Entropy weight method coupled with an improved DRASTIC model to evaluate the special vulnerability of groundwater in Songnen Plain, Northeastern China

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ABSTRACT

The Songnen Plain in northeast China is the only remaining black soil agricultural area in the world and is an important food base for China. The groundwater resources in this area are abundant, but human activities have caused them polluted. This paper established a groundwater vulnerability assessment to characterize the influence of human activities which used an entropy weight method. The index was tested using the nitrate pollution distribution in the groundwater to verify the effectiveness of this method. The results showed that areas with high specific vulnerability were distributed in the northern and eastern parts of the Songnen Plain and were consistent with areas that showed serious nitrate pollution of the groundwater. The correlation coefficient between these areas was 0.2536, which greatly improved the vulnerability assessment without superimposing human activities in the model. The results clearly showed that human activities increased groundwater vulnerability on the Songnen Plain. The evaluation method provided a reference for similar evaluations and a basis for the protection and management of groundwater resources in this region.

Key words | DRASTIC model, entropy weight method, groundwater resource management, groundwater vulnerability, nitrate pollution, Songnen Plain

HIGHLIGHTS

- Establishing a groundwater vulnerability assessment method to characterize the influence of human activities using an entropy weight method.
- Entropy weight method coupled with an improved DRASTIC model to evaluate the special vulnerability of groundwater for water management.

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INTRODUCTION

Groundwater is an important source of water for human populations (Cassardo & Jones 2011; Salman et al. 2019). Historical experience shows that water shortages not only seriously affect normal life but can also lead to disease outbreaks, wars and other unexpected hazards (Falkenmark 2013; Eliasson 2015; Mancosu et al. 2015; Egbueri 2020). Given the unsustainable population and economic growth, coupled with the failure to prevent groundwater pollution from industrial wastewater discharges and from heavy use of pesticides and fertilizers (Bosch et al. 1991; Khosravi et al. 2018; Li et al. 2020), more groundwater gets seriously polluted, especially shallow groundwater resources (Gejl et al. 2019; He et al. 2019). In many parts of China, shallow groundwater is an important source of drinking water (Lü et al. 2016; Jia et al. 2018; Hao et al. 2020). Because of its subterranean nature, groundwater pollution is typically a long-term and difficult-to-control issue (Ahmad & Al-Ghouti 2020). Therefore, rational planning and utilization of groundwater resources to avoid groundwater pollution are far more important than post-contamination treatment (Clemens et al. 2020; Erostate et al. 2020; Thomann et al. 2020).

Groundwater management encompasses a broad range of activities including prevention of groundwater contamination. Vulnerability and pollution risk assessments to identify risk zones are the very first important steps to generate useful information for devising strategies aimed at groundwater protection to contamination. Delineating vulnerable zones helps water resource managers to divert
groundwater development activities to other safer areas and, hence, can minimize cost of water treatment (Shrestha et al. 2017). This article carried on the groundwater vulnerability research, which is of great importance to the allocation and protection of groundwater resources (Foster et al. 2013; Machiwal et al. 2018); it is largely defined by the propensity and possibility of pollutants reaching a certain location above the uppermost boundary of an aquifer.

Research into Chinese groundwater vulnerability began in the mid-1990s (Margat 1968; Gogu & Dassargues 2000). It has progressed rapidly since then (Ibe et al. 2001; Gogu et al. 2003; Polemio et al. 2009; Shirazi et al. 2012; Kumar et al. 2015; Wachniew et al. 2016; Iván & Mádil-Szőnyi 2017). The most common and classic evaluation model used to evaluate groundwater vulnerability is the DRASTIC method, proposed by the US Environmental Protection Agency in 1987 (Rahman 2008; Saidi et al. 2011; Barzegar et al. 2019). The evaluation index of the DRASTIC model is based on the variables selected by US hydrogeological experts (Shirazi et al. 2012). Many efforts have improved the DRASTIC model to make it applicable to different hydrogeological conditions (Nobre et al. 2007; Saidi et al. 2010; Wu et al. 2014; Zhang et al. 2016), although these improvements are often limited to adjusting the parameters of the model. In practice, it is dubious to extend the weightings of this method to other regions because of the variable geographic setting of each evaluation area (Mendoza & Barmen 2006). Clearly, the geological and hydrogeological conditions also vary (Denny et al. 2007). Instead, the evaluation indicators should be selected according to the specific conditions of the evaluation area, considering the natural attributes of the evaluation area, and assigning a relative importance to each index. Thus, the correct weighting of variables directly determines the accuracy of the evaluation results (Singh et al. 2015).

The Songnen Plain hosts both large-scale commercial grain and oil production. The region of the Second Songhua River has 210 million hectares of arable land, with an annual grain output of 16.7 billion kg, accounting for 61% of Jilin Province. Groundwater is an important source of water for crop growth in this region. However, recent survey data showed that the shallow groundwater of the Songnen Plain had been variably contaminated by nitrate (Zhu et al. 2013; Bian et al. 2015). Therefore, there is an urgent need to carry out an evaluation of the groundwater vulnerability to nitrate on the Songnen Plain, in order to guide protection and management of the regional groundwater resources. In the past, vulnerability assessments were mostly focused on the water-resource scale or the basin scale. To evaluate a large-scale area, such as the Songnen Plain, it requires not only the correct evaluation parameters but also an improved model, in which the weight of each evaluation index is determined for this area. In order to evaluate the vulnerability of groundwater scientifically and reasonably, improve the reliability of the evaluation results, and provide guidance for the management of groundwater resources in the study area, using the hydrogeological characteristics of the Songnen Plain, this article reconstructed evaluation model indicators and used the entropy weight method and the cusp catastrophe model to determine the weights of each index. The results of the modified DRASTIC model evaluation were compared with the nitrate distribution generated by human activities in the study area to verify the accuracy of the model.

STUDY AREA AND DATA

The Songnen Plain is one of three major plains in Northeast China. It is located in the central part of the Songliao Basin, bound by the Xing’an Mountains and Changbai Mountains and Songliao Watershed. It is traversed by the Songhua and Nenjiang Rivers. The geographical coordinates of the study area are 43°36’–49°26’ N and 121°21’–128°18’ E, defining a total area of 180,500 km². Its location is shown in Figure 1.

The Songnen Plain is a semi-enclosed, asymmetrical basin, with a height difference of 400 m and a low gently inclined central region. Influenced by the difference in tectonic activity among different regions, the geomorphology of the region can be divided into three types: erosional landforms, denuded landforms, and stacked landforms.

The Songnen Plain has a typical East Asian continental monsoon climate. It is cold and dry in winter, hot and rainy in summer, with an average annual temperature of 3.8 °C, average annual precipitation of 484.57 mm, and an average annual evaporation of 1,498.1 mm. The main surface water systems are the Songhua River, Nen River, Second Songhua
River, and its tributaries. According to the latest ‘Songliao Basin Water Resources Bulletin’, the volume of the water resources of the Songnen Plain is 9.6 billion m³.

A total of 1,409 groundwater sampling sites were investigated on the Songnen Plain as part of this study. The sampling was conducted from 2013 to 2015. The sampling points are evenly distributed within the study area, as shown in Figure 2. Most of the sampling points were situated in residential areas, such as villages. This is because most of the sampling sites were water wells used by villagers. These wells typically have no anti-seepage measures, such as hardening of the ground around the well. Typically, the wells are simple structures, with no buried gravel, and depths of less than 20 m. The ground surface comprises mostly clay and silt, while the aquifer is mainly fine sand; the groundwater depth ranges from 1 to 10 m below the surface.

Samples were collected in strict accordance with the technical specifications for water sample collection. The site location was fixed by a GPS three-parameter calibration, water level measurement error was less than 1 cm, and the
well water was sampled using pre-treated sample bottle. Reagents, such as volatile organics, were neutralized with two drops of concentrated hydrochloric acid. The collected samples were stored at 4°C and transferred to laboratory storage within 5 days.

Two sets of parallel samples were collected for quality control. In order to identify the groundwater quality and analyze the hydrochemical characteristics of the study area, analytical testing of 31 inorganic components (Na⁺, K⁺, Ca²⁺, TFe, Mn, Al, NH₄⁺, PO₄³⁻, H₂SiO₃, Cr⁶⁺, Br, NO₂⁻, As, Hg, Se, Cl⁻, SO₄²⁻, F⁻, NO₃⁻, I⁻, HCO₃⁻, CO₃²⁻, COD₅Cr, total hardness, TDS, Cd, Cu, Pb, Zn) of the groundwater was completed by the Experimental Testing Center of the Shenyang Geological Survey. The detection and analysis methods were based on full-spectrum direct reading plasma spectroscopy (ICP-OES; Optima 5300DV Spectrometer, USA), ultraviolet spectrophotometry (COL; PerkinElmer Lambda 950, USA), and ion chromatography (IC; Thermo Fisher ICS2000, USA), supplemented by atomic fluorescence spectrometry (AFS; Titan...
The DRASTIC formula is formulated as follows: 

\[ D_i = \sum_{j=1}^{7} (W_j \times R_j), \]  

where \( D_i \) represents the score of the DRASTIC index; \( W_j \) represents the weight of factor \( j \); and \( R_j \) represents the score of factor \( j \).

Single-parameter sensitivity analyses explore the contribution of individual variables and use the same weights as the DRASTIC method. Therefore, it is particularly important to use an appropriate method to calculate the weight of each parameter. At present, the methods for weight calculation are divided into two types: subjective and objective methods. The subjective weighting method determines weights solely according to the preference or judgments of decision-makers, and the potential uncertainty in this method is its main disadvantage. The objective weighting method calculates weights based on actual observations, without any consideration of the decision-makers’ preferences, and does not benefit from the expert knowledge or experience of the decision-makers. Thus, this paper uses weights determined using the entropy weight method.

The entropy method is a measure of the uncertainty formulated in terms of probability theory (Clausius 1867). It is used to describe irreversible phenomenon involving motion or a process and was introduced into information theory by Shannon (1948). Nowadays, this method has been widely applied to various research fields to determine factor weights (Brunsell et al. 2011; Singh 2011; Ruddell et al. 2013; Islamoglu et al. 2015; Xu et al. 2016; Işık & Adali 2017). Information entropy is the measurement of the disorder degree of a system (Harmancioglu 1980). It measures the amount of useful information based on the data provided (Gao et al. 2020). When the difference in value among evaluated objects of a given indicator is high, and the entropy is small, this illustrates that this indicator provides useful information, and its weighting should be high. In contrast, if the difference is smaller and the entropy is high, the relative weight will be smaller. Hence, entropy theory is an objective way of determining weights (Zou et al. 2006). According to Zou et al., the evaluation process is generally divided into three steps (Qiu 2002; Zou et al. 2006; Wu et al. 2011).

Step 1: normalization of the original matrix

Suppose \( m \) evaluation indicators and \( n \) evaluation objects form the original matrix of indicators, \( X = [x_{ij}]_{m \times n} \), as follows:

\[
x = [x_{ij}]_{m \times n} = \begin{bmatrix}
x_{11} & x_{12} & \cdots & x_{1n} \\
x_{21} & x_{22} & \cdots & x_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
x_{m1} & x_{m2} & \cdots & x_{mn}
\end{bmatrix}
\]  

\((i = 1, 2, \ldots, m; \ j = 1, 2, \ldots, n)\),

where \( x_{ij} \) presents the performance value of the \( i \)th alternative on the \( j \)th criterion.
Normalization of this matrix gives Equation (3):

\[ R = (r_{ij})_{m \times n}, \]  

(3)

where \( r_{ij} \) is the data for the \( j \)th evaluation object of the indicator and \( r_{ij} \in [0,1]. \)

Among these indicators, when bigger is better, this yields

\[ r_{ij} = \frac{x_{ij} - \min (x_{ij})}{\max (x_{ij}) - \min (x_{ij})} \]  

\( (i = 1, 2 \ldots, m \text{ and } j = 1, 2, \ldots, n), \)  

(4)

but when smaller is better, this yields

\[ r_{ij} = \frac{\max (x_{ij}) - x_{ij}}{\max (x_{ij}) - \min (x_{ij})} \]  

\( (i = 1, 2 \ldots, m \text{ and } j = 1, 2, \ldots, n). \)  

(5)

**Step 2: calculation of entropy**

For \( m \) indicators and \( n \) evaluation objects in the evaluation problem, the entropy of the \( i \)th indicator is defined as follows:

\[ e_i = -\frac{\sum_{j=1}^{m} f_{ij} \ln f_{ij}}{\ln m} \]  

\( (i = 1, 2 \ldots, m \text{ and } j = 1, 2, \ldots, n), \)

(6)

where \( f_{ij} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}} \) and \( 0 < e_i < 1. \)

If \( f_{ij} \) is all the same value, then the entropy value of each criterion is the maximum value \((e_i = 1).\) If \( f_{ij} \) is all 0, then \( \ln f_{ij} \) is also 0 in value.

**Step 3: calculation of the weight of entropy**

The weight of the entropy of the \( i \)th indicator can be formulated as follows:

\[ W_i = \frac{1 - e_i}{n - \sum_{i=1}^{m} e_i} \]  

where \( \sum_{i=1}^{n} w_i = 1, \)

(7)

where the weight has a value \( 0 \leq w_i \leq 1. \)

**RESULTS AND DISCUSSION**

Based on the survey results and the hydrogeological characteristics of the study area, this paper obtained six representative indicators of the DRASTIC model. The data for \( D \) were from actual measurements of the groundwater level at the sampling points. \( R \) was derived from meteorological data released by the government department. \( S \) was derived from actual survey data. \( T \) was determined from the official digital elevation model, having 30 m × 30 m accuracy. \( I \) and \( C \) were derived from geological survey results. This article did not use the index \( A \) because attributes of \( A \) were closely related to \( I \) and \( C, \) furthermore, if the index \( A \) is used for evaluation, it will reduce the impact of the other indicators, making it difficult to accurately assess the vulnerability of the regional groundwater. According to the characteristics of each index, each attribute of each index has a score. Generally, the attribute of the index is more likely to cause groundwater pollution, and it will get a higher score. Limited by the availability of survey data, some indicators in this assessment could only use interpolation method with available data to obtain the situation without survey data area, which might bring certain uncertainty to the assessment results. The spatial distribution of each indicator was plotted using the spatial analysis module in Arc GIS 10.3 software (Esri, Redlands, CA, USA). These results are shown in Figure 3.

According to the characteristics of each index and the information it contained, the weights of each index were calculated using the entropy weight method. The weight calculation results are shown in Table 1. According to the scores and weights of each indicator, this new ‘DRSTIC’ model was used to calculate the inherent vulnerability of the regional groundwater (Figure 4).

To assess whether human activities have an impact on the regional groundwater quality, this paper conducted a hydrogeological analysis of the shallow groundwater aquifer, the distributions of characteristic pollutants related to human activities, and hydrochemical characteristics.

The Songnen Plain evolved from Mesozoic and Cenozoic subsidence basins, in which continental clastic sediments were deposited to a thickness of more than 8,000 m. Thus, the Songnen Plain is a large-scale groundwater aquifer.
Figure 3 | Indicator scores of the DRSTIC model. (a–f) Results for depth of the water table (D), net recharge (R), soil media (S), topography (T), impact of the vadose zone media (I), and conductivity of the aquifer hydraulic (C), respectively.
system comprising Quaternary pore water, Neogene fissure water, Paleogene fissure water, and Cretaceous pore and fracture water. The regional shallow groundwater resource receives input from precipitation and recharge from adjacent mountainous areas to the west, north, and east. It flows through the western piedmont plain, northern high plain, and the eastern undulating high plain, collecting into three streams flowing to the south. The shallow groundwater system interacts with the surface water system, comprising the Nenjiang, Second Songhua River, and Songhua Rivers. Rain moves downwards by means of subsurface flow and drains to the rivers. During runoff, evaporation and human usage consume a large amount of water, and only a small amount flows out of the study area.

Table 1 | Weights of the DRSTIC model indicators (D, depth of the water table; R, net recharge; S, soil media; T, topography; I, impact of the vadose zone media; and C, conductivity of the aquifer hydraulic)

| Indicators | D | R | S | T | I | C |
|------------|---|---|---|---|---|---|
| Weight     | 5.0 | 2.3 | 4.9 | 2.4 | 1.0 | 0.3 |

Figure 4 | Groundwater vulnerability within the study area based on the DRSTIC model.
Runoff, circulation, and the regional aquifer characteristics are all conducive to self-cleaning of the groundwater system, maintaining good water quality under natural conditions. However, according to our test results, the shallow groundwater in the study area is locally contaminated by nitrate. The proportion of groundwater samples whose nitrate concentration was more than 0.5 mg/L (China groundwater quality standard class III) was 77.4%. The average concentration of nitrate was 67.2 mg/L, and the highest concentration is 1,000.0 mg/L. The distribution of nitrate in the shallow groundwater of the study area is shown in Figure 5. Clearly, high nitrate concentration areas are mainly in the northeast and southeast of the plain. Among them, values in the northeast are highest, reflecting pollution from agricultural areas and some industrial agglomeration areas; high values in the southeast reflect industrial and densely populated urban areas.

Based on sample test results, the groundwater samples were classified using the Shukalev classification, yielding a map reflecting groundwater chemistry. The Shukalev classification, shown in Figure 5, provides a visual representation of the nitrate distribution, highlighting areas of high pollution.

Figure 5 | Distribution of nitrate within the shallow groundwater of the study area.
classification is based on the concentrations of six major ions ($\text{Na}^+$, $\text{Ca}^{2+}$, $\text{Mg}^{2+}$, $\text{HCO}_3^-$, $\text{SO}_4^{2-}$, $\text{Cl}^-$, $\text{K}^+$ combined with $\text{Na}^+$) and groundwater salinity.

Using groundwater index values, a Piper three-line diagram for shallow and deep groundwater hydrochemical types in the evaluation area was constructed from the groundwater survey data (Figure 6). The main water chemistry type of the shallow groundwater in the study area was the $\text{HCO}_3^–\text{Ca}$ type, accounting for 24.83% of all samples. This was followed by $\text{HCO}_3^–\text{Ca}·\text{Mg}$, $\text{HCO}_3^–\text{Na}·\text{Ca}$, $\text{HCO}_3^–\text{Na}·\text{Mg}·\text{Ca}$, $\text{HCO}_3·\text{Cl}^–\text{Ca}$, and $\text{HCO}_3·\text{Cl}^–\text{Na}·\text{Ca}$ types. Although the shallow groundwater mainly resides in unconsolidated Quaternary deposits, the chemical composition of the groundwater is complex and varied, suggesting that it is greatly affected by environmental conditions and human activities. From the piedmont to the plains, especially in populated areas, the chemical signature of the groundwater varies. This reflects flow velocities of downstream runoff, residence times of water-rock interactions, and inputs from human activities, especially artificial mixing such as groundwater exploitation, etc. (Zhang et al. 2006; Li et al. 2014, 2018). Human activities have led to changes in groundwater chemistry in this region, and
clearly do have an impact on the regional groundwater quality.

Because the regional groundwater has been affected by human activities, this paper selected additional indicators that reflect groundwater quality in the region, based on the distribution of characteristic pollutants and the driving forces of water pollution, mainly groundwater extraction (E) and land-use (L). Water extraction data are available from the Water Resources Bulletin of each city, while, land-use information comes from China’s 2015 satellite remote sensing image data. In order to couple the above indexes into the model and draw a quantitative evaluation conclusion, the E and L indexes were assigned by the same principle as other indexes in the DRSTIC model, and the principle is that the attribute of the index is more likely to cause groundwater pollution, then it will get a higher score. The specific scores of E and L in this paper came from the Delphi method. The spatial distribution of each indicator was plotted using ArcGIS 10.3 (Figure 7).

The entropy weight method was used to calculate the weights of variables E and L. The weight of E was 3.3, while the weight of L was 5.0. This gave rise to a new model, DRSTIC-EL. This article superimposed each indicator to obtain groundwater vulnerability, as shown in Figure 8.

Typically, areas with high special vulnerability of groundwater are mainly distributed in the north and east of the Songnen Plain. These high vulnerability areas are consistent with those having serious nitrate pollution (Figure 5). Human activities can cause the increase of nitrate concentration in groundwater (Jakobczyk-Karpierz et al. 2017; Teng et al. 2019). Under the same conditions, the regional nitrate concentration with high vulnerability of groundwater should be higher.

To verify the accuracy of the evaluation results, they were fitted with the distribution of nitrate in the shallow groundwater of the study area. A correlation analysis showed that the correlation coefficient between these two distributions was 0.2536. Comparing the vulnerability of groundwater and the distribution of nitrate in the study area, the correlation coefficient increased from 0.0752 to 0.2536. This shows that human activities do affect the groundwater in the study area, making it more vulnerable to pollution. Comparing Figures 4 and 5, it is clear that the regions with serious nitrate pollution and those with high intrinsic groundwater vulnerability do not coincide, and that the correlation coefficient between them also does not indicate an obvious relationship. This indicates that the shallow groundwater of the Songnen Plain has good self-cleaning potential. Although
the correlation coefficient is not statistically significant, given the large evaluation area and dataset, correlation analysis at each grid point is only based on the software platform, and the relationship between the vulnerability of groundwater and nitrate pollution cannot be compared reliably at the regional scale. However, many studies have shown that human activities, such as groundwater extraction, agricultural, and mining activities, lead to increases in groundwater vulnerability, supporting the conclusions of this study (Ahmed 2009; Albuquerque et al. 2013; Douglas et al. 2018; Modibo 2019). Despite all this, the quantitative impact of the above activities on groundwater vulnerability is still far from clear, and whether there are other influencing factors is not clear. The research results of this paper are more inclined to determine groundwater vulnerability characteristics from a macro perspective to provide guidance for water resource management.

Figure 8 | Groundwater vulnerability within the study area based on the DRSTIC-EL model.
CONCLUSIONS

A vulnerability assessment of the shallow groundwater aquifer of the Songnen Plain was conducted using an improved DRSTIC-LE model coupled with an entropy weight method to calculate the weighting of its indices. The evaluation results showed that the areas with high specific vulnerability of groundwater on the Songnen Plain are distributed to the north and east, consistent with areas affected by serious nitrate pollution of the groundwater. The correlation coefficient between them was 0.2536, an improvement over the result obtained from the direct calculation of the correlation coefficient between vulnerability and nitrate pollution. Chemical analysis of groundwater types also suggested that human activities have increased groundwater vulnerability on the Songnen Plain and made groundwater more vulnerable to pollution.

This paper outlines a new way to evaluate the vulnerability of groundwater and validates this method using a case study. Our validation shows the applicability of the evaluation method to groundwater protection and management. Although groundwater vulnerability assessment is difficult to achieve the refined assessment of each zone, in the area of regional groundwater resource management, groundwater vulnerability assessment undoubtedly provides a reliable reference in the macro aspect, which can relatively accurately measure the degree of regional groundwater vulnerability to pollution. Our assessment of groundwater vulnerability at such a large regional scale was limited by data availability. In the future or similar studies, more data should be obtained to improve the accuracy and reliability of the assessment.

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DATA AVAILABILITY STATEMENT

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

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