



Fuzzy vulnerability mapping of urban groundwater systems to nitrate contamination



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ARTICLE INFO

Article history:

Received 14 December 2016

Received in revised form

8 June 2017

Accepted 25 June 2017

Keywords:

Modified DRASTIC index

Fuzzy set theory

Urban aquifer

Specific vulnerability mapping

Nitrate contamination

ABSTRACT

The aim of this study is to develop a new fuzzy optimization model to find the optimal factor weights of modified DRASTIC index for groundwater vulnerability mapping an urban aquifer to nitrate contamination. Eight factors including water table depth, recharge, aquifer media, soil media, topography, impact of vadose zone, hydraulic conductivity, and land use are considered and rated. A fuzzy linear regression is formulated between the values of eight factors and corresponding nitrate concentration in groundwater. An optimization model based on real code genetic algorithm with objective of minimizing the sum of the fuzzy spread of the regression coefficients is implemented. Aquifer of Mashhad metropolis (northeast of Iran) is chosen to evaluate the proposed model. The results show the proposed model is a promising tool for weighting the factors with avoiding the subjectivity and also ambiguities accompanied by parameters to produce an accurate specific vulnerability mapping of an urban aquifer.

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1. Introduction

Groundwater vulnerability mapping is considered as an essential component of sustainable land-use planning, particularly in metropolitan areas of developing countries (Mazari-Hiriart et al., 2006). Delineating regions that groundwater resources are vulnerable to pollution allows appropriate precautionary measures to be taken to appropriately locate domestic wells (Brindha and Elango, 2015). There are three general tools for assessing the groundwater vulnerability to contamination (National Research Council, 1993; Neh et al., 2015): statistical methods, process-based simulation models, and overlay/index methods. Overlay/index methods as DRASTIC (Aller et al., 1987) and Susceptibility Index (SI) (Ferreira and Oliveira, 2004) are the most widely used approaches that aggregate the hydrogeological factors which control the migration of contaminants into the aquifer by assigning a numeric index to each parameter (Wang et al., 2012). Secunda et al. (1998) proposed the modified DRASTIC index (MDI) method which is an efficient attempt to consider the real conditions of many study regions by

incorporating the land use effects on the aquifer vulnerability mapping (Joekar-Niasar and Ataie-Ashtiani, 2003; Brindha and Elango, 2015). Despite of the proposing large kind of modifications, Commonly, practitioners have to deal with two types of uncertainties in applying overlay/index methods: one epistemic uncertainty associated with a set of hydrogeological factors due to the limitation of data and knowledge, and the linguistic uncertainty of the final groundwater vulnerability categories (e.g. “low” or “high” vulnerability) (Shouyu and Guangtao, 2003). However, the sensitivity analysis (Babiker et al., 2005) and fuzzy rule-based techniques (Dixon, 2005; Rajabi and Ataie-Ashtiani, 2016), combining fuzzy pattern classification and psychophysics' principles (Bojorquez-Tapia et al., 2009) are addressed for the later problem. Studies in recent years have used overlay/index models in a fuzzy logic-based environment for delineation of groundwater vulnerable zones to account for uncertainty (Wu, 2011). It is a qualitative evaluation tool and in order to validate and compare the final map and taking into account the effect of pollution type, the correlation of the observed concentration of nitrate (Brindha and Elango, 2015) in groundwater with the model results is often used. Nitrate contamination is a widespread pollution index for the impacts of human interference on groundwater by way of excessive use of chemicals and fertilizers

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in agricultural section and dumping of animal waste and seepage from wastewater systems (Joekar-Niasar and Ataie-Ashtiani, 2009; Hajhamad and Almasri, 2009). It can be used as an appropriate contamination for detecting susceptible locations and as an indicator for assessing the specific vulnerability mapping (Shrestha et al., 2016).

The index/overlay methods for specific vulnerability mapping of an aquifer are subjective in assigning numerical values to the descriptive entities and relative weights for the different attributes without any revising (Pacheco et al., 2015). These predefined factor weights do not reflect the particularities of the physical characteristics of studied areas, and provides doubtful results depends on the data availability, scale of mapping, and required accuracy and may introduce a large bias into the final map (Shrestha et al., 2016). For instance, determining highly vulnerable zones in an urban contamination groundwater setting using predefined weight of features (especially for land use pattern) without regard to local policies, urban planning, plant or industry establishment, special economic zones and agricultural activities, and diversity of hydrogeological settings likely generate inaccurate result (Shen et al., 2016).

The implemented approaches to reduce the subjectivity of factor weights such as single-parameter sensitivity analysis (Huan et al., 2012) reduced the DRASTIC features just to the three explicative features: topography (T), recharge (R) and aquifer material (A). Fijani et al. (2013) adopted a non-linear mapping between the DRASTIC parameters and observed nitrate concentrations in Maragheh–Bonab aquifer in Iran by using four types of supervised artificial neural network (ANN) models. Pacheco et al. (2015) compared the five above mentioned adjustment approaches to the DRASTIC factor weights and concluded that correspondence analysis may be recommended as the best technique. In a previous study, Asadi et al. (2017) introduced a new approach for modifying well-known parameters of common vulnerability indexes based on their influences on contamination attenuation in contaminated urban areas by nitrate. They applied the proposed approach in several index methods to investigate the capability of the modified parameters to increase correlation coefficient of all employed index methods with the measured nitrate concentration in Mashad aquifer, Iran.

Another approach to attain more realistic vulnerability maps by DRASTIC method is incorporating the fuzzy logic by setting up factors as typical membership functions with real values in the interval [0,1] instead of variables with integer values between 1 and 10 (Dixon, 2005). So far, the aim of fuzzy logic to DRASTIC model was returning the truth degree of integer values of each factor as an extension of real valuations, and no attempt has been made to use this approach for adjustment of factor weights in DRASTIC model. To fill this gap, the main objective of this study is developing a fuzzy logic optimization model to adjust the factor weights of modified DRASTIC index (MDI), to address the uncertainty associated with the weights of eight factors, and to reduce the subjectivity of factor weights. The present model incorporates fuzzy set theory with asymmetric triangular membership function in a linear correlation between the eight MDI factors and corresponding nitrate concentrations in groundwater. The parameters of the fuzzy coefficients related to various features are optimized using a real code genetic algorithm (GA) with the objective to minimize the total fuzziness of the factor weights. The proposed approach aimed at reducing systematically the subjectivity and the ambiguity accompanied by the factor weighting in overlay/index models to provide the more accurate vulnerability map of aquifers in urban areas.

2. Methods

2.1. Proposed model

In the proposed model, vulnerable zones are identified based on eight parameters representing hydrogeological features of the aquifer: depth to groundwater (D), recharge (R), aquifer media (A), soil media (S), topography (T), impact of vadose zone (I), hydraulic conductivity of the aquifer (C), land use (L) and one additional target parameter nitrate (N). The corresponding ratings (r) for eight parameters D, R, A, S, T, I, C, L are identified according to the vulnerability potential of each feature (as listed in Table 1), whereas the values of nitrate concentration are not rated and remain in its actual values. The higher value of 'r' attributed to each region shows the more tendency to contamination (Chandoul et al., 2015). In the next step, fuzzy linear regression (FLR) analysis has been conducted between the gridded rating of the eight parameters D, R, A, S, T, I, C, L as independent variables and corresponding nitrate concentration (N) as dependent variable (Fig. 1).

In the fuzzy regression analysis, the vectors of fuzzy output variable (estimated nitrate concentrations), \tilde{N}_i^* ($i = 1, 2, \dots, n$) is related to the vector of non-fuzzy input variables $X = [D, R, A, S, T, I, C, L]^T$ using fuzzy regression coefficients $\tilde{M} = [\tilde{D}, \tilde{R}, \tilde{A}, \tilde{S}, \tilde{T}, \tilde{I}, \tilde{C}, \tilde{L}, \tilde{B}]^T$ as follows (Zahraie and Hosseini, 2009; Hosseini and Mahjouri, 2014):

$$\tilde{N}_i^* = \tilde{D} \times D_i + \tilde{R} \times R_i + \tilde{A} \times A_i + \tilde{S} \times S_i + \tilde{T} \times T_i + \tilde{I} \times I_i + \tilde{C} \times C_i + \tilde{L} \times L_i + \tilde{B} \quad (1)$$

The fuzzy output variable and the fuzzy regression coefficients are considered as asymmetric triangular membership functions $\mu_{\tilde{N}_i}(N_i)$ and $\mu_{\tilde{X}_i}(X_i)$, respectively as follows:

$$\mu_{\tilde{N}_i^*}(N_i^*) = 1 - \frac{|N_i^* - N_i^c|}{k_N \times N_i^s} \quad (2-1)$$

$$\mu_{\tilde{X}_i}(X_i) = 1 - \frac{|X_i - X_i^c|}{k_X \times X_i^s} \quad (2-2)$$

where N_i^c, X_i^c and N_i^s, X_i^s are the centers, spreads of estimated nitrate concentrations and fuzzy regression coefficients (D, R, A, S, T, I, C, L), respectively. k_N and k_X are the skewness factors of nitrate and fuzzy regression coefficients, respectively. For a symmetric membership function, the skewness factors equal unity. Therefore, the Equation (1) is calculated as

$$\begin{aligned} \tilde{N}_i^*(N_i^c, N_i^s, k_N, h_N) = & \tilde{D}(D^c, D^s, k_D, h_D) \times D_i + \tilde{R}(R^c, R^s, k_R, h_R) \times R_i \\ & + \tilde{A}(A^c, A^s, k_A, h_A) \times A_i + \tilde{S}(S^c, S^s, k_S, h_S) \\ & \times S_i + \tilde{T}(T^c, T^s, k_T, h_T) \times T_i + \tilde{I}(I^c, I^s, k_I, h_I) \\ & \times I_i + \tilde{C}(C^c, C^s, k_C, h_C) \times C_i \\ & + \tilde{L}(L^c, L^s, k_L, h_L) \times L_i + \tilde{B}(B^c, B^s, k_B, h_B) \end{aligned} \quad (3)$$

where \tilde{B} is the fuzzy constant of the regression. The confidence level of h which is named h -cut indicates the confidence level (or target level of belief of) fuzzy variables of \tilde{N}_i and \tilde{X}_i as shown in Fig. 2. In the other words, any fuzzy coefficient having a membership level higher than a given level $h \in (0, 1)$ is in the certainty domain. As h -cut changes, the center values of fuzzy coefficients remain

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