Water and soil environmental vulnerability of artificial oases in arid areas and its temporal and spatial differentiation and evolution

Cundong Xu\textsuperscript{a,b,c}, Zijin Liu\textsuperscript{a,b,c,*}, Xinglin Zhu\textsuperscript{a,b,c}, Junjiao Tian\textsuperscript{a,b,c}, Fengyou Gu\textsuperscript{a,b,c} and Yan Wang\textsuperscript{a,b,c}

\textsuperscript{a} School of Water Resources, North China University of Water Resources and Electric Power, Zhengzhou 450046, China
\textsuperscript{b} Key Laboratory for Technology in Rural Water Management of Zhejiang Province, Hangzhou 310018, China
\textsuperscript{c} Henan Provincial Hydraulic Structure Safety Engineering Research Center, Zhengzhou 450046, China
*Corresponding author. E-mail: 1556135694@qq.com

ABSTRACT

The water and soil environmental vulnerability in arid areas is mainly affected by vegetation, hydrology, terrain, and climate. To accurately evaluate the water and soil environmental vulnerability and its evolution in the Jingtaichuan Pumping Irrigation District in China, this paper, taking 1994, 2006, and 2018 as typical years, selects 13 index factors that directly or indirectly drive the water and soil environmental evolution in this area, and adopts the cloud theory and analytic hierarchy process to determine the weight of each index factor. Spatial analysis technique and supervised classification were used to obtain and standardize the spatial distribution raster maps of each index factor. The multi-source data fusion was performed according to the index weight to analyze the evolution characteristics of soil and water environmental vulnerability. The results showed that soil salinity, vegetation coverage, and land use type have a significant impact on the water and soil environmental vulnerability in this irrigation area, and most of the area is at mild risk. High risk mainly occurs in closed hydrological units in the eastern part of the irrigation area. From 1994 to 2018, the evolution process can be divided into two stages, namely the ‘environmental deterioration stage’ and the ‘environmental restoration stage’. The results showed that the water and soil environment of the irrigation area is developing in a healthy way.

Key words: cloud theory, Jingdian Irrigation District, remote sensing, vulnerability, water and soil environment

HIGHLIGHTS

- It fused spatial data with long series monitoring data to analyze the vulnerability of soil and water environment in typical dryland irrigation areas.
- A hierarchical analysis method improved by introducing cloud theory determined the weights of each index factor.
- Soil salinity, vegetation cover and land use type are the key factors affecting the vulnerability of soil and water environment in arid irrigation areas.

1. INTRODUCTION

Water and soil environment is an indispensable carrier for organisms to carry out life activities. It is an environmental foundation necessary for the development of agriculture and economy in a region. The water and soil environmental vulnerability is an important indicator to measure the degradation of the water and soil environment and the level of the ecological restoration technology (Braimoh and Vlek 2004; Wang et al. 2012; Biazin and Sterk 2013). Previous studies revealed that the vulnerability of the soil and water environment in some areas has undergone fundamental changes (Setegn et al. 2009; Angelovicová & Fazekašová 2014; Lamsal et al. 2017; Felix et al. 2019; Xu et al. 2019). These changes are mainly caused by vegetation, hydrology, terrain, and climate, with obvious manifestations. However, the internal evolution and change often take place slowly. Therefore, it is necessary to reveal the influencing process and driving mechanism of various factors on the water and soil environmental vulnerability at the spatial and temporal scale through field experiments, long-term monitoring data, and space remote sensing data, which can contribute to the study of the evolution of water and soil environment in arid areas.

The research on the vulnerability of regional water and soil environment at home and abroad has achieved many important results. For example, Rosa et al. (2000) analyzed the vulnerability of soil erosion in Western Europe and its hidden impact on crop productivity based on the ImpelERO model; Qing et al. (2016) took the Qiandao Lake as the study area, integrated the
fuzzy analytic hierarchy process (FAHP) and geographic information system (GIS), and analyzed the changes in environmental vulnerability of the Qiandao Lake area from 1991 to 2010; Stampoulis et al. (2016) analyzed the water ecological vulnerability of different hydrogeological units in East Africa under extreme hydrological conditions using the WindSat microwave radiation measuring technique, to explore the impact of the dynamic hydrologic cycle on the ecological environment of water-deficient areas; Xu et al. (2011) made a systematic evaluation on the environmental vulnerability of the Pearl River Delta region using the analytic hierarchy process (AHP) and GIS based on remote sensing data. These results lay a foundation for the study of regional water and soil environment, but there are some deficiencies. In terms of research content: on the one hand, the cost of investigation poses a certain limitation to the selection of evaluation index factors, and the single or subjective method used to determine the weight of each index may have a great impact on the objectivity and accuracy of the environmental vulnerability evaluation results, which makes it difficult to accurately assess the water and soil environmental vulnerability under the combined effect of multiple factors. On the other hand, different study areas have different characteristics. The current research on environmental vulnerability evaluation mainly uses administrative regions, such as provinces, cities, and counties as evaluation units, and fewer studies are about the long-term water and soil environmental vulnerability with the study area spatially divided into grid units. In terms of research methods: on the one hand, it cannot describe the randomness and fuzziness of different environmental factors in driving the evolution of the water and soil environment in the irrigation area. On the other hand, determining the weight of each evaluation index for the water and soil environmental vulnerability is easily affected by personal subjectivity and empiricism, decreasing the accuracy and reliability of the evaluation results. The cloud theory was proposed by academicians Li Deyi of the Chinese Academy of Engineering in the 1990s to deal with fuzziness and uncertainty (Li et al. 2004). It is more advantageous in describing the randomness and uncertainty of fuzzy evaluation systems. Previous research results have shown that the cloud model can successfully realize the conversion between qualitative concepts and quantitative values based on the principle of cloud generator. It has been widely used in many research fields and achieved good evaluation results (Zhou et al. 2014; Xu et al. 2017).

This study uses the cloud theory to improve the conventional AHP, avoiding experts’ empirical and subjective determination of the index weight. This paper combines the long-term monitoring data, spatial data, and geographic information data to ensure the comprehensiveness and reliability of the evaluation data in the space-air-ground dimensions. Based on the above methods and data, a water and soil environmental vulnerability evaluation model was constructed and used to evaluate the water and soil environmental vulnerability of China’s Jingdian Irrigation District. The purpose of this study was: (1) to study the dynamic evolution process and characteristics of various factors affecting the vulnerability of the water and soil environment in the irrigation area; (2) to evaluate the vulnerability of the water and soil environment in the entire area and analyze its evolution from 1994 to 2018; (3) to guide the water and soil environmental governance and sustainable development in the irrigation area.

2. MATERIALS AND METHODS

2.1. Study area

The Jingdian Irrigation District in northwestern China’s Gansu Province sits between 103°20’–104°04’E and 37°26’–38°41’N (Figure 1). Affected by the geological structure and hydrological and topographical features, this irrigation area is divided into closed hydrogeological units – Caowotan and Luyang basins and open hydrogeological units – Yanghuzitan and Daduntan basins from east to west. With the total irrigated area of about 6.15 x 10^4 hni², this irrigation area is 1,470–2,368 m above sea level, and extends about 40 km from north to south and about 120 km from east to west. It borders the Tengger Desert to the north, Changling Mountain to the south, and the Yellow River to the east. In the zone of typical temperate continental climate, this irrigation area is dry with little rainfall, and features large inter-annual and day–night temperature differences. The average annual sunshine duration is up to 2,714 hours, the average annual temperature is 8.77 °C, the average annual rainfall is 185.6 mm, and the average annual evaporation is 2,433.8 mm. Long-term monitoring data show that, since the pumping irrigation in 1994, the groundwater level in part of the irrigation area has gradually increased, and the chemical features of groundwater have constantly changed, due to the irrigation mode without drainage; coupled with high evaporation, low rainfall, and unique landform, a number of water and soil environmental problems have gradually appeared in the irrigation area, posing challenges to its water and soil environmental vulnerability (Xu 2010). The above problems have severely hindered the local social, economic and ecological development. In this regard, this paper selects the representative Jingdian Irrigation District as the study area to analyze the evolution of water and soil environmental vulnerability, which is of high research value.
2.2. Index selection and data sources

To further reveal the temporal and spatial differentiation of the water and soil environmental vulnerability in the irrigation area, this paper, based on the actual situation of the study area and under the principles of scientificity, completeness and availability of data, selects the water and soil environmental vulnerability and its temporal and spatial differentiation characteristics as the target hierarchy; the soil vegetation, water resources, terrain, hydrology, and climate that significantly affect the water and soil environmental vulnerability as the criterion hierarchy; the soil salinity, vegetation coverage, land use type, and soil electrical conductivity that can reflect the water and salt content, soil erosion, deductive process of land resource utilization, and soil physical and chemical properties as the index factors of soil vegetation; the surface irrigation volume, groundwater depth, and groundwater salinity that reflect the movement and chemical properties of surface and ground water as the index factors of water resources; the elevation, slope, and aspect that directly participate in the geological structure of the water and soil environmental system as the index factors of terrain; the average annual precipitation, average annual evaporation, and average annual temperature as the index factors of climate that reflect hydrological and meteorological conditions in the area. On this basis, an evaluation index system for the water and soil environmental vulnerability of the study area was established. To make the analysis results more feasible and authentic, we selected three time nodes, namely 1994, 2006, and 2018 because: (1) these three years are highly representative. In 1994, the irrigation area was initially built, and the total irrigated area reached 40,100 hm², with an annual water-lifting volume of 366 million m³, mainly distributed in the eastern part; in 2006, the rehabilitation of the irrigation area was basically completed, and the total irrigated area reached 58,000 hm², with an annual water-lifting volume of 551 million m³; in 2018, the irrigation area was basically the same as its current situation, and the total irrigated area reached 68,500 hm², with an annual water-lifting volume of 660 million m³. (2) The data of these three years are complete enough for the research. (3) The intervals of these three representative years are both 12 years, meeting the periodicity of the data, which can make the evaluation results closer to the actual situation.

The basic data and index factor data in this study were derived from the following sources. (1) Landsat 5 remote sensing images in 1994 and 2006 and Landsat 8 remote sensing images in 2018 downloaded from the Geospatial Data Cloud website (http://www.gscloud.cn/). After geometric correction, image registration, image mosaic and cropping, the preprocessing results of remote sensing images were obtained, as shown in Figure 2. Different gray values in the figure represent different land use conditions in the irrigation area. The preprocessing result map is mainly used for later interpretation and extraction of land use information and topographical factors. (2) Based on the Land Survey Report of Jingtaichuan Irrigation District over the Years (1971–2018) and the field survey of groundwater resources in Jingtaichuan, 44 salinity sampling points were selected (Figure 2(a)). Soil samples of 0–20 cm, 20–40 cm, 40–60 cm, 60–80 cm, and 80–100 cm were taken using a soil auger and then extracted in the laboratory to analyze the corresponding salinity and soil electrical conductivity. (3) Data of groundwater...
depth and groundwater salinity were obtained from 32 monitoring wells arranged in the irrigation area (Figure 2(b)). (4) Data for surface irrigation volume and average annual precipitation were obtained from 29 water monitoring instruments and RS-QXYL-M automatic rainfall measuring stations deployed in the irrigation area (Figure 2(c)). (5) Data on average annual evaporation and average annual temperature were obtained from 21 miniature evaporation measuring meters and digital temperature measuring instruments installed in the irrigation area (Figure 2(d)). (6) The land use types were obtained from Landsat8.OLI data. In the ArcGIS10.2 Spatial Analyst module, ISO (interactive self-organization) clustering was performed first, and through image recognition and based on the actual land use conditions in the study area, the interpretation characteristics of images were divided into nine categories: cultivated land, mild saline-alkali land, moderate saline-alkali land, severe saline-alkali land, grassland, dry land, fixed sandy land, mobile sandy land, and gobi, according to the classification principle that representative pixels are in the same category. Finally, the maximum likelihood classification was used to extract the spatial distribution of each interpretation characteristics. Other supplementary materials included Report on Wasteland Resources and Their Development and Utilization in Jingtai County, Gansu Province (1971–2018), Statistics on Water Diversion and Consumption in the Irrigation Area from 1972 to 2018, and Hydrogeological Investigation Survey Report on Hexi Corridor (2018). Specific data sources and corresponding processing methods are shown in Table 1.

2.3. Interpolation accuracy validation analysis

Spatial interpolation refers to converting the limited data in the research scope into continuous surface set data using the ArcGIS software to reflect the corresponding changes of a variable in unknown parts of the study area. Commonly used spatial interpolation methods include the inverse distance weighted (IDW) method, trend surface method, spline method, and natural neighbor method based on the principle of deterministic interpolation, as well as the ordinary kriging method and universal kriging method based on the principle of geostatistical interpolation. Before interpolation analysis based on the spatial interpolation theory, data should be checked whether to meet the normal distribution. In this study, we used an Origin9.1 normal QQ graph analysis tool to test the sampled data, and found that the normal QQ test results basically present a normal distribution; thus, we performed the spatial variability analysis. In addition, we also introduced an error matrix to verify the accuracy of spatial interpolation and optimized the spatial interpolation method of each index (Kali et al. 2003; Li et al. 2016). The error matrix is a typical accuracy evaluation method in spatial interpolation, which evaluates the accuracy of spatial interpolation by calculating the comparative sequence between the measured pixel and the reference pixel. It mainly includes overall accuracy, producer accuracy, user accuracy, and Kappa coefficient. We just needed to consider the overall correct classification area and verify the accuracy of classification results in this study; thus, only the overall accuracy and Kappa coefficient were introduced (Shahid et al. 2018; Shahid et al. 2020). The calculation formulas are as follows:

$$\text{OA} = \frac{\sum_{i=1}^{r} n_{ii}}{N}$$

$$\text{Kappa} = \frac{P_0 - P_c}{1 - P_c}$$
where, OA is the overall accuracy; \( N \) is the total number of pixels; \( n_{ij} \) is the number of correctly classified pixels; \( r \) is the number of classifications; \( P_0 \) is the overall classification accuracy, that is, the ratio of the number of correctly classified samples to the total number of samples; \( P_c \) is the expected value of the correct classification under random conditions. When the Kappa coefficient is greater than 0.75, it is generally believed that there is a high consistency between the simulated results and the measured results. When the Kappa coefficient is less than 0.4, the consistency is relatively low.

In the ArcGIS-Spatial Analyst-interpolation analysis module, the kriging method, IDW method, spline method, natural neighbor method, and trend surface method were used for spatial interpolation of each evaluation index factor. After the accuracy comparison and optimization, the final interpolation method for each index was determined (Table 2).

As seen in the above table, higher overall interpolation accuracy and Kappa coefficient were obtained by comparing the selected index factor interpolation methods, which had higher interpolation value. Since the ArcGIS-Spatial Analyst-surface analysis and ISO clustering-maximum likelihood classification inversion analysis both showed that the raster data such as elevation, slope, aspect, land use type, and vegetation coverage are highly consistent, the accuracy validation was not made separately in the study.

### Table 1 | Evaluation indexes and data sources of water and soil environmental vulnerability in Jingdian Irrigation District

| Criterion hierarchy | Index factor | Unit | Data source | Data acquisition | Data type |
|---------------------|--------------|------|-------------|------------------|----------|
| Soil vegetation \( Y_1 \) | \( Z_1 \) soil salinity | % | Sampling point | Laboratory analysis + spatial interpolation | Vector data |
|                      | \( Z_2 \) vegetation coverage | % | Geospatial Data Cloud | Remote sensing inversion | Raster data |
|                      | \( Z_3 \) land use type | – | Geospatial Data Cloud | ArcGIS-Spatial Analyst-ISO clustering – maximum likelihood classification | Raster data |
| \( Z_4 \) soil electrical conductivity | S/m | Sampling point | Laboratory analysis + spatial interpolation | Vector data |
| Water \( Y_2 \) | \( Z_5 \) surface irrigation volume | \( 1 \times 10^4 \) m³ | Water monitoring equipment | Monitoring data + spatial interpolation | Vector data |
|                      | \( Z_6 \) groundwater depth | m | Monitoring well | Elevation conversion + spatial interpolation | Vector data |
| \( Z_7 \) groundwater salinity | g/l | Monitoring well | Laboratory analysis + spatial interpolation | Vector data |
| Terrain \( Y_3 \) | \( Z_8 \) altitude | m | Geospatial Data Cloud | Remote sensing inversion | Raster data |
|                      | \( Z_9 \) slope | ° | Geospatial Data Cloud | ArcGIS-Spatial Analyst – surface analysis | Raster data |
|                      | \( Z_{10} \) aspect | – | Geospatial Data Cloud | ArcGIS-Spatial Analyst – surface analysis | Raster data |
| Climate \( Y_4 \) | \( Z_{11} \) average annual precipitation | mm | Rainfall measuring gauge | Monitoring data + spatial interpolation | Vector data |
|                      | \( Z_{12} \) annual evaporation | mm | Miniature evaporation measuring meter | Monitoring data + spatial interpolation | Vector data |
|                      | \( Z_{13} \) average annual temperature | °C | Geospatial Data Cloud | Monitoring data + spatial interpolation | Vector data |

2.4. Evaluation factor weight cloud model

When experts use the conventional AHP to compare the influencing factors of water and soil environmental vulnerability in pairs and determine the judgment matrix and the significance of each factor, they are easily affected by their values and experience. The algebraic operation for determining weights based on the conventional principle of set-valued statistics is relatively simple, and using a single numerical scale to describe the experts’ scoring it is easy to ignore the uncertainty
and discreteness generated in the scoring process. In addition, the water and soil environmental evolution and response process in arid irrigation areas is fuzzy, complex, and uncertain. It is difficult to use a single accurate value to characterize the relationship between the response index and the water and soil environmental evolution and response. The characterization of results is also full of uncertainty and does not conform to human language habits. The cloud theory can well describe the randomness and uncertainty of fuzzy systems, freely convert qualitative concepts and quantitative values, and combine the randomness and fuzziness of targets through uncertain languages, so as to overcome the shortcomings of the conventional AHP. Based on this, this paper introduces the uncertainty cloud theory into the AHP to improve the comprehensive evaluation of the water and soil environmental vulnerability in the irrigation area.

According to the cloud theory, each cloud model is characterized by its corresponding expectation (Ex), entropy (En), and hyper-entropy (He), namely \( C(\text{Ex}, \text{En}, \text{He}) \) (Guan et al. 2016). Expectation (Ex) reflects the center-of-gravity position of cloud droplets, which respectively represent the central value of the water and soil environmental vulnerability, driving process, and inducing factors’ weight and membership; entropy (En) describes the fuzziness and randomness of cloud droplets, which respectively represent the possible value ranges of the water and soil environmental vulnerability, driving process, and influencing factors’ weight and membership; hyper-entropy (He) describes the thickness of clouds and mainly reflects the dispersion of cloud droplets, which respectively represent the deviation from the central value of the water and soil environmental vulnerability, driving process, and influencing factors’ weight and membership.

On the Satty scale of the classic AHP, experts are required to use a natural number between 1 and 9 to determine the relative importance of two factors (Nguyen and Nahavandi et al. 2016; Wang et al. 2017). In this study, we introduced the normal cloud theory and improved it by constructing a pairwise comparison judgment matrix based on influencing factors on the cloud model scale (Table 3).

The judgment matrix was constructed by the cloud model scale first, and then the square root method was used to calculate the weight of inducing factors. The weight cloud model was obtained by calculating elements of each row in the pairwise comparison judgment matrix. Calculation formulas of expectation (Ex), entropy (En), and hyper-entropy (He) (Zhang

| Importance comparison | Cloud model of scale criteria \( C(\text{Ex},\text{En},\text{He}) \) |
|-----------------------|---------------------------------|
| \( S_i \) is more important than \( S_j \)       | \( C_4(9,0.33,0.01) \)         |
| Absolutely            | \( C_3(7,0.33,0.01) \)         |
| Strongly              | \( C_2(5,0.33,0.01) \)         |
| Obviously             | \( C_1(3,0.33,0.01) \)         |
| Slightly              | \( C_0(1,0,0) \)               |
| \( S_i \) and \( S_j \) are equally important | \( C_2(1,0.33/9,0.01/9) \)   |
| \( S_i \) is not as important as \( S_j \)    | \( C_1(1/5,0.33/25,0.01/25) \) |
| Slightly              | \( C_2(1/7,0.33/49,0.01/49) \) |
| Obviously             | \( C_2(1/9,0.33/81,0.01/81) \) |

Table 2 | Interpolation method and accuracy of each evaluation index factor

| Index                     | Unit         | Overall accuracy (%) | Kappa |
|---------------------------|--------------|----------------------|-------|
| Soil salinity             | %            | 75.00                | 0.7376|
| Soil electrical conductivity | S/m         | 63.00                | 0.6513|
| Average annual precipitation | mm          | 71.00                | 0.7004|
| Surface irrigation volume | \( 1 \times 10^4 \) m³ | 73.00                | 0.7131|
| Groundwater depth         | m            | 72.00                | 0.7094|
| Salinity of groundwater   | g/L          | 69.00                | 0.6885|
| Average annual evaporation | mm          | 74.00                | 0.7294|
| Average annual temperature | %            | 76.00                | 0.7493|

Table 3 | Scale criteria of cloud model of vulnerability of water and soil environment
et al. 2014) are shown as follows:

\[
Ex_i = \frac{\left( \prod_{j=1}^{n} Ex_{ij} \right)^{\frac{1}{n}}}{\sum_{i=1}^{n} \left( \prod_{j=1}^{n} Ex_{ij} \right)^{\frac{1}{n}}}
\]  
(3)

\[
En_i = \frac{\left( \prod_{j=1}^{n} En_{ij} \right)^{\frac{1}{n}}}{\sum_{i=1}^{n} \left( \prod_{j=1}^{n} En_{ij} \right)^{\frac{1}{n}}}
\]  
(4)

\[
He_i = \frac{\left( \prod_{j=1}^{n} He_{ij} \right)^{\frac{1}{n}}}{\sum_{i=1}^{n} \left( \prod_{j=1}^{n} He_{ij} \right)^{\frac{1}{n}}}
\]  
(5)

According to the said formulas, the cloud model synthetic weight \( W_i (Ex_i, En_i, He_i) \) of 15 water and soil environmental vulnerability evaluation factors can be obtained.

2.5. Classification of water and soil environmental vulnerability

Based on the previous studies and the actual situation of this study area (Wang et al. 2012; Chen et al. 2016), the characteristic value \( EVI \) of environmental vulnerability was used to describe the water and soil environmental vulnerability in Jingdian Irrigation District, which was calculated by formula (6):

\[
EVI = \sum_{i=1}^{n} Y_1X_1 + Y_2X_2 + Y_3X_3 + \ldots + Y_nX_n
\]  
(6)

where, \( EVI \) represents the characteristic value of soil and water environmental vulnerability; \( Y_i \) represents the index factor value; \( X_i \) represents the corresponding weight value of each index factor; and \( n \) represents the number of indexes.

To further enhance the comparability of the comprehensive index of water and soil environmental vulnerability in the study area in temporal and spatial distribution, the comprehensive index \( EVI \) was standardized according to formula (7):

\[
S_i = \frac{EVI_i - EVI_{min}}{EVI_{max} \times 10}
\]  
(7)

where, \( S_i \) represents the standardized value of the comprehensive index of soil and water environmental vulnerability in the i-th year, which ranges from 0 and 10; \( EVI_i \) represents the actual value of the comprehensive index of soil and water environmental vulnerability in the i-th year; \( EVI_{max} \) represents the maximum value of the comprehensive index of soil and water environmental vulnerability in three periods; and \( EVI_{min} \) represents the minimum value of the comprehensive index of soil and water environmental vulnerability in three periods.

Based on the standardization of \( S_i \) and with reference to the standards of environmental vulnerability evaluation in existing studies, the water and soil environmental vulnerability of Jingdian Irrigation District was divided into five levels as per the specific characteristics (Table 4).
3. RESULTS

3.1. Weight of each index factor

We calculated the synthetic weight $W_i (Ex_i, En_i, He_i)$ for the impact of each index factor on the water and soil environmental vulnerability using the cloud theory-based improved AHP, and ranked the evaluation factors in the index hierarchy with their expectation $Ex$ as the first sorting element, entropy $En$ as the second sorting element, and hyper-entropy $He$ as the third sorting element (Xu et al. 2017). Accordingly, the total ranking of 13 indexes in the criterion hierarchy to the target hierarchy was obtained (Table 5).

As shown in Table 5, the factors affecting the vulnerability of the water and soil environment in the study area on regional scale are ranked as follows as per their importance: soil salinity > vegetation coverage > land use type > surface irrigation volume > groundwater depth > groundwater salinity > soil electrical conductivity > average annual evaporation > average annual precipitation > average annual temperature > elevation > slope > aspect. It can be seen that soil salinity, vegetation coverage, and land use type are the main index factors that affect the vulnerability of the water and soil environment on regional scale and its temporal and spatial differentiation process, followed by three moisture factors (surface irrigation volume, groundwater depth, and groundwater salinity), and three hydrometeorological factors (average annual evaporation, average annual precipitation, and average annual temperature). Topographical factors have the least impact on the temporal and spatial differentiation of the soil and water environmental vulnerability. The main reasons are that, in the oasis ecosystem, the soil state, vegetation coverage, and land use type are key factors that control the water and soil environmental evolution, and have the greatest impact on the temporal and spatial differentiation of the water and soil environment on the regional scale; water that transfers surface and underground solute factors directly participates in the soil–water–atmosphere continuum cycle, so it has a great impact on the regional water and soil environment; hydroclimatic factors, as representative factors of regional microclimate, participate in the regional water circulation, provide power for water and heat transfer, and play a potential driving role in the temporal and spatial differentiation of the regional water and soil environment; topographical factors, as the objective vector of the water and soil environment, only affect the temporal and spatial differentiation of the water and soil environment on a micro-scale, and has the minimal contribution to the large-scale regional water and soil environmental vulnerability.

### Table 4 | Division of soil and water environment vulnerability in Jingdian Irrigation District

| Vulnerability       | Grade | $S_i$ | Ecological characteristics                                                                 |
|---------------------|-------|-------|-------------------------------------------------------------------------------------------|
| Slight              | I     | 1–2   | The environmental system is perfect in structure and function, and bears little pressure. It is stable, with strong resistance to external interference, high self-resilience, and low vulnerability. |
| Mild                | II    | 2–4   | The environmental system is relatively perfect in structure and function, and bears little pressure. It is stable, with strong resistance to external interference and high self-resilience. However, there are possible abnormalities. The environmental vulnerability is relatively low. |
| Moderate            | III   | 4–6   | The environmental system structure and function can be maintained; the bearable pressure comes near the threshold value; the system is not stable, and sensitive to external interference; it is less resilient, and there have been some abnormalities; the environmental vulnerability is relatively high. |
| Severe              | IV    | 6–8   | The environmental system structure and function have been damaged; the pressure becomes large; the system is unstable, and highly sensitive to external interference; it is hard to restore after being damaged; there are many abnormalities; the environmental vulnerability is high. |
| Extremely severe    | V     | 8–10  | The environmental system structure and function are severely worsening; the pressure becomes extremely large; the system is unstable, and extremely sensitive to external interference; damage is very hard to be repaired, and may be irreversible; there are a great number of abnormalities; the environmental vulnerability is extremely high. |
| Index | \( Y_1 \) | \( Y_2 \) | \( Y_3 \) | \( Y_4 \) | Synthetic weight | Sort |
|-------|-------|-------|-------|-------|----------------|-----|
| \( X \) | 0.468 | 0.471 | 0.471 | 0.279 | 0.275 | 0.275 | 0.075 | 0.095 | 0.095 | 0.178 | 0.109 | 0.109 | \( (0.144,0.170,0.170) \) | 1 |
| \( Z_1 \) | 0.308 | 0.361 | 0.361 | \( (0.144,0.170,0.170) \) | 1 |
| \( Z_2 \) | 0.264 | 0.342 | 0.342 | \( (0.120,0.161,0.161) \) | 2 |
| \( Z_3 \) | 0.256 | 0.194 | 0.194 | \( (0.120,0.091,0.091) \) | 3 |
| \( Z_4 \) | 0.172 | 0.103 | 0.103 | \( (0.080,0.049,0.049) \) | 7 |
| \( Z_5 \) | 0.395 | 0.353 | 0.353 | \( (0.110,0.097,0.097) \) | 4 |
| \( Z_6 \) | 0.314 | 0.333 | 0.333 | \( (0.088,0.092,0.092) \) | 5 |
| \( Z_7 \) | 0.291 | 0.314 | 0.314 | \( (0.081,0.086,0.086) \) | 6 |
| \( Z_8 \) | 0.373 | 0.403 | 0.403 | \( (0.028,0.038,0.038) \) | 11 |
| \( Z_9 \) | 0.524 | 0.314 | 0.314 | \( (0.024,0.030,0.030) \) | 12 |
| \( Z_{10} \) | 0.303 | 0.283 | 0.283 | \( (0.023,0.027,0.027) \) | 13 |
| \( Z_{11} \) | 0.342 | 0.519 | 0.519 | \( (0.061,0.083,0.083) \) | 9 |
| \( Z_{12} \) | 0.423 | 0.321 | 0.321 | \( (0.075,0.051,0.051) \) | 8 |
| \( Z_{13} \) | 0.235 | 0.160 | 0.160 | \( (0.042,0.025,0.025) \) | 10 |
3.2. Characteristics of temporal and spatial distribution of each index factor
3.2.1. Temporal and spatial distribution of soil salinity
We carried out the spatial interpolation of the measured soil salinity data in the three periods using the ArcGIS-Spatial Analyst module (Figure 3 and Table 6). According to Figure 4 and Table 6, in 1994, a great number of land resources were newly exploited due to massive land reclamation. The short irrigation time and washing salinity by irrigation made the soil salinity lower; during the period from 1994 to 2006, because of the increasing human-induced disturbance on water and soil resources in the irrigation area and the long-standing unreasonable irrigation mode, the soil salinity rose sharply, with the

![Figure 3](https://example.com/fig3.png)

**Figure 3** | Soil salinity. (a) 1994. (b) 2006. (c) 2018.

| Characteristics of soil salinity in the three periods of Jingdian Irrigation District |
|---|---|---|---|
| **Years** | **1994** | **2006** | **2018** |
| Minimum value (%) | 0.0324 | 0.0496 | 0.0382 |
| Maximum value (%) | 1.2948 | 3.1871 | 3.1284 |
| Average value (%) | 0.6817 | 1.9864 | 1.9685 |

![Table 6](https://example.com/table6.png)

**Table 6** | Characteristics of soil salinity in the three periods of Jingdian Irrigation District

![Figure 4](https://example.com/fig4.png)

**Figure 4** | Vegetation coverage. (a) 1994. (b) 2006. (c) 2018.
range expanding from 0.0324%–1.2948% in 1994 to 0.0496%–3.1871%, and the average salt salinity was 1.3047% higher than that in 1994; during the period from 2006 to 2018, due to a series of desalination measures such as washing salinity by irrigation and adding alkali drainage ditches, soil in the irrigation area continued to desalt. By 2018, except for the closed hydrogeological units in the eastern part, the soil salinity in other parts of the irrigation area significantly declined, and the characteristic value of the salt concentration decreased from 0.0496%–3.1871% to 0.0382%–3.1284%. The expansion of secondary salinized land was effectively controlled.

3.2.2. Temporal and spatial distribution of vegetation coverage

We inverted the model through ArcGIS software and calculated the area of land with different levels of vegetation coverage in 1994, 2006, and 2018 (Table 7 and Figure 4).

It can be seen from Figure 4 and Table 7 that, in Jingdian Irrigation District, the land with low vegetation coverage or below shares a relatively large area. However, from 1994 to 2018, the area of land with low vegetation coverage (including extremely low vegetation coverage) was shrinking, down from 76.6% in 1994 to 58.16% in 2018, the area of land with medium vegetation coverage increased from 0.47% in 1994 to 2.19% in 2018, and the area of cultivated land rose from 22.93% in 1994 to 39.65% in 2018, showing a significant expansion.

3.2.3. Temporal and spatial distribution of land use type

We interpreted the remote sensing images through visual interpretation and the maximum likelihood classification method, and extracted the land use information of the irrigation area in 1994, 2006, and 2018 (Figure 5).

We used ArcGIS10.2 statistical function to extract the area of each land use type (Table 8).

From the Table 8, it can be found that: in 1994, the gobi accounted for the largest proportion in the whole study area, as high as 34.13%; while the cultivated land only accounted for 20.14%. After years of irrigation by pumping and manual reclamation, the cultivated land expanded, and the gobi, grassland, and dry land shrank, forming a clear contrast. The gobi area

Table 7 | Changes of vegetation coverage in Jingdian Irrigation District in the third stage

| Years | Extremely low coverage (0–10%) | Low coverage (10%–30%) | Medium coverage (30%–60%) | High coverage (60%–100%) | Cultivated land |
|-------|---------------------------------|------------------------|---------------------------|--------------------------|-----------------|
| 1994  | Area hm² 183,424.68            | 46,908.61              | 1,262.92                  | 150.34                   | 68,949.65       |
|       | The proportion % 61            | 15.6                   | 0.42                      | 0.05                     | 22.93           |
| 2006  | Area hm² 130,141.32            | 73,189.45              | 4,299.96                  | 781.81                   | 92,283.66       |
|       | The proportion % 43.28         | 24.34                  | 1.43                      | 0.26                     | 30.69           |
| 2018  | Area hm² 83,052.29             | 91,832.62              | 5,472.67                  | 1,112.57                 | 119,226.04      |
|       | The proportion % 27.62         | 30.54                  | 1.82                      | 0.37                     | 39.65           |

Figure 5 | Classification of land use types. (a) 1994. (b) 2006. (c) 2018.
reduced from 102,645.41 hm\(^2\) in 1994 to 64,382.78 hm\(^2\) in 2018, grassland area from 72,651.85 hm\(^2\) in 1994 to 61,856.47 hm\(^2\) in 2018, and dry land area from 8,851.70 hm\(^2\) in 1994 to 6,827.94 hm\(^2\) in 2018, while the cultivated land area increased from 60,584.58 hm\(^2\) in 1994 to 117,258.65 hm\(^2\) in 2018. Among all land types, the sand area accounted for the least proportion, and due to the restriction of local climate conditions and the large-scale afforestation by local residents, its area reduced from 50,195.19 hm\(^2\) in 1994 to 44,723.57 hm\(^2\) in 2018. The long-standing extensive and unreasonable irrigation mode and the high vaporization and low rainfall contributed to the concentration of deep-layer salt on the soil surface under the capillary action, enlarging the land salinization or secondary salinization area. From 1994 to 2006, the saline and alkaline land increased from 1.75% to 2.04%, mainly distributed in the connection area of Caowotan Town and Manshuitan Township. From 2006 to 2018, with the implementation of water-saving irrigation modes, such as furrow irrigation and border irrigation, the irrigation amount was controlled reasonably to realize the combination of irrigation and drainage. Targeted measures including biological, chemical, and engineering solodization were taken to slow down the expansion of the saline and alkaline land, and the proportion of saline and alkaline land decreased from 2.04% in 2006 to 1.64% in 2018.

### Table 8 | Changes in land use types from 1994 to 2018

| Land use types          | 1994 Area hm\(^2\) | 1994 Proportion % | 2006 Area hm\(^2\) | 2006 Proportion % | 2018 Area hm\(^2\) | 2018 Proportion % |
|-------------------------|--------------------|-------------------|--------------------|-------------------|--------------------|-------------------|
| Heavily saline-alkali land | 865.24          | 0.28              | 954.28             | 0.31              | 914.65             | 0.30              |
| Moderate saline-alkali land | 1,235.75         | 0.41              | 1,584.93           | 0.52              | 1,128.54           | 0.37              |
| Mild saline-alkali land | 3,215.51          | 1.06              | 3,654.89           | 1.21              | 2,924.35           | 0.97              |
| Place of residence | 450.98             | 0.15              | 1,385.97           | 0.46              | 1,423.68           | 0.47              |
| Cultivated land | 60,584.58          | 20.14             | 96,485.21          | 32.18             | 117,258.65         | 38.89             |
| Grassland | 72,651.85          | 24.16             | 65,579.28          | 21.87             | 61,856.47          | 20.52             |
| Dry land | 8,851.70           | 2.94              | 7,596.28           | 2.53              | 6,827.94           | 2.26              |
| Gobi | 102,645.41         | 34.13             | 75,369.48          | 25.13             | 64,382.78          | 21.35             |
| Fixed sand | 18,542.68         | 6.16              | 18,236.79          | 6.08              | 16,358.75          | 5.46              |
| Mobile sand | 31,652.51         | 10.52             | 28,967.25          | 9.66              | 28,364.82          | 9.40              |

### 3.2.4. Temporal and spatial distribution of soil electrical conductivity

The soil electrical conductivity can be used to objectively reflect the regional soil quality and its physiochemical properties. From Figure 6, it is seen that from 1994 to 2006, as the soil salinity concentrated, the zwitterion content in the soil increased and so did the soil electrical conductivity. From 2006 to 2018, a series of salt elimination measures were taken to decrease the

![Figure 6](http://iwaponline.com/ws/article-pdf/21/6/2646/932846/ws021062646.pdf)
soil electrical conductivity. Combined with the soil salinity changes shown in Figure 3, the soil electrical conductivity is positively correlated to the soil salinity, which proves that the regional soil salinity is the key factor driving the change in physicochemical properties of soil.

3.2.5. Temporal and spatial distribution of surface irrigation volume

Based on the temporal and spatial distribution diagram of the surface irrigation volume (Figure 7), the surface irrigation volume witnessed a general increase from 1994 to 2018, mainly due to the continuous improvement of the ancillary irrigation equipment within the irrigation area during this period. The land resources in the irrigation area were continuously developed, leading to the expansion of cultivated land. In addition, with the implementation of some non-profit development modes and ecological breeding modes, water demand rose year after year. Concerning the overall spatial distribution of irrigation volume, the open hydrogeological units in the western part of the study area were irrigated greatly, but the irrigation volume of the closed hydrogeological units in the eastern part declined, which was mainly because the secondary salinization in the closed hydrogeological units worsened and salt-tolerant corps were planted in partial areas only. Therefore, a small amount of water was needed.

3.2.6. Temporal and spatial distribution of groundwater depth

As shown in Figure 8, the groundwater depth in the study area was generally decreasing. Among them, the change of groundwater depth was the most obvious in the Yanghuzitan Town and Daduntan Town in the open hydrogeological units, and Caowotan Town and Luyang Town in the closed hydrogeological units. The groundwater depth in Yanghuzitan Town decreased from 75 m–85 m in 1994 to 65 m–55 m in 2018, and that in Daduntan Basin from 55 m–65 m in 1994 to 45 m–55 m in 2018. It can be seen that the overall groundwater depth in the area from Yanghuzitan Town to Haizitan Town decreased by about 10 m, and that in the area from Manshuitan Town to Caowotan Town in the closed hydrogeological units declined from 65 m–80 m to 45 m–65 m. The area with the groundwater depth of 0–10 m in Luyang Town continued to expand, so that the area with the depth of 10 m–20 m in the surrounding area almost disappeared in 2018. The area with the depth of 65 m–80 m in Xiquan Town was also shrinking.

ArcGIS extraction tool was used to extract the characteristic values of groundwater depth in Jingdian Irrigation District in three periods (Table 9).

From Table 9 above, the minimum groundwater depth in the irrigation area reduced by 3.5491 m from 3.5781 m in 1994 to 0.3690 m in 2018, and the maximum groundwater depth reduced by 9.3249 m from 78.2584 m in 1994 to 68.9335 m in 2018. It can be seen that the groundwater replenishment in the irrigation area increased significantly due to unscientific irrigation methods such as long-term irrigation without drainage, unreasonable irrigation and drainage, broad irrigation, and excessive irrigation quotas. The transition from the basic balance between recharge and discharge to groundwater discharge or extraction less than recharge led to the trend of decreasing groundwater depth in some areas year by year.

Figure 7 | Surface irrigation volume. (a) 1994. (b) 2006. (c) 2018.
### 3.2.7. Temporal and spatial distribution of groundwater salinity

As shown in Figure 9, the area with groundwater salinity ranging from 1.5 g/L to 1.9 g/L in the open hydrogeological units gradually expanded from the Yanghuzitan Town in 1994 to the Yanghuzitan Town and Haizitan Town in 2018. From 1994 to 2006, the groundwater salinity of Sitan Town in the irrigation area decreased first and then increased. In the closed hydrogeological units, the groundwater salinity from Luyang Town to Caowotan Town increased from 2.9 g/L–4.4 g/L in 1994 to 4.4 g/L–5.9 g/L in 2018. According to the overall interpolation results of groundwater salinity and inter-annual changes, the groundwater salinity in the irrigation area was increasing overall.

#### Table 9 | Characteristic values of groundwater depth in Jingdian Irrigation District

| Years | 1994 | 2006 | 2018 |
|-------|------|------|------|
| Minimum value (m) | 3.5781 | −0.2744 | −0.3690 |
| Maximum value (m) | 78.2584 | 70.2103 | 68.9335 |
| Average value (m) | 45.9219 | 41.6029 | 37.7474 |

#### Figure 8 | Groundwater depth. (a) 1994. (b) 2006. (c) 2018.

#### Figure 9 | Salinity of groundwater. (a) 1994. (b) 2006. (c) 2018.
The ArcGIS extraction tool was used to extract the characteristic values of groundwater salinity in the Jingdian Irrigation District in three periods (Table 10).

It can be seen from the above table that the minimum groundwater salinity increased from 1994 to 2006, which was because groundwater salinity increased and oscillated in the solute migration zone. The maximum groundwater salinity increased from 4.3285 g/L in 1994 to 5.8335 g/L in 2018, which was because that in the catchment and salt accumulation area, the dissipation of shallow groundwater caused salt migration and accumulation, leading to the gradual increase of groundwater salinity.

3.2.8. Topographical index factors
The inversion raster map of topographical factors (Figure 10) showed that the overall elevation of the study area was between 1,470 and 2,368 m, and gradually increased like an arc from east to west. The terrain sloped gently, with a slope of 0–25°, which was suitable for agricultural production and had little impact on the ecological environment.

3.2.9. Climatic index factors
As shown in Figure 11, the average annual precipitation in the study area was 162–191 mm. With the relatively uniform spatial distribution, it was typical of arid climate. The average annual evaporation was 2,274–2,358 mm. The average annual evaporation in the eastern part was higher, which was positively correlated with the high soil salinity in this part. The main reason was that soil salinity, driven by evaporation, moved to the surface through capillarity and intensified soil salinization. The average annual temperature was 7.90–9.59 °C. The high temperature mainly concentrated in the northern part of the study area, and decreased in an arc to both sides. With relatively low temperature throughout the year, the area was typical of temperate climate.

3.3. Temporal and spatial distribution of regional water and soil environmental vulnerability
According to the weights of the evaluation index factors (Table 4) and the grading standards for the water and soil environmental vulnerability in Jingdian Irrigation District (Table 5), ArcGIS software was used for weighted stack of the vulnerability

Table 10 | Characteristic values of groundwater salinity in Jingdian Irrigation District

| Years | 1994  | 2006  | 2018  |
|-------|-------|-------|-------|
| Minimum value (g/L) | 1.5169 | 1.5734 | 1.4822 |
| Maximum value (g/L) | 4.3285 | 4.8228 | 5.8335 |
| Average value (g/L) | 2.5850 | 3.5992 | 3.8952 |

Figure 10 | Topographic interpretation. (a) Elevation. (b) Slope. (c) Aspect.
evaluation index factors, and finally the spatial distribution diagrams of water and soil environmental vulnerability in the irrigation area in 1994, 2006 and 2018 were obtained (Figure 12).

As can be seen from the spatial distribution of water and soil environmental vulnerability in 1994, the overall water and soil environmental vulnerability of the irrigation area was below Levels IV and V. Level II and Level III fragile areas covered about two-thirds of the study area. Level I and Level IV fragile areas covered about one-third of the study area. Level IV fragile areas were mainly distributed in the closed hydrogeological units of Luyang Town and Caowotan Town, and some of the cultivated land in these areas had been salinized. Level III fragile areas were distributed around Jingtai County and Yanghuzitan Town. Level II fragile areas were distributed in the northern part of the irrigation area, and Level I fragile areas were mainly near Xiquan Town. According to the spatial distribution of water and soil environmental vulnerability in 2006, from 1994 to 2006, the water and soil environmental vulnerability in the northern part of the irrigation area did not change much, and that in some parts of Daduntan Town and Bingcaowan Town evolved from Level II to Level I. This was because during this period, these gobi areas were gradually cultivated by local residents after pumping irrigation, that is, the land use type was changed from gobi to cultivated land. In addition, the vulnerability of local areas of Luyang Town and Caowotan Town changed greatly. Level III fragile areas had gradually evolved to Level IV, and showed a tendency towards Level V. The reason was that the groundwater level rose sharply in these areas after pumping irrigation. During the hydrothermal transport caused by strong evaporation, deep-layer soluble salt ions were transported to the soil surface along with capillary water. The rapid
increase and accumulation of surface soil salinity aggravated the evolution of secondary salinization in this area, destroyed the primitive soil and water environment, and led to the escalation of vulnerability. According to the spatial distribution of water and soil environmental vulnerability in 2018, since water-saving irrigation methods such as border irrigation and furrow irrigation were carried out to control the irrigation amount and groundwater level, and measures were taken to prevent the secondary salinization, the highly fragile areas in Caowotan Town and Manshuitan Town in 2006 were greatly reduced, with the soil and water environmental vulnerability evolving from Level V to Level IV, from Level IV to Level III. Overall, the soil and water environment tended to evolve into a safe state.

4. DISCUSSION

To objectively and accurately evaluate the spatial evolution of water and soil environmental vulnerability in the irrigation area from 1994 to 2018, we selected 13 key driving factors from four aspects, namely soil vegetation, hydrology, terrain, and climate, when constructing the index system. Moreover, there was no obvious correlation between the index systems. Judging from the ranking of index weights, soil salinity, vegetation coverage, land use type, and surface irrigation volume have the strongest driving effect on the water and soil environment. With the increase of soil salinity, the internal soluble salt content and pH increased accordingly, but the soil physical properties deteriorated, decreasing the soil fertility. This is basically consistent with the results of previous studies (Zhang et al. 2018). The vegetation coverage also has a great impact on the vulnerability of the water and soil environment in the irrigation area. On the one hand, as the plant species and quantity decrease, the biomass and vegetation coverage also reduce, and the community structure tends to be single, destroying the stability of the water and soil environment; on the other hand, vegetation coverage can inhibit the activity of soil organic matter through the surface temperature to a certain extent, causing decline in the soil quality, and accordingly affecting the vulnerability of water and soil environment (Huang et al. 2014; Liu et al. 2020). Under the long-term disturbance of human activities, the land use type in the irrigation area has changed its original existing form and evolution trend. Previous studies have shown that changes in the land use pattern caused by human activities are one of the important reasons for changes in the regional water and soil environmental vulnerability. In areas where the land use pattern changes frequently, the changes in water and soil environmental vulnerability are exceptionally significant (Wang et al. 2005; Lu et al. 2011). Surface irrigation volume is the most active factor affecting the evolution of water and soil environment. The Jingdian Irrigation District is an artificial oasis formed by engineering water diversion and irrigation. The diversion of such a large amount of water into the originally deserted and barren land in a short time changes its original habitat and hydrogeological conditions.

The water and soil environmental vulnerability evaluation shows comprehensive, complex, and ambiguous characteristics, while the current methods are unable to achieve a comprehensive, scientific and objective evaluation. Based on the summary of previous research results, we selected the Jingdian Irrigation District in the arid northwestern China with unique natural conditions, took ‘green’ and ‘wet’ as the main determinants and ‘dry’ and ‘hot’ as the main manifestations of the water and soil environmental vulnerability in arid areas, and made a macro, rapid, objective evaluation of the water and soil environmental vulnerability in Jingdian Irrigation District based on remote sensing and evaluation models, to reveal the evolution mechanism and process of environmental vulnerability in the study area.

5. CONCLUSIONS

To clarify the evolution trend of the water and soil environmental vulnerability in Jingdian Irrigation District and reveal the main influencing factors driving the evolution of the water and soil environment in the irrigation area, 13 key factors were selected from four aspects: soil vegetation, hydrology, terrain, and climate, the corresponding long-term monitoring data and test data were expressed using space technology, and the accuracy of the expression results was verified. The spatial processing results of all indexes are reliable and accurate, providing good conditions for the research and ensuring the credibility of the research results. The main results obtained in this study are as follows:

(1) The cloud theory-based improved AHP and multiple data fusion were applied to analyze the vulnerability of the soil and water environment in the study area from 1994 to 2018. The results showed that the soil salinity, vegetation coverage, land use type, and surface irrigation volume are the main factors influencing the evolution of water and soil environmental vulnerability in Jingdian Irrigation District.
After spatial overlaying of the selected 13 key factors, we found that the overall water and soil environmental vulnerability in the study area remained below grade IV. The extremely vulnerable zone is mainly distributed in the eastern part of the study area. The environmental degradation risk in the western part is lower than that in the eastern part.

The evolution of water and soil environmental vulnerability in the study area can be divided into two stages from 1994 to 2018. Phase 1 from 1994 to 2006 is the process of environmental deterioration, and Phase 2 from 2006 to 2018 is the process of environmental restoration.

This is a relatively novel research method, which can be used to effectively evaluate the evolution of the water and soil environment in the irrigation area and helps to better plan and manage the land and water resources in arid areas around the world.

ACKNOWLEDGEMENTS
This work was supported by the National Nature Science Foundation of China (Grant No. 51579102); University Scientific and Technological Innovation Talents Programme of Henan, China (Grant No. 19IRTSTHN030); Zhongyuan Science and Technology Innovation Leading Talent Support Program of Henan, China (Grant No. 204200510048). Zhejiang Province Key R&D Programme, China (2021C03019). Sincere gratitude is extended to the editor and anonymous reviewers for their professional comments, which greatly improved the presentation of the paper.

CONFLICT OF INTEREST
The authors have no conflict of interest to declare.

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

REFERENCES
Angelovicová, L. & Fazekašová, D. 2014 Contamination of the soil and water environment by heavy metals in the former mining area of Rudnany (Slovakia). Soil & Water Research 9 (1), 18–24.
Biazin, B. & Sterk, G. 2013 Drought vulnerability drives land-use and land cover changes in the Rift Valley dry lands of Ethiopia. Agriculture Ecosystems & Environment 160, 100–113.
Braimoh, A. K. & Vick, P. L. G. 2004 The impact of land-cover change on soil properties in northern Ghana. Land Degradation and Development 15 (1), 65–74.
Chen, J., Yang, X., Yin, S. & Wu, K. S. 2016 The vulnerability evolution and simulation of the social-ecological systems in the semi-arid area based on the VSD framework. Acta Geographica Sinica 71 (07), 1172–1188 (in Chinese).
Felix, O. D. H., Dickkrüger, B., Steup, G., Yira, G., Hoffmann, T., Rode, M. & Naeschen, K. 2019 Modeling the effect of land use and climate change on water resources and soil erosion in a tropical West African catchment (Dano, Burkina Faso) using SHETRAN. Science of the Total Environment 653, 431–445.
Guan, S., Kang, Z. X. & Peng, C. 2016 Analysis on cloud characteristics of wear acoustic emission signal for vehicle cutting tool. Transactions of the Chinese Society of Agricultural Engineering 32 (20), 63–69 (in Chinese).
Huang, J. G., Wei, X. H., Wang, X. Z., Zhou, H. Y. & Li, H. X. 2014 Effect of vegetation degradation on soil organic matte and nutrient in process of rocky desertification in typical karst area of Northern Guangdong. Soil and Fertilizer in China 15, 15–18.
Kali, E. S., Leif, G. O., Nathan, J. H., Brezonik, P. L. & Bauer, M. E. 2003 Extending satellite remote sensing to local scales: land and water resource monitoring using high-resolution imagery. Remote Sensing of Environment 88 (1–2), 144–156.
Lamsal, P., Kumar, L., Atreya, K. & Pant, K. P. 2017 Vulnerability and impacts of climate change on forest and freshwater wetland ecosystems in Nepal: a review. Ambio 46 (8), 1–16.
Li, D., Liu, C., Du, Y. & Xu, H. 2004 Artificial intelligence with uncertainty. Journal of Software 15 (11), 1583–1594 (in Chinese).
Li, J., Li, C. & Yin, Z. 2016 ArcGIS based kriging interpolation method and its application. Bulletin of Surveying and Mapping 32 (20), 63–69 (in Chinese).
Liu, X., Wang, Y. & Yang, W. 2020 Study on soil quality evaluation methods under the background of vegetation degradation in Qinghai-Tibet Plateau. Journal of Lanzhou University (Natural Sciences) 56 (02), 143–153.
Lu, Y., Su, W. & Hua, C. 2011 Analysis of ecological vulnerability in Zuojiang river basin based on landscape pattern and ecosystem sensitivity. Research of Soil and Water Conservation 18 (03), 78–82 + 87.
Nguyen, T. & Nahavandi, S. 2016 Modified AHP for gene selection and cancer classification using type-2 fuzzy logic. IEEE Transactions on Fuzzy Systems 24 (2), 273–287.
Qing, G., Yao, Z., Ligang, M., Jiadan, L., Ke, W., Kefeng, Z., Xiaobin, Z. & Li, S. 2016 Assessment of reservoir water quality using multivariate statistical techniques: a case study of Qiandao Lake, China. *Multidisciplinary Digital Publishing Institute* 8 (3), 243.

Rosa, D. D. L., Moreno, J. A. & Mayol, F. 2000 Assessment of soil erosion vulnerability in western Europe and potential impact on crop productivity due to loss of soil depth using the ImpelERO model. *Agriculture Ecosystems & Environment* 81 (03), 179–190.

Setegn, S. G., Srinivasan, R., Dargahi, B. & Melesse, A. M. 2009 Spatial delineation of soil erosion vulnerability in the Lake Tana Basin, Ethiopia. *Hydrological Processes* 23 (26), 3758–3760.

Shahid, M., Cong, Z. & Zhang, D. 2018 Understanding the impacts of climate change and human activities on streamflow: a case study of the Soan River basin, Pakistan. *Theoretical and Applied Climatology* 134 (1–2), 205–219.

Shahid, M., Rahman, K. U., Balkhair, K. S. & Nabi, A. 2020 Impact assessment of land use and climate changes on the variation of runoff in Margalla Hills watersheds, Pakistan. *Arabian Journal of Geosciences* 13 (5), 1–14.

Stampoulis, D., Andreadis, K. M., Granger, S. L., Fisher, J. B., Turk, F. J., Behranghi, A., Ines, A. V. & Das, N. N. 2016 Assessing hydro-ecological vulnerability using microwave radiometric measurements from WindSat. *Remote Sensing of Environment* 184, 58–72.

Wang, J., Zhao, G. & Du, C. 2005 Analysis on the regional ecological environment vulnerability based on the information of spatial structure of landscapes. *Arid Zone Research* 03, 317–321.

Wang, R., Zhao, G., Yu, Z., Zhang, Y. & Zhang, H. 2012 Assessment of land use effects on environmental vulnerability by ecological niche suitability model. *Transactions of the Chinese Society of Agricultural Engineering* 28 (11), 218–224 (in Chinese).

Wang, M., Pei, H., Sun, J. S., Tan, X. Y. & Zhang, X. Q. 2017 Comprehensive evaluation on quality and safety of *Ganoderma lucidum* based on improved analytic hierarchy process. *Transactions of the Chinese Society of Agricultural Engineering* 33 (4), 302–308 (in Chinese).

Xu, C. 2010 Research on the Effect of Local Water and Soil Environment Caused by Water-Salt Transportation in Jing-Dian Irrigation District. *Doctoral dissertation*, Lanzhou University (in Chinese).

Xu, Q., Huang, M., Liu, P. L. & Li, R. Q. 2011 Integrated assessment of eco-environmental vulnerability in Pearl River Delta based on RS and GIS. *Chinese Journal of Applied Ecology* 22 (11), 2987–2995 (in Chinese).

Xu, C., Cheng, H., Wang, Y., Wang, R. R., Liu, L. Y. & Zhang, R. 2017 Improved multi-level fuzzy evaluation model based on cloud theory for evaluation of soil salinization degree. *Transactions of the Chinese Society of Agricultural Engineering* 35 (24), 88–95 (in Chinese).

Xu, C., Tian, J., Wang, G., Nie, J. & Zhang, H. 2019 Dynamic simulation of soil salt transport in arid irrigation areas under the HYDRUS-2D-Based rotation irrigation mode. *Water Resources Management* 35 (10), 3499–3512.

Zhang, Q., Zhang, Y. & Zhong, M. 2014 A cloud model based approach for multi-hierarchy fuzzy comprehensive evaluation of reservoir-induced seismic risk. *Journal of Hydraulic Engineering* 45 (1), 87–95 (in Chinese).

Zhang, Y., Wang, R. & Bai, Q. 2018 Development and change of soil salinization in Hetao irrigation area of Inner Mongolia. *Journal of Irrigation and Drainage* 37, 118–122.

Zhou, Q., Zhang, X. & Wang, Z. 2014 Land use ecological risk evaluation in Three Gorges Reservoir area based on normal cloud model. *Transactions of the Chinese Society of Agricultural Engineering* 30 (23), 289–297 (in Chinese).