

Optimization of irrigation water use efficiency evaluation indicators based on DPSIR-ISD model

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ABSTRACT

The evaluation of irrigation water efficiency plays an important role in the efficient use of agricultural water resources and the sustainable development of agriculture. In order to make the evaluation of irrigation water use efficiency indicators more comprehensive and scientific, this paper constructs a new optimal model of evaluation indicators. By combining the Driver-Pressure-State-Impact-Response (DPSIR) model with the Information Significance Difference (ISD) evaluation indicators model, a novel DPSIR-ISD evaluation indicators combination model was constructed. Ten riverside irrigation areas in the Sanjiang Plain of northeastern China were selected for analysis. The results show that the DPSIR-ISD model was used to reduce the number of indicators from 44 to 14; these 14 indicators reflected 91.88% of the original information. The DPSIR-ISD method proposed in this paper takes into account the completeness and simplicity of the indicators system, and is more in line with the actual situation in the field. These results can provide a simpler and more convenient system for optimizing indicators for the study of evaluation indicators used to analyze irrigation water use efficiency.

Key words | DPSIR-ISD, evaluation indicators optimization, irrigation water use efficiency, riverside irrigation area, Sanjiang Plain

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INTRODUCTION

Water is widely considered to be the most important natural resource. The 2016 China Water Resources Bulletin (Ministry of Water Resources of the PRC 2017) shows that agricultural production accounts for more than 60% of the total water consumption in China, far exceeding living, industrial, and ecological needs for water. Most agricultural water is used for irrigation. However, as the most populous country in the world, China lacks abundant per capita water resources,

which are far below the international average (Kang *et al.* 2017), making improving the efficiency of irrigation water use particularly urgent. The evaluation indicators of irrigation water use efficiency provide an important tool for agricultural water use research, and are a necessary prerequisite for the in-depth study of water-conserving irrigation methods and the optimal allocation of water resources. However, a systematic method that can be used to clearly evaluate

the standard of irrigation water use efficiency is still lacking. This has created many difficulties in the subsequent implementation of the water resource management system.

As early as 1977, the International Commission on Irrigation and Drainage proposed a standard for irrigation water use efficiency (Marinus 1979). It is based on the efficiencies of the three separate operations by which water is moved through an irrigation system: conveyance, distribution, and field application. However, this standard is not very mature (Kang & Cai 1996). Many experts and scholars have been studying this (McGuckin *et al.* 1992; Boubaker *et al.* 2007; Watto & Mugeru 2015); although research in this field has been continuously improving, no clear and widely accepted definitions on irrigation water use efficiency exist for the methods of expression, measurement methods, research angles, influencing factors, evaluation indicators, etc. The evaluation of irrigation water use efficiency has evolved from the initial classic definition of efficiency to the new classical efficiency; however, the evaluation of water resource productivity has experienced a transition from an evaluation of engineering efficiency to an evaluation of economic efficiency, while the evaluation scale has gradually extended to larger scales (Lei 2010). Currently, the more commonly used treatment methods for evaluating indicators of irrigation water use efficiency are to directly determine indicators through relevant data or experience, and analyze and calculate all of the indicators to obtain weights (Li *et al.* 2014) or contribution rates (Li *et al.* 2015), so as to evaluate water use. In this way, when evaluating the efficiency of irrigation water use, many factors will need to be analyzed. This not only increases the difficulty of analysis and the workload, but may also make it difficult to reflect the information comprehensively because the selected indicators are one-sided or the selection of indicators is too broad to grasp the main impact information so that the results are not accurate enough.

In the late 1970s, Canada developed the State-Response model (Svarstad *et al.* 2008). Later, the Organization for Economic Co-operation and Development and the United Nations Environment Programme developed the Pressure-State-Response model from the State-Response model. Because the Pressure-State-Response model focuses on man-made stress and responses (UNEP/RIVM 1994), regardless of the behavioral factors behind any anthropogenic stress, the model

was extended to the Driver-State-Response and the Driver-Pressure-State-Impact-Response (DPSIR) models to facilitate use of a wider range of applications (Niemeijer & de Groot 2008; Lin *et al.* 2009). The DPSIR model has gradually evolved and is widely recognized (Ehara *et al.* 2018). Many experts and scholars have used the DPSIR model in several ways. These include the conceptualization of research systems and the evaluation of developmental case studies (Wolfslehner & Vacik 2011; Bezlepikina *et al.* 2014); monitoring river water quality, water resources sustainably, and developing agricultural resources (Faber & van Wensem 2012; Song & Frostell 2012; Sun *et al.* 2016); conducting ecological protection activities; external factors driving the effects of land management on ecosystems and conducting ecosystem risk assessment (Maxim *et al.* 2009; Lozoya *et al.* 2011; Kohsaka *et al.* 2013; Cook *et al.* 2014); and so on.

Additionally, Chen and Chi (Chen & Chi 2014) proposed the Information Significance Difference (ISD) model and applied it to the screening of green industry evaluation indicators. The ISD model is an objective indicator screening method based on mathematical calculations. It is more objective and comprehensive than other models while avoiding the duplication of indicator information. The DPSIR and ISD models have not been combined and applied in the screening of indicators. This paper proposed an DPSIR-ISD model as a new method used to optimize the indicators and to evaluate irrigation water use efficiency by combining subjective indicator selection and objective calculation. Although the result is a combination of two models, the operation is very simple and convenient for practical application. The DPSIR model makes up for the purely objective calculation of the ISD model without the disadvantage of incorporating subjective considerations; the ISD model improves upon the subjective selection required for using the DPSIR model. The latter model is too broad, so that the main information obtained is not significant enough, and the indicator information is redundant. DPSIR-ISD model combines subjective selection with objective calculation, so that the two models complement each other, making the preferred results more scientific and complete.

The research goals of this paper are as follows:

- (1) Construct a preferred DPSIR-ISD model for the indicators used to evaluate irrigation water use efficiency.

- (2) Propose a scientific, reasonable, and easy-to-operate system for evaluating the efficiency of irrigation water use efficiency indicators.
- (3) Analyze the performance of the DPSIR-ISD optimization model for evaluating the efficiency of indicators for irrigation water use.

MATERIALS AND METHODOLOGY

Study area

The Sanjiang Plain (Liu *et al.* 2012; Liu *et al.* 2017; Zhang *et al.* 2019) is located in Heilongjiang Province in northeastern China, and has one of the three largest black belts of soil in the world. The soils are mainly black soil, meadow soil, chernozem soil, and dark brown loam. The black soil has an organic matter content of 3–5%. This region has the highest cultivated land area and per capita cultivated land in China. The region features fertile soil, with climatic conditions suitable for many crops, good

light conditions, as well as having rain and heat available in the same season, making the vast and flat plains suitable for growing crops and for large-scale mechanized farming. As a result, the region has the highest level of agricultural mechanization in China with a great potential for agricultural production. It is the most important grain-producing area in China. However, after years of high-intensity development and cultivation, the local area has excessively extracted groundwater in order to increase the grain output, resulting in the continuous decline of the groundwater level in some areas. Under such a background, land managers need to know how to properly construct an evaluation indicator system used to analyze irrigation water use efficiency, an urgent need that should be addressed to ensure regional food security and ecological security.

Ten riverside irrigation areas were selected for analysis, namely, Bawusan, Daxing, Hamatong, Jiangchuan, Jinxi, Longtouqiao, Songjiang, Wutonghe, Youyi, and Xingfu. All of the areas are on the Sanjiang Plain (Figure 1). Each of these irrigation areas are close to a surface water source.

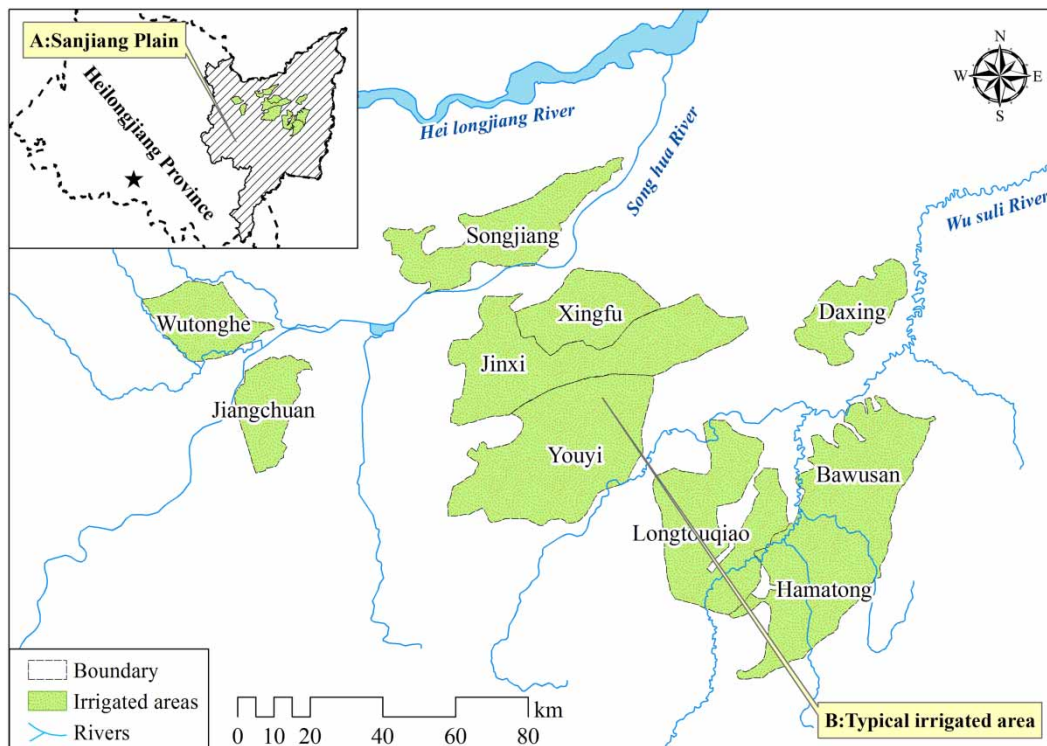


Figure 1 | Location of the study area showing the 10 areas analyzed here; an inset figure shows the location of the study areas within the Sanjiang Plain and Heilongjiang Province, China.

The construction of a water diversion project provides a natural advantage in the geographical proximity of the study area reducing the investment required for engineering an irrigation system.

The basic information of each irrigation area is shown in Table 1. Although the selected irrigation areas are all along rivers, 80% of them use groundwater for irrigation or use groundwater as the main source of irrigation water. If part of the groundwater is replaced by surface water, surface water irrigation or combined surface water and groundwater irrigation can greatly improve and guarantee the availability of irrigation water, alleviate the problem of serious unsustainable exploitation of groundwater in this area, and realize the sustainable development of water resources and maintain the ecological balance of the region.

Data sources

Statistical data sources

Because lag time is involved in the reporting of data statistics, the current study used 2013 as the data year. The hydrometeorological, agricultural, and economic data were derived from the [Statistics Bureau of Heilongjiang Provincial State Farms Administration \(2014\)](#), the Jiansanjiang Administration (local authority), the Hongxinglong

Administration (local authority), and reports on irrigation projects in irrigation areas.

Experimental data source

Water quality data were acquired from sampling experiments conducted as a part of field research. The experimental scheme is to take representative wells in each irrigation area as sampling points, and take three water samples at each sampling point; the selected groundwater quality parameters included pH, COD_{Mn} , $\text{NH}_3\text{-N}$, $\text{NO}_3\text{-N}$, Cl^- , F^- , SO_4^{2-} , Fe (total iron) and Mn (total manganese), were selected. pH was measured using a PHS-3C pH meter (Shanghai INESA Scientific Instrument Co., Shanghai, China), and the remaining parameters were measured using a Hach DR 2800 Spectrophotometer (Hach Company in Loveland, Colorado, USA) (Liu et al. 2017). The average concentrations of three water samples at each point were used to represent the concentration at this point. The concentration of each parameter was measured as the average concentration of three water samples collected at each point. The data were obtained by the improved projection pursuit model to determine the groundwater quality fitting value for evaluating the level of water quality.

Because the sampling time was the ponding period in May 2018, to ensure the consistency of the statistical data and the experimental data year, 6 years (2013–2018) of data were analyzed. The data analysis was based on several factors in the study area including the proportions of cultivated area and of paddy field area, as well as the total amounts of chemical fertilizer, nitrogen fertilizer, and pesticides applied per ha. The data from 2013 were prolonged according to changes in the data laws from 2013 to 2018. Groundwater quality grade was used to classify these areas (Liu et al. 2017).

Research method

DPSIR model

To clarify the selected indicators and make them more comprehensive, this paper adopted the DPSIR model that is widely used as the primary screening tool in the field of spatial scale environment. The DPSIR model employs a

Table 1 | Size and water sources for the 10 irrigation areas analyzed here

Irrigation area name	Spatial extent of each irrigation area (ha)	Water source
Bawusan	118,152	Well irrigation + self-flow
Daxing	80,000	Well irrigation
Hamatong	89,633	Well irrigation + water lifting
Jiangchuan	37,167	Well irrigation + water lifting
Jinxi	118,280	Well irrigation + water lifting
Longtougiao	49,700	Water storage
Songjiang	61,507	Water lifting
Wutonghe	31,268	Well irrigation + water lifting
Youyi	188,812	Well irrigation
Xingfu	53,200	Well irrigation + water storage

causal chain (Ehara *et al.* 2018), starting from the Drive (D; economic and social development, water resources supplement) through Pressure (P; pollution and waste, etc.) to the State (S; the status of water resources and irrigation areas) and the Impact on irrigation systems for humans and irrigation areas (I; output value, irrigation water supply changes, etc.), which ultimately leads to human Response (R; policies, plans, and actions). Meanwhile, human Response constrains the D, P, S, and I (Smeets & Weterings 1999; Ehara *et al.* 2018).

Many factors affect the efficiency of irrigation water use. These factors are related to the natural conditions of the irrigation area, the irrigation system used, the level of economic development, personnel management, crop type, the local environment, and many other factors. The indicator layer can be formulated in many ways: according to water balance, flow weights and their thresholds, water reuse, and total consumptive use (Haie *et al.* 2012); classification according to different types of water losses (Carter *et al.* 1999); according to the natural conditions of the irrigation area, irrigation conditions, crop planting structure, irrigation engineering measures, irrigation technology, irrigation area infrastructure and water saving facilities, irrigation district management level, economic policy and water supply price (Huang *et al.* 2018a); according to the status of water-saving renovation project, irrigation method, planting structure, water resources management, irrigation district land management water-saving matching status, irrigation district management level, economic policy and water supply price (Huang *et al.* 2018b). To minimize the interference of subjective factors, the DPSIR model was used as a preliminary screening tool to constrain the primary selection indicators within the framework of the DPSIR model. The DPSIR model helps us analyze information from a causal perspective and focus on important information. According to the DPSIR, the indicator layers are divided into five types of layers as follows: Drive layer (D)—the indicators that can drive the effects of irrigation on water use efficiency in the irrigated area, including economic development factors, irrigation water sources, technology planting, etc.; Pressure layer (P)—indicators of pressure on irrigation water use efficiency, including water shortages, water pollution and wastewater, water consumption, cultivated land area, etc.; State layer (S)—indicators reflecting the current

status of the efficiency of irrigation water use in irrigated areas, including planting development in the irrigation districts, water supply, and operational status of water conservation facilities; Impact layer (I)—indicators reflecting the effects of the efficiency of irrigation water use on changes in irrigation areas, including water-conservation measures, farmers' income, food production, etc.; Response layer (R)—reflecting indicators of policies, measures, and actions adopted to improve irrigation water use efficiency in irrigated areas, including soil and water conservation, afforestation, personnel management, maintenance, and investment in water conservation facilities, water fee collection, etc.

Dimensionalization of indicator data

After the initial screening indicator was determined, the data should be first made dimensionless to avoid the adverse effects of units and dimensions on the data (Chen & Chi 2014). Dimensionless is a common method to avoid the influence of units on data. In this way, the characteristics representing different attributes (different units) are comparable.

ISD model

The ISD model is based on the principal component analysis (PCA) of indicators and Pearson's correlation analysis between indicators to judge the significance of each indicator, and to eliminate the selection indicators with weak information significance and information redundancy. The preliminary indicators were screened by the ISD model according to the five indicator layers described above as D, P, S, I, and R. The analysis of the indicators is mainly divided into two steps: principal component and Pearson's correlation coefficient analyses. The Statistical Package for the Social Sciences (SPSS) software was used in the analysis as follows:

(1) Principal component analysis

Principal component analysis employed Equation (1):

$$Y_i = \alpha_{i1}X_1 + \alpha_{i2}X_2 + \dots + \alpha_{ip}X_p + \beta, \quad (1)$$

where Y is the i^{th} principal component ($i = 1, 2, \dots, k$; k is the number of retained principal components); X_i is the i^{th}

indicator ($i = 1, 2, \dots, p$; p is the number of indicator); α_{ij} is the j^{th} component of the eigenvector corresponding to the i^{th} eigenvalue of the correlation coefficient matrix of the indicator value; β is the constant residual.

The specific steps are as follows:

Step 1: Determine the correlation coefficient matrix $A_{m \times n}$ of the dimensionless indicator value.

Step 2: Calculate the eigenvalue λ_i ($i = 1, 2, \dots, p$) of the matrix $A_{m \times n}$; λ_i represents the total variance of the indicator data explained by the i^{th} principal component Y_i ; the variance contribution of the principal component to the original indicator is u_i :

$$u_i = \frac{\lambda_i}{\sum_{i=1}^p \lambda_i}. \quad (2)$$

Step 3: The i^{th} eigenvalues are arranged from small to large, and the principal component (Chen & Chi 2014) is selected according to the requirement of a cumulative variance contribution rate $\geq 85\%$. The load coefficient matrix of the i^{th} indicator on the j^{th} principal component is obtained:

$$h_{ij} = \frac{g_{ij}}{\sqrt{\lambda_i}}. \quad (3)$$

Step 4: Screen out the indicators with the most significant impact on the evaluation under the i^{th} ($i = 1, 2, \dots, p$) principal component. The greater the absolute value of the load factor, the more important the indicator is, and the more it should be retained. Set a threshold N ($0 < N < 1$); this article sets N to 0.8 (Chen & Chi 2014). If $|h_{ji}| > N$, the j^{th} indicator is retained, and if $|h_{ji}| < N$, the j^{th} indicator is deleted. In the same indicator layer, any indicator with a small load factor under the same main component was deleted to ensure that the retained indicators have a significant impact on the comprehensive evaluation results.

(2) Pearson's correlation coefficient analysis

Pearson's correlation coefficient is a kind of linear correlation coefficient that is used to reflect the degree of linear correlation between two variables (Pearson 1920; Wang et al. 2018). This paper uses this to measure the degree of correlation between indicators, and deletes one that reflects relatively weak information or relatively difficult to obtain

data between two highly correlated indicators. This avoids a duplication of information between indicators and optimizes the indicator model (Cook et al. 2014).

Step 1: Pearson's coefficient analysis was conducted on retained indicators in the same indicator layer:

$$m_{ij} = \frac{\sum_{k=1}^n (M_{ki} - \bar{M}_i)(M_{kj} - \bar{M}_j)}{\sqrt{\sum_{k=1}^n \sqrt{(M_{ki} - \bar{M}_i)^2 (M_{kj} - \bar{M}_j)^2}}} \quad (4)$$

where m_{ij} is the correlation coefficient between the i^{th} and j^{th} indicators; M_{ki} is the value of the i^{th} indicator of the k^{th} evaluation object; \bar{M}_i is the average of the i^{th} indicator; M_{kj} is the value of the j^{th} indicator of the k^{th} evaluation object; and \bar{M}_j is the average of the j^{th} indicator.

Step 2: If the Pearson's correlation coefficient of two indicators is greater than 0.7, they are highly correlated with each other. In this paper, the threshold was set to 0.7. When the correlation coefficient between two indicators is greater than 0.7, the relatively weaker of the two in reflecting information should be deleted.

Discrimination of the rationality of the evaluation indicator system

If more than 90% of the original information can be reflected by the optimized indicators, the construction of the indicators system is reasonable. The extent to which the final retained indicator reflects the information of the primary screening indicators represents the information contribution ratio of the post-screening indicators to the primary screening indicators:

$$I = \frac{S_g}{S_h} = \frac{\frac{1}{n-1} \sum_{j=1}^g \sum_{i=1}^n (X_{ij} - \bar{X})^2}{\frac{1}{n-1} \sum_{j=1}^h \sum_{i=1}^n (X_{ij} - \bar{X})^2}, \quad (5)$$

where S_g is the sum of the variances of the final retained indicator samples; S_h is the sum of the variances of all of the indicator samples after the primary screening; g is the number of final retained indicators; h is the number of all of the indicators after the primary screening; and n is the

number of indicator samples. The specific operation process of evaluation of the efficiency of irrigation water efficiency use is shown in Figure 2.

RESULTS AND ANALYSIS

Framework design of the system used to evaluate irrigation water use efficiency and initially select indicators

To reduce the interference of subjective factors, the predecessors' viewpoints and high-frequency indicators (Carter et al. 1999; Haie et al. 2012; Koç 2013; Huang et al. 2018a, 2018b) are constrained in the DPSIR model. All high-frequency indicators are selected and divided by the D, P, S, I, and R indicators of the DPSIR model. A total of 50 indicators were initially screened to evaluate efficiency of irrigation the study area. The specific indicator information is shown in Table 2. The preliminary results are analyzed as follows. Because the flat terrain in the study area is suitable for large-scale mechanization of agricultural operations, the

degree of mechanization is very high and exceeds 98% for all of the irrigation districts in the study area. No significant difference was observed between the irrigation districts, so the indicator D9 was eliminated. In addition, in the same indicator layer, the information in indicators D10 and D7, as well as R10 and R5 was duplicated; therefore, D10 and R10 were deleted. The statistical data of the study area are not perfect and lack some necessary information; as a result, indicators S12, R8, and R9 were deleted. Ultimately, 44 indicators were identified in accordance with the principles of sound science, comprehensiveness, and accessibility.

Screening and analysis of information significance indicators

With the excessive number (44) of primary screening indicators, it was difficult to grasp the main information, so it was necessary to reduce the number of indicators by using PCA. By using SPSS software to calculate the indicators with the absolute value of each load factor, the cumulative variance contribution rate reaches 85% or more.

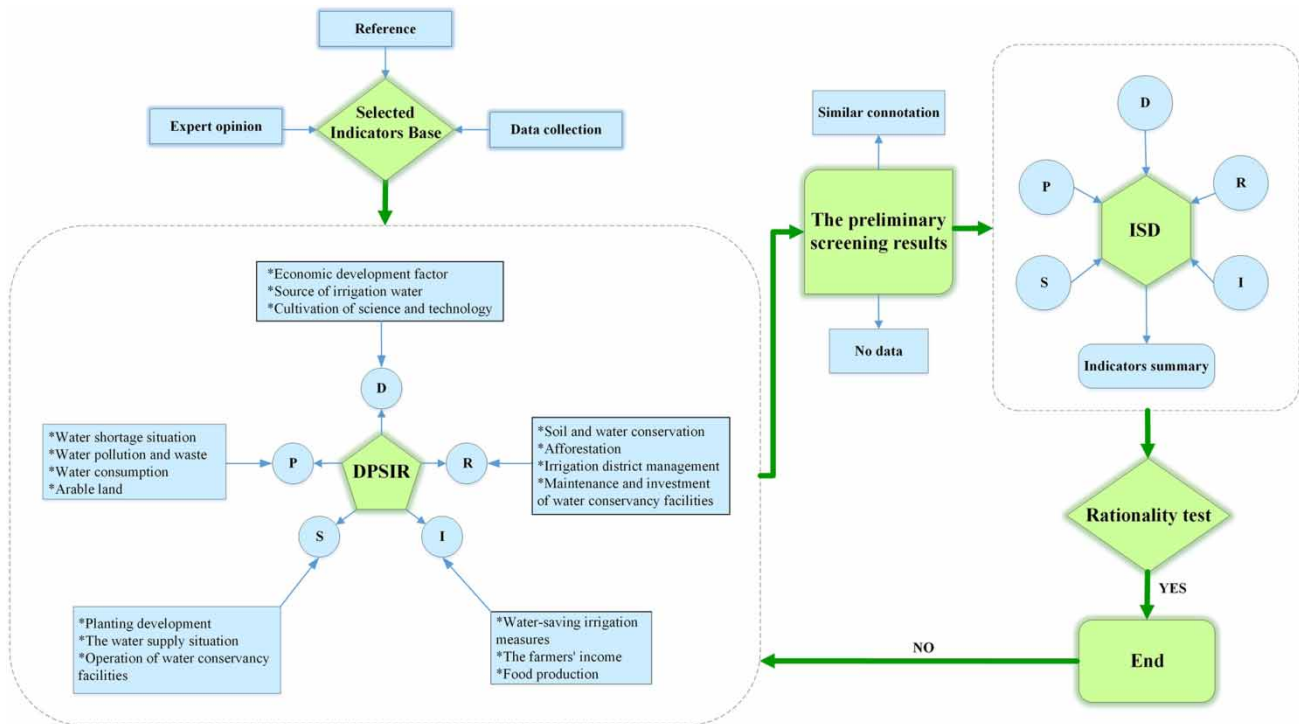


Figure 2 | Evaluation indicator optimization process framework.

Table 2 | Basic information of the primary screening indicators

Indicator layer	Number	Name	Unit	Type	Number	Name	Unit	Type
Drive	D1	Annual average precipitation	mm	+	D6	Precipitation infiltration replenishment coefficient	—	+
	D2	Per capita GDP	Dollar/year	+	D7	Primary industry GDP growth rate	%	+
	D3	Number of irrigation and drainage stations	per ha	+	D8	Agricultural commodity output value growth rate	%	+
	D4	Groundwater per capita exploitation	m ³	+	D9	Agricultural machinery operating rate	%	+
	D5	Number of electromechanical wells	per ha	+	D10	Agricultural output growth rate	%	+
Pressure	P1	Well irrigation area ratio	%	—	P6	Groundwater extraction rate	%	—
	P2	Proportion of cultivated land area	%	—	P7	Per capita water consumption	m ³ /year	—
	P3	Water shortage rate	%	—	P8	Guarantee ability of irrigation design	%	+
	P4	Annual water requirement	10 ⁴ m ³	—	P9	Water supply capacity	%	+
	P5	Deviation rate of groundwater ecological water level	%	—				
State	S1	Per capita water resources	m ³	+	S7	Surface water development and use rate	%	—
	S2	Coverage of forest and grass	%	+	S8	Agricultural land development and use rate	%	—
	S3	Water conservation facilities matching rate	%	+	S9	Groundwater quality level	—	—
	S4	Supporting project integrity rate	%	+	S10	Saving irrigation area rate	%	+
	S5	Per capita cultivated area	ha	—	S11	Achievement rate of diversion capacity of canal head	%	+
	S6	Water conservation project facilities area proportion	%	+	S12	Engineering maintenance cost satisfaction rate	%	+
Impact	I1	Effective irrigation rate of cultivated land	%	+	I6	Proportion of agricultural output value	%	+
	I2	Water efficiency of canal system	—	+	I7	Crop water productivity	kg/m ³	+
	I3	Water efficiency in field	—	+	I8	Irrigation water consumption	mm/ha	—
	I4	Effective coefficient of irrigative water use	—	+	I9	Rate of impervious lining of main canal	%	+
	I5	Growth rate of per capita disposable income	%	+				
Response	R1	Proportion of water conservation investment	%	+	R6	Water price in place	%	+
	R2	Afforestation area	%	+	R7	The proportion of farmland shelterbelt area	%	+
	R3	Investment in water conservation project per unit area	Dollar/ha	+	R8	Area ratio of field engineering matching renovation	%	+
	R4	Levy rate of water fee	%	+	R9	Eco-engineering ratio	%	+
	R5	Number of workers per unit area	pers/ha	+	R10	Personnel density per unit area	pers/ha	+

To balance the comprehensiveness and significance of the indicators in this analysis, the indicator with an absolute value of the load factor greater than 0.8 was selected for the next level of analysis, the number of indicators was reduced

from 44 to 16 in the initial screening. The PCA results are shown in [Table 3](#).

Pearson's correlation analysis was performed on each indicator in the same indicator layer to avoid duplication

Table 3 | Principal component analysis results

Indicator layer	Cumulative %	Indicator	Component
D	92.64	D1	0.91
		D5	0.94
		D7	0.90
P	87.31	P2	0.87
		P5	-0.80
S	88.54	S1	0.81
		S2	0.91
		S9	0.82
I	88.94	I1	0.88
		I2	0.94
		I3	0.91
		I4	0.96
		I8	0.85
R	86.80	R3	0.93
		R4	-0.82
		R5	-0.81

D, Driver; P, Pressure; S, State; I, Impact; R, Response.

of information between indicators; the Pearson's correlation matrix was calculated. The results show that in the I layer, for I1 and I2, as well as I2, I3, and I4, Pearson's correlation coefficients were greater than 0.6, indicating that these groups have a significant relationship. Therefore, these indicators cover information with obvious repetition. To make each indicator reflect relatively independent information, in a single indicator layer, only one of the indicators covering duplicated information can be retained. The other indicators reflecting redundant information can be deleted. According to the indicator data, the degree of difficulty and general acceptance can be obtained; therefore, indicators I2 and I3 were deleted. Finally, 14 evaluation indicators of irrigation water use efficiency were determined as follows: D1, D5, D7, P2, P5, S1, S2, S9, I1, I4, I8, R3, R4, and R5.

Analysis of the results of the indicator system

In the DPSIR-ISD optimization results, D1, D5, D7, I1, I4, I8, R3, and R5 are all relatively high-frequency indicators used in this field of study. These indicators reflect natural precipitation, groundwater development, and economic

development in an irrigated area as well as the irrigation area, effective use of irrigation water, irrigation water consumption, water conservation project investment, irrigation district management, etc. Having groundwater level deeper than or less than the ecological water level required by crops will cause ecosystem degradation. If the groundwater level is too deep, the ecosystem will be seriously degraded; but if the groundwater level is too shallow, the soil will be salinized (Wang *et al.* 2001). However, the local groundwater level has been continuously reduced in the study area, and the factors influencing the ecologically-sound groundwater water level cannot be ignored, so the indicator P5 was introduced. Because the irrigation area has been cultivated for many years, chemical fertilizers have continuously accumulated in the groundwater when they were leached from the soil. This has affected the quality of irrigation water, and increased the $\text{NH}_3\text{-N}$ and $\text{NO}_3\text{-N}$ content, so the indicator S9 was introduced. These two indicators were retained in the optimized results, which is in line with the actual situation of the study area. The final optimization indicator results can basically reflect the irrigation water use efficiency of the study area, and can be used for the evaluation of irrigation water use efficiency.

DISCUSSION

Rationality analysis of indicator system

To determine the rationality of the indicator system, the sum of sample variances of indicators preliminarily screened (44 indicators) and ultimately selected indicators (14 indicators) were named as S44 and S14, respectively. The information contribution rate of the ultimately selected indicators to the original indicators was obtained as:

$$I = S14/S44 = 91.88\%$$

The final number of indicators accounted for 31.82% of the original number of indicators, indicating that the indicator system uses 31.82% of the original indicator system to reflect 91.88% of the original information, which is reasonable in reflecting information capabilities.

Reliability analysis of indicator system

To verify the reliability of the indicator system, two methods were compared in this study. One is the system clustering (SC-ISD) method, which first uses (SC) to determine the objective indicators and then to carry out ISD analysis. The method is compared with the DPSIR-ISD method, which first carries out DPSIR, a form of subjective stratification. The other uses the ISD method to calculate directly, remove the step of indicator stratification, and make objective analyses of all primary screening indicators directly. The results show that the three indicators retained by DPSIR-ISD, SC-ISD, and ISD are D5, S2, and I4. The number of indicators in the final optimization system was 14, 10, and 14; specifically, the number of indicators $\text{DPSIR-ISD} = \text{ISD} > \text{SC-ISD}$.

The SC-ISD method selected only nine indicators. This number of indicators is too small and the results that reflect that the original information only accounts for 77.82% of the variability in the data. Therefore, the SC-ISD method has a poor ability to interpret the original information in the indicators. The system clustering method is commonly used for objective indicator stratification. The SC-ISD method reduces the influence of subjective factors. In the final result, only one indicator was retained in the D, P, and I layers, including D7 as an economic driving indicator. P5 is an indicator that is closely related to crop growth and can reflect the groundwater level pressure in the irrigation area. R5 is an indicator reflecting the management of the irrigation area. It is not retained in the results, indicating that the method does not take into account economic development, the groundwater environment, irrigation district management, and other factors. However, this part of the factor is indispensable and can comprehensively reflect the indicators of irrigation water use efficiency in the irrigated area. Therefore, the results obtained by this method are not comprehensive enough; that is, the DPSIR-ISD method is superior to the SC-ISD method in terms of comprehensiveness.

The ISD method is an objective analysis method. That is, all variables are calculated by mathematical formulas in the whole selecting process, and no subjective factors are involved in the operation process, so that the results are objective. Without the stratification of indicators, all of the

primary selection indicators would be directly calculated. When the primary indicators have been selected, no model constraints exist, which easily leads to the incompleteness of the selected indicators in the database of primary indicators and they cannot cover all of the influencing factors. In this way, the primary indicators will cause the screening results to be unbalanced in various aspects of the number of indicators, resulting in some aspects of the number of indicators being too many or too few, or even have an overall lack of good indicators. Because this paper applied the same primary indicator selection library when comparing methods, this disadvantage of the ISD method is not particularly obvious in the results. Compared with the ISD that does not directly divide the indicator layer, the DPSIR-ISD emphasizes the subjective consideration of the actual situation of the study area, which is more in line with the facts. Therefore, the DPSIR-ISD is significantly better than the other two methods in terms of the number of indicators, reflecting the comprehensiveness of the information and the actual situation of the study area.

Application of indicator system and prospect analysis

The primary selection library of this indicator system is composed of high-frequency indicators that have been widely used by experts and scholars so that these indicators can reflect the characteristics of the research area. The scope is comprehensive and the selection is reasonable. The results obtained by screening the indicators in a scientific and rational way are applicable. The goal of the indicator system is to apply to the evaluation of irrigation water use efficiency in irrigation districts, to provide a basis for the rational allocation and management of irrigation water, to achieve a scientific method to the supply of irrigation water and to ensure food security. Improving water use efficiency will relieve the contradiction between water resources and food production. These indicators are also factors influencing the efficiency of irrigation water use in irrigation districts, which can help people to avoid some human waste of water resources more easily. Irrigation water use efficiency in irrigation districts is a complex system under the influence of many factors. In the future, we need to analyze how to effectively combine the construction of an irrigation environment monitoring network, make

full use of emerging technologies such as big data analysis, as well as artificial intelligence, and analyze the multi-parameter coupling effect. It is an important research direction to optimize the evaluation indicators of irrigation water use efficiency under the background of multi-parameter coupling.

CONCLUSIONS

The process of selecting evaluation indicators is not clear and transparent enough, which often leads to subjective results that are not scientifically sound. To avoid this, this paper adopted the selection of indicators used to evaluate efficiency of irrigation water use based on mathematical calculations. This method combines subjective and objective techniques, which are clearly defined and can reduce the interference of subjective factors. Maintaining the balance between scientifically sound analysis principles and practical application was used as the basic principle of indicator selection. Simplified operation is conducive to the promotion of these methods.

- (1) In this paper, the optimization model of indicators used to evaluate irrigation water use efficiency based on DPSIR-ISD is introduced in detail. The results are real, reliable, and repeatable. After verification, the results obtained are more objective and comprehensive. The purpose of this new method is to provide a more simple and convenient choice for use in evaluation indicator research related to irrigation water use efficiency. If it can be flexibly used in combination with the actual situation of the study area, this method can be applied more widely.
- (2) The efficiency of irrigation water use is closely related to human activities. Positive interventions that enhance human factors, such as the construction of water-conserving irrigation facilities that reduce losses during the transport and use of irrigation water, the provisioning of adequate numbers of skilled management personnel, and the awareness of farmers related to water conservation, will have a positive effect on improving the efficiency of irrigation water use.
- (3) Due to the limited data available for collection, this paper only analyzes data from 2013 in space, but this

is not combined with a temporal analysis. If the sequence of time can be increased, the results will be more complete and provide more details.

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