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Research Article

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Posted Date: May 14th, 2021

DOI: https://doi.org/10.21203/rs.3.rs-460619/v1

Version of Record: A version of this preprint was published at Environmental Earth Sciences on April 1st, 2022. See the published version at https://doi.org/10.1007/s12665-022-10350-8.

Assessment of groundwater vulnerability based on the modified DRASTIC model: A case study in Baicheng City, China

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Abstract

Accurate assessment of groundwater vulnerability objectively reflects an area's potential for groundwater pollution and provides a reference basis for pollution control and prevention. The main objective of this study was to modify the original DRASTIC model to improve the consistency of groundwater vulnerability assessment results with regard to the actual conditions of the study area. To optimize the assessment objectivity, two additional factors that are influenced by human activities (land use and degree of groundwater extraction) were added to form the DRASTICLE model. Then, based on the correlation between all factors and measured nitrate concentrations, the improved

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three-scale analytic hierarchy process (AHP) and the weights of evidence (WOE) methods were used to reassign the factor weights of the original DRASTIC model. The area under the receiver operating characteristic (ROC) curve, denoted as AUC, was used to quantitatively evaluate the accuracy of all five models (original DRASTIC model AUC: 0.62). By modifying the factors and weights, the four new models showed better performance, AUC values were 0.75, 0.76, 0.85, and 0.78 for the AHP-DRASTIC, AHP-DRASTICLE, WOE-DRASTIC, and WOE-DRASTICLE models, respectively. This indicates that the modified models could more accurately convey groundwater vulnerability in the study area. The WOE-DRASTIC model, which had the best performance, was then used to assess groundwater vulnerability in 2000 and 2010. In 2000, 2010, and 2018, the proportion of areas with very high groundwater vulnerability increased from 5.14% to 6.34% to 7.93%, respectively. Meanwhile, the proportion of areas with very low vulnerability also increased, from 72.63% to 75.07% to 81.60%; demonstrating a situation of extremes. Findings of this study are expected to provide a new theoretical basis for the Baicheng municipal government in China to better manage and exploit groundwater resources.

Keywords: Groundwater vulnerability; DRASTIC; Three-scale analytic hierarchy process; Weights of Evidence; Nitrate

1. Introduction

Groundwater is an important drinking water resource because of its good seasonal storage capacity, stable temperature, nonsusceptibility to pollution, and convenience for exploitation. Baicheng City is an important commodity grain base in China, and groundwater is the main water source in most parts of the area, with 90% of water resources utilization from groundwater. In recent years, with the increase in population, the development of industry and agriculture as well as urban expansion have led to an increase in the extraction of groundwater, and further, the quality of groundwater has also deteriorated. Nitrate pollution is one of the main characteristics of groundwater pollution(Almasri, 2008; Jhariya, 2019), and is mainly caused by agricultural pesticides, chemical fertilizers, and industrial wastewater pollution. Polluted groundwater conditions are not easy to identify, and once present, such pollution is difficult to control and remediate. Therefore, to improve the sustainable development and utilization of groundwater, it is necessary to develop more effective prevention and control programs for groundwater pollution. Groundwater vulnerability assessment is the premise of such resource protection, facilitating rational development as well as better land use planning and groundwater resource management.

Three main methods for groundwater vulnerability assessment include: process-based simulation (Huan et al., 2016), statistical (Bonfanti et al., 2016), and index-overlay (Gogu & Dassargues, 2000; Huan et al., 2012). There is a wide global application of the index-overlay method; the representative models mainly include

DRASTIC, SINTACS, AVI, and GOD (Ferreira & Oliveira, 2004; Ghazavi & Ebrahimi, 2015). The DRASTIC model (Aller et al., 1987) is the most widely used at present, owing to its ease of operation and ease of obtaining parameters. Moreover, its groundwater vulnerability assessment results can be presented in the form of a vulnerability map, which intuitively explains the distribution of groundwater vulnerability (Al-Adamat et al., 2003; Victorine Neh et al., 2015). However, in recent years, scholars have found the DRASTIC model to have certain deficiencies in the selection of model factors and weights. For example, the method fixes the weight and rates of each factor, without considering the actual real-world conditions, particularity of the study area (Rahim Barzegar et al., 2015; Brindha & Elango, 2015). Another limitation of DRASTIC is that it does not consider the effects of human activities on groundwater pollution. Therefore, it has become necessary to optimize the DRASTIC model such that more objective results can be achieved in combination with the actual conditions of the study area.

Theoretically, optimization of the DRASTIC model can be divided into two main aspects. First is the optimization of the assessment factors, which can be carried out by modifying the rating of factors, removing existing factors(An & Lu, 2018), or adding other parameters(Khosravi et al., 2018; Omotola et al., 2020). Gogu and Dassargues (2000) ,Babiker et al. (2005)and Wang and Yang (2008) have all suggested the addition of land use into the evaluation model because this factor is strongly related to groundwater vulnerability. Accordingly, Kazakis and Voudouris (2015) and Wu et al.

(2018) added land use factors to modify the model, and were able to improve the model's accuracy. At the same time, for this study, different degrees of groundwater over-exploitation are known to exist in certain parts of the study area, therefore this study adds not only land use (L)(Khan & Jhariya, 2019; Sener & Davraz, 2012) but also the degree of groundwater extraction (E) (Abu-Bakr, 2020) into the DRASTIC model to obtain the DRASTICLE model.

The second aspect is to optimize the weight of the parameters (R. Barzegar et al., 2018; Sahoo et al., 2016) . To do this, we refer to Pacheco et al. (2015), who adopted five methods to modify the weights of the DRASTIC model, and Khosravi et al. (2018) who applied four objective methods to modify the original DRASTIC model. Other modification strategies include the analytic hierarchy process (AHP)(Bai et al., 2012; Sener & Davraz, 2012; Thirumalaivasan et al., 2003), artificial neural network, fuzzy logic(Rezaei et al., 2013), logistic regression(Antonakos & Lambrakis, 2007) and the weights of evidence (WOE)(Khosravi et al., 2018) which are used to optimize the weights of parameters in DRASTIC models. In this study, two objective methods were used to modify the weights: the improved three-scale AHP and the WOE. The analytic hierarchy process (Saaty & Kearns, 1985) is simple to operate and has strong practicability and adaptability. The traditional AHP determines the judgment matrix using the nine-scale principle, yet with this method it is challenging to determine a reasonable judgment matrix because of the difficulty in grasping the importance degree among the parameters. Therefore, for this study, the three-scale method (Zuo, 1988)

was adopted to simplify the model, which is conducive for comparing the relative relations between parameters. In the improved three-scale AHP, the correlation between each parameter and nitrate concentration in the model was calculated and compared to determine the importance of the parameters, which overcomes the artificial subjectivity of the AHP and improves the accuracy of groundwater vulnerability assessment. Similarly, WOE is a geological statistical method that can solve the spatial analysis of multi-source information. The combination of the mature geographic information system platform and corresponding expansion module has not only been widely used in metallogenic prediction(Zhang et al., 2016), but has also been extended to other similar fields, particularly risk analyses such as landslide sensitivity analyses(Hong et al., 2017) and karst collapse risk zone division (Perrin et al., 2015). Barber et al. (1998) first applied WOE to regional groundwater vulnerability assessments with good results. Because of the high solubility and fluidity of nitrate, this compound easily transports to groundwater and is a good reflection of the degree of groundwater pollution (Shrestha et al., 2016; Voutchkova et al., 2021; Wang & Yang, 2008); thus, nitrate was selected as the response factor.

The main objective of this study was to use the DRASTIC model to evaluate groundwater vulnerability in the study area. First, the improved three-scale AHP and WOE were used to optimize the parameter weights of the DRASTIC model. Second, two additional parameters, land use and degree of groundwater extraction, were added to obtain the DRASTICLE model. To verify the accuracy and reliability of the model,

a receiver operating characteristic (ROC) curve was drawn based on the nitrate concentration, and the areas under the curve (AUC) of the DRASTIC, AHP-DRASTIC, AHP-DRASTICLE, WOE-DRASTIC, and WOE-DRASTICLE models were compared. The most effective model was identified and then used to evaluate the groundwater vulnerability of the study area in 2000 and 2010 and further analyze the associated temporal and spatial distribution of groundwater vulnerability.

2. Study area

Baicheng City is located in the northwestern part of Jilin Province, China, west of Songnen Plain, and east of the Horqin Grassland, and covers an area of approximately 25600 km^2, between longitude 121°38′06″ to 124°23′56″E and latitude 44°13′57″ to 46°18′15.8″N (Fig. 1). The climate is a temperate continental monsoon with obvious seasonal changes. The average annual precipitation is approximately 400 mm, with an uneven distribution throughout the year. The average annual evaporation is 1340 mm, and the annual average temperature is 4.7℃. Low hills are situated in the northwest of the study area, with elevations of 300–662.6 m. The northeastern and southeastern plains are 130–140 m above sea level; in the southwest, a latent desert area is situated 150–180 m above sea level. From the northwest to the southeast, the terrain of Baicheng comprises successive low mountains, hills, and plains, and is slightly uplifted in the southwest (Feng, 2019). The strata mainly include Carboniferous, Permian, Jurassic, Cretaceous, Neogene, and Quaternary.

In 2018, the Baicheng sub-center of the Jilin Water Environment Monitoring

Center performed sampling of 51 shallow groundwater monitoring wells in the city plain area during both April and September, which were tested for water quality parameters. The main items exceeding the standard were nitrate, ammonia nitrogen, manganese, fluoride, and arsenic. It shows that groundwater has suffered from different degrees of pollution. Associated land use types in the area are mainly cultivated land, accounting for approximately 60% of the study area, followed by grassland and saline-alkali land. From 2000 to 2018, the area of cultivated land and artificial surface both increased gradually, and the proportions of grassland and forest accordingly, gradually decreased.

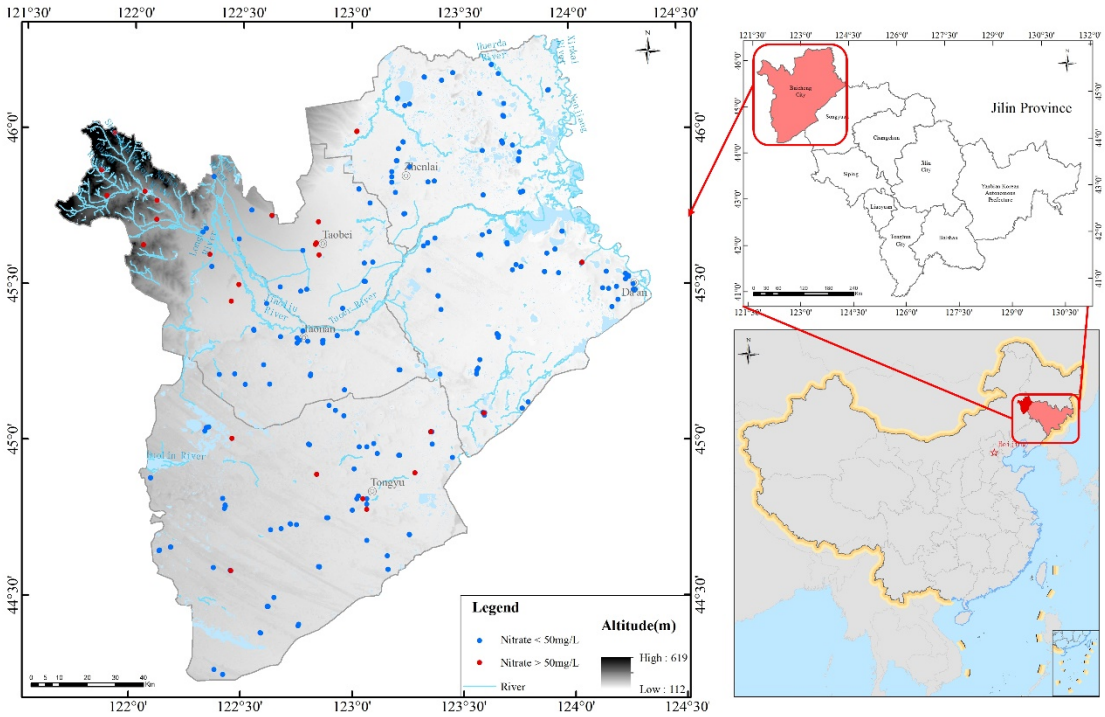

Fig. 1 Location map of the study area and showing locations of sampling wells and nitrate distribution.

3. Materials and methods

3.1 Source of data

The meteorological data and hydrogeological data used in this study were collected and derived from the results of field measurements and sampling analysis by the project team. Data of groundwater depth, hydrochemistry, and groundwater exploitation were either provided by the Baicheng Water Resources Management Center or measured in the field by the project team. The groundwater depth data were collected from 1990 to 2018 at long-term monitoring wells, with each well dataset covering January–December, measured every five days, and the number of monitoring wells varied from 120–160 to per year. Nitrate data were collected from 202 wells in November 2017 by the project team and 52 wells were tested by the Baicheng Water Resources Management Center in April 2018. In addition, a total of 205 hydrogeological boreholes were collected from this area.

Land use type data grids of Baicheng City in 2000, 2010, and 2018 with a resolution of 30 × 30 m were downloaded from the National Catalogue Service for Geographic Information (http://www.webmap.cn/main.do?method=index) and GLOBELAND30 (http://www.globallandcover.com/home.html?type=data).

3.2 DRASTIC model for groundwater vulnerability

The DRASTIC model is mainly aimed at assessing the vulnerability of an unconfined aquifer. The model selects seven factors affecting groundwater flow and pollutant transport as vulnerability assessment parameters: depth to groundwater (D), net recharge (R), aquifer media (M), soil media (S), topography (T), impact of the

178 vadose zone (I), and conductivity of the aquifer (C). For this study, each parameter was
179 classified according to its range of variation and internal attributes, and the
180 corresponding vulnerability ratings were given; the larger the rating, the higher the
181 vulnerability grade. The rating and weight of each factor for groundwater vulnerability
182 have been previously described by Aller et al. (1987). The groundwater vulnerability
183 index (VI) was calculated using Eq. 1:

$$\mathrm{VI} = D_r D_w + R_r R_w + A_r A_w + S_r S_w + T_r T_w + I_r I_w + C_r C_w \quad (1)$$

184 where the subscripts r and w represent the ratings and weights for the seven
185 parameters of the DRASTIC model, respectively.

186 Bojórquez-Tapia et al. (2009) indicated that five categories of groundwater
187 vulnerability should be appropriate for conveying meaningful information to planners,
188 decision-makers, and stakeholders. Therefore, in this study, the groundwater
189 vulnerability index was divided into five categories: very low, low, moderate, high, and
190 very high.

191 3.3 Preparation of DRASTIC parameters

192 Based on the original DRASTIC model, two factors affected by human activities,
193 namely the type of land use (L) and degree of groundwater extraction (E), were added
194 to generate the DRASTICLE model. All factors used in the model are described for this
195 study as follows.

196 *Depth to groundwater* (D). The depth to groundwater determines the contact time
197 between the surface pollutants and aeration zone media before entering the aquifer.

198 Generally speaking, the greater the depth to groundwater, the greater the probability of
199 pollutant attenuation and oxidation, and the lower the vulnerability of groundwater. The
200 inverse distance weight tool of ArcGIS was used to process the groundwater table depth
201 data of 120 long-observation wells in the research area, and the depth of the
202 groundwater distribution map in the area was obtained. The groundwater depth was
203 divided into five depth groups: 1.2–1.5, 1.5–4.6, 4.6–9.1, 9.1–15.2, and 15.2–17.3 m,
204 and the corresponding ratings were given. The results are presented in Fig. 2a.

205 *Net recharge* (R). Contaminants on the surface or soil can be transported vertically
206 to groundwater through recharge water and transported within the aquifer. The greater
207 the precipitation recharge, the greater the possibility of pollutants reaching the aquifer,
208 that is, the greater the vulnerability trend of groundwater pollution. Many recharge
209 sources of groundwater exist in the study area, including precipitation infiltration,
210 lateral recharge in mountainous areas, river channel leakage, and well irrigation return
211 recharge. The net recharge ranged from 51.2 to 236.8 mm and was divided into three
212 categories, the results of which are shown in Fig. 2b.

213 *Aquifer media* (A). The pore characteristics of the aquifer media determine the
214 velocity of groundwater flow and affect the adsorption, diffusion, and dispersion of
215 pollutants. In general, larger aquifer medium particles and more pores leads to the
216 presence of better permeability, and lower probability of the pollutants being diluted
217 and attenuated; thus, the higher the groundwater vulnerability. The object of this study
218 was an unconfined aquifer, for which the fissure water aquifer was dominated by granite,

and the pore water aquifer was dominated by gravelly pebbles, loess sub-sand, and silty-fine sand. The Taoer River Fan phreatic aquifer is mainly composed of gravel and pebble gravel; sandy alluvial lacustrine plain is dominated by medium fine sand, fine sand, and silt, and the lithology of the swamp and saline-alkali valley is dominated by loess sandy soil (Fig. 2c).

Soil media (S). The soil medium affects the amount of surface water infiltrating underground, as well as the ability of pollutants to enter the aeration zone vertically. The surface of the study area is overlain by Upper Pleistocene and Holocene systems. The underlying Lower Pleistocene material is mainly distributed in the platform, which is a glacial moraine with a high clay content. The moraine deposits of the Upper Pleistocene Zhenxi Ice Age are mainly distributed in the fan and in the Taoer River and Jiao Liu River valleys. The upper ice-water accumulation layer is mainly composed of gravel, sand, and gravel with minimal clay, and is interbedded with clay, sub-clay, and fine sand lenses. The alluvium of the Guxiangtun Formation, which is mainly distributed in the alluvium plain, is a loess-like subsandy soil. Holocene alluvial deposits, which are distributed in the floodplain of the Taoer, Jiaoliu, and Hanhe rivers, as well as along the periphery of the fan front, are mainly composed of gravel, sand, gravel, and feature a subsandy soil layer. The associated aeolian sediments are comprised of yellow and white fine sand (Fig. 2d).

Topography (T). Slope mainly affects the infiltration of atmospheric precipitation. The lower the slope, the more infiltration is generated; thus, the higher the potential for

pollution. Slope distribution was extracted from digital elevation model data of Baicheng City using the ArcGIS surface analysis tool. The terrain in the study area is relatively gentle overall, though the hilly area in the northwest is relatively steep, with a topographic slope of up to 70%. The slopes in the area were categorized as 0–2%, 2–6%, 6–12%, 12–18%, and >18% (Fig. 2e).

Impact of the vadose Zone (I). The vadose zone controls the length of the infiltration path and seepage path of the surface water. The soil layer of the vadose zone has a remarkable ability to adsorb and block the entry of pollutants into groundwater. The better the sorting, the finer the particles and the higher the clay content of the vadose zone medium; thus, the worse the permeability, the stronger the adsorption and purification ability, the stronger the pollution prevention performance, and the weaker the groundwater vulnerability, hence the greater the vulnerability of the groundwater. The main lithologies in the vadose zone of the study area were found to be clay gravel, sub-sand, silty sand, loess sub-sand, sub-sand, gravel, gravel-bearing loess sub-sand, silt sub-clay, sand gravel, loess sub-clay, and gravel-bearing sub-sand. In the Taoer River Fan area, the lithology of the vadose zone was mainly gravel, while the valley area was sub-clay, and in the western low plain, the vadose zone was mainly silty sand and loess sub-sandy soil (Fig. 2f).

Conductivity of the aquifer (C). It controls the flow rate of groundwater and the migration rate of pollutants into aquifers. The conductivity of the aquifer varied significantly. Using the obtained permeability coefficient values of 157 wells, the

261 distribution of hydraulic conductivity in the area was obtained by simple kriging
262 difference values, and the distribution pattern was roughly the same as the lithological
263 distribution, ranging from 0.65–470.36 m/d. The Taoer River Fan had the largest
264 hydraulic conductivity (Fig. 2g).

265 *Land use* (L). The types and degree of pollution of pollutants produced by different
266 land use types in the study area varied widely, while the surface cover can also be
267 expected to have a great impact on the interception capacity of pollutants and the
268 manner in which pollutants enter the aquifer. Typically, the vulnerability of
269 groundwater in industrial areas is high, mainly because the distribution of factories is
270 concentrated, and if the production wastewater is not discharged according to
271 regulatory standards or is treated improperly and leakage occurs, the wastewater will
272 likely become a potential source of groundwater pollution. In agricultural areas, wide-
273 spread application of a variety of pesticides, fertilizers, and livestock and poultry
274 manure can easily produce surface pollution sources, which pose a threat to
275 groundwater quality. In green belt areas, such as grassland and forest, surface plants
276 have the function of reducing surface runoff, reducing soil erosion, and adsorbing
277 pollutants, thus such plants have a certain protective effect on groundwater, and the
278 vulnerability of groundwater in these areas is lowest. The land use types in the study
279 area were mainly divided into artificial surface, forest, water bodies, wetland, shrubland,
280 cultivated land, grassland, and bare land (Fig. 2h).

281 *Degree of groundwater extraction* (E). Groundwater exploitation intensity is

another major factor affecting groundwater vulnerability. Excessive exploitation of groundwater leads to an increased drop in groundwater levels and a larger scope of groundwater draw-down funnels, resulting in an increased hydraulic gradient. Meanwhile, as the formation of surface water and surrounding runoff stimulates groundwater recharge; groundwater becomes more vulnerable to pollution, which increases the vulnerability of the groundwater environment. The degree of groundwater extraction is the ratio of the actual extraction amount to the recoverable amount. The degree of groundwater extraction in Taobei District was 94%, the proportion of Taonan City in the Huolin River Basin was 14%, and most of the other areas were between 20% and 50% (Fig. 2i).

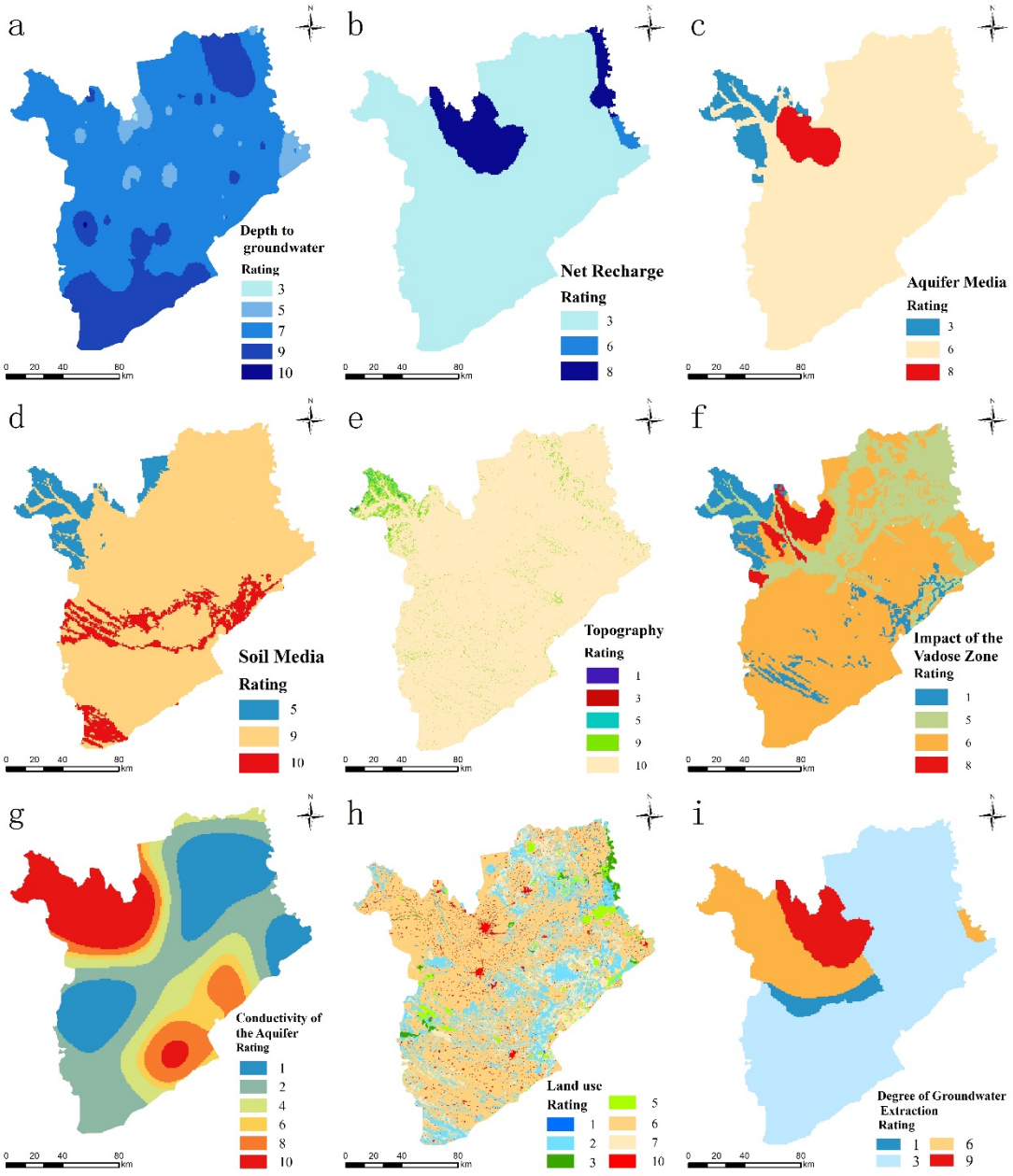

Fig. 2 Maps of groundwater vulnerability conditioning factors：(a) depth to groundwater, (b) net recharge, (c) aquifer media, (d) soil media, (e) topography, (f) impact of the vadose zone,(g) conductivity of the aquifer, (h) land use, and (i) degree of groundwater extraction.

3.4 Factors correlation test

The evaluation factors in the model were expected to be relatively independent

and have no strong correlation; therefore, multi-collinearity diagnosis was performed among the evaluation factors (Arabameri et al., 2019; O'Brien, 2007) to derive the tolerance and variance inflation factor (VIF), with the thresholds of tolerance < 0.1 and VIF >10 indicating strong multi-collinearity. The random point creation tool of ArcGIS which was adopted to create 10000 random points in the research area, extract the rating values of nine parameters corresponding to each point, and calculate the tolerance and VIF using SPSS software.

3.5 Optimization of DRASTIC model weights

3.5.1 Three-scale analytic hierarchy process

The three-scale AHP was used to modify the weights of the original DRASTIC and DRASTICLE models, and has the same calculation steps as the traditional AHP. The three-scale method was used to replace the original nine-scale method in order to better construct the judgment matrix. The AHP was required to compare and judge parameters and determine the order of their importance, the significance scale comparison is presented in Table 1. In order to determine the magnitude relationship, a correlation analysis between each parameter and the actual nitrate concentration was carried out; the higher the correlation with nitrate, the more important the parameter. In this way, the degree of importance of each parameter in the vulnerability assessment could be determined.

Table 1 Significance scale meaning table

Scale value	Description of two-factor relationship

0	The ci factor is less important than the cj factor
1	The ci factor is as important as the cj factor
2	The ci factor is more important than the cj factor

319

320 The VI of the AHP-DRASTIC and AHP-DRASTICLE models were calculated
321 according to Eqs. 1 and 2 , respectively.

322 $$VI = D_r D_w + R_r R_w + A_r A_w + S_r S_w + T_r T_w + I_r I_w + C_r C_w + L_r L_w + E_r E_w \quad (2)$$

323 where the subscripts r and w represent ratings and weights for the nine parameters
324 of the DRASTICLE model, respectively.

325 **3.5.2 Weights of evidence**

326 Weights of evidence (WOE) (Agterberg & F., 1989) is a geostatistical quantitative
327 prediction method based on binary (existing or non-existent) images and Bayes' rule
328 under the assumption of independent conditions.

329 Assuming that the study area is A(T) km^2, and the study area is divided into cells
330 of area U km^2, the total number of cells in the study area is N(T)= A(T)/U. Assuming
331 that there are N(D) cells with response factor (D) distribution, the probability of the
332 occurrence of a response factor in any cell selected in the research area is P(D)= N(D)/
333 N(T), which is called the prior probability. It is assumed that the prior probabilities of
334 each cell are equal throughout the study area. Then, the prior probability is expressed
335 in terms of the odds (O):

$$O(D) = \frac{P(D)}{1 - P(D)} = \frac{N(D)}{N(T) - N(D)}. \quad (3)$$

The weights are calculated as follows:

$$W^+ = ln\frac{P\{B|D\}}{P\{B|\bar{D}\}} = ln\frac{N(B\cap D)/N(D)}{N(B\cap \bar{D})/N(\bar{D})}; \quad (4)$$

$$W^- = ln\frac{P\{\bar{B}|D\}}{P\{\bar{B}|\bar{D}\}} = ln\frac{N(\bar{B}\cap D)/N(D)}{N(\bar{B}\cap \bar{D})/N(\bar{D})}; \quad (5)$$

where B is the model factor, and D is the response factor (nitrate concentration). The weight contrast is $C = W^+ - W^-$, and the standard deviation of the weight difference is $\sigma = \sqrt{\sigma^2(W^+) + \sigma^2(W^-)}$,where $\sigma^2(W^+)$ and $\sigma^2(W^-)$ are the variances of W^+ and W^-, respectively. The final weight is $W = \frac{C}{\sigma(C)}$.

The WOE requires that the distribution of predictors relative to the response factor satisfy condition independence. For n predictors, if all are conditionally independent with respect to the response factor, the logarithm of the odds is:

$$\ln R = \ln\left\{O\left[\frac{D}{B_1^k B_2^k \cdots B_n^k}\right]\right\} = \sum_{j=1}^{n} W_j^k + lnO(D); \quad (j = 1,2,3\cdots, n). \quad (6)$$

Finally, by using the formula $P = \frac{R}{1+R}$, the logarithm of the posterior odds can be transformed into posterior probability.

3.6 Comparison and validation of models

To validate and compare the accuracy of the five models, the ROC curve (Mukherjee & Singh, 2020) was used to evaluate and compare the results of different models, which takes each value of the predicted results as the possible judgment threshold, and calculates the corresponding sensitivity and specificity accordingly. The false positive rate (1 – specificity) is taken as the horizontal coordinate, and the true positive rate, that is, sensitivity, is drawn as the vertical coordinate. The area under the

ROC curve, the AUC value, is a good measure of the model's predictive accuracy, and ranging in value from 0.5 to 1; the larger the value, the stronger the judgment of the model. In this study, an ROC curve was drawn based on the groundwater nitrate concentration and groundwater vulnerability index.

4. Results and discussion

4.1 Multi-collinearity diagnosis

The results of the multi-collinearity diagnosis for each evaluation factor are presented in Table 2. The tolerance and VIF were 0.35–0.97 and 1.04–2.84, respectively, both meeting the conditions of tolerance >0.1 and VIF <10, which indicates that there was no overlap among the nine evaluation factors; thus, the conditions were independent and could participate in the model evaluation.

Table 2 Multi-collinearity diagnosis test for all conditioning factors

Factors	Tolerance	VIF
Depth to Water	0.89	1.12
Net Recharge	0.46	2.18
Aquifer Media	0.53	1.87
Soil Media	0.52	1.93
Topography	0.85	1.18
Impact of the Vadose Zone	0.66	1.52
Conductivity of the Aquifer	0.62	1.62
Land use	0.97	1.04
Degree of Groundwater Extraction	0.35	2.84

4.2 Groundwater vulnerability assessment using original DRASTIC model

According to the original DRASTIC model, the minimum and maximum values of the groundwater vulnerability assessment index in the study area were 94 and 193,

respectively. Groundwater vulnerability was classified into five categories based on the Jenks method in ArcGIS, and a groundwater vulnerability distribution map was drawn (Fig. 3a).

The very low (I) vulnerability region accounted for 9.32% of the study area, mainly distributed in the hilly area in the northwest. The areas with low (II) vulnerability were the most distributed, accounting for 41.25% of the study area; the moderate (III), high (IV), and very high (V) vulnerability regions accounted for 28.97%, 15.12%, and 5.35% of the study area, respectively. Based on this, the overall groundwater vulnerability in the study area was considered relatively low.

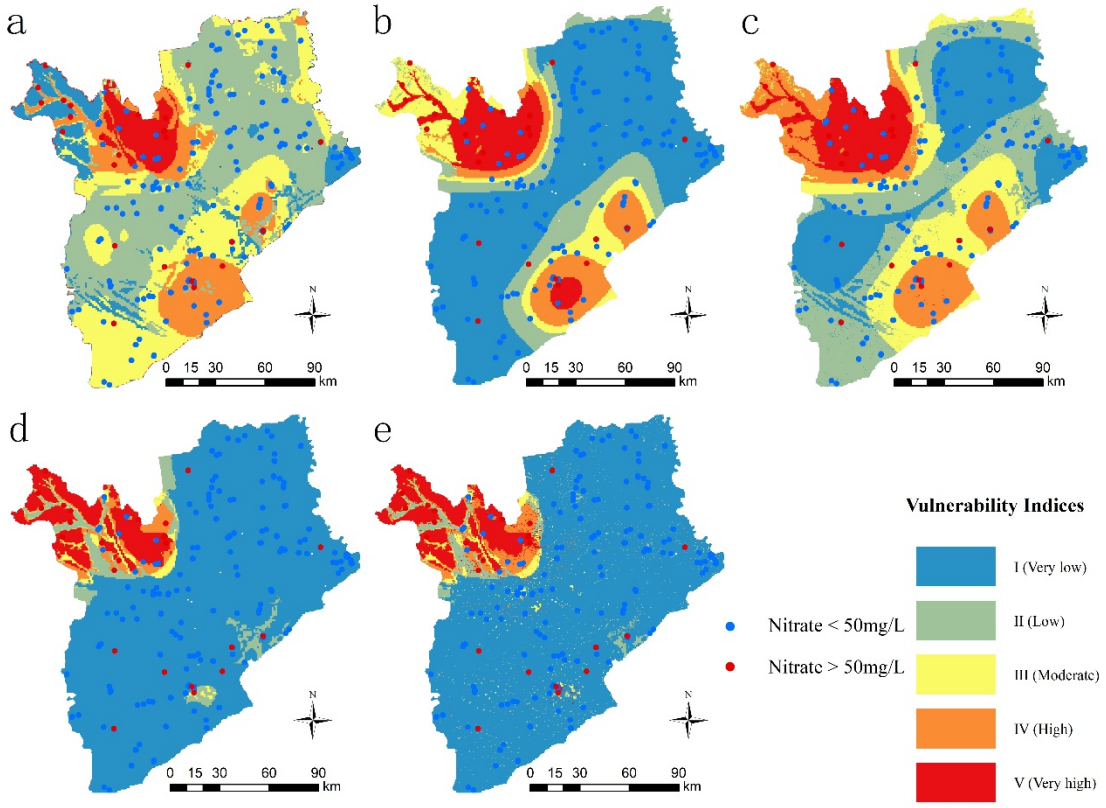

Fig. 3 Groundwater vulnerability maps: (a)DRASTIC, (b)AHP-DRASTIC, (c) AHP-DRASTICLE, (d)WOE-DRASTIC, (e) WOE-DRASTICLE.

4.3 Groundwater vulnerability assessment using three-scale AHP

To verify the consistency of the judgment matrix, the consistency index values of the AHP-DRASTIC and AHP-DRASTICLE models were 0.025 and 0.047, respectively, both of which were <1, indicating that the normalized weight values passed the consistency test. The weights of the evaluation factors for the two models are listed in Table 3.

Table 3 Modified weights of the AHP-DRASTIC and AHP-DRASTICLE factors

Factors	Weight	
	AHP-DRASTIC	AHP-DRASTICLE
D (Depth to Groundwater)	0.019	0.010
R (Net Recharge)	0.030	0.023
A (Aquifer Media)	0.152	0.097
S (Soil Media)	0.257	0.244
T (Topography)	0.087	0.060
I (Impact of the Vadose Zone)	0.050	0.037
C (Conductivity of the Aquifer)	0.405	0.359
L(Land use)		0.015
E(Degree of Groundwater Extraction)		0.156

According to the weights in Table 3, the evaluation factors of the two models were weighted and superimposed to obtain the distribution map of groundwater vulnerability in the study area, as shown in Figs. 3b, c. According to the two models, the groundwater vulnerability in the study area was very low (I) and low (II).

4.4 Groundwater vulnerability assessment using WOE

Taking the nitrate concentration as the response factor, there were 254 nitrate points in the study area. Monitoring wells with $NO_3^- \geq 50$ mg/L were selected as the response factor occurrence point, and there were 26 points with $NO_3^- \geq 50$ mg/L. The

probability of the occurrence of the response factor was P(D) = 0.102, and the prior probability odds were $O(D)=\frac{P(D)}{1-P(D)}=0.114$. The weights calculated according to Eqs. 4 and 5 are shown in Supplementary Table S.

According to the weights in Attached Table A, among the factors affecting groundwater vulnerability, depth to groundwater (D) at 4.6–9.1 m had the highest impact (1.668) on groundwater vulnerability, net recharge (R) at 177.8–254 mm, aquifer media (A) at sand and gravel, soil media (S) at loam, topography (T) at 2–6%, impact of the vadose zone (I) at sand and gravel, conductivity of the aquifer (C) at >81.5 m/d, land use (L) at artificial surface, and degree of groundwater extraction (E) at 50–70% had the most effect on groundwater pollution probability, respectively.

According to Eq. (6), the posterior probabilities of the response factors of the WOE-DRASTIC and WOE-DRASTICLE models were calculated. The results were classified into five categories using the Jenks method, as shown in Figs. 3d, e. The assessment of groundwater vulnerability by WOE showed that the vulnerability of the WOE-DRASTIC and WOE-DRASTICLE models were mainly very low (I), accounting for 81.60% and 81.52% of the total area, respectively.

4.5 Evaluation and comparison of model results

As can be seen from Fig. 4, the AUC of the original DRASTIC model is the minimum (0.62), improved by the three-scale AHP, and the AUCs of AHP-DRASTIC and AHP-DRASTICLE were 0.75, and 0.76, respectively. The AUC of WOE-

DRASTICLE was 0.78, and the AUC of WOE-DRASTIC was the largest at 0.845. This indicates that the results of the two methods (AHP and WOE) were better than those of the traditional DRASTIC assessment. The three-scale AHP method with the addition of two evaluation factors yielded better model results, while the result of WOE-DRASTIC (seven factors) was better than WOE-DRASTICLE with nine factors. This is because the weights calculated for a small number of classes are more robust than those calculated using a large number of classes, and this is particularly critical when a relatively small number of points are in the training data(Antonakos & Lambrakis, 2007).

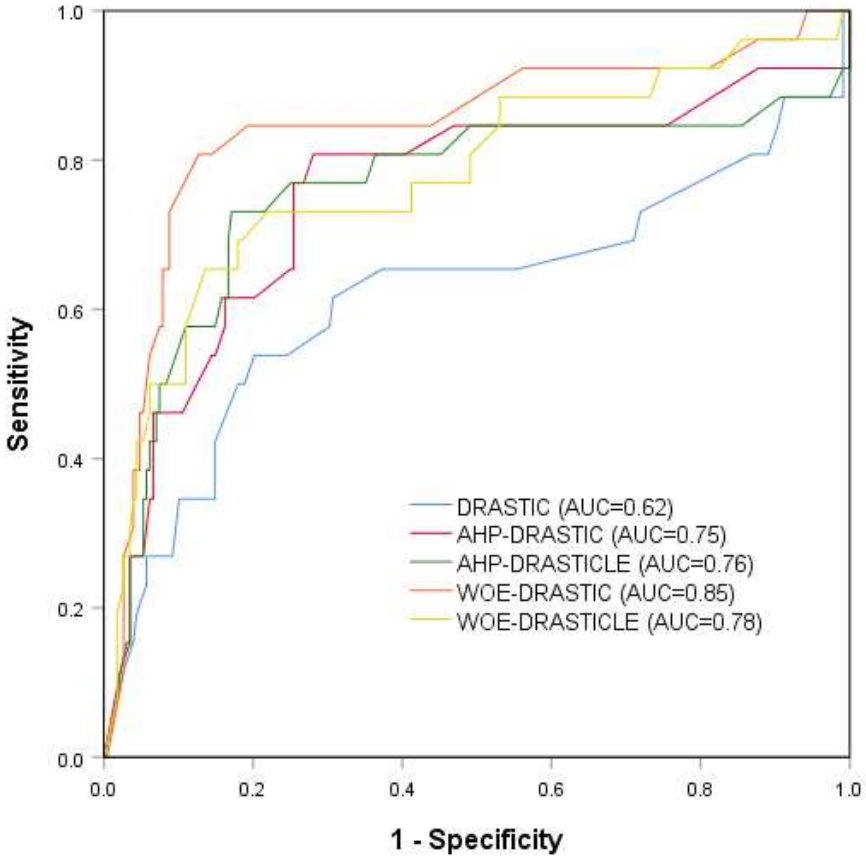

Fig. 4 ROC curve

4.6 Changes in groundwater vulnerability over time

To study the temporal and spatial pattern change of groundwater vulnerability, explore its distribution characteristics in different periods, and predict its development trend, the most effective model, the WOE-DRASTIC model, was selected to evaluate the groundwater vulnerability in 2000 and 2010. The distribution of groundwater vulnerability is shown in Fig. 5. In 2000, the very low (I) vulnerability zone accounted for 72.63%, and the very high (V) vulnerability zone accounted for only 5.14%, mainly distributed in the Taoer River Fan. In 2010, the areas of very low (I) and very high (V) groundwater vulnerability accounted for 75.07% and 6.34%, respectively. The very low (I) vulnerability zone for 81.60% and the very high (V) vulnerability zone for 7.93% in 2018. From 2000 to the present, the proportion of very low vulnerability zones in groundwater has been gradually increasing, but at the same time the very high vulnerability zones have also been increasing, with extreme cases. This is related to the depth of groundwater data.

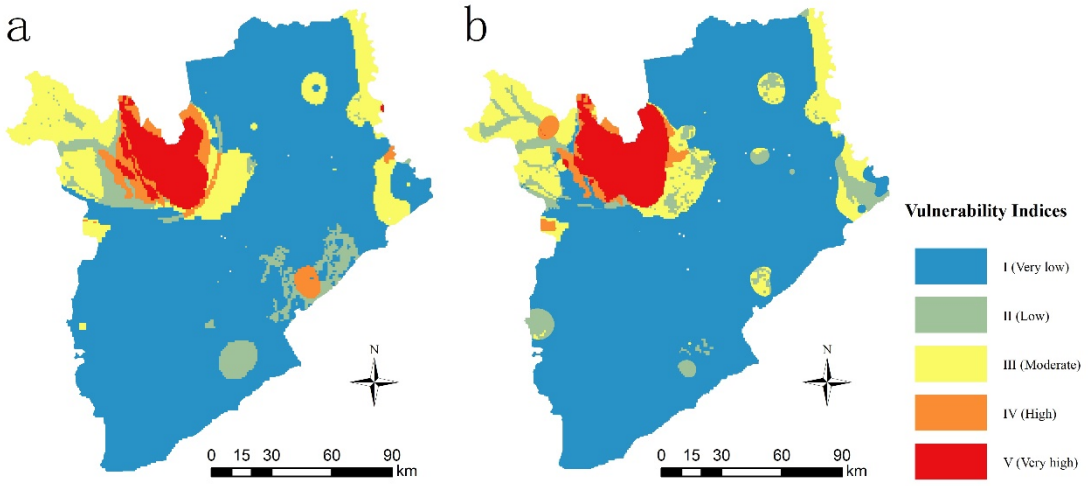

Fig. 5 Groundwater vulnerability maps: (a) WOE-DRASTIC for 2000, (b) WOE-DRASTIC for

2010.

4.7 Discussion

The concept of the DRASTIC model is used to evaluate groundwater vulnerability in the area. The traditional DRASTIC was first used to evaluate the inherent vulnerability of the aquifer, which is predominantly a low (II) vulnerability (41.25%) zone, with high (IV) and very high (V) vulnerability zones accounting for 20.47%. As can be seen from Fig. 3a, 50% of the points with nitrate > 50 mg/L fall into high (IV) and very high (V) vulnerability zones, and the remaining 50% are mainly distributed in low (II) vulnerability zones. Finally, 49.6% of nitrate < 50 mg/L points are distributed in the very low (I) and low (II) vulnerability zones.

The seven parameters in the traditional DRASTIC model merely consider the geological and hydrogeological conditions of the study area and do not consider the effect of human activities on groundwater. The two added parameters, used to generate the DRASTICLE model, combined with the three-scale AHP and WOE to modify the weights of the parameters, found different results as follows. The results of the AHP-DRASTIC model showed that the very low (I) vulnerability zones had the highest distribution (55.05%), and the high and very high vulnerability zones showed 19.82%. A total of 61.5% of the nitrate > 50 mg/L points fell in the high and very high vulnerability zones and 19% in the very low vulnerability zone. Only 16.2% of the nitrate < 50 mg/L points fell in the high and very high vulnerability zones and 64% in the very low vulnerability zone. The evaluation results of AHP-DRASTICLE showed

good dispersion, with 73.1% of nitrate >50 mg/L points falling in high and very high vulnerability zones and 82.5% of nitrate <50 mg/L points falling in moderate, low, and very low vulnerability zones. After adding the two parameters, the accuracy of the evaluation results was further improved. While only 38.5% and 57.7% of the nitrate >50 mg/L points for WOE-DRASTIC and WOE-DRASTICLE fell in the high and very high vulnerability zones, respectively, 94.7% and 77.6% of the nitrate <50 mg/L points fell in the very low vulnerability zone. These results show that the evaluation results are more reliable with the addition of two parameters and improved parameter weighting.

The WOE results show that depth to groundwater at 4.6–9.1 m had the highest impact (1.668) on vulnerability, implying that shallower groundwater levels are not necessarily more vulnerable to pollution. Moreover, with increased net recharge to the aquifer, the chance of contaminants entering the groundwater becomes greater and the degree of protection against pollution becomes smaller, with net recharge at 177.8–254 mm having the greatest impact. In general for aquifer media, the larger the medium particles, the more fissures in the aquifer, and the higher the permeability; thus, the greater the vulnerability of the aquifer. This was reflected in the model results, which indicated that sand and gravel had the highest rates. Generally, the type of soil, amount of expansion and shrinkage, and size of the media particles determine the size of soil contamination susceptibility. Soils with relatively thick layers, high organic matter content, and smaller particles have a high capacity to absorb contaminants, as well as good anti-fouling properties, and low vulnerability. The results of this study show that

soil media had great influence on loam, but not gravel. In general regarding topography, the topographic slope affects the surface runoff volume, runoff velocity, runoff direction, and residence time. The gentler the slope, the more pollutants leach, and the more likely they will leach into the groundwater. The results of this study showed that topography had the greatest effect at 2–6%, not 0–2% as was expected from research by Khosravi et al. (2018). In general, if the clay gravel content in the vadose zone is higher and the granules are finer, the permeability of groundwater will be lower. In this study, the WOE results show that the impact of the vadose zone had the greatest influence on sand and gravel. Generally, the hydraulic conductivity coefficient of an aquifer reflects the hydraulic permeability of an aquifer, which determines the migration rate of pollutants in the aquifer and the difficulty of pollutants entering the groundwater system. In this study, the results showed that when the conductivity of the aquifer was >81.5 m/d, the groundwater vulnerability was high. The artificial surface had the greatest influence on the groundwater vulnerability assessment, likely because the farmers raise livestock and grow crops and vegetables on their land, thus the associated animal waste, pesticides, and fertilizers can lead to substantial pollution of groundwater. The degree of groundwater extraction at 50–70% had the greatest effect on groundwater pollution probability.

The AUC of the ROC curve shows that both the improved AHP-DRASTIC and WOE-DRASTIC had better evaluation results than the traditional DRASTIC. Meanwhile, AHP-DRASTICLE was better than AHP-DRASTIC, indicating that the

evaluation results are more reliable with the addition of two evaluation factors for the influence of human activities. The result of WOE-DRASTIC was better than that of WOE-DRASTICLE because of no enough training points. Findings suggest that both weight and evaluation factors should be further considered in the improvement of the model.

5. Conclusions

This study evaluates the vulnerability of groundwater in Baicheng City and optimizes the traditional DRASTIC method to better represent the actual vulnerability distribution of groundwater. The factors and weights of the DRASTIC method were improved. In consideration of the influence of human activities on groundwater, two factors, land use and degree of groundwater extraction, were added to the evaluation factors. The three-scale AHP and WOE methods were used to improve the weight of the factors. The results of the five models (DRASTIC, AHP-DRASTIC, AHP-DRASTICLE, WOE-DRASTIC, WOE-DRASTICLE) were compared using the ROC curve. Results showed that the model improvements proposed in this study had obvious effects: the model evaluation results were more accurate and had a higher correlation with nitrate concentration. Moreover, the evaluation results were shown to have improved accuracy after adding two factors to the AHP method. For the WOE method, the AUC of WOE-DRASTICLE was smaller than that of WOE-DRASTIC, which is to in the case of the few training points, the fewer evaluation factors, hence the evaluation results had higher accuracy. In the future research, if more training points exist, it can

be considered to add more evaluation factors into the WOE method.

The WOE-DRASTIC model was selected to evaluate the groundwater vulnerability of Baicheng City in 2000 and 2010 and found that the groundwater vulnerability in this region was mainly very low and low. From 2000 to 2018, the proportion of low groundwater vulnerability also increased gradually from 72.63% to 81.60%. The high vulnerability was distributed in the Taoer River fan in the northwest of the study area. Importantly, it should be noted that groundwater pollution may still occur in very low or low vulnerability areas, though compared with areas of high vulnerability, these areas are less vulnerable to human activities and natural environmental pollution. Overall, it is recommended that government departments should facilitate reasonable control of groundwater pollution prevention and extraction according to changes in groundwater vulnerability in the region. This study therefore provides a theoretical basis for the Baicheng municipal government to manage and exploit groundwater resources.

Supplementary Material

Table S Spatial correlation between nitrate and factors using WOE model

Factors	Range	Class	No.of pixels	Percentage of domain(%)	No.of nitrate	Percentage of nitrate(%)	W+	W-	Sc	C	C/Sc
D	15.2-22.9	3	19525	0.07	0	0.00	None	0.001	None	None	None
	9.1-15.2	5	1477578	5.16	1	3.85	-0.294	0.014	1.020	-0.308	-0.302
	4.6-9.1	7	20997450	73.36	23	88.46	0.187	-0.837	0.614	1.024	1.668
	1.5-4.6	9	6116909	21.37	2	7.69	-1.022	0.160	0.736	-1.182	-1.606
	0-1.5	10	12045	0.04	0	0.00	None	0.000	None	None	None
R	50.8-101.6	3	31404	88.35	21	80.77	-0.090	0.501	0.498	-0.591	-1.187
	101.6-177.8	6	278	0.78	0	0.00	None	0.008	None	None	None
	177.8-254	8	3862	10.87	5	19.23	0.571	-0.099	0.498	0.669	1.345
A	Metamorphic/Igneous	3	1706500	5.96	3	11.54	0.661	-0.061	0.614	0.722	1.176
	Massive Sandstone	6	25564772	89.28	17	65.38	-0.311	1.172	0.412	-1.483	-3.598
	Sand and Gravel	8	1364024	4.76	6	23.08	1.578	-0.214	0.465	1.791	3.849
S	Loam	5	2099007	7.34	6	23.08	1.146	-0.186	0.465	1.332	2.861
	Sand	9	23941055	83.71	20	76.92	-0.085	0.348	0.465	-0.433	-0.930
	Gravel	10	2559880	8.95	0	0.00	None	0.094	None	None	None
T	>18	1	2090	0.01	0	0.00	None	0.000	None	None	None
	12-18	3	10724	0.04	0	0.00	None	0.000	None	None	None
	6-12	5	94208	0.33	0	0.00	None	0.003	None	None	None
	2-6	9	1046784	3.66	1	3.85	0.050	-0.002	1.020	0.052	0.051
	0-2	10	27451069	95.97	25	96.15	0.002	-0.048	1.020	0.050	0.049
I	Silt/Clay	1	2738401	9.61	5	19.23	0.694	-0.113	0.498	0.806	1.620
	limit loam	5	7216826	25.33	3	11.54	-0.786	0.169	0.614	-0.956	-1.557
	Sandstone	6	17277701	60.63	13	50.00	-0.193	0.239	0.392	-0.432	-1.101
	Sand and Gravel	8	1263549	4.43	5	19.23	1.467	-0.168	0.498	1.635	3.287

C	0-4.1	1	7210489	25.19	2	7.69	-1.186	0.210	0.736	-1.396	-1.897
	4.1-12.2	2	8382437	29.29	3	11.54	-0.931	0.224	0.614	-1.155	-1.882
	12.2-28.5	4	3721649	13.00	1	3.85	-1.218	0.100	1.020	-1.318	-1.292
	28.5-40.7	6	1931868	6.75	1	3.85	-0.562	0.031	1.020	-0.593	-0.581
	40.7-81.5	8	2781926	9.72	3	11.54	0.172	-0.020	0.614	0.192	0.313
	>81.5	10	4595235	16.05	16	61.54	1.344	-0.781	0.403	2.124	5.270
L	Forest	1	88719	0.31	0	0.00	None	0.003	None	None	None
	natural grass	2	5762547	20.13	3	11.54	-0.556	0.102	0.614	-0.659	-1.073
	Wetland	3	321146	1.12	0	0.00	None	0.011	None	None	None
	Water Bodies	5	848979	2.97	0	0.00	None	0.030	None	None	None
	Cultivated Land	6	17314166	60.48	6	23.08	-0.963	0.666	0.465	-1.629	-3.501
	Bareland	7	3401822	11.88	0	0.00	None	0.127	None	None	None
	Artificial Surface	10	891087	3.11	17	65.38	3.045	-1.029	0.412	4.074	9.883
E	0-20%	1	1127	3.17	0	0.00	None	0.032	None	None	None
	20%-50%	3	25153	70.77	11	42.31	-0.514	0.680	0.397	-1.194	-3.007
	50%-70%	6	6198	17.44	10	38.46	0.791	-0.294	0.403	1.085	2.690
	80%-100%	9	3066	8.63	5	19.23	0.802	-0.123	0.498	0.925	1.858

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Acknowledgment

This study was supported by the National Natural Science Foundation of China, Research on the Impact of In-situ Oil Shale Exploitation on Groundwater Environment [project number 41572216], the China Geological Survey project, regional water resources survey methods, and groundwater ecological threshold survey research [project number DD20190340], Geological Exploration Fund of Jilin Province, Geothermal Resources Survey in the Middle and West of Jilin Province [project number 2018-13]; Special Project of the Provincial University Co-Construction Program-Frontier Science and Technology Guidance Category, Research on the Interdependent Ecosystem and Sustainable Utilization of Natural Mineral Water in Changbai Mountain [project number SXGJQY2017-6]; Key research and development program of Shaanxi Province, Construction of Big Data Platform for Geotechnical Engineering [project number 2017ZDCXL-SF-03-01-01]. The authors would like to thank Jilin Jingyu field scientific observation and research base of volcanoes and mineral springs, which provided the necessary data to conduct this study. We thank the anonymous reviewers and editors who contributed valuable comments, which were useful in improving the quality of the manuscript.

Author contribution: Mingjun Liu: Writing - original draft, Data curation, Formal analysis. Changlai Xiao: Conceptualization, Writing -review, Supervision, Funding acquisition. Xiujuan Liang: Methodology & editing, Formal analysis.

Data availability The dataset used and/or analyzed during the current study are

available from the corresponding author on reasonable request.

Compliance with ethical standards

Ethics approval and consent to participate Not applicable.

Consent for publication Not applicable.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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