◉ Environmental Systems Research

Mapping groundwater nitrate contaminant risk using the modified DRASTIC model: a case study in Ethiopia

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Abstract

Background: Nitrate contamination of groundwater often occurs in urban and industrial areas due to point and non-point sources of anthropological activities. Groundwater constitutes a a significant portion of the water supply system for Bahir Dar City in Ethiopia, though the level of groundwater pollution is not known. This study was conducted to assess the the extent of the aquifer and groundwater pollution (nitrate) based on contaminant vulnerability risk mapping using the GIS integrated modified DRASTIC model. A field survey was conducted to collect samples from boreholes for nitrate analysis and to modify the DRASTIC model.

Results: Compared to the original intrinsic vulnerability assessment, land use as external factors changed from moderate-high to high vulnerability class from 18 to 88%. The FR-APH modified model showed a good correlation (0.53) compared to the other methods. Based on the FR-APH modified model, about 31% of the area was under moderate to high and high vulnerability range, 39% was under moderate vulnerability range while 30% was under low and moderate to low vulnerability range.

Conclusions: The integrated vulnerability map showed high risk in the central part of the City due to the flat slope and shallow depth to groundwater. Besides, the sensitivity analysis indicated that the contribution of aquifer media and vadose zone to contaminant risk was found trivial. In general, groundwater at Bahir Darwas found vulnerable to nitrate contamination and needs proper management.

Keywords: Drastic model, GIS spatial analysis, Groundwater vulnerability

Introduction

Groundwater is a potential alternative source of domestic water supply for the main cities, towns, and villages due to its less initial cost, better water quality, and availability throughout the year compared to surface water sources (Mengistu et al. 2019; Nwobodo et al. 2015). However, groundwater contamination by nitrate is increasing locally and globally in general (Hu et al. 2005). A water quality study in Sub-Saharan countries by Lapworth et al. (Lapworth et al. 2017) showed that domestic waste

contamination occurred in shallow wells, especially in highly populated cities. Among the major groundwater quality problems in Ethiopia, are high microbial and nitrate concentrations in shallow unconfined aquifers around major cities (Mengistu et al. 2019).

Regardless of challenges associated with contaminants, several research findings (Worqlul et al. 2017; Siebert et al. 2010; Gowing et al. 2020) indicated that groundwater will remain the main source of fresh water in the face of climate change and variability. People use groundwater for drinking and domestic purposes using various extraction systems from the aquifer and its contribution to surface water sources (Schwartz 2003). However, groundwater contamination has significantly degraded due to population pressure and unwise water use without

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considering the sustainability of ecosystem services (Morris et al. 2006). Groundwater contamination is driven by different factors including hydrogeological variations and human-induced activities (Iqbal et al. 2015). A significant contamination level has been induced through the disposal of human and animal wastes, hazardous wastes, by-products of mining and oil operations, leaks from sanitary sewer lines and septic tanks, and agricultural activities such as tillage, fertilizer, and chemical applications (Schwartz 2003). A rapid assessment of drinking water quality in Ethiopia by Dagnew (2007) showed that 32% of the wells were contaminated with nitrate. Besides, several research findings revealed that protecting groundwater resources is a wise approach and relatively cheaper than remediation and restoration of a contaminated aquifer (Al-Rawabdeh et al. 2014; Neshat and Pradhan 2015a; Ceplecha et al. 2004; Li et al. 2014).

Along with springs, groundwater serves as the main source of domestic water supply for Bahir Dar City of Ethiopia (Oscar Veses 2016, Abiye and Kebede 2011). According to Goshu and Akoma (2011a), nitrate concentration was high in Bahir Dar City shallow groundwater wells and showed a decreasing trend from the city center to the border, possibly due to anthropogenic effects from the population density or geological variation. Assessment of groundwater contaminant risk and providing a vulnerability map is an essential pathway for managing groundwater and the environment (Yu et al. 2010; Piscopo 2001), which allows managers to make evidence-based decisions (Sener and Davraz 2013).

Several techniques exist to estimate groundwater vulnerability such as process-based simulation models, statistical methods, and overlay-index methods (Iqbal et al. 2012). According to Aller et al. (Aller 1985), DRASTIC is the most widely applied overlay index method for groundwater vulnerability assessment (Ghosh et al. 2020; Liang et al. 2019; Zouhri and Armand 2019; Rupert 2001; Bartzas et al. 2015; Shrestha and Luo 2018). The model uses seven parameters of the natural system (depth to water, net recharge, aquifer media, soil media, topography, the impact of vadose zone, and hydraulic conductivity) to estimate the vulnerability of an aquifer to contamination (Al-Rawabdeh et al. 2014). On the other hand, the DRASTIC model is open for improvement (Neshat and Pradhan 2015a; Afshar et al. 2007; Pacheco and Fernandes 2013; Rupert 2001) since the model uses parameter weights that are more subjective (Neshat and Pradhan 2015a).

Milkiyas et al. (Tabor et al. 2011) assessed the bacteriological and physicochemical quality of drinking water samples taken from consumers. Goshu et al. (2010) evaluated anthropogenic fecal pollution impact in Bahir Dar. Goshu and Akoma (2011b) conducted a water quality assessment of ground and surface water resources of Bahir Dar and peri-urban areas from different sources. However, the spatial variation of groundwater pollution related to hydrogeological and anthropogenic conditions is lacking. Therefore, the main objective of this study was to investigate the vulnerability of groundwater to nitrate contamination for Bahir Dar City using the modified DRASTIC model. The specific objectives included: a) producing intrinsic and specific vulnerability maps, b) investigating the spatial distribution of nitrate contamination, and c) modifying the DRASTIC Vulnerability Index based on the observed nitrate concentration.

Material and methods
Description of the study area
This study was conducted in the Ethiopian highlands at the capital city of Amhara Regional State, Bahir Dar (11.50 to 11.530, and 37.40 to 37.530, and an altitude of 1800 m above mean sea level). The city has a flat plateau earth structure (Fenta and Technology 2017) covering a total area of about 213 km2. The city borders Lake Tana, the largest freshwater lake in Ethiopia (Vijverberg et al. 2009), and the source of the Blue Nile river crossing the city middle way. The mean annual temperature in the study area is 26 °C and the annual precipitation ranges from 1200 to 1600 mm with the " Woina Dega" or "subtropical" agro-ecological zone (Mehari et al. 2015). Bahir Dar is one of the largest and fast-growing cities in Ethiopia (Fenta and Technology 2017, Goshu and Aynalem 2017) with an estimated population size of about 294,749 as of the 2014 census (Birara and Kassahun 2018). The city relies mostly on groundwater sources and springs for drinking water supply. The other source of drinking water supply for the city is Lake Tana.

Data type, source, and method of collection
The main data used for this study and their sources are as shown in Table 1.

DRASTIC model
In this study, the DRASTIC model was used to provide a reasonable estimate for the vulnerability of an aquifer to contamination with a relatively minimum data requirement (Al-Rawabdeh et al. 2014). The model uses seven parameters of the natural system (i.e., depth to water, net recharge, aquifer media, soil media, topography, the impact of vadose zone, and hydraulic conductivity). Each parameter was then weighted from 1 to 5 where the most significant parameters had weights of 5 and the least significant parameter (Al-Rawabdeh et al. 2014; Piscopo 2001; Rosen 1994). The rates and weights were multiplied for each parameter and added together to produce the

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Table 1 Data used in this study and their sources

Data type	Source of data	Spatial Resolution
Depth to the water table, Aquifer media, Geology, and Hydraulic Conductivity	Amhara Water Work and Drill Enterprise	–
Soil Media	Amhara Design and Supervision Works Enterprise	90 m × 90 m
Precipitation	Ethiopia National Meteorology Agency	–
Digital Elevation Model	The National Aeronautics and Space Administration (NASA) Landsat Imager Resolution	30 m × 30 m
Land use	Amhara Design and Supervision Works Enterprise	30 m × 30 m
Nitrate	Water samples were collected from wells and analyzed in the laboratory for nitrate concentration	–

vulnerability index (Aller et al. 1987a) as shown in the equation (Eq. 1).

$$VI = D_r D_w + R_r R_w + A_r A_W + S_r S_W + T_r T_W + I_r I_W + C_r C_W \tag{1}$$

where, D, R, A, S, T, I, and C are the seven parameters of the DRASTIC model, and the subscript r and w represented, respectively, the rating value and weighting of the factor depending on the influence of the contamination.

After computing the vulnerability index (VI), susceptible areas to groundwater contamination were identified (Wang et al. 2007). Weights were assigned for various hydrological settings based on Aller (1985) and Secunda (1998) as shown in Table 2. The rate was assigned from 1 (i.e., lower groundwater contamination potential) to 10 (i.e., higher groundwater contamination potential) based on Aller (1985) for all parameters, except recharge, which was based on NRCS (2014) and Piscopo (2001) as shown in Table 3.

Depth to groundwater
The depth to the water table determines the depth of material through which the contaminant travels before it reaches the water table. This parameter was derived from 22 groundwater wells' water table data. The data were used to prepare the depth to water table layers based on Aller et al. Aller et al. (1987a). The depth to groundwater map was prepared through interpolation of the data using the inverse distance weight method (Tirkey et al. 2013; Nadiri et al. 2017) with grid size 30 m × 30 m. The inverse distance weight method is more suitable for non-uniform borehole distribution and flat topography (Gilman and Bailey 2006).

Net recharge
The net recharge refers to the amount of water that penetrates the ground surface and reaches the water table that would potentially transport contaminants. Various data were used for the determination of the net recharge such as topography, rainfall, and soil permeability based on Piscopo (Piscopo 2001) as shown in the equation (Eq. 2). More net recharge is associated with more vulnerability to contamination.

$$Net\ Recharge = Slop(\%) + precipitation + Soil permeability \tag{2}$$

Table 2 Description and original weights of the intrinsic and specific model parameters (Babiker et al. 2005)

Model parameters	Parameter description, original weight
Depth to water	Represents the depth from the surface to the groundwater table levels, 5
Net Recharge	Represents the amount of water that penetrates the ground surface and the water table responsible for contaminant transport, 4
Aquifer media	Refers to the saturated zone material properties, which controls the pollutant attenuation processes, 3
Soil media	Refers to the uppermost weathered portion of the unsaturated zone and controls the amount of recharge that can infiltrate downward, 2
Topography	Refers to the slope of the land surface, it dictates whether the runoff will remain on the surface to allow contaminant percolation to the saturated zone, 1
Impact of vadose zone	Refers to the unsaturated zone material; it controls the passage and attenuation of the contaminated material to the saturated zone, 5
Hydraulic conductivity	Refers to the ability of the aquifer to transmit water, hence determining the rate of the flow of contaminant within the groundwater system, 3

Table 3 The relative weights and rates of DRASTIC parameters (Aller 1985) and (Secunda et al. 1998) for various hydro-geological settings

Rating	depth to the water table	Net recharge	Aquifer media	Soil media	Topography	Impact of vadose zone	Hydraulic conductivity
	Range (m)	Range (mm/yr)	Range	Range	Range (%)	RANGE	Range (m/day)
10	0–1.5		Karst limestone	Thin or absent	0–2	Karst limestone	>80
9	1.5–4.5	>250	Basalt	Sandy	2–6	Basalt	
8		175–250	Sand and gravel	Peat		Sand and Basalt	40–80
7	4.5–9			Shrinking		Metamorphic/Igneous	
6		100–175	Bedden sand-ston,	Sandy loam		Limstone/sandstone	30–40
5	9–15		Glacia till	Loam	6–12		
4			Weathered	Silt loam			12–30
3	15–22	50–100	Metamorphic/igneous	Clay loam	12–18	Sily/clay/shale	
2	22–30		Massive shale	Muck			4–12
1	>30	<50		Non-shrinking	>18	Confining layer	<4

Aquifer media

Aquifer media refers to the lithology of the saturated zone (Saidi et al. 2009). Aquifer media governs the route and path length of the groundwater flow system. Anthropogenic and geologic conditions originating from contaminant sources, and water–rock interactions are among the major factors that control the chemical quality of groundwater (Şener et al. 2017). The aquifer media affects the effective surface area of material through which contaminant may meet the aquifer. An aquifer media layer was prepared from 17 groundwater well logs and classified based on Aller et al. (Aller et al. 1987a).

Soil media

The soil media represent the top weathered portion of the unsaturated zone with significant biological activities (Aller et al. 1987a). Soil type would significantly affect the amount of recharge that infiltrates into the water table and hence plays a vital role in the contaminant transport process. The soil data obtained from Amhara Design and Supervision Enterprise (ADSWE) was converted into grid coverage interpolated by the Inverse Distance Weight (IDW) method and classified based on Aller et al. (Aller et al. 1987a).

Topography (landscape slope)

Topography controls contaminant runoff and retention on the surface. Therefore, the greater the chance of infiltration, the higher the pollution potential associated with the landscape slope (Aller 1985). The slope in percent was calculated from the digital elevation model (DEM) using surface spatial analysis and classified based on (Aller et al. 1987a).

Impact of vadose zone

The vadose zone refers to the unsaturated or discontinuously saturated zone above the water table (Piscopo 2001). The depth and geology data from Amhara Water Work and Drill Enterprise (AWWDE) was computed using the equation (Eq. 3), and rated and classified based on (Aller et al. 1987a) to produce a vadose zone impact map.

$$\text{Vadose zone Impact} = \frac{1}{\text{Totaldepth}} \sum_{i=1}^{n} \text{Depth}_{li}\text{Ratingg}_{li}$$

(3)

Hydraulic conductivity

The hydraulic conductivity represents the ability of the aquifer to transmit water and controls the rate of contaminant migration from the source to the aquifer (Aller et al. 1987b). It determines the speed of contaminant transfer into the groundwater and their times of residence and migration into the saturated zone (Zouhri and Armand 2019). The permeability and secondary porosity are the major factors that determine the water-bearing potential of an area. Unsaturated hydraulic conductivity and transmissibility were used to estimate the movement of contaminants into the aquifer and typical values were obtained from 13 pump wells test.

Land use

Intrinsic vulnerability refers to the vulnerability of groundwater to contaminants generated by human activities taking into account the inherent geological,

hydrological, and hydrogeological characteristics of an area without considering the nature of the contaminants (Doerfliger et al. 1999; Zwahlen 2003). On the other hand, specific vulnerability refers to the vulnerability of groundwater to particular contaminants or a group of contaminants taking into account the contaminant properties and their relationship with the various components of intrinsic vulnerability (Gogu and Dassargues 2000b).

Land use practices, particularly in agriculturally dominated and anthropogenic areas evidenced to have a significant effect on groundwater quality (Almasri and Kaluarachchi 2004; McKay 2001). The original DRASTIC model was modified by adding the land use parameter to assess the vulnerability parameters for the potential risk of groundwater contamination due to anthropogenic factors. The potential risk was calculated using the equation (Eq. 4) considering land use as external anthropological activity based on Al-Adamat (Al-Adamat et al. 2003). The potential risk was calculated based on Pacheco and Fernandes (2013) as shown in Eq. 5.

$$V_{Specific} = V_{Intrinsic} + L_r \qquad (4)$$

Nitrate concentration assessment
Nitrate is highly soluble and does not readily sorb to solid surfaces, such as soil, thus allowing nitrate to have high mobility [22]. The mobility of nitrate makes it prone to leaching through the soil as it moves with infiltrating water into the subsurface [23]. Nitrate is widely used and considered an essential indicator of groundwater quality or contamination (Neshat and Pradhan 2015a). Groundwater samples were collected from 24 wells located in different aquifers. A one-liter polyethylene bottle was used to collect the samples and laboratory analysis for nitrate was conducted using the spectrophotometric method Al-Rawabdeh et al. (2014) at Amhara Design and Supervision Enterprise (ADWWSE) laboratory. Groundwater samples were stored in a refrigerator until laboratory analysis to prevent deterioration and changes in water quality. The Inverse Distance Weight (IDW) interpolation method was used to provide the spatial distribution of nitrate across the base. To validate and compare the derived results between groundwater vulnerability and nitrate concentration, Pearson's correlation was used (Neshat and Pradhan 2015b). The Pearson's correlation coefficient (r) serves as a measure of the linear dependence between the vulnerability index and observed nitrate concentration was determined (Gheisari 2017) as shown in Fig. 7.

Probability-based statistical model for rate adjustment
The frequency Ratio (FR) model was considered as a bivariate statistical method to modify the rates of
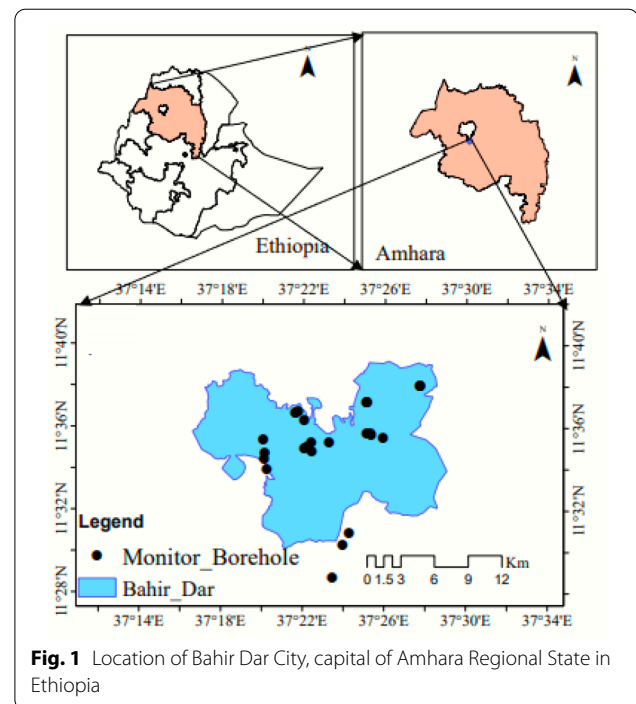

Fig. 1 Location of Bahir Dar City, capital of Amhara Regional State in Ethiopia

DRASTIC parameters based on the spatial distribution of contaminants and hydrogeological parameters as explained in Neshat and Pradhan (Neshat and Pradhan 2015a). The FR model was based on observed relationships between the distribution of nitrates and the DRASTIC parameters (Yu et al. 2010). Ranges of FR for each factor were computed from their relationships with the nitrate samples using the equation (Eq. 5).

$$FR = \frac{\frac{A}{B}}{\frac{C}{D}} = \frac{E}{F} \qquad (5)$$

where A is the area of a class or range for each DRASTIC parameter, B is the total area of each parameter; C is the total number of nitrate occurrences in the class of each parameter, D is the number of the total nitrate in the study area, E is the percentage of area in the class of each parameter, and F is the percentage of nitrate in the class of each parameter (Fig. 1).

The observed nitrate measured at 24 monitoring wells from January to May 2020 every two weak was used to modify the rate of parameters in the DRASTIC model. A probability-based statistical ranking model was used for rate adjustment of vulnerability mapping in the study area. The rate of parameters was set based on the average amount of nitrate concentration in each class with the highest mean of nitrate concentration and the other rates were modified linearly based on the relation.

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Map removal sensitivity analysis

Map removal sensitivity analysis represents the sensitivity associated with removing one or more maps (Lodwick et al. 1990). Map removal sensitive analysis was performed to evaluate and check if all necessary parameters were incorporated in the DRASTIC model (Gogu and Dassargues 2000a; Napolitano and Fabbri 1996). The map removal sensitivity measure, defined by Lodwick et al. (Lodwick et al. 1990), is expressed in terms of variation index S as shown in the equation (Eq. 6).

$$S = \left(\frac{\frac{V}{N} - \frac{V'}{n}}{V} \right) \times 100 \qquad (6)$$

where S is the sensitivity index, V is the unperturbed vulnerability index (original DVI calculated), V' is perturbed vulnerability index (calculation of DVI after map removal), and N and n are the numbers of data layers used to compute V and V' respectively.

Single parameter sensitivity analysis (SPSA)

In the modified DRASTIC model, subjectivity can affect the final evaluation results, as it is unavoidable in the selection of ratings and weights (Şener and Şener 2015). The sensitivity analysis validates the impact of each evaluation parameter on the groundwater vulnerability assessment (Liang et al. 2019). Single-parameter sensitivity analysis is a widely used method to assess the impact of selected parameters on groundwater vulnerability assessment (Napolitano and Fabbri 1996) and helps to understand the effect of subjectivity and weights allocated to each parameter (Babiker et al. 2005; Gogu et al. 2003). The single parameter sensitivity analysis was used and adopted in this study to evaluate the effect of each factor on the vulnerability index (Huan et al. 2012a). The single parameter sensitivity analysis (SPSA) is introduced by Napolitano and Fabbri (Napolitano and Fabbri 1996) as shown in the equation (Eq. 7):

$$W = \frac{P_r P_w}{V} \times 100 \qquad (7)$$

where W refers effective weight of each parameter, Pr and Pw are the rating value and the weight of each parameter, respectively, and V is the overall vulnerability index.

Analytic hierarchy process (AHP)

The analytic hierarchy process (AHP) is a method coupled with the experience and knowledge of experts or users to determine the parameter and criteria (Neshat et al. 2014; Li et al. 2018). The AHP method provides a hierarchical mecha-

nism for combining expert opinions to derive the standard weight of the criteria (Chakraborty et al. 2011). The AHP proposed by Saaty (Saaty 1980) is a widely accepted method for multi-criteria decision-making purposes (Liang et al. 2019; Vogel 2008; Saaty 2008; Duc 2006, Zhu and Dale 2001). The method serves as a measurement theorem that uses discrete and continuous binary comparisons in multiple hierarchical structures (Güler and Yomralıoğlu 2017). The method uses a pairwise comparison of factors based on a relative scale which ranges from 1 to 9, where the higher and lower value refers to extreme importance and equal importance, respectively, (Saaty 1980). The quality of the overall set of pairwise comparisons is evaluated through the Consistency Ratio (CR) analysis (Elaalem et al. 2011). Constructing a set of pairwise comparison matrices is the most important component of the AHP method, which permits the comparison between various criteria (Neshat and Pradhan 2015a) as shown in the equation (Eq. 8) as matrix 'A'.

$$A = \begin{bmatrix} & D & R & A & S & T & I & C & Lu \\ D & 1 & 2 & 3 & 4 & 5 & 3 & 3 & 7 \\ R & 1/2 & 1 & 2 & 3 & 4 & 2 & 2 & 5 \\ A & 1/3 & 1/2 & 1 & 2 & 3 & 2 & 1 & 4 \\ S & 1/4 & 1/3 & 1/2 & 1 & 2 & 2 & 1 & 4 \\ T & 1/5 & 1/4 & 1/3 & 1/2 & 1 & 1/2 & 1/3 & 2 \\ I & 1/3 & 1/2 & 1/2 & 1/2 & 2 & 1 & 1/2 & 3 \\ C & 1/3 & 1/2 & 1 & 1 & 3 & 2 & 1 & 3 \\ Lu & 1/7 & 1/5 & 1/4 & 1/4 & 1/2 & 1/3 & 1/3 & 1 \end{bmatrix}. \quad (8)$$

A uniform random test of a matrix is required to analyze whether the eigenvectors of the matrix are reasonable, including Consistency Index (CI) (Eq. 9), largest eigenvalue (λ_{max}) (Eq. 10), and consistency ratio (CR) (Eq. 11) based on (Saaty 1987). When CR = 0, the matrix has complete consistency, and as the CR increases, the consistency of the matrix becomes worse; When CR < 0.1, it is considered that the consistency condition is satisfied, indicating that the weight distribution is reasonable (Saaty 1980).

$$CI = \frac{\lambda_{max} - m}{m - 1} \qquad (9)$$

$$\lambda_{max} = \frac{1}{n} \sum_{i=1}^{n} \frac{A.W}{W} \qquad (10)$$

$$CR = \frac{CI}{RI} \qquad (11)$$

where, RI is a random index, which was used to eliminate the inconsistency of the matrix caused by the influence of the number of matrices.
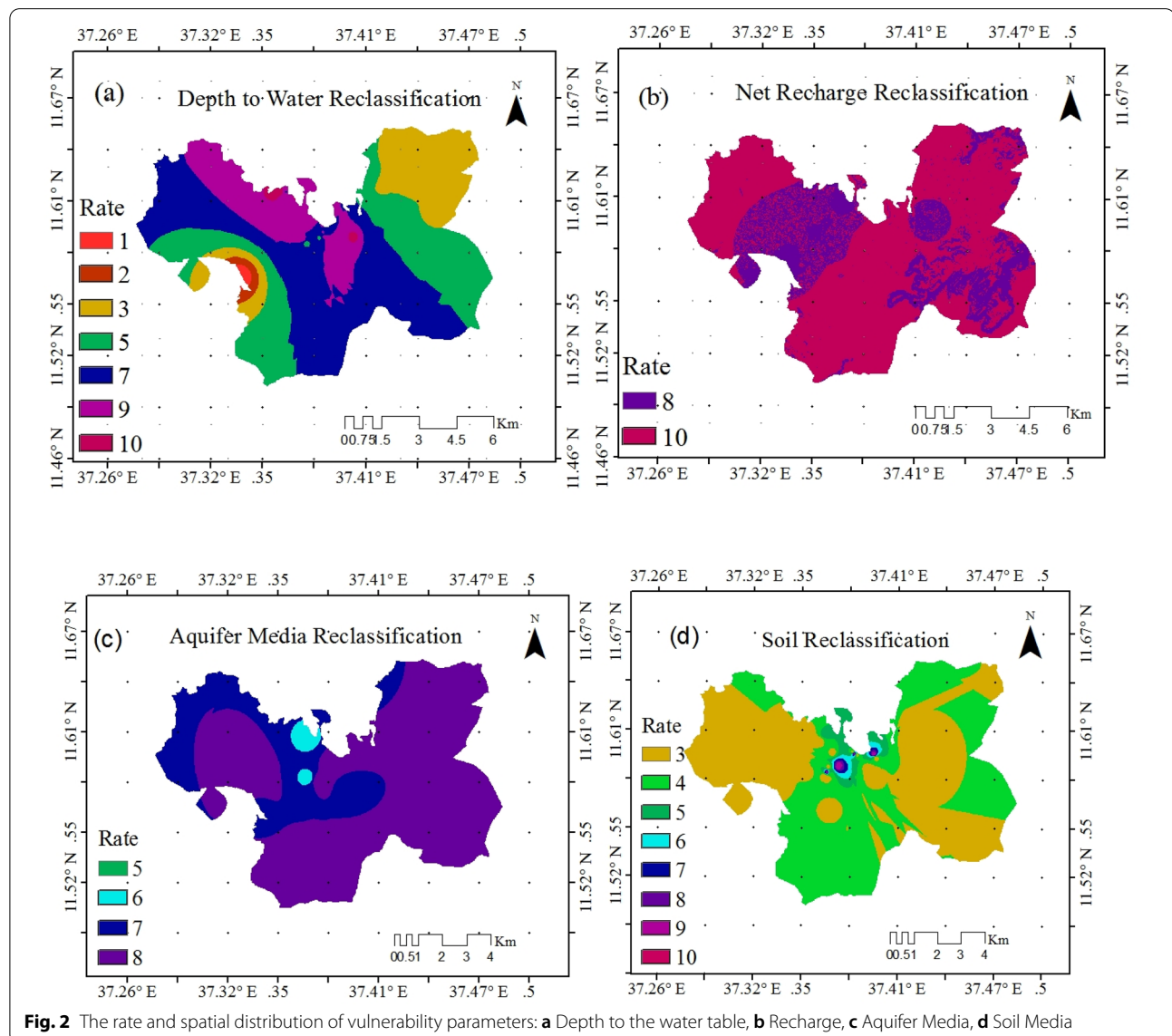
Results and discussion

First, the rating of the seven parameters in the DRAS-TIC model and their relation to groundwater contamination are presented and discussed followed by intrinsic and specific vulnerability results. Second, the spatial distribution of nitrate and its correlation with intrinsic and specific vulnerability index is presented followed by results of rate modifications using observed nitrate concentration. Finally, the results of single parameters sensitivity analysis, map removal sensitivity analysis, and modification using the analytical hierarchical process are presented and discussed.

The DRASTIC parameters

Depth to groundwater (D) and Net Recharge (R)

The ranking of depth to groundwater varied from 1 (low) to 10 (high) (Fig. 2a). The depth to groundwater varied from 2 to 37 m over Bahir Dar city. The depth of the water table in the central part of the city and near the lake (Lake Tana) were less than 10 m indicating high susceptibility to contamination, whereas, the depth to the water table increases gradually to 37 m towards the boundary of the city indicating less vulnerability to contamination (Zouhri and Armand 2019; Tilahun and Merkel 2010). This was due to the significant correlation

Fig. 2 The rate and spatial distribution of vulnerability parameters: **a** Depth to the water table, **b** Recharge, **c** Aquifer Media, **d** Soil Media

between depth to groundwater and the length of time required for nitrate contaminant to reach the groundwater (Ceplecha et al. 2004; Tesoriero and Voss 1997). On the other hand, the net recharge ranking ranged from 8 (∼27%) to 10 (∼73%). Most areas of Bahir Dar city were classified as high recharge areas due to a relatively high annual precipitation of 1451 mm (Kebede et al. 2006) and gentle landscape slopes (Mengistu 2003; Wegedie 2018). A higher recharge amount is associated with higher contaminant transport to the water table due to an increased movement of pollutants (Varol and Davraz 2010; Pedreira et al. 2015).

Land use and Topography

Land use ranking ranged from 4 (moderate, ∼6%) to 8 (high, ∼10%) as shown in (Fig. 3d). Most of Bahir Dar city had moderate to high vulnerability due to urbanization and associated activities. This includes wastes (industrial, municipal, and domestic solid and liquid wastes) that are being dumped with no centralized sewage system (Goshu et al. 2010). Besides, agricultural activity such as the farming of crop, plant, and animal production around the city border (Wegedie 2018) provide input for groundwater contamination. That is from increased use of agricultural inputs such as manure,
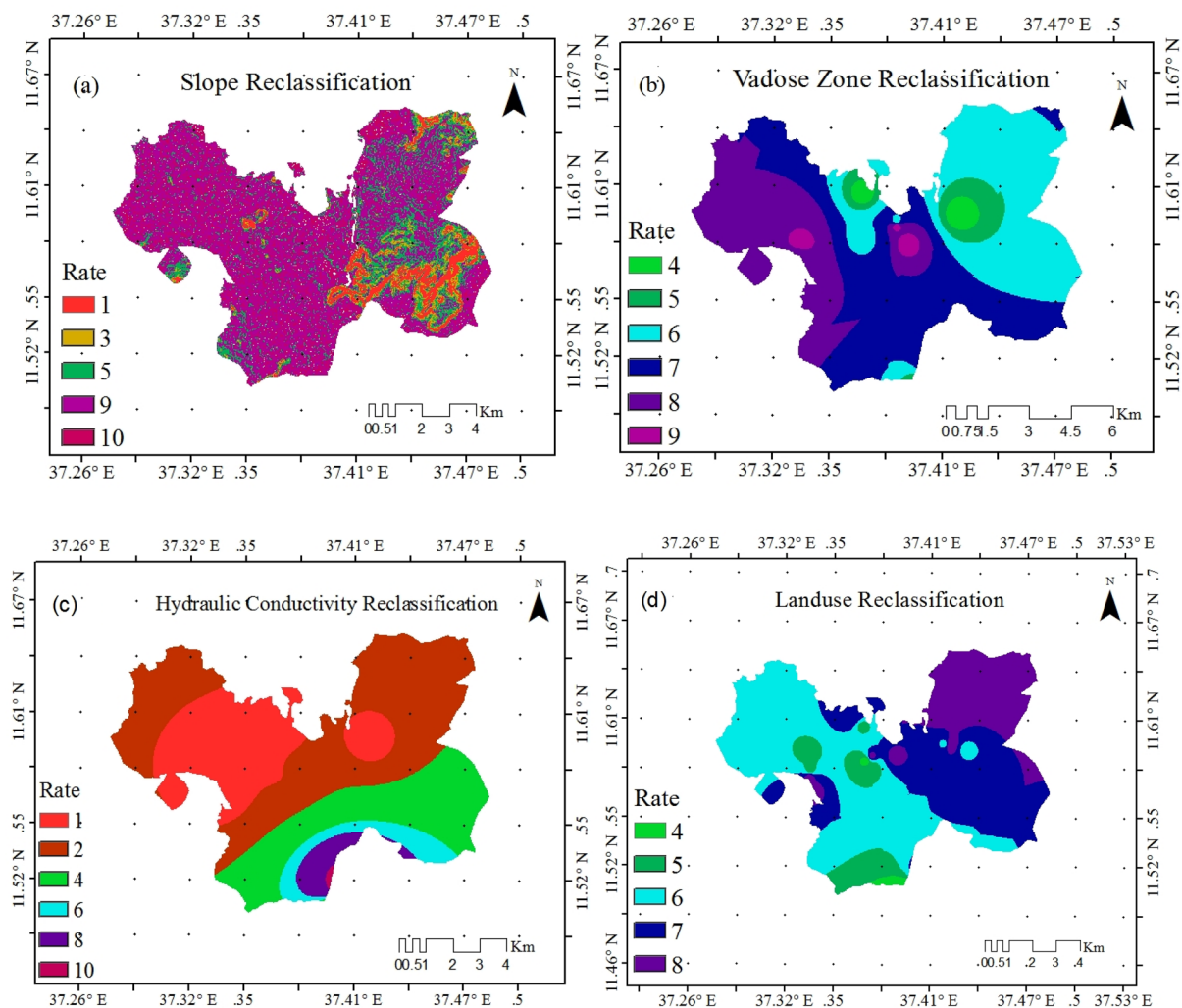
Fig. 3 The rate and spatial distribution of vulnerability parameters: **a** slope, **b** Impact of the vadose zone, **c** Hydraulic conductivity, **d** Land use of the study area

fertilizers, and pesticides which have an increased contaminant loading potential (Goshu et al. 2010). On the other hand, topography or slope rankings in the city ranged from 1 (low) to 10 (high) as shown in Fig. 3a. The highest topographic vulnerability was in the flat areas of the city close to Lake Tana, while the foothill and mountainous areas had a lower vulnerability.

Soil and aquifer media

Soil media rankings in Bahir Dar city ranged from 3 to 8 (Fig. 2d), depending on soil grain size distribution. Groundwater vulnerability associated with soil media in most parts of the city (~97%) was low because the soil type is dominated by clay and silt (i.e., low permeability). The dominant soil types in the study area were found clay (~52%) and silt (~45%). The rest of the soil types in the city include loam, sandy loam, sand, and gravel. The presence of fine-grain materials such as clay and silt within the soil cover decreases intrinsic permeability, and retard or prevents contaminant migration (Added and Hamza 2000) as they increase contaminant travel time (Tilahun and Merkel 2010). On the other hand, Aquifer media ranking in the city range from 5 (moderate) to 8 (high) (Fig. 2c). The vulnerability zones were moderate to highly fractured vesicular basalt (high vulnerability).

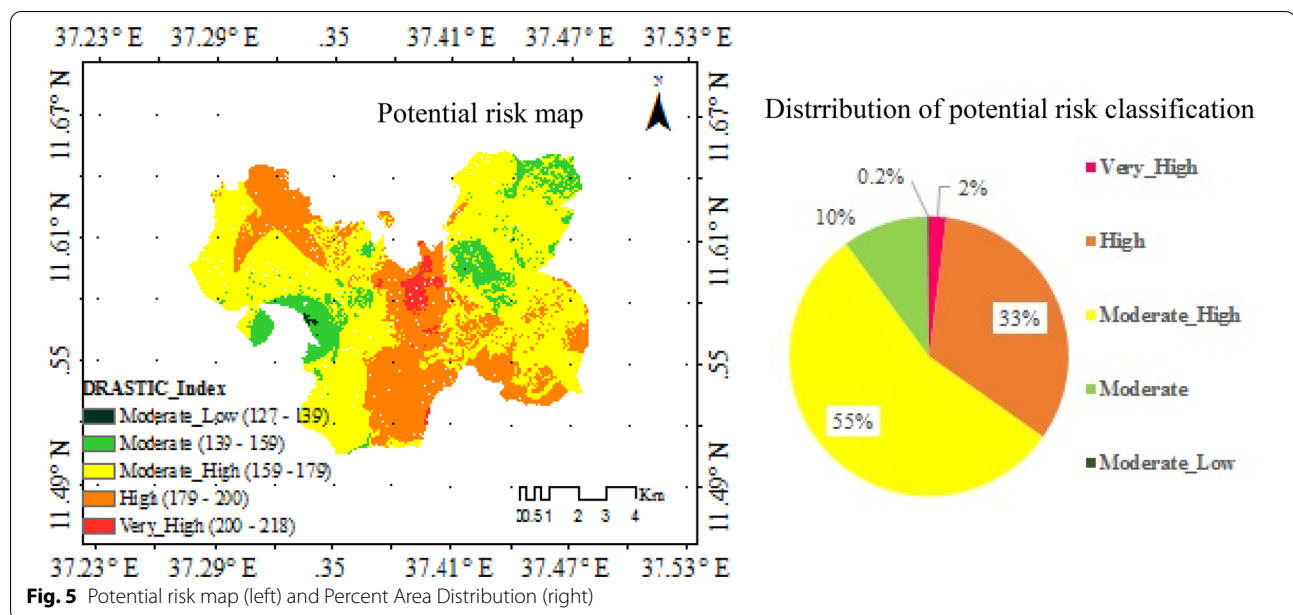### The impact of vadose zone and hydraulic conductivity

The impact of the vadose zone ranged from 4 (moderate) to 9 (high) (Fig. 3b) based on Sheikhy Narany et al. (2014).

Most areas of Bahir Dar city showed moderate to higher vadose zone vulnerability. The highest vulnerability was observed along the northwest part of the city because of the gravel size layer of the vadose zone. The vadose zone has a similar influence as that of soil cover on the contaminant potential of an aquifer depending on permeability and the attenuation characteristics of the media (Zghibi et al. 2016). Larger grain sizes, such as gravels depict higher permeability and lower ability to filter contamination (Rahman 2008). On the other hand, hydraulic conductivity ranking in the city ranges from 1(low) to 10 (high). Most of the city's low rating values were due to the low rate of horizontal water flows through the aquifer as observed from pumping test data. The higher the hydraulic conductivity, the faster the water and contaminants circulate in the aquifer (Zouhri and Armand 2019).

Intrinsic and potential vulnerability

The range of vulnerability index was between 105 to 182 as shown in Fig. 4. The values were reclassified into 5 classes based on Aller (Aller et al. 1987a). The DRASTIC map showed the vulnerability was predominately moderate to low (32%) around the border (northeast) part of the city with some agricultural activities; moderate vulnerable (49%) in the middle part of the city which covered about 18% of the study area (Fig. 4). The DRASTIC Vulnerability Index (DVI) results were found low (105 to 119), moderate to low (119 to 139), moderate (139 to

Fig. 4 Intrinsic DRASTIC Index (left) and Area Percentage Distribution (right)

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**Fig. 5** Potential risk map (left) and Percent Area Distribution (right)

159), moderate to high (159 to 1799), and high (179 to 182) vulnerability based on Aller (Aller et al. 1987a).

The results of potential risk map showed that the majority of Bahir Dar city was in the range of moderately high to very highly vulnerable as shown in Fig. 5. The DVI results were moderate low (127 to 139), moderate (139 to 159), moderately high (159 to 179), high (179 to 200), and very high (200 to 218) vulnerability. The central part of the city showed a higher vulnerability to contamination due to the combined effects of shallow depth to groundwater (about 1.5 m from the surface), gentle slope, and other anthropological activities such as discharge of industrial and domestic sewage effluents, septic tanks, and high population density. However, it was categorized as moderate and moderate-high vulnerability towards the boundary of the city due to relatively deep groundwater water table, which reduced the vulnerability, but with more agricultural activities. Based on the specific vulnerability map, most of the area (~ 55%) falls under the moderate-high vulnerability class and about 33% of the area was under the high vulnerability category. Compared to the intrinsic vulnerability, the area under moderate-high and high vulnerability class was increased from 18 to 88% for the specific vulnerability. This showed the significant effect of human activity on the vulnerability of groundwater to contamination.

Spatial distribution of nitrate

A relatively higher nitrate concentration was observed towards the outer part of Bahir Dar city, near Lake Tana (Fig. 6) due to the influence of the built-up area and agricultural activities. A similar result had been reported

Fig. 6 Nitrate spatial distribution map
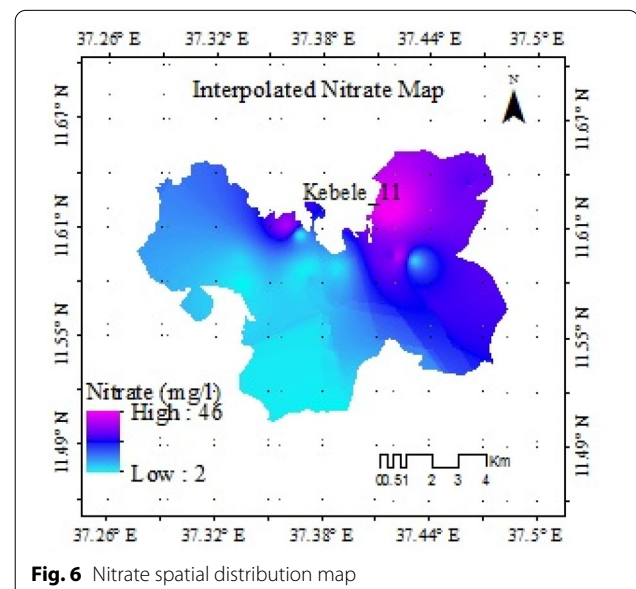
by Goshu and Akoma (2011a). The concentration in the northeast part of the city was higher because this area is near Lake Tana as the major solid and liquid wastes were disposed of. Besides, land use has a great contribution to the higher concentration of nitrate. Urban and agricultural areas are shown to contribute to nitrate contamination in groundwater from fertilizers, manures, and septic systems (Tesoriero and Voss 1997). The groundwater contamination caused by diffuse nitrate sources may pose a risk to human health and the environment (Lake et al. 2003). The use of artificial fertilizers, disposal of wastes, and changes in land use were the main factors
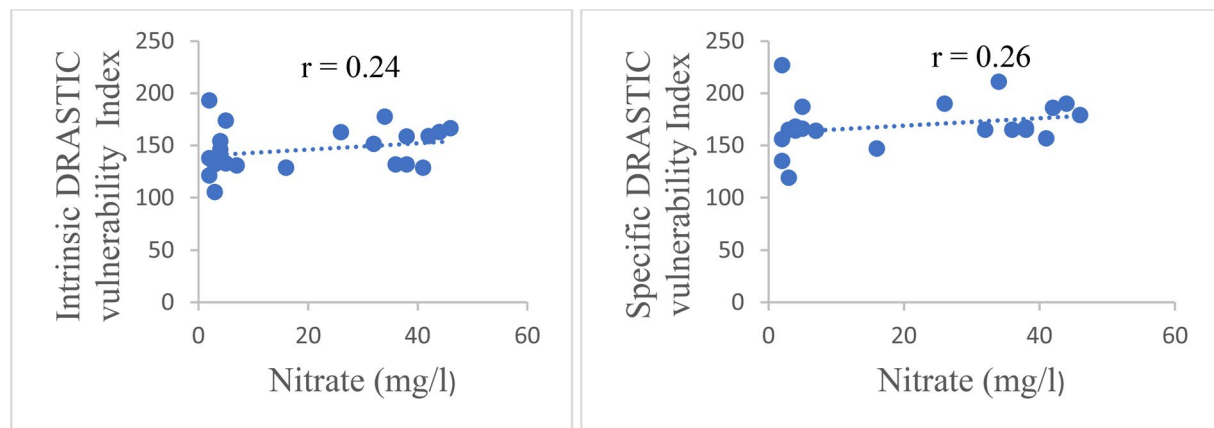
Fig. 7 Correlation between Intrinsic DRASTIC vulnerability index and NO3 (left) and Correlation between Specific DRASTIC vulnerability index and NO3 (right)
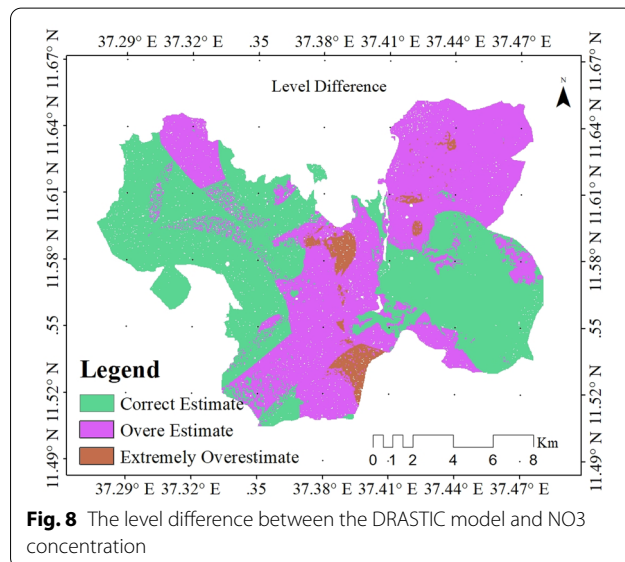

Fig. 8 The level difference between the DRASTIC model and NO3 concentration

responsible for the progressive increase in nitrate levels in groundwater supplies (WHO 1985). The observed nitrate concentration exceeded the maximum contaminant level (10 mg/l) of nitrate set by (Consortium 2000).

The Pearson correlation coefficient for the intrinsic and specific DRASTIC model was found 0.24 and 0.26, respectively, as shown in Fig. 7. The value showed that the Intrinsic DRASTIC model and the Specific DRASTIC could not properly represent the contamination potential and the vulnerability map. Hence, the model needs modification of the vulnerability map for a reasonable representation of the contamination potential.

Level difference

The level difference between the nitrate concentration and groundwater vulnerability classification was used as a criterion for assessing the performance of the DRASTIC model (Huan et al. 2012b). The vulnerability index and nitrate classification were divided into the same number of classes and the level difference was obtained by calculating the absolute value of the two variables. According to Stigter et al. (2006), the vulnerability assessment is classified as correct if the level difference is from −1 to 1, overestimated if the absolute value of the level difference is from 2 to 3, and extremely overestimated when the absolute value of the level difference is from 4 to 5." Based on to this classification (Fig. 8), 51% of the area is correctly estimated, 46% is overestimated and 3% is extremely overestimated.

Rate modification using nitrate concentration

The Modified specific DRADTIC index was reclassified into 7 classes as shown in Fig. 9. In the modified FR-DRASTIC method, 16% of the area was laid under moderate vulnerability class, 30% moderate-high vulnerability class, 28% high vulnerability, and 24% under very high vulnerability class. About 1% of the area was categorized as low or very low vulnerability to contamination. The Pearson's correlation coefficient between observed nitrate and the modified intrinsic DRASTIC index was 0.45 while the correlation between measured nitrate and modified specific vulnerability was 0.5. This showed that the rate modification improved the performance of the DRASTIC model for predicting the vulnerability index.
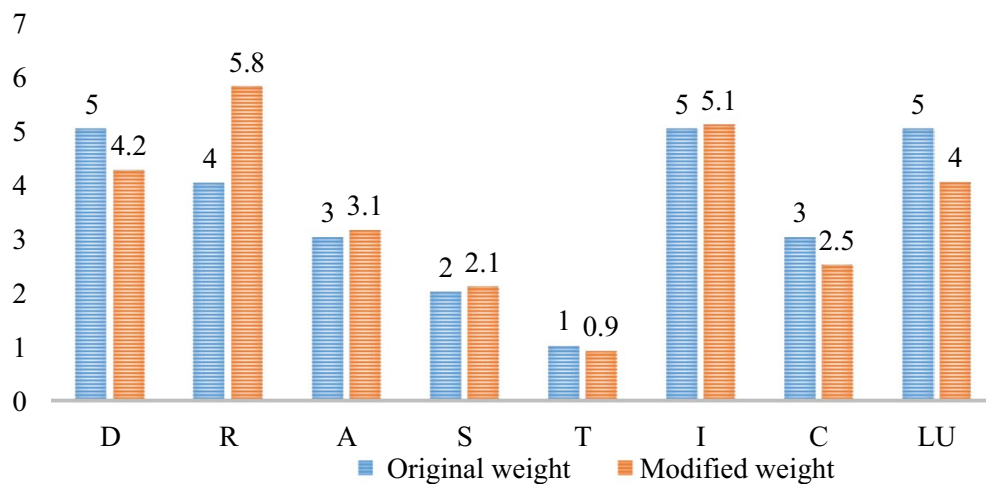
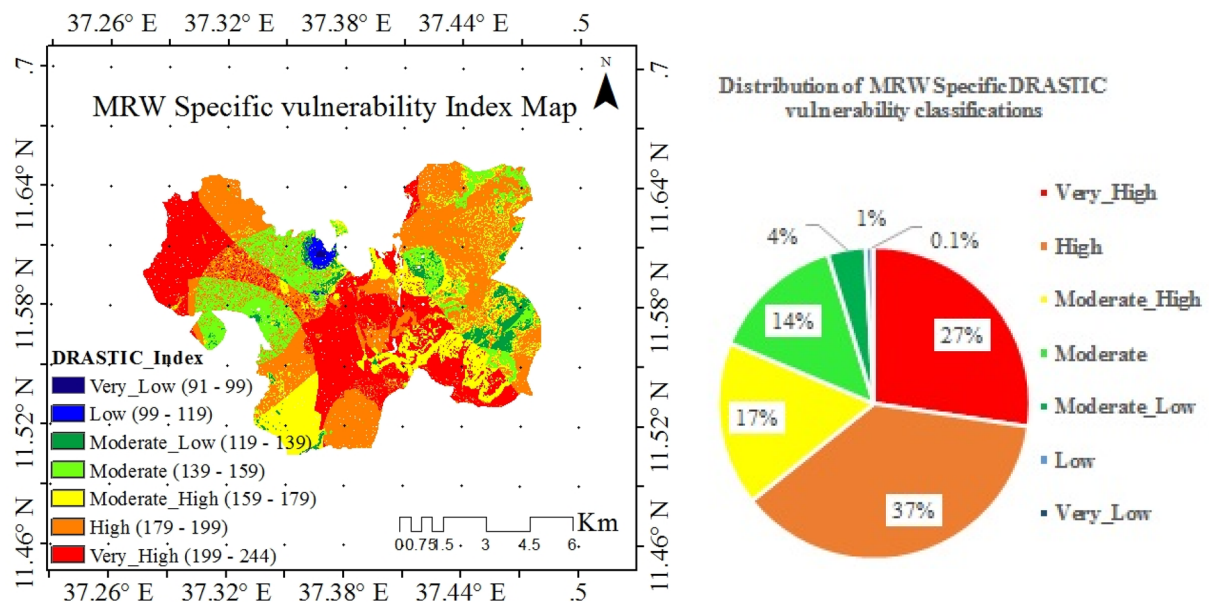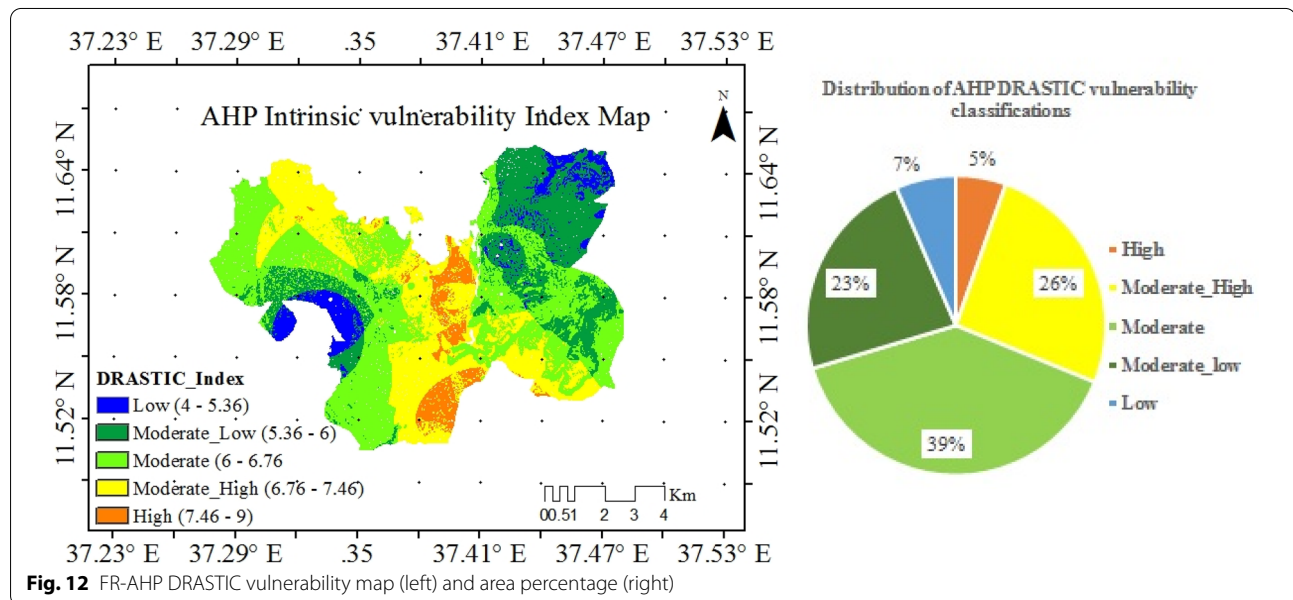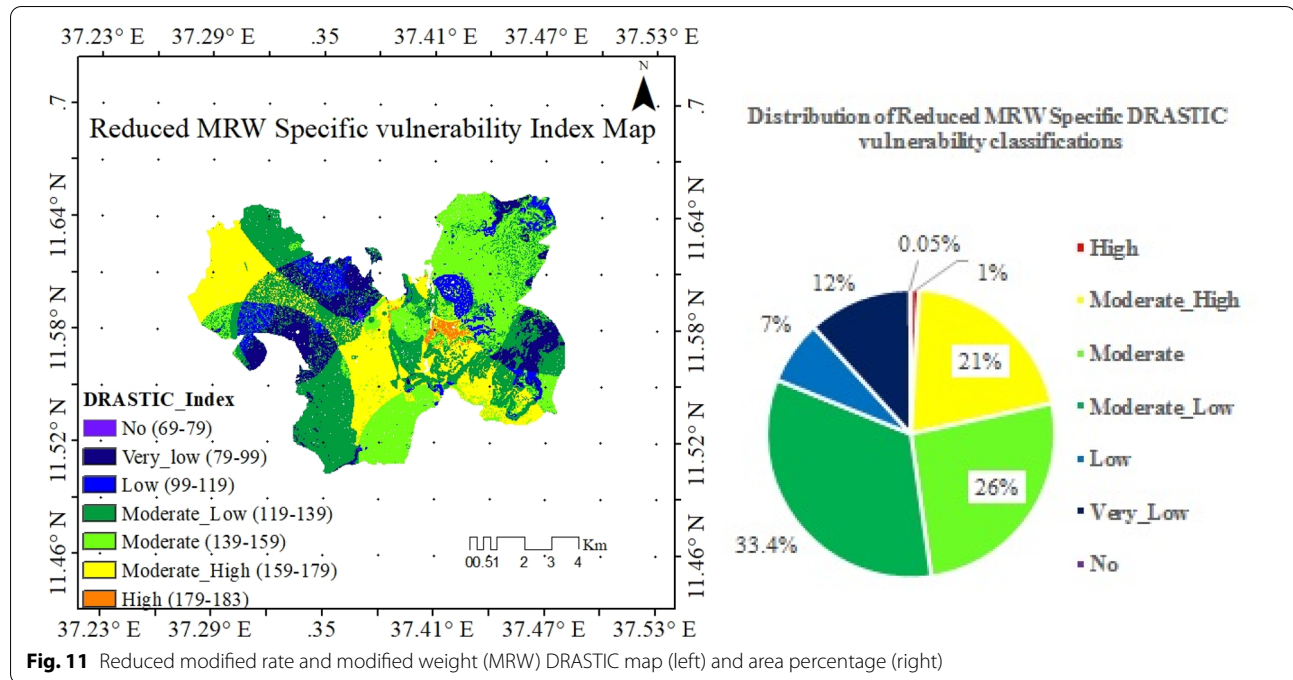**Fig. 9** Weight of Parameters before and after modification

Fig. 10 Modified-rates Specific DRASTIC map (left) and area percentages (right)

Single parameter sensitivity analysis (SPSA)

Aquifer vulnerability methods require validation to reduce subjectivity in the selection of rating ranges and to increase reliability (Leal and Castillo 2003). Based on the results, net recharge had the highest effect in single-parameter sensitivity analysis based on the equation (Eq. 9) because it had the highest mean modified weight (5.8) among all other parameters whilst topography showed the least sensitivity (0.9). In addition, aquifer media, soil media, and impact of vadose less exceeded original weight and had the mean modified weight of 3.1, 2.1, and 5.1, respectively. The rest of the parameters showed lower weight compared to the original weight (Fig. 10). Figure 11 below shows the vulnerability map after the modification.

Fig. 11 Reduced modified rate and modified weight (MRW) DRASTIC map (left) and area percentage (right)

Fig. 12 FR-AHP DRASTIC vulnerability map (left) and area percentage (right)

$$MRWDI = 4.2 \times D_{rmod} + 5.8 \times R_{rmod} + 3.1 \times A_r mod$$
$$+ 2.1 \times S_{rmod} + 0.9 \times T_{rmod} + 5.1 \times I_{rmod}$$
$$+ 2.5 \times C_{rmod} + 4 \times LU_{rmod}$$

(12)

where MRWDI is the modified rate weight DRASTIC index, the parameter subscript r and mod are the modified rate.

Sensitivity analysis and modification

The highest vulnerability to groundwater contamination was from the net recharge parameter (mean value of 9), followed by the aquifer media which has a mean value of 6.5. Topography, depth to water, hydraulic conductivity, and land use has the following values in order 5.6, 5.3, 5.2, and 5. The coefficient of variance of hydraulic conductivity, topography, and depth of water was high; 61.6, 61.4, and 61.3, respectively. On the other hand, aquifer

Table 4 The APH derived criteria weights

Criteria	Depth to water	Net recharge	Aquifer media	Soil	Topography	Vadose zone	Hydraulic conductivity	Land use
Weight	0.305	0.198	0.130	0.095	0.048	0.077	0.115	0.032

and vadose zone were the least variables during multiple map removal sensitive analysis. Finally, the reduced modified weight and rate map was prepared by removing both aquifer and vadose (Fig. 12).

Analytical hierarchy process (AHP)

The consistency ratio for all parameters was less than 0.1 for the pairwise comparison weight adjustment. This indicated the acquired expert opinion was consistent and suitable for implementation of the AHP—DRASTIC model for developing risk mapping. The Pearson correlation between analytical hierarchy process DRASTIC Index and observed nitrate concentration was 0.53. This showed a better correlation than the DRASTIC Index and the other methods. The results were in agreement with Neshat and Pradhan (2015a). Incorporating the fuzzy set theory for the assignment of weights for each feature associated with the potential source of vulnerability allows human reasoning to be incorporated in the control algorithm, coping with the parameter's imprecision (Asadi et al. 2017). Based on the FR-APH modified model, 31% of the area was under moderate to high and high vulnerability range, 39% was under moderate vulnerability range while 30% was under low and moderate to low vulnerability range (Fig. 12). Compared to the original DRASTIC method, the vulnerable areas under high and moderate to high class were highly increased. The DRASTIC weight is shown in Table 4.

Conclusion

Groundwater quality evaluation is critically important for the protection and sustainable management of groundwater resources, which are variably vulnerable to ever-increasing human-induced physical and chemical pressures. Modeling and mapping of groundwater vulnerability were critical for groundwater management. The first intrinsic vulnerability showed most of the area (67%) rely on moderate or moderate-high vulnerability class. In addition, to consider anthropological activity, the specific map was prepared by incorporating the land use feature. The specific vulnerability map showed that most of the area ($\sim$88%) showed moderate or moderate to high vulnerability. Based on the FR-Modified model, most of the area ($\sim$82%) was under moderate to high, high, or very high vulnerability range while about 81% was under moderate-high to very high range based on single parameters sensitivity analysis. Based on the FR-APH method, about 65% of the area was under the moderate to high or high vulnerability range. The result depicted that groundwater at Bahir Dar city is at the risk of contamination and hence needs management attention. A probability-based statistical model for the rate adjustment techniques improved the model. Besides, the incorporation of expert opinions and judgments in the FR-APH mothed further improved the model.

Declarations

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