Localization of Groundwater Vulnerability Assessment Using Catastrophe Theory

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Abstract Groundwater vulnerability is assessed by the DRASTIC method, which is more popular among the alternatives available. The challenge taken on board is to treat its inherent subjectivity in estimating the values of the embedded weights as recommended by USEPA for all aquifers. This paper uses a catastrophe based multi-objective evaluation system and applies it to the DRASTIC method to avoid undue preferences by decision maker. Thus, catastrophe fuzzy membership functions are used to treat the dependency of state variables on control parameters and thereby to determine the weights embedded in DRASTIC parameters. The proposed method estimates the weights of DRASTIC parameters with respect to local condition of study area. The Maragheh-Bonab aquifer in Iran is under threat by agricultural and industrial activities and therefore its vulnerability is assessed by the proposed method as well as by the general and pesticide DRASTIC methods. Comparison of results with the special distribution of nitrate-N (NO3-N) shows that the improved DRASTIC has a higher correlation index with respect to the general and pesticide DRASTIC methods. Also in seeking more reliability, the addition of new parameters is possible in the proposed method.

Keywords Groundwater vulnerability · DRASTIC method · Catastrophe theory · Nitrate-N

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1 Introduction

Delineation of vulnerable regions to groundwater contamination introduced by USEPA remains a more popular groundwater vulnerability assessment method in comparison to the general and pesticide DRASTIC indexes. Aller et al. (1987) introduced the DRASTIC method for use by USEPA (United State Environmental Protection Agency), which collected the understanding of 40 hydrogeologits, though subjective in essence, and integrated them under the DRASTIC method drawing on their contributions concerning a number of groundwater basins in the United States. This method which is the Point Count System Model (PCSM) method, consisting of seven parameters: depth to water, recharge, aquifer media, soil media, topography, the impact of the vadose zone media, and hydraulic conductivity. Several researches has been contributed to to the groundwater vulnerability assessment by DRASTIC method even without any changes (Assaf and Saadeh 2009; Chitsazan and Akhtari 2009; Voudouris et al. 2010; Moratalla et al. 2011; Edet 2014).

In spite of worldwide usage, the DRASTIC method has been criticized because parameter weights often do not meet the geological and hydrogeological conditions of the study area. In order to adjust the DRASTIC method to local conditions, some parameters have been added (Huan et al. 2012; Albuquerque et al. 2013; Saha and Alam 2014) or subtracted (Shirazi et al. 2012; Sener and Davraz 2015) to DRASTIC parameters in their studies.

The methods which reduce the subjectivity of parameters weights are categorized to three groups (Pacheco et al. 2015): (i) Single-parameter sensitivity analysis, proposed by Napolitano and Fabbri (1996) by assigning the individual parameter's weight by comparing pre-described and computed weights. Although, this approach has been used in numerous studies (Huan et al. 2012; Neshat et al. 2014a; Wu et al. 2014), it has disadvantages including: (a) increasing and decreasing of parameters evaluate just in limited range (e.g. ±10 %) versus model response changes, and (b) the effect of interaction between parameters is not considered (Krause et al. 2009); (ii) The calibration approach which was proposed by Panagopoulos et al. (2006) and the weights are modified based on correlation analysis between factor ratings and nitrate concentrations in the study area (Javadi et al. 2011; Huan et al. 2012; Neshat et al. 2014a); this method is not applicable for the areas with any field measurement of nitrate concentration; (iii) Analytic Hierarchy Process (AHP) as the third approach was developed by Saaty (1980); the weights assigning is performed by constructing a series of Pair-Wise Comparison Matrices (PCMs) which compares each parameter with one another; this method has been used in computation of rating and/or weights of DRASTIC parameters in few studies (Neshat et al. 2014b; Neshat and Pradhan 2015; Sener and Davraz 2015); In spite of its wide usage, this method is located in the subjective groups of weighting methods and the final result relies on the experts' judgment.

The purpose of the current study is to apply a catastrophe based multi-objective evaluation system for USEPA's groundwater vulnerability assessment (DRASTIC). The novelty of the paper is in presenting a new method to the localization of DRASTIC method by catastrophe fuzzy membership functions. So a hierarchy is proposed, in which rating and weights of DRASTIC parameters are determined with respect to the local condition of the study area, instead of subjective understanding. The presented

method applied to a case study of Maragheh-Bonab plain, East Azerbaijan, Iran. Although the Maragheh-Bonab aquifer contains rich groundwater resources, industrial and agricultural activities now pose threat to this valuable resource. So the necessity of studying groundwater vulnerability is raised to control human health in this region. The results of this method will be compared with the general and pesticide DRASTIC methods.

2 DRASTIC Method

Nowadays GIS-based DRASTIC method is believed to be the most popular method for groundwater vulnerability assessment. DRASTIC is an acronym for depth to water (groundwater depth) (D), recharge (R), aquifer media (A), soil media (S), topography (T), impact of the vadose zone media (I), and hydraulic conductivity (C). After preparation of DRASTIC parameters using ArcGIS, each parameter is rated from 1 to 10 to present the relative significance of each range with regard to pollution potential (Aller et al. 1987). Same ratings are considered in the general and pesticide DRASTIC methods. Then the seven DRASTIC parameters are weighted ranging from 1 to 5 based on experts' judgment by Delphi approach (Aller et al. 1987). These weights are different in the general and pesticide DRASTIC methods, but are constant for each region. Finally pollution potential or DRASTIC Index is computed by:

$$\text{DRASTIC Index} = D_R D_W + R_R R_W + A_R A_W + S_R S_W + T_R T_W + I_R I_W + C_R C_W \quad (1)$$

where D_r, R_r, A_r, S_r, T_r, I_r, and C_r are ratings and D_w, R_w, A_w, S_w, T_w, I_w, and C_w are the weights of DRASTIC parameters. The higher computed value of DRASTIC Index indicates vulnerable region to groundwater pollution potential.

3 Improvement of DRASTIC Method Based on Catastrophe Theory

Catastrophe theory was proposed by Thom (1972), to describe the systems with discontinues behavior. This theory defines independent parameters (known as control parameters) as a function of the dependent variable (known as a state variable) for assessing stability analysis of systems.

The multi-criteria decision making method based on catastrophe theory, sketch an objective hierarchy that obtains a catastrophe fuzzy membership function by normalization of bifurcation set. In this method instead of assigning weights by expert judgment, the dependency of state variable on control parameters is evaluated through catastrophe fuzzy membership function. This approach was proposed first by Cheng et al. (1996) for evaluating guided missile destroyer. Then it has been used in the different multi-objective decision making problems such as risk assessment (Zhang et al. 2009; Wang et al. 2011; Chen et al. 2012), identifying groundwater potential zone (Ahmed et al. 2014; Sadeghfam et al. 2016), and determining water security in the context of global environmental change (Xiao-jun et al. 2014).

In order to reduce subjectivity of DRASTIC method, the catastrophe based multi-criteria decision making method is designed using flowchart shown in Fig. 5: Column 1 represents

raw data processing by ArcGIS software package; Column 2 describes DRASTIC parameters which are known as processed data layers; Columns 3–4 describe procedures for the normalization of data layers; Column 5 is outlined in "Multi-criteria decision making method based on catastrophe theory" produces weighting values for the data layers. Then the improved DRASTIC index is calculated by the outputs from Column 4 (normalized data layers) and Column 5 (weightings for each data layer) in Box 6 (Weighted Overlay Analysis). Further details about Fig. 1 would be presented in the following sections.

3.1 Raw Data Processing and Processed Data Layers (Fig. 1 – Columns 1–2)

The data needed for DRASTIC data layers preparation are either in the form of raw format (e.g. paper maps, non-appropriate form of digital maps, and images of satellite) or discrete statistical information. The ArcGIS Software packages are used to preprocessing, digitizing the raw maps. The Kriging spatial interpolation technique is applied to transform the statistical discrete information to continuous surface.

3.2 Normalization of Data Layers (Fig. 1 – Columns 3–4)

On account of two important concerns, all of the DRASTIC parameters should be normalized after building the processed data layers. Since different layers have different units of measurement, the units on layers would be dimensionless in the normalization step. Also the lower and upper band of each layer is not located at the same ranges. Therefore by normalization of data between 0 and 1, these problems will be solved. Normalization of layers is adopted instead of rating assignment in the General and Pesticide DRASTIC methods. Therefore, assigning different ratings for various classes of data layers will not be needed in the proposed method. Among the DRASTIC parameters, five of them have a direct proportionality with groundwater
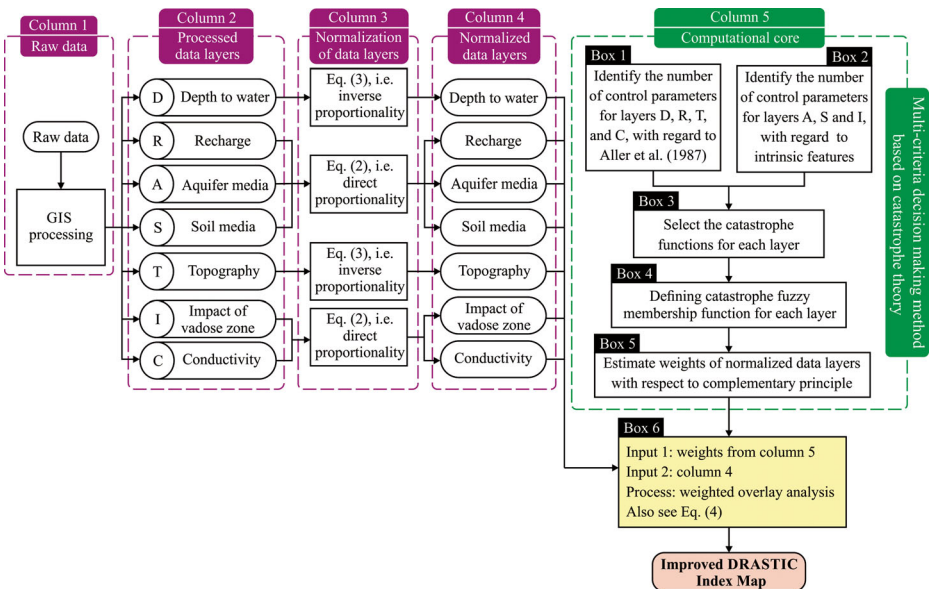

Fig. 1 A General methodological flowchart of an improved DRASTIC method based on catastrophe theory

pollution potential include: recharge, aquifer media, soil media, impact of vadose zone media, and hydraulic conductivity (Fig. 1 – Column 3). The higher values of these parameters result in higher groundwater pollution potential. On the other hand, lower values of a few parameters led to higher groundwater pollution potential. These parameters which have inverse proportionality with groundwater pollution potential, include: groundwater depth and topography (Fig. 1 – Column 3).

The normalization formula of the "direct proportionality" layers defined by;

$$X_i^n = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \tag{2}$$

and Eq. (3) shows the normalization formula of the "inverse proportionality" layers,

$$X_i^n = \frac{X_{\max} - X_i}{X_{\max} - X_{\min}} \tag{3}$$

where, i is the counter of an arbitrary cell. X_{max} and X_{min} are, respectively, maximum and minimum value of a parameter. X_i^n is the normalized value of an arbitrary cell i.

3.3 Multi-Criteria Decision Making Method Based on Catastrophe Theory (Fig. 1 – Columns 5)

3.3.1 Identification of the Number of Control Parameters (Fig. 1 – Boxes 1–2)

Since different control parameters led to different effect on state variable, determination of control parameters of DRASTIC parameters is a crucial step. Control parameter numbers of four DRASTIC parameters (groundwater depth, recharge, topography, and hydraulic conductivity) are determined with regard to Aller et al. (1987) classification numbers. But this trend is not applicable for three parameters include aquifer media, soil media, and impact of vadose zone media. The ratings of Aller et al. (1987) are used just for quantifying the mentioned layers. The classification number of these parameters is determined with regard to their intrinsic features. In different word, the number of parameters' classes is determined so that the similarity of media types within the classes and differences of media types between the classes, are maximized.

3.3.2 Selection of the Catastrophe Functions for each Layer (Fig. 1 – Box 3)

The type of catastrophe function is selected with regard to numbers of control parameters or classification numbers (see Table 1). As an example, since the recharge is classified into two classes, i.e., it has two control parameters, so cusp catastrophe is appropriate function.

3.3.3 Definition of Catastrophe Fuzzy Membership Function for each Layer (Fig. 1 – Box 4)

The mean values of each control parameter is calculated in the ArcGIS software package. The fuzzy catastrophe membership functions and related features are summarized in the Table 1 (Cheng et al. 1996). In the following equations, x_a, x_b, x_c, x_d, and x_e are state variables corresponding to control parameters (a, b, c, d, and e).

Table 1 Catastrophe fuzzy membership functions (Cheng et al. 1996)

Name	State Variable	Control parameter	Normalization formula
Cusp	1	2	$x_a = a^{1/2}, x_b = b^{1/3}$
Swallowtail	1	3	$x_a = a^{1/2}, x_b = b^{1/3}, x_c = c^{1/4}$
Butterfly	1	4	$x_a = a^{1/2}, x_b = b^{1/3}, x_c = c^{1/4}, x_d = d^{1/5}$
Wigwam	1	5	$x_a = a^{1/2}, x_b = b^{1/3}, x_c = c^{1/4}, x_d = d^{1/5}, x_e = e^{1/6}$

3.3.4 Estimate the Weights of Data Layers (Fig. 1 – Box 5)

After defining catastrophe fuzzy membership functions for each layer, one of following principles should be selected: non-complementary principle; and complementary principle (Zhang et al. 2009). In the non-complementary principle, control parameters cannot offset each other. Therefore the minimum value of normalized control parameters represents the state of system. On the other hand, in the complementary principles, control variables are complementary to each other. Therefore, the mean value of control parameters shows the state of system. In the groundwater vulnerability assessment, complementary principle is determinant. Then whole DRASTIC parameters are weighted with regard to mean value of normalized control parameters. In order that maximum weigh assigns to the parameter which has maximum value of state of system, and the minimum weight vice versa.

3.4 Performing the Weighted Overlay Analysis - (Fig. 1 – Box 6)

The weighted overlay analysis is performed by raster calculator of ArcGIS to obtain improved DRASTIC Index map. This step requires two inputs and these are taken from the Column 4 and 5, as follows,

$$\text{Normalized DRASTIC Index} = D_R D_N + R_R R_N + A_R A_N + S_R S_N + T_R T_N + I_R I_N$$
$$+ C_R C_N \tag{4}$$

where D_N, R_N, A_N, S_N, T_N, I_N, and C_N are normalized DRASTIC maps and D_w, R_w, A_w, S_w, T_w, I_w, and C_w are the weights of DRASTIC parameters based on catastrophe theory.

4 Study Area

4.1 Aquifer Characteristics

The plain of Maragheh-Bonab shown in Fig. 2, comprises of southern part of the East Azerbaijan province, northwest of Iran. It is bounded by longitudes 45° 57′ E and 46° 15′ E and latitudes 37° 15′ N and 37° 27′ N. The study area is bounded to the north by Mount Sahand; to the east and south by Malekan plain; and to the north-west by plain of Ajabshir plain. This region covers an area of approximately 330 km² and is composed of alluvial deposits. Maragheh and Bonab are the main cities in the study region and Sufichay (the River Sufi) is the major river of the plain, stemmed from Mount Sahand.
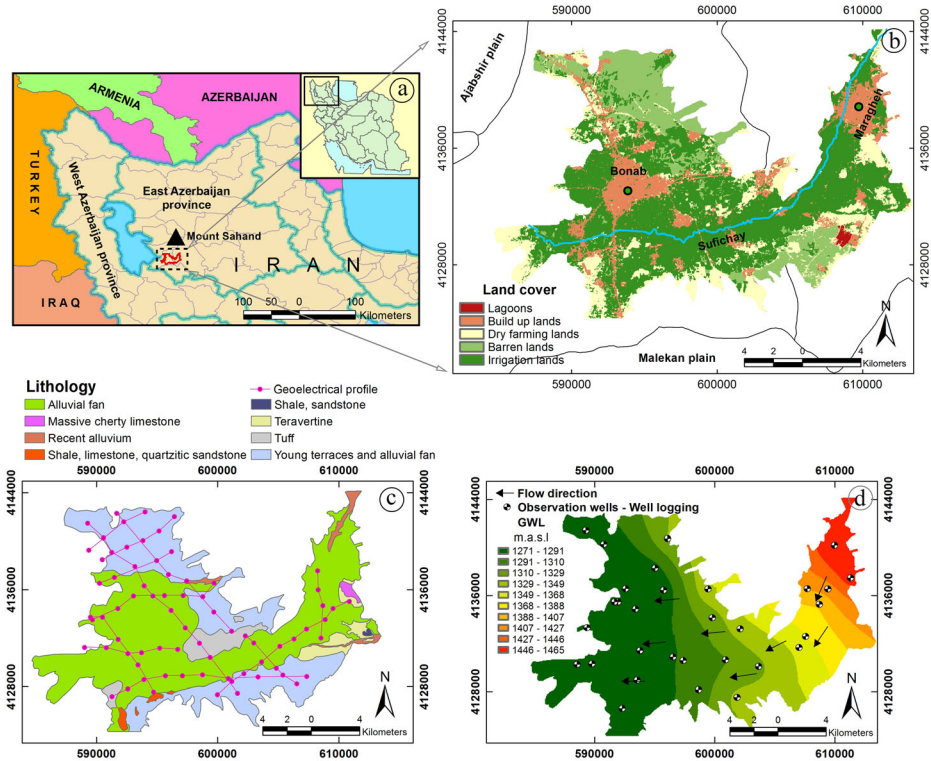
Fig. 2 Study area characteristics: **a** Location map; **b** Land cover, cities, and river; **c** Lithology map and geoelectrical profiles; **d** Groundwater level map

Quaternary deposits form the main hydrological and water bearing features, in which aquifers are formed by single layer, unconfined, and heterogeneous alluvial. Figure 2c depicts the lithology map of the aquifer. The geo-electrical survey was conducted in the plain (1964) to delineate thickness of the Maragheh-Bonab aquifer (see geoelectrical profiles in Fig. 2c). It was found that the bedrock of the plain is Miocene formations with generally dipping to the center of plain (from lower than 20 m to greater than 70 m).

Some relevant information about the Maragheh-Bonab aquifer is summarized for its relevance. This is known to have 65 deep and 6852 semi-deep abstraction water wells, 51springs and 48 qanats. Estimates indicate that approximately 39 million m^3 of groundwater was withdrawn (East Azerbaijan Regional Water Authority 2010) from the wells.

The annual average of groundwater level (GWL) map is plotted based on interpolating 33 monitoring wells (2014) by Ordinary Kriging technique (Fig. 1c). According to this figure, the groundwater flow direction is from northeast to the west of the plain. Also, recharge is from Sufichay that percolates into the aquifer through overlying unsaturated materials, in addition to recharge from surrounded mountains.

4.2 Climate

According to Emberger method (Emberger 1930), the study area is characterized by the semi-arid and cold climate zones. The Iranian Meteorological Organization reported that the average

annual precipitation and the mean annual temperature are, respectively, 346.2 mm and 12.83 °C between a 10-year period (2004–2014) at Maragheh station. The annual potential evaporation is 1440 mm, which is four times higher than the average annual precipitation. The average annual precipitation in the Maragheh–Bonab plain and surrounding mountainous area is 281 and 368 mm, respectively. The mean annual relative humidity is 50 %.

4.3 Land Cover and Pollutants

Figure 2b illustrates the land cover of Maragheh-Bonab plain. In order to preparation of this figure, satellite image of Landsat8 OLI[1] sensor in August 2014 have been used. In the preprocessing step, transforming operation of digital number to radiance, and atmospheric correction of FLAASH[2] via existing calibration parameters in the image's metadata file, are performed in Envi Software. Then by selecting training area on image, supervised classification through maximum likelihood method is applied for land cover map preparing. In the Fig. 2b, Irrigated lands, barren lands, dry farming land, buildup lands, and lagoons (belongs to Kaveh-Soda Company) encompass, respectively, 50.44 %, 16.61 %, 17.60 %, 15.03 %, and 0.32 % of the total plain area. So in spite of industrial pollutants, the agricultural activities are the most important non-point source pollutant which threatens Maragheh-Bonab aquifer. Fijani et al. (2013) assessed Maragheh-Bonab aquifer vulnerability optimized DRASTIC method and supervised committee machine artificial intelligence (SCMAI) which used nitrate-N concentration for training and validating SCMAI. In this study DRASTIC method is localized without considering pollutant concentration by multi-criteria decision making method based on catastrophe theory.

5 Result and Discussion

5.1 Raw Data Processing and Processed Data Layers

The processed data for each of DRASTIC data layers are listed in the Fig. 3. The groundwater depth layer (Fig. 3a) is prepared by interpolating monthly groundwater depth average of 33 observation wells during 15-years period (1999–2014) by Ordinary Kriging method. The mean recharge value is calculated by groundwater balance during the 15-year period (1999–2014). Then the recharge map (Fig. 3b) is interpolated by Ordinary Kriging. The maps of Aquifer media and impact of vadose zone media (Fig. 3c and f) are quantified by Aller et al. (1987) with regard to well logging data. Then it transformed to continuous format by Ordinary Kriging spatial interpolation. The soil map (Fig. 3d) is prepared by digitizing paper soil map of study area in ArcGIS. Then the map is quantified by Aller et al. (1987). The slope map (Fig. 3e) is obtained from ASTER[3] DEM[4] data with 28 m spatial resolution. The hydraulic conductivity map (Fig. 3g) is calculated by pumping test and interpolated by Ordinary Kriging method. Figure 2d illustrates the location of 33 observation wells and well logging which have been incorporated in the spatial interpolation.
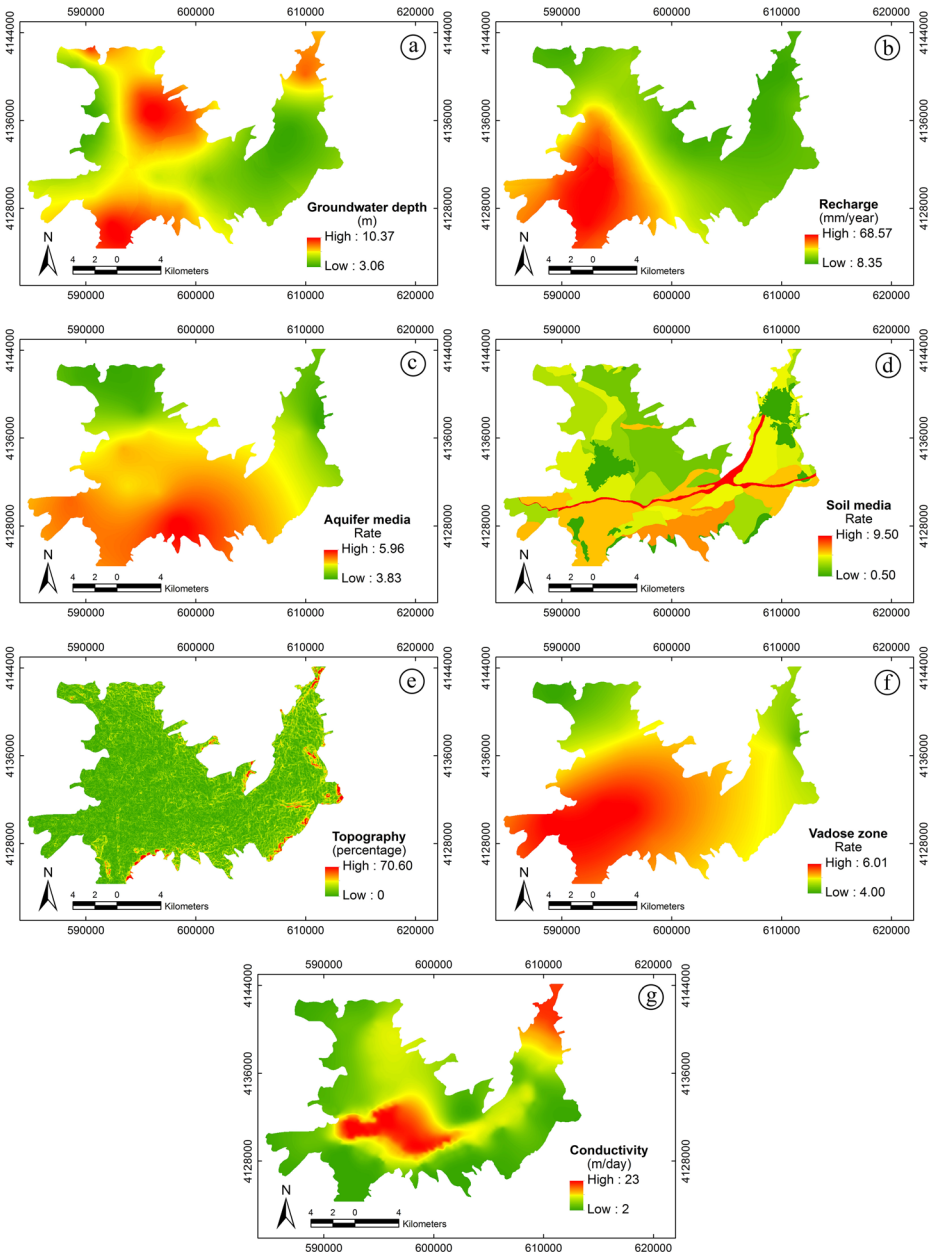
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[1] Operational Land Imager
[2] Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes
[3] Advanced Spaceborne Thermal Emission and Reflection Radiometer
[4] Digital Elevation Model

Fig. 3 The data layers of DRASTIC parameters: **a** Depth to water; **b** Recharge; **c** Aquifer media; **d** Soil media; **e** Topography; **f** Impact of the vadose zone media; **g** Hydraulic conductivity

5.2 Normalization of Data Layers

Normalization of processed data layers (Fig. 3) have been performed based on Eqs. 2–3 and the procedures in Section 2.2.

5.3 Multi-Criteria Decision Making Method Based on Catastrophe Theory (Table 2)

Table 2 shows the outcome of multi-criteria decision making process based on catastrophe theory in order to assign the weights of DRASTIC parameters. In this method the dependency of state variables (DRASTIC parameters) on control parameters (parameters classes) is determined by the catastrophe fuzzy membership functions.

5.3.1 Identification of the Number of Control Parameters (Table 2 – Columns 1–2)

Some of the parameters are classified as same as USEPA's DRASTIC method by Aller et al. (1987) include: groundwater depth, recharge, topography, and hydraulic conductivity (Column 1). But aquifer media, soil media, and impact of vadose media are the layers that after quantifying by Aller et al. (1987) recommendation, have been classified based on intrinsic characteristics of them (Column 1). The number and types of classes is determined based on predominant media of classes (Column 2).

5.3.2 Selection of the Catastrophe Functions for each Layer (Table 2 – Column 3)

The type of catastrophe functions for each DRASTIC parameters is selected based on classification number.

5.3.3 Definition of Catastrophe Fuzzy Membership Function for each Layer (Table 2 – Columns 4–6)

The mean value of each class is calculated by weighted averaging (Column 4). Since different media exist in the each classes, the thickness of each median stratum considered as the weights of them. Then these values are normalized based on Eqs. 2–3 (Column 4). The catastrophe fuzzy membership functions, are calculated based on Table 1 (Column 5).

5.3.4 Estimate the Weights of DRASTIC Parameters (Table 2 – Columns 7–8)

At the end, the state variables are weighted according to calculated priority by complementary principle (Column 7). In this step, higher weights assign to the variables with higher calculated priority (Column 8). Since the 7 parameters are contributed to this study, the weights are assigned from 7 to 1, with regard to corresponding calculated priority. The priority of recharge and impact vadose zone media are the same (0.5), therefore they weighted equally by 2. The weights of the general, pesticide, and improved DRASTIC are compare in Column 9.

5.4 Performing the Weighted Overlay Analysis to Delineate Groundwater Vulnerability

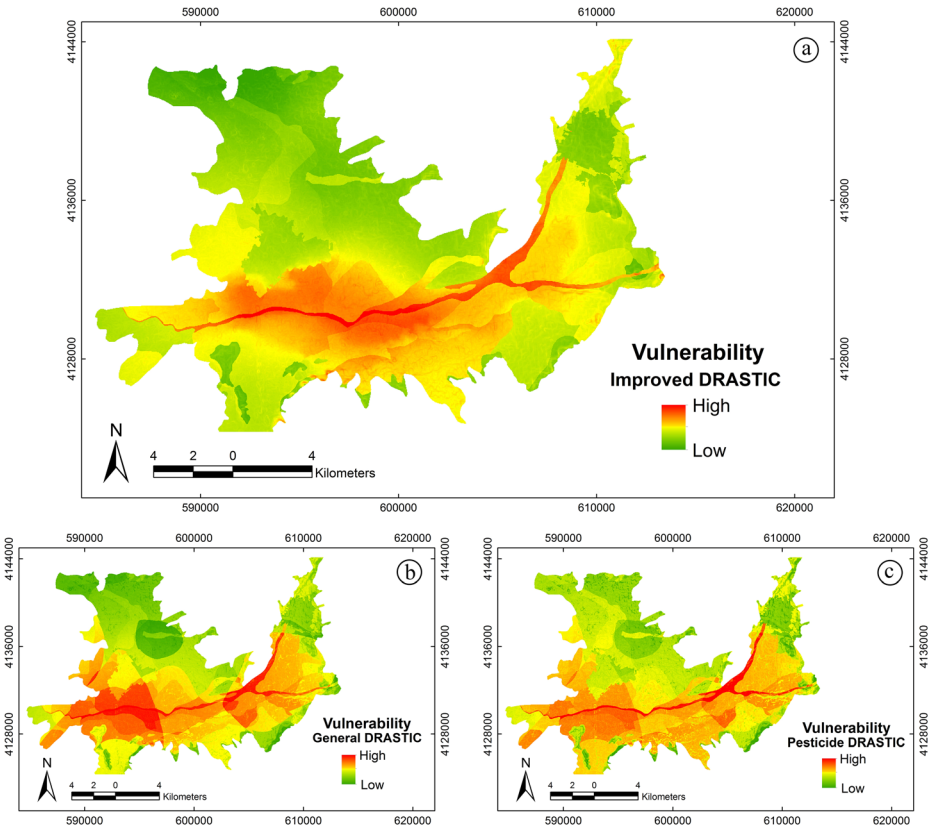Figure 4 illustrates the vulnerability map via general DRASTIC (Fig. 4a), pesticide DRASTIC (Fig. 4b), and improved DRASTIC (Fig. 6c) methods after performing the weighted overlay analysis. In this figure, DRASTIC index is reflected in red-to-green color spectrum so that the red, yellow and green colors illustrate, respectively, high, moderate, and low risk regions as a view of groundwater vulnerability.

Table 2 Details of catastrophe weighing method for the improved DRASTIC method

Column number	1			2	3	4	5	6	7	8	9	
DRASTIC parameters	Classification range			Linguistic expression or predominate media	Catastrophe function	Mean	Normalized Value of mean	Catastrophe fuzzy membership function	Priority based on complementary principle	DRASTIC Weights		
										Improved	General	Pesticide
Depth to water (m)	3.06 < Class1 < 4.60			Low	Swallowtail	3.94	1.00	1.00	0.60	4	5	5
	4.60 < Class2 < 9.10			Moderate		6.63	0.53	0.81				
	9.10 < Class3 < 10.37			High		9.63	0.00	0.00				
Recharge (mm/year)	8.35 < Class1 < 50.80			Low	Cusp	24.13	0.00	0.00	0.50	2	4	4
	50.80 < Class2 < 68.57			High		59.98	1.00	1.00				
Aquifer media (rate)	3.83 < Class1 < 4.10			Clay, Silt, and very fine Sand	Swallowtail	4.01	0.00	0.00	0.59	3	3	3
	4.10 < Class2 < 5.05			Sand and a little clay and silt		4.65	0.48	0.78				
	5.05 < Class3 < 5.96			Gravel, Sand, and a little clay and silt		5.33	1.00	1.00				
Soil media (rate)	0.5 < Class1 < 0.7			Build-up and rocky area	Butterfly	0.5	0.00	0.00	0.64	6	2	5
	0.70 < Class2 < 3.50			Clay, silty clay, silty loam, clay loam		2.56	0.31	0.67				
	3.50 < Class3 < 5.60			Loam, clay loam, sandy loam, loamy sand		4.71	0.62	0.89				
	5.60 < Class4 < 9.50			Gravel, sand, gravel or sandy loam		7.24	1.00	1.00				
Topography (percent)	0.00 < Class1 < 2.00			Low	Wigwam	1.19	1.00	1.00	0.75	7	1	3
	2.00 < Class2 < 6.00			Relatively low		3.44	0.91	0.97				

Table 2 (continued)

| Column number	1				2	3	4	5	6	7	8	9	
DRASTIC parameters	Classification range				Linguistic expression or predominate media	Catastrophe function	Mean	Normalized Value of mean	Catastrophe fuzzy membership function	Priority based on complementary principle	DRASTIC Weights		
											Improved	General	Pesticide
	6.00	<	Class3	< 12.00	Moderate		7.82	0.73	0.92				
	12.00	<	Class4	< 18.00	Relatively high		17.39	0.46	0.86				
	18.00	<	Class5	< 70.60	High		25.80	0.00	0.00				
Vadose Zone media	4.00	<	Class1	< 5.30	Clay, silt, and very fine sand	Cusp	4.84	0.00	0.00	0.50	2	5	4
	5.30	<	Class2	< 6.01	Silt, sand, and very fine gravel		5.68	1.00	1.00				
Conductivity (m/day)	2.00	<	Class1	< 4.00	Low	Swallowtail	2.94	1.00	1.00	0.63	5	3	2
	4.00	<	Class2	< 12.00	Moderate		7.62	0.68	0.88				
	12.00	<	Class3	< 23.00	High		17.37	0.00	0.00				

Fig. 4 Vulnerability map using different methods: **a** Improved DRASTIC by catastrophe theory; **b** General DRASTIC; **c** Pesticide DRASTIC

5.4.1 Evaluation and Validation of three DRASTIC Methods

The concentration of nitrate-N from the aquifer is used to validate different DRASTIC methods. Figure 5 shows the spatial distribution of nitrate-N concentration which is interpolated by inverse distance weighting (IDW) technique from 285 samples of measured data during June and August 2006. The measured samples were analyzed based on standard methods (American Public Health Association, 1998).

The correlation index (*CI*) presented by Fijani et al. (2013) used in order to evaluation of correlation between DRASTIC models and nitrate-N concentration. Higher CI indicates higher correlation. In this approach, both nitrate-N samples and DRASTIC Index at the same wells were divided into three groups, namely, low, moderate, and high. Notably, DRASTIC index and nitrate-N concentration is classified evenly to three classes. But the boundary between low and moderate classes in the nitrate-N concentration is determined based on the USEPA's recommendation, i.e., 10 mg/l. Then the number of samples that located in the same nitrate-N and DRASTIC Index group was multiplied by 3. Also the number of samples with a difference of 1 (e.g., high nitrate-N samples are located in the moderate DRASTIC Index, or vice versa) and 2 (e.g., low nitrate-N samples are located in high DRASTIC Index, or vice versa) in the DRASTIC Index and nitrate-N samples was multiplied, respectively, by 2 and 1. The
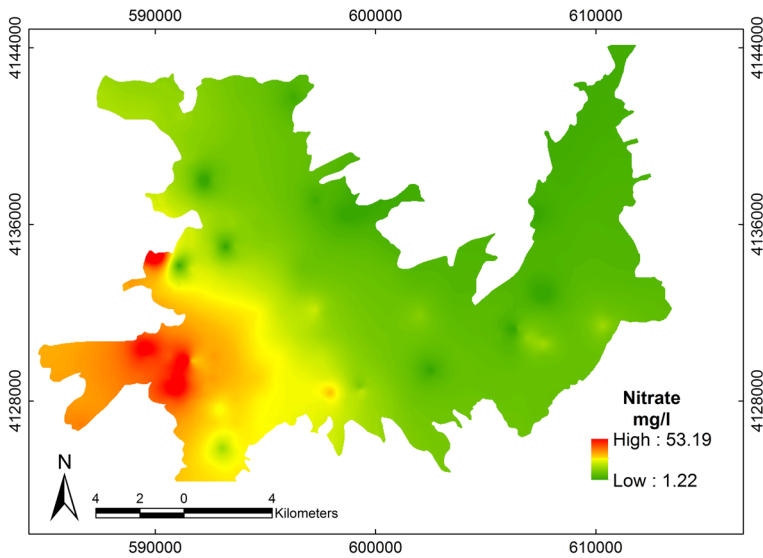
Fig. 5 Spatial distribution of nitrate-N in the Maragheh-Bonab aquifer

coincidence of nitrate-N samples with three DRASTIC methods are presented in Table 3. As an example CI is calculated for general DRASTIC as $(3 + 67 + 36) \times 3 + (41 + 108 + 1 + 13) \times 2 + (16 + 0) \times 1 = 660$. According to the result of computed CI in Table 3, the improved DRASTIC method shows higher CI than general and pesticide DRASTIC methods.

Further details about result of different methods have been presented in Fig. 6. The numerical proportion of different classes from the total samples of nitrate is illustrated in the pie chart Fig. 6a. According to Fig. 6a only 1.40 % of total samples are placed in the high classes (nitrate concentration between 36.30 and 53.88 mg/l). Also 42.46 % and 56.14 % total samples are located, respectively, at moderate (nitrate concentration between 10 and

Table 3 Comparison of different DRASTIC methods with nitrate-N concentration by correlation index (CI)

		Nitrate-N samples		
		High	Moderate	Low
Improved DRASTIC	High	1	15	7
	Moderate	3	90	92
	Low	0	16	61
		$CI = 715$		
General DRASTIC	High	3	41	16
	Moderate	1	67	108
	Low	0	13	36
		$CI = 660$		
Pesticide DRASTIC	High	3	34	12
	Moderate	1	85	113
	Low	0	2	32
		$CI = 675$		
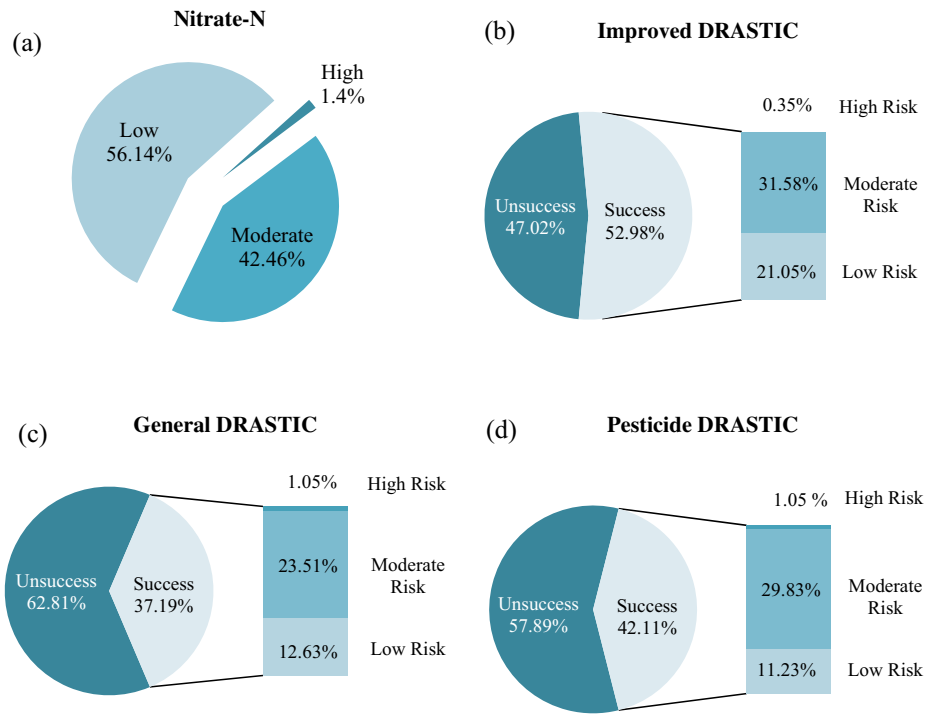
Fig. 6 Numerical proportion of **a** nitrate-N samples; coincidence success of nitrate-N classes with the same classes in **b** Improved DRASTIC index; **c** General DRASTIC index; **d** Pesticide DRASTIC index

36.30 mg/l) and low (nitrate concentration between 1.13 and 10 mg/l) classes. Figure 6b to d illustrates the successful coincidence of nitrate-N classes with the same classes in DRASTIC index versus unsuccessful of each method. According to this figure, improved DRASTIC has a better success likelihood prediction of nitrate-N samples than others except in the high class of nitrate samples. Since only 1.4 % of nitrate-N samples dedicated to the high class, it could be acclaim that improved DRASTIC has higher performance than other investigated methods.

The proposed method improves DRASTIC method, with regard to local condition. In other word, computing dependency of control parameters (classification) on state variables (DRAS-TIC parameters) by catastrophe theory, determines the weights of normalized and dimensionless parameters. Hence the local condition is considered instead of subjective preference which is constant for each region. Based on the mentioned advantages and result of current study, this method to is recommended for practitioners.

6 Conclusion

In this study a catastrophe-based multi-objective decision making evaluation system is applied to DRASTIC method for assessing groundwater vulnerability. The ratings and weightings of DRASTIC method, contributing to the vulnerability of groundwater, are assigned based on experts' judgment in the USEPA recommendation. The catastrophe theory is used to reduce this subjectivity by using catastrophe fuzzy membership function. In the proposed approach, the rating assignment step of DRASTIC method is substituted by normalization step.

Therefore instead of using the recommended ratings, the normalized values of each parameter are used in this study. Also the DRASTIC parameter weights are assigned by intrinsic features of parameters instead of expert preference. The calculated weights by catastrophe theory are not constant in the different region. Therefore the DRASTIC method is improved by considering the local conditions of the case study. Moreover, addition of a new parameter is possible in the process of calculation; whereas the DRASTIC method needs to define rating and weighing of a new parameter. The application of proposed method in the Maragheh-Bonab aquifer under threat from industrial and agricultural activities, reveals that the improved DRASTIC has a higher correlation index (CI) and success likelihood prediction of nitrate-N samples than general and pesticide DRASTIC methods. In spite of its wide capabilities, it has a limitation of selecting up to 5 catastrophe function types in the regions that have very wide parameters variation. Further researches could be contributed to adjust classifications numbers of USEPA recommendation with regard to this limitation.

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