer and the $n-1$ layer, that is, the relationship between the indicator layer and the middle layer. In the matrix $Z_{(i,j)}$, $i$ represents the $i$th indicator of the $n-1$ layer, and $j$ represents the $j$th indicator of the $n$th layer. If $j$ is related to $i$, then $Z_{ij} = 1$; otherwise, $Z_{ij} = 0$. If the first indicator of the indicator layer has a relationship with the first system in the middle layer, then $Z_{11} = 1$. If the second indicator of the indicator layer is not related to the third system in the middle layer, then $Z_{32} = 0$.

$$Z = \begin{bmatrix}
    z_{11} & \cdots & z_{1j} \\
    \vdots & \ddots & \vdots \\
    z_{i1} & \cdots & z_{ij}
\end{bmatrix}$$  \hspace{1cm} (10)

**Constructing the inclusion criteria matrix** $Y_{(i,j)}$. According to Dale’s eight single-indicator selection principles, the overall principle covers the entire indicator system, and thus, the overall principle is not considered. Therefore, a matrix of $j$ rows and seven columns is constructed to select and optimize the individual indicators.

$$Y = \begin{bmatrix}
    y_{11} & \cdots & y_{17} \\
    \vdots & \ddots & \vdots \\
    y_{j1} & \cdots & y_{j7}
\end{bmatrix} = (Y_1, Y_2, Y_3, Y_4, Y_5, Y_6, Y_7)^T$$  \hspace{1cm} (11)

where $j$ represents the indicator number of the $n$th floor and 7 represents the seven selection conditions. When the indicator meets the selection condition $g$, $Y_{gj} = 1$; otherwise, $Y_{gj} = 0$.

To achieve a complete indicator system, select the five principles of measurable, vulnerable, typical, controllable, and stable to form the selection condition $g$. The indicators that meet the selection condition $g$ are directly selected; otherwise, they are determined. Based on the above principles, a vector $P$ that satisfies the selection criteria of these five principles is established. The selection criteria of these five principles are set to 1, and the remaining pending conditions are 0; that is, $P = [1, 1, 0, 1, 1, 0, 1]$.

**Optimizing the indicator system**. The target function optimized by the selected matrix to the indicator can be set as follows:

$$\min Q = \sum_{m=1}^{j} y_{im}$$  \hspace{1cm} (12)

and must meet the following constraints: when the evaluation indicator meets the previously set five selected principles, $y_{im} = 1$ and $P \cdot Y_{im} \geq 5$; $y_{im} = 1$ represents the $m$th indicator in the specific indicator layer, and if $y_{im} = 0$, then the $m$th indicator is not selected.

To construct the vector $YI = [y_{i1}, y_{i2}, \ldots, y_{i7}]$ in order to ensure the connection between the indicator layers, it is necessary to satisfy $YI \cdot Z > 0$, which indicates that the lower indicator is associated with the upper indicator.

The cumulative contribution rate from PCA reaching 0.85 was selected as the criterion for judging the completeness of indicators. The sum of the weights of the indicator system satisfies Equation (13) to meet the completeness requirement (Wang 2010; Chen et al. 2018):

$$YI \cdot W_{yi} \geq 0.85$$  \hspace{1cm} (13)

where $W_{yi} = (w_{y1}, w_{y2}, \cdots, w_{yi})$ is a matrix composed of all specific indicator weights.

The specific steps are shown in Figure 2. The reader can refer to the Supplementary Material for more detail regarding how we set the experimental scheme and data extension methods framework design for agricultural soil–water resource.

**RESULTS**

**Indicator system framework design and primary indicator**

**Indicator primary library**

Based on previous research results (Jing 2010; Wang et al. 2014; Liu et al. 2019c), 59 indicators were initially selected from many potential evaluation indicators. The specific indicators and level framework are shown in Table 3.
Figure 2 | Resilience evaluation indicator optimization process of ASWRS.
Table 3 | The preliminary selection database and standard compliance for the evaluation system indicator of ASWRS

| System                | Indicator                                                      | Unit                  | Standard conformity accuracy | Correlation |
|-----------------------|----------------------------------------------------------------|-----------------------|------------------------------|-------------|
| Water Resource System (WRS) | Precipitation (WRS1)                                              | mm                   | MVPTR                        | +           |
|                        | Evaporation (WRS2)                                               | mm                   | MVPTR                        | -           |
|                        | Water Resources Per Capita (WRS3)                               | 10³ m³               | MPTC                         | +           |
|                        | Water Resource Availability Per Capita (WRS4)                   | 10³ m³               | MVPTC                        | +           |
|                        | Water Resources Per Unit Area (WRS5)                            | 10³ m³/hm²           | MPR                          | +           |
|                        | Water Resource Development Utilization (WRS6)                   | %                    | MVPTCR                       | -           |
|                        | Groundwater Level Fluctuation (WRS7)                             | m                    | MVPCR                        | -           |
|                        | Water Supply Module (WRS8)                                      | 10³ m³/hm²           | MVPTCRS                      | -           |
|                        | Water Environmental Quality Composite Index (WRS9)               |                     | MVPTCR                       | -           |
|                        | Water Resource Availability (WRS10)                              | %                    | MPR                          | +           |
|                        | Surface Water Resource Amount (WRS11)                            | 10³ m³               | MPR                          | +           |
|                        | Groundwater Resource Amount (WRS12)                             | 10³ m³               | MPR                          | +           |
| Soil Resource System (SRS) | Land Utilization Rate (SRS1)                                    | %                    | MVTPC                        | -           |
|                        | Agricultural Land Utilization Rate (SRS2)                       | %                    | MVTPC                        | +           |
|                        | Reclamation Rate (SRS3)                                         | %                    | MVTPCS                       | -           |
|                        | Construction Land Rate (SRS4)                                   | %                    | MPC                          | -           |
|                        | Unused Land Rate (SRS5)                                         | %                    | MPC                          | +           |
|                        | Soil Environmental Quality Composite Index (SRS6)                |                     | MVPTCR                       | -           |
|                        | Elevation (SRS7)                                                 | m                    | MPS                          | -           |
|                        | Arable Land Index (SRS8)                                        | %                    | MPCR                         | +           |
|                        | Multiple Cropping Index (SRS9)                                  | %                    | MPCS                         | -           |
| Agricultural System (AS) | Proportion of Agricultural Water (AS1)                           | %                    | MVPTCRS                      | +           |
|                        | Irrigation Water Consumption Per Unit Area (AS2)                 | m³/hm²               | MVPTC                        | -           |
|                        | Grain Yield Per Unit Area (AS3)                                 | kg/hm²              | MVPTR                        | +           |
|                        | Effective Irrigation Rate of Farmland (AS4)                     | %                   | MVPTR                         | +           |
|                        | Proportion of Paddy Fields (AS5)                                | %                    | MVPTCS                       | +           |
|                        | Amount of Pesticide Application Per Unit Area (AS6)              | kg/hm²              | MVPTCR                       | -           |
|                        | Amount of Fertilizer Applied Per Unit Area (AS7)                 | kg/hm²              | MVPTCR                       | -           |
|                        | Land Environmental Quality Composite Index (AS8)                 |                     | MVPTCR                       | -           |
|                        | Effective Coefficient of Irrigative Water Utilization (AS9)     | %                    | MVR                          | +           |
| Social System (SS)     | Population Density (SS1)                                        | /hm²                 | MPTCRS                       | -           |
|                        | Education Employee Proportion (SS2)                              | %                    | MPCR                         | +           |
|                        | Agricultural Employee Proportion (SS3)                           | %                    | MVPTCRS                      | +           |
|                        | Per Capita Domestic Water Consumption (SS4)                     | m³/d                | MPCR                         | -           |
|                        | Per Capita Arable Land (SS5)                                    | hm²                 | MVPTCS                       | +           |
| Economic System (ES)   | Per Capita GDP (ES1)                                             | CNY                  | MVPTCRS                      | +           |
|                        | Annual GDP Growth Rate (ES2)                                    | %                    | MVPTCRS                      | +           |
|                        | Water Consumption Amount Per Unit Output Value of Ten Thousand Yuan (ES3) | m³/CNY               | MVPTCR                       | -           |
|                        | Water Output Value of Agricultural Water Supply (ES4)            | CNY/m³              | MVPTR                        | +           |
|                        | Per Capita Net Income (ES5)                                     | CNY                  | MVPTCRS                      | +           |
|                        | Agricultural Property Output Rate (ES6)                          | 10⁴¥/hm²            | MVPTCR                       | +           |
|                        | GDP Energy Consumption (ES7)                                     | Standard coal/CNY   | MVPTCR                       | -           |
| Management System (MS) | Water Employee Proportion (MS1)                                  | %                    | MVPTCRS                      | +           |
|                        | Water Conservancy Project Investment Growth Rate (MS2)           | %                    | MVPTCRS                      | +           |
|                        | Water Supply Facility Completion Rate (MS3)                     | %                    | MVPTCS                       | +           |
|                        | Engineering Renewal Rate (MS4)                                  | %                    | MVPTCR                       | +           |
|                        | Public Satisfaction with the Environment (MS5)                   | %                    | VTR                          | +           |
|                        | Legal System Perfect Rate (MS6)                                 | %                    | VT                           | +           |
|                        | Agricultural Water Conservancy Information (MS7)                 | %                    | VR                           | +           |

(continued)
Indicator screening

The selection principle for individual indicators was combined with the data for the study area and considered with reference to expert advice and a large number of documents. After comprehensive consideration, the conformity of the indicator standard was determined, and the correlation between indicators and system resilience was determined (‘＋’ indicates a positive correlation, and ‘－’ indicates a negative correlation). The results are shown in Table 3.

Due to imperfect data collection in the study area, no long-term monitoring data existed, and the indicators WRS10, WRS11, WRS12, SRS7, AS9, EES7, EES8, and EES9 were excluded. There is a high degree of local land levelling, and the terrain is flat; thus, the indicator SRS8 was excluded. The study area is located at high latitudes and experiences cold weather. The crop growing period is one year, and there is no option for multiple cropping (Han et al. 2017). Therefore, the indicator SRS9 was excluded. Because there is no accurate measurement standard that can be counted and quantified, the indicators MS5, MS6, and MS7 were excluded. Because no change occurred throughout the year, the indicator weight could not be calculated; thus, the indicator EES10 was excluded. Therefore, following the principles of a scientific, complete and accessible indicator system, a total of 14 indicators were eliminated, leaving 45 indicators.

Indicator weight determination

The evaluation indicator system for ASWRS resilience was determined based on statistical data from 1997 to 2016 for the study area. The weight of the middle tier was determined using the BFCM, and the weight of the indicator layer was determined by the CRITIC method. Finally, the combined weight was calculated. The results are shown in Table 4.

Indicator system optimization and selection

In accordance with the inclusion criteria matrix formula combined with the evaluation indicator system for ASWRS resilience, the selection criteria matrix \( Y(45 \times 7) \) and the relationship matrix \( Z(7 \times 45) \) were constructed.

According to the assessment model for the resilience indicator of the ASWRS and the Dale indicator selection criteria, the following can be calculated.

\[
YI = P \cdot Y' = [WRS_1, WRS_2, WRS_3, WRS_4, WRS_5, WRS_6, WRS_7, 1, WRS_9, SRS_1, SRS_2, 1, SRS_4, SRS_5, SRS_6, 1, AS_2, AS_3, AS_4, 1, AS_6, AS_7, AS_8, SS_1, SS_2, 1, SS_4, 1, 1, 1, ES_3, ES_4, 1, ES_6, ES_7, 1, 1, 1, MS_4, 1, 1, EES_3, EES_4, EES_5, EES_6],
\]

which shows that 14 indicators have been selected and that 31 indicators need further screening. At the same time, to ensure the interrelationships between the middle layers...
and to prevent the middle layers of the entire indicator system from being disconnected, \( YI \cdot Z > 0 \) should be satisfied.

\[
YI \cdot Z = [1 + WRS_1 + WRS_2 + WRS_3 + WRS_4 + WRS_5 + WRS_6 + WRS_7 + WRS_9 + 1 + SRS_1 + SRS_2 + SRS_4 + SRS_5 + SRS_6 + SRS_7 + AS_1 + AS_2 + AS_3 + AS_4 + AS_5 + AS_6 + AS_7 + AS_8 + SS_1 + SS_2 + SS_4 + SS_5 + SS_6 + SS_7 + ES_3 + ES_4 + ES_5 + ES_6 + ES_7 + MS_4 + ES_8 + EES_3 + EES_4 + EES_5 + EES_6]
\]

Thus, this condition has been met.

According to the indicator system, the principles of selection and completeness are optimized and are simultaneously concise and operable. The PCA method with a cumulative contribution rate of 85% of the criteria was used for further selection and optimization of the indicators, using the formula \( YI \cdot W_{ij} \geq 0.85 \) to ensure the completeness of the indicator.

At the same time, to ensure that the objective function had an optimal solution:

\[
\min Q = \sum_{m=1}^{I} y_{im} = 14 + WRS_1 + WRS_2 + WRS_3 + WRS_4 + WRS_5 + WRS_6 + WRS_7 + WRS_9 + 1 + SRS_1 + SRS_2 + SRS_4 + SRS_5 + SRS_6 + SRS_7 + AS_1 + AS_2 + AS_3 + AS_4 + AS_5 + AS_6 + AS_7 + AS_8 + SS_1 + SS_2 + SS_4 + SS_5 + SS_6 + SS_7 + ES_3 + ES_4 + ES_5 + ES_6 + ES_7 + MS_4 + ES_8 + EES_3 + EES_4 + EES_5 + EES_6.
\]

Not all \( y_i \) can be 0; thus, for the remaining 31 indicators to be determined, the ten indicators \( SS_4, SS_5, SS_6, WRS_4, WRS_5, WRS_7, WRS_8, WRS_9, SRS_1, SRS_2, SRS_3, \), and \( ES_6 \) which had smaller weights, were discarded. The remaining indicators guaranteed the completeness of the indicator system at 85.75%, which met the optimization conditions.

Finally, the following 35 indicators were selected for the evaluation indicator system of ASWRS resilience: \( WRS_1, WRS_2, WRS_3, WRS_4, WRS_5, WRS_6, WRS_9, SRS_1, SRS_2, SRS_3, \)
SRS4, SRS5, SRS6, AS1, AS2, AS3, AS4, AS5, AS6, AS7, AS8, SS3, SS5, ES1, ES2, ES5, MS1, MS2, MS3, MS4, EES1, EES2, EES3, EES4, EES5 and EES6.

**DISCUSSION**

**Rationality analysis of algorithm results**

To verify the reliability of the indicator selection process in this paper, three comparison methods were included. The first comparison method used the AHP method to calculate the middle-layer weight and the CRITIC method to calculate the indicator-layer weight. Then, a final combination weight was calculated as the product of the weights obtained with the two methods. The second method directly involves the calculation of the weight of each indicator using the CRITIC method. The last method involves the use of the AHP method to calculate the weight of each indicator.

The weight calculation results are shown in Table 5.

In addition, the above indicator optimization model was used to satisfy and ensure the following objective function:

\[
\min Q = \sum_{m=1}^{M} w_i y_i \cdot Z > 0, \quad Y_i \cdot W_{IP} \geq 0.85.
\]

Finally, the AHP-CRITIC method was used to calculate the optimal solution for \( \min Q = 33 \) and \( Y_i \cdot W_{IP} = 0.8554 \); the CRITIC method was used to calculate the optimal solution for \( \min Q = 38 \) and \( Y_i \cdot W_{IP} = 0.8551 \); and the AHP method was used to calculate the optimal solution for \( \min Q = 30 \) and \( Y_i \cdot W_{IP} = 0.8527 \). The AHP method was more suitable for weight calculation with fewer indicators.

For the 45 indicators in this paper, the calculation result using the AHP method was too subjective. The results excluded 15 indicators too often. Therefore, the accuracy of the indicator system was affected, and this method was not considered. The eliminated indicators for each method are shown in Figure 3.

Based on the three remaining weight determination methods, ES3 and ES6 were removed, and the indicators WRS6, SS1, SS2, SS4, ES4 and ES7, which were removed by the BFCM-CRITIC method, were also eliminated by the AHP-CRITIC method. The BFCM-CRITIC method removed 80% of the same indicators, while the AHP-CRITIC method excluded indicators from the MS, ES, SS and EES. The main reason for these exclusions was that the middle-layer weight of the four systems determined by the AHP method was small. As a result, the combination weights of the indicators in the four systems were too small, and the indicators were in turn eliminated. The AHP method was more subjective.

Table 5 | Indicator weights under different weighting algorithms

| Middle layer | Indicator layer | BFCM-CRITIC | AHP-CRITIC | CRITIC | AHP |
|--------------|----------------|-------------|------------|--------|-----|
| WRS          | WRS1           | 0.0219      | 0.0279     | 0.0225 | 0.0117 |
|              | WRS2           | 0.0278      | 0.0354     | 0.0206 | 0.0117 |
|              | WRS3           | 0.0159      | 0.0203     | 0.0241 | 0.0073 |
|              | WRS4           | 0.0159      | 0.0203     | 0.0241 | 0.0188 |
|              | WRS5           | 0.0256      | 0.0326     | 0.0211 | 0.0073 |
|              | WRS6           | 0.0157      | 0.0201     | 0.0241 | 0.0299 |
|              | WRS7           | 0.0216      | 0.0275     | 0.0217 | 0.0460 |
|              | WRS8           | 0.0158      | 0.0201     | 0.0241 | 0.0299 |
|              | WRS9           | 0.0195      | 0.0248     | 0.0218 | 0.0664 |
| SRS          | SRS1           | 0.0222      | 0.0283     | 0.0243 | 0.0172 |
|              | SRS2           | 0.0551      | 0.0703     | 0.0208 | 0.0474 |
|              | SRS3           | 0.0229      | 0.0291     | 0.0243 | 0.0474 |
|              | SRS4           | 0.0265      | 0.0338     | 0.0229 | 0.0112 |
|              | SRS5           | 0.0230      | 0.0293     | 0.0243 | 0.0279 |
|              | SRS6           | 0.0300      | 0.0382     | 0.0230 | 0.0779 |
| AS           | AS1            | 0.0250      | 0.0318     | 0.0234 | 0.0082 |
|              | AS2            | 0.0195      | 0.0248     | 0.0207 | 0.0131 |
|              | AS3            | 0.0204      | 0.0260     | 0.0209 | 0.0131 |
|              | AS4            | 0.0204      | 0.0261     | 0.0210 | 0.0220 |
|              | AS5            | 0.0206      | 0.0262     | 0.0211 | 0.0220 |
|              | AS6            | 0.0264      | 0.0337     | 0.0241 | 0.0573 |
|              | AS7            | 0.0259      | 0.0330     | 0.0240 | 0.0573 |
|              | AS8            | 0.0215      | 0.0274     | 0.0219 | 0.0562 |
| SS           | SS1            | 0.0166      | 0.0086     | 0.0241 | 0.0229 |
|              | SS2            | 0.0188      | 0.0097     | 0.0239 | 0.0034 |
|              | SS3            | 0.0243      | 0.0126     | 0.0211 | 0.0145 |
|              | SS4            | 0.0192      | 0.0099     | 0.0243 | 0.0053 |
|              | SS5            | 0.0272      | 0.0141     | 0.0208 | 0.0089 |
| ES           | ES1            | 0.0091      | 0.0063     | 0.0209 | 0.0045 |
|              | ES2            | 0.0637      | 0.0442     | 0.0220 | 0.0071 |
|              | ES3            | 0.0099      | 0.0069     | 0.0205 | 0.0116 |
|              | ES4            | 0.0100      | 0.0069     | 0.0209 | 0.0116 |
|              | ES5            | 0.0093      | 0.0064     | 0.0209 | 0.0031 |
|              | ES6            | 0.0091      | 0.0063     | 0.0208 | 0.0284 |
|              | ES7            | 0.0114      | 0.0079     | 0.0209 | 0.0188 |
| MS           | MS1            | 0.0156      | 0.0074     | 0.0208 | 0.0106 |
|              | MS2            | 0.0200      | 0.0096     | 0.0214 | 0.0177 |
|              | MS3            | 0.0167      | 0.0080     | 0.0212 | 0.0061 |
|              | MS4            | 0.0272      | 0.0130     | 0.0231 | 0.0036 |
| EES          | EES1           | 0.0219      | 0.0193     | 0.0206 | 0.0340 |
|              | EES2           | 0.0347      | 0.0306     | 0.0244 | 0.0086 |
|              | EES3           | 0.0316      | 0.0279     | 0.0240 | 0.0514 |
|              | EES4           | 0.0213      | 0.0188     | 0.0207 | 0.0216 |
|              | EES5           | 0.0217      | 0.0191     | 0.0209 | 0.0057 |
|              | EES6           | 0.0220      | 0.0194     | 0.0208 | 0.0136 |
which affected the accuracy of the final indicator system results. The indicator WRS$_2$ was removed by the CRITIC method, which had a great impact on the restoration power of the ASWRS; this is a meteorological indicator that is rarely found in the evaluation indicator system. SRS$_2$ and AS$_2$ are important indicators and should be retained. Based on the status quo of this study area, we know that in the indicator system established by the BFCM-CRITIC method, the representative indicators, such as WRS$_7$, SRS$_3$, AS$_6$, AS$_7$, SS$_3$, EES$_4$, and EES$_6$, are selected through optimization. In comparison with the AHP-CRITIC method, which combines the same subjective and objective weights, the BFCM-CRITIC method reduces the impact of the subjective weight on the final result. In comparison with the CRITIC method, which calculates only the objective weights, the AHP method emphasizes the subjective consideration of the actual situation in the study area. The sorted result for the final determined magnitude for the influence of indicators is intuitive and shows that the method adopted in this paper is suitable for selecting a resilience evaluation indicator system for ASWRSs. Among the indicators that were deleted, when calculating the indicator weight for the economic system, the objective weight of indicator ES$_3$ was 0.5203, resulting in a smaller weight for the remaining indicators ES$_3$, ES$_4$, ES$_5$, and ES$_7$ in the economic system.

**Comparative analysis of evaluation results**

To verify the rationality of the indicator system constructed in this paper, the similarities and differences in the indicators used to measure the resilience are compared and analysed in
order to avoid the impact of regional and research content differences on the resulting analysis. By referring to the results and content of research in similar areas, a comparative analysis was carried out considering three aspects: the construction of the indicator system, the selection of initial indicators and the difference in the screening indicator layer (Perrings 2006). The results are shown in Table 6.

The initial indicator is the basis for optimizing the indicators. In view of the complexity of research on the resilience of ASWRS, the selected indicators should not only meet the extensive requirements but also meet the requirements of comprehensiveness and observability. Compared with the research results from the other five studies, both the primary indicators and the remaining indicators selected in this paper cover the scope of previous indicators and are more extensive and comprehensive. Although the screening methods and processes are different, the remaining indicators are basically the same as the results for the screening indicators, and a total of 28 identical indicators account for 80%, which indicates that the indicators screened in this paper are reasonable and comprehensive.

**CONCLUSIONS**

Regional agricultural soil–water resources represent a complex, large system, and resilience is a basic attribute that can be used to describe the operational status of such systems (Milman & Short 2008). Constructing a complete resilience evaluation indicator system is a primary task for the green environmental sustainable development of ASWRS. The selection of indicators plays an important role in research on resilience. The establishment of an evaluation indicator system also provides a good theoretical basis for calculating the next step of resilience.

1. By constructing an indicator optimization model, choosing the criteria for indicator selection, setting up a framework for the evaluation indicator system, determining the hierarchical relationship, and determining the indicator selection and optimization matrix, the final number of evaluation indicators was filtered from 59 to 35. Ensuring that the completeness of the indicator system reached 85.75% meant that the indicator system became more compact and more adaptable. According to influence, the indicators ranked from large to small as follows: ES₂, SRS₂, EES₂, SRS₃, WRS₂, MS₄, SS₅, SRS₄, AS₆, AS₇, WRS₅, AS₁, SS₃, SRS₅, SRS₁, EES₆, EES₁, WRS₁, EES₄, WRS₇, AS₈, EES₄, AS₇, AS₃, MS₂, AS₂, WRS₉, MS₃, WRS₈, MS₁, ES₅, and ES₁.

2. Based on the current conditions in the research area, the BFCM is combined with the CRITIC method to determine the combination weights of the indicator

| Research content | Research method | Number of primary indicators | Number of remaining indicators | Number of same indicators |
|------------------|-----------------|------------------------------|-------------------------------|--------------------------|
| This paper       | Agricultural soil–water resource composite system resilience | An indicator optimization model based on the Dale criterion and the combined weight of BFCM-CRITIC | 59 | 35 | Accumulate the same amount 28 |
| Liu et al. (2019b) | Cumulative contribution rate and grey relational degree | 50 | 28 | 18 |
| Liu et al. (2017) | Agricultural water resource composite system resilience | An indicator optimization model based on the Dale criterion | 44 | 32 | 8 |
| Liu et al. (2019a) | Flood disaster system resilience | Clustering analysis | 43 | 15 | 4 |
| Li et al. (2020)  | Agricultural soil and water resource system harmony | Variation coefficient-R clustering-grey correlation advantage model | 79 | 22 | 9 |
| Liu et al. (2020b) | Irrigation water use efficiency | Driver-pressure-state-impact-response model with the information significance difference | 50 | 14 | 8 |
optimization model. The AHP-CRITIC method, the AHP method and the CRITIC method are used for verification, and the results show that the indicator weights determined in this paper are more reliable than other weights for the current conditions in this study area. Compared with the other three methods, the BFCM-CRITIC method eliminates 80% of the same indicators. It prevents the use of subjective or objective weights alone and effectively screens out representative indicators. The final established indicator system includes indicators that are representative of the WRS, SRS, AS, SS, ES, MS, and EES and more comprehensively reflect the factors that influence the resilience of the ASWRS in Jiansanjiang Administration.

(3) Notably, the use of multiple linear regression analysis extended the historical data that were missing environmental parameters. The use of a sum of indicator system weights $>0.85$ as an indicator of completeness may have had an impact on the preferred results for the indicators. In the future, to ensure the breadth of the evaluation indicators of the restoration capacity of regional ASWRSs, determining how to more accurately derive missing historical data for related indicators and how to more reasonably determine the completeness of the indicator system are worth further study.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

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