# Groundwater Vulnerability Assessment Using a GIS-Based Modified DRASTIC Model in Agricultural Areas

by


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Thesis submitted to the
Faculty of Graduate and Postdoctoral Studies
in partial fulfillment of the requirements for the degree of Master of Applied Science in
Civil Engineering


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**Abstract**

DRASTIC model is the most widely used method for aquifer vulnerability mapping which consists of seven hydrogeological parameters. Despite of its popularity, this technique disregards the effect of regional characteristics and there is no specific validation method to demonstrate the accuracy of this method. The main goal of this research was developing an integrated GIS-based DRASTIC model using Depth to water, Net Recharge, Aquifer media, Soil media, Topography, Impact of vadose zone and Hydraulic Conductivity (DRASTIC). In order to obtain a more reliable and accurate assessment, the rates and weights of original DRASTIC were modified using Wilcoxon rank-sum non-parametric statistical test and Single Parameter Sensitivity Analysis (SPSA). The methodology was implemented for the Shahrekord plain in the southwestern region of Iran. Two different sets of measured nitrate concentrations from two monitoring events were used, one for modification and other for validation purposes. Validation nitrate values were compared to the calculated DRASTIC index to assess the efficacy of the DRASTIC model. The validation results obtained from Pearson's correlation and chi-square values, revealed that the modified DRASTIC is more efficient than original DRASTIC. The modified rate/weight DRASTIC (spline) model showed the highest correlation coefficient and chi square value as 0.88 and 72.93, respectively, compared to -0.3 and 25.2 for the original DRASTIC (spline) model. The integrated vulnerability map showed the high risk imposed on the southeastern part of the Shahrekord aquifer. In addition, sensitivity analysis indicated that the removal of net recharge parameter from the modified model caused larger variation in vulnerability index showing that this parameter has more impact on the DRASTIC vulnerability of the aquifer. Moreover, Aquifer media (A), Topography (T) and Impact of vadose zone (I) were found to have less effect and importance compared to other variables as expected. Therefore, reduced modified DRASTIC model was proposed by eliminating A, T and I parameters. Pearson's correlation coefficient and chi-square value for the reduced model were calculated as 0.88 and 100.38, respectively, which was found to be as reliable as full modified DRASTIC model.

**Acknowledgements**

Firstly, I would like to thank my supervisor, Dr. Majid Sartaj who helped me step-by-step during my academic career.

I also want to express my special thanks of gratitude to my co-supervisor, Dr. Bahram Daneshfar for his helpful advice and comments during my project. Thanks for the infinite support and time.

Special thanks are due to Dr. K. Mohammadi for his sincere cooperation in providing the data.

Lastly, I would also like to thank my beloved family, especially my husband, without their support I would have never been able to start and finish this degree.

## Dedication

This is dedicated to my beloved mother.

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# List of Symbols

A: Aquifer media
AHP: Analytical Hierarchy process
b: Thickness of aquifer (m)
C: Hydraulic conductivity
CI: Consistency index
D: Depth to water
DI: DRASTIC Index
EPA: Environmental Protection Agency
FR: Frequency ratio
GIS: Geographic Information System
H: High
k: Hydraulic conductivity (m/d)
I: Impact of vadose zone
IDW: Inverse Distance Weighting
L: Low
M: Moderate
MH: Moderate High
ML: Moderate Low
MRW DRASTIC: Modified rate and weight DRASTIC
n: Number of layers
P: Probability of contaminant concentration
r: Pearson's correlation coefficient
R: Net recharge
S: Sensitivity index
S: Soil media
SPSA: Single Parameter Sensitivity Analysis
T: Transmisivity ($m^2$/d)
T: Topography
V: Overall vulnerability index
V: Unperturbed vulnerability index
V': Perturbed vulnerability index
VH: Very High
VL: Very Low
W: Weight of parameter
WoE: Weights of evidence
$\lambda_{max}$: Maximum consistency vector
$\chi^2$: Chi-square value

# Chapter 1

# Introduction

## 1.1 Background

Groundwater could be considered as one of the most important natural resources in order to develop a society, especially in arid and semi-arid regions. In many countries with limited sources of water, groundwater is the only water supply. Groundwater accounts for about 90% of the freshwater supply available for mankind and provides roughly one third of the worlds drinking water [11]. Population growth and severe demands on these resources can result in shortage of water in future years. Despite of the significance of groundwater as the most important component of sustainable development, it has not received enough attention when it comes to its protection against pollution. This invaluable resource has been at risk of depletion and pollution [53], therefore, it seems vital to protect it from pollution and deterioration. If an aquifer gets polluted, then remediation would be difficult, costly and at times impossible [12, 52]. During last decades, intense agriculture activities and fertilizer application have resulted in groundwater contamination, which has become a critical issue. In addition to agricultural activities, release of municipal and industrial wastes have caused an increase in contaminants in subsurface environment.

Contamination of groundwater can result in poor water quality, health problems and high costs of treatment. Assessment of aquifer vulnerability is an important step in order to plan and implement any plan for protection of groundwater resources against contaminants such as nitrate. In recent years, modeling groundwater contamination and knowledge of where pollution may occur has received considerable attention and environmental managers and responsible authorities have been interested in evaluating groundwater vulnerability to pollution and likelihood of contaminants concentration exceeding acceptable levels [83]. Many approaches have been developed to assess aquifer vulnerability; overlay and index based techniques [7], process based simulation techniques [51] and statistical techniques [21]. DRASTIC is one of the most frequently used models for vulnerability assessment of groundwater resources. It is an overlay and index model introduced to produce vulnerability scores for different locations by combining several hydrogeological layers. Despite its popularity, this technique disregards the type of pollution and the effect of regional characteristics. Also, there is not a specific validation method to demonstrate the accuracy of this method. Thus, this model could be modified according to specifications of pollutants and aquifers. Nitrate contamination of aquifers is a significant problem in many agricultural areas [11]. Nitrate, the primary form of nitrogen, is not in groundwater system naturally but it can be one of the predominant contaminants associated with agricultural activities. It has high solubility and mobility and can easily reach groundwater. Thus it could be a serious threat to groundwater resources. Therefore, measured nitrate concentrations from monitoring wells can be used to associate and correlate the contaminant in the aquifer to the vulnerability index.

## 1.2 Research Objective

The main objective of this research was to determine the feasibility of DRASTIC model for assessment of aquifer vulnerability in agricultural areas by verifying the model output vs field measurements for nitrate concentration in groundwater. It was also intended to modify this model within the study area by modifying the weights and rates used in the original DRASTIC model. Therefore, a data driven component was added to DRASTIC model to introduce a hybrid model for vulnerability assessment. Also, the possibility of modifying DRASTIC model by eliminating some of the parameters which have less impact on outcome was investigated. This could result in a more simple model with less number of parameters and as a results less amount of required input data to enhance its performance in predicting the vulnerability of groundwater resources. DRASTIC model uses seven parameters, mainly characteristics of the aquifer, to assess the vulnerability or potential for groundwater contamination. These include: Depth to water, net Recharge, Aquifer media, Soil media, Topography, Impact of vadose zone and hydraulic Conductivity (DRASTIC). It is an empirical model introduced by Environmental Protection Agency (US EPA, 1985). Since DRASTIC model disregards the effects of regional characteristics and particular type of contaminants, it must be modified based on specifications of aquifer and pollutant. In order to obtain a more accurate and reliable vulnerability assessment, the rates and weights of DRASTIC parameters were calibrated. Therefore, rates were modified using nitrate concentrations representing the extent of pollution in the groundwater system. The relative importance of the DRASTIC method parameters through Single Parameter Sensitivity Analysis (SPSA) was evaluated. Moreover, variation index was measured using map removal sensitivity analysis, to identify the sensitivity of vulnerability map towards removing one or more maps. Lastly, an additional objective was to implement the combined use of DRASTIC and Geographical Information System (GIS) as an effective method for groundwater vulnerability mapping and water resource management.

## 1.3 Thesis Layout

This dissertation contains five chapters. Chapter 1 is introduction, comprising the background, objectives, and layout of the thesis. In chapter 2, a literature review on the groundwater vulnerability mapping and the available techniques in order to evaluate vulnerability is presented. Chapter 3 is the materials and methodology used in this study. Results and discussion are provided in chapter 4. A summary of the conclusions and the suggested future work is discussed in Chapter 5.

# Chapter 2

# Literature Review

## 2.1 Groundwater vulnerability

In recent years, modeling of large scale groundwater contamination and the need for strategic planning for aquifers protection have received considerable attention [8, 9]. Groundwater contaminants include inorganic pollutants such as arsenic, aluminum, lead, mercury, fluoride, iron, and nitrate and man made organic pollutants such as pesticides, plasticizes, and chlorinated solvents [40]. Accordingly, it is essential to monitor and evaluate groundwater quality especially in regions where groundwater is the main source for drinking water.

The concept of groundwater vulnerability to contamination was developed by Margat [62] which provides a better understanding of ground water sensitivity against pollution with respect to geological, hydrological and meteorological conditions. Because many aquifers are permeable, shallow, unconfined and highly susceptible to contamination so it could be considered as a powerful measure in planning for protection of aquifers. Groundwater vulnerability is a relative, dimensionless and non measurable feature which relies on geological and hydrogeological properties of an aquifer [10, 35]. Assessment of vulnerability gives researchers the opportunity to evaluate the risk and sensitivity of an aquifer to get contaminated and constitutes an essential component of management options to preserve the groundwater quality [99]. Vulnerability assessment must be objective, scientific and based on accurate evidence [68]. As aquifer vulnerability assessment is an inexact estimation [56], it is considered as a tool for predicting potential contaminants, but not necessarily for appropriate level of pollution [81].

It is now more than forty years since the vulnerability concept was proposed, but there is not a perfect and complete definition of aquifer vulnerability. Foster in 1987 defined vulnerability as "the intrinsic characteristics which determine the sensitivity of various parts of an aquifer to being adversely affected by an imposed contamination load" [37]. The best way to map aquifer vulnerability is the evaluation by a three dimensional model which takes into account all characteristics of aquifer and its variability with space and time. In practice, due to amount and quality of available data, budget and time constraints, the output of vulnerability assessment would be a two dimensional map where at each point different properties of aquifer be integrated to predict the potential pollution.

## 2.2 Vulnerability mapping

Recently, several groundwater vulnerability and risk mapping approaches have been developed to estimate the sensitivity of groundwatabler to contamination. Vulnerability mapping is a valuable tool for environmental planning and decision making using indexing methods coupled with GIS-based spatial analysis commonly relied upon to ascertain aquifer vulnerability [59]. It divides a region to several hydrogeological areas with various levels of sensitivity from contamination point of view [32]. Groundwater vulnerability can be categorized into intrinsic vulnerability and specific vulnerability [27]. Intrinsic vulnerability is independent of particular contaminants and assesses sensitivity of aquifer to human activities or nature [67], while the latter considers vulnerability to one or more contaminants [41]. Intrinsic vulnerability parameters, such as soil media, depth to water and net recharge have been changed extensively due to anthropogenic activities. On the other hand, specific vulnerability is used to define groundwater vulnerability to a specific contaminants by taking into account the contaminants' physico-chemical properties and their relationships [41].

Basically, there are three available techniques for creating vulnerability maps: overlay and index based techniques [7, 25, 28, 37, 61]; process based simulation techniques [39, 50, 51, 85, 95]; and statistical techniques [21, 64, 93, 96]. Although, with respect to particular factors and under specific circumstances they have strengths and weaknesses.

### 2.2.1 Overlay and index methods

The overlay and index methods are the most widespread techniques in vulnerability mapping due to low requirement on field data. These methods include a set of subjective ratings and weights which consider different physical and hydrogeological factors to control movement of pollutants through the unsaturated zone till they reach the watertable and spread [7]. Overlay and index methods are often preferred because of availability of the required data and relatively simple procedures. Actually, these methods include important parameters in groundwater vulnerability evaluation without attempting to fully describe the processes that lead to contamination. Despite of simplicity and convenience, there are some disadvantages in vulnerability mapping using overlay and index methods. Firstly, this system assumes a linear relationship between vulnerability and parameters while some studies have shown non-linear superposition [76]. Secondly, all weights and rates are subject to expert judgment which introduce a subjective effect into result [38]. Thirdly, the value for ratings are discretized that could introduce additional error. There are many index systems for groundwater vulnerability mapping, including SINTACS [26], GOD [37], AVI [92], PI [42], GLA [44] and DRASTIC [7] which is the most widely used technique for vulnerability mapping.

### 2.2.2 Process based simulation model methods

Process-based methods predict contaminant flow and transport using simulation models and the required data for this method must be obtained by indirect techniques [16]. These methods may use the advective-dispersive solute transport approach along with different chemical reaction models that can describe the dynamics a pollutant may undergo. Process-based simulation models require analytical or numerical solutions to mathematical equations that present coupled processes affecting contaminant transport. Methods in this class range from indices based on simple transport models to analytical solutions for one-dimensional transport of contaminants through the unsaturated zone to coupled, unsaturated-saturated, multiple-phase, two- or three-dimensional models. These approaches are different from others in that many of them attempt to predict contaminant transport in both space and time [46]. Meeks and Dean (1990) used a one-dimensional advection-dispersion transport model to develop a leaching potential index, which simulates vertical movement through a soil to the watertable [66]. Soutter and Pannatier (1996) expressed groundwater vulnerability as the ratio between the cumulative pesticide flux reaching mean watertable depth and the total quantity of pesticide applied [91].

Process-based models such as Visual ModFlow provide excellent tools to predict water flow and pollutant transport under specific hydrogeologic conditions in the unsaturated zone, in particular those that are highly layered (heterogeneous), and for chemical process that undergo multiple chemical processes or chemical reactions [46]. The most important disadvantage of this method is that they need a large volume of input data with considerable calculation power and difficulties in calibration process [46].

### 2.2.3 Statistical methods

Statistical methods using different degrees of complexities in statistics, identify parameters which are affecting groundwater contamination and they are suitable for specific regions [14]. They produce a correlation between explanatory parameters and contaminant concentration [65]. These methods have been used in the evaluation of vulnerability using probability models and results are expressed as probabilities. In general, these models include multiple independent variables and use a contaminant concentration or a probability of contamination as the dependent variable [46]. Teso (1996) proposed a logistic regression model containing independent variables related to the soil texture. The dependent variable was defined as the contamination status of soil sections (uncontaminated vs. contaminated) and groundwater vulnerability was thus assessed through the estimation of a sections probability of its containing a contaminated well [93]. Worrall and Kolpin (2004) introduced a logistic regression model of groundwater contamination that brings together variation in chemical properties with land use, soil and aquifer characteristics.

Undoubtedly, simulation and statistical techniques provide more accurate information for water resource managers by relying on professional judgments, hence, they are preferred over the overlay index methods in the event required input data are available [36]. More or less, all vulnerability models consider similar factors for predicting contamination, the only difference is the type of approach they apply for integration [57].

## 2.3 DRASTIC vulnerability mapping

DRASTIC is one of the most well-known and widely used parametric vulnerability mapping techniques. It was developed through an EPA (Environmental Protection Agency) project in the United States with the purpose of helping managers, planners and administrators. DRASTIC can be used in extensive regions due to low cost of application and easy to collect data requirements [7]. According to Panagopoulos (2006) "the selection of many parameters and their interrelationship decreases the probability of ignoring some important parameters, restricts the effect of an incidental error in the calculation of a parameter and so enhances the statistical accuracy of the model" [82]. This overlay index vulnerability method is based on physical and hydrogeological characteristics of aquifer to assess intrinsic vulnerability [4, 7]. DRASTIC method is easy to implement and many researchers have applied it for evaluating groundwater vulnerability around the world. It has been applied in many regions to evaluate groundwater vulnerability, for instance in Iran [1, 68, 75], Jordan [5], Europe [23, 31, 72], United states [84] and Africa [79]. This methodology uses seven hydrogeological parameters which considering various parameters decreases the probability of misjudging and enhances the reliability of vulnerability index [86]. DRASTIC acronym stands for quantitative and categorical variables including: Depth of water, net Recharge, Aquifer media, Soil media, Topography, Impact of vadose zone and hydraulic Conductivity. Figure 2.1 displays the schematic diagram of DRASTIC parameters.

DRASTIC model is according to Delphi approach accomplished by a committee of

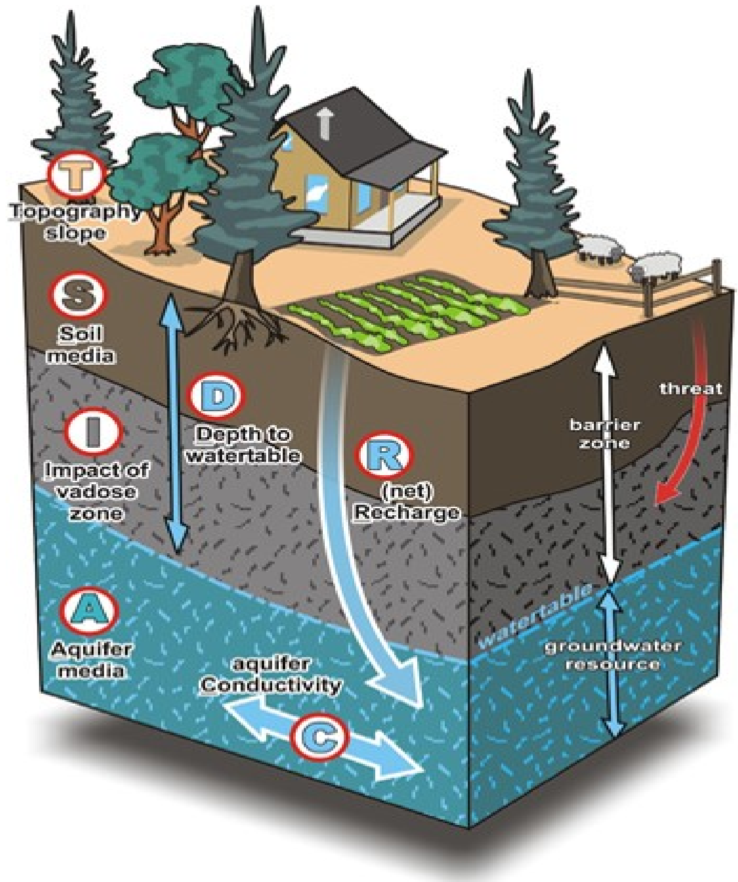



Figure 2.1: Definition of DRASTIC parameters, (Source: www.frakturmedia.net)

experts so the weight and rates of parameters may not be changed. Groundwater vulnerability mapping using DRASTIC assumes some points which are [7]:

- The contaminant is released at the earth's surface (use of fertilizers, burning of coal and leaching of metals from coal-ash tailings etc.).
- The contaminant flushes into the groundwater through precipitation.
- The contaminant moves with the velocity of water.
- The concerned area should be 100 acres (0.4 km$^2$) or larger.

The original DRASTIC index (DI) was calculated by applying a linear combination of all parameters as demonstrated by Eq. 2.1:

$$DI = D_W.D_R + R_W.R_R + A_W.A_R + S_W.S_R + T_W.T_R + I_W.I_R + C_W.C_R \tag{2.1}$$

where DI is the DRASTIC index, D, R, A, S, T, I, and C are the seven parameters; factors with W subscript show the weight and parameters with R subscripts are the rate of the parameters. The vulnerability index is a dimensionless index and relative measure of susceptibility to pollution; regions with a higher DRASTIC index value are more vulnerable than those with a lower index. The range of index can be from 70 to greater than 200. Also, in this method, the parameters are weighted from 1 to 5 and the rates are from 1 to 10, based on the relative contribution to potential contamination. DRASTIC parameters have been explained briefly in the following sections.

### 2.3.1 Depth to Water (D)

Depth to water is one of the most important parameters in DRASTIC technique which describes the distance that contaminant must travel from the surface to reach groundwater table [7]. In another word, it is the vertical distance from ground surface to water table, top of saturated zone, in the aquifer. It could be determined using topography and groundwater level contour maps. By subtracting elevations from groundwater level, depth to water would be calculated. In general, potential for contamination decreases with increasing D, as deeper watertable implies less chance for contamination to occur.

### 2.3.2 Net Recharge (R)

Net groundwater recharge is the main driving force for transferring contaminants to an aquifer. The total amount of water that reaches the watertable have been indicated as net recharge. Net recharge might be estimated from the rainfall infiltration, irrigation return flow, evapotranspiration and absorption wells in the study area. The more recharge shows more vulnerability to contamination [7]. The main source of recharge could be either river leakage or rainfall. The groundwater recharge map could also be prepared using isotope studies [20].

### 2.3.3 Aquifer Media (A)

Aller (1987) defined aquifer as a rock formation which yield sufficient amount of water for use. Aquifer media refers to consolidated and unconsolidated rocks (such as sand, gravel or limestone) which serves as an aquifer [7]. This parameter is essential to control the route, path length and movement of contaminants. In general terms, large sediment size, higher permeability and lower attenuation capacity can result more vulnerability to pollution. Aquifer media map could be prepared using geological information.

### 2.3.4 Soil Media (S)

The soil media represents the top weathered portion of unsaturated zone with significant biological activities [7]. It is the top part of vadose zone and its characteristics are important in potential pollution while by increasing the depth of soil, infiltration will be decreased. Generally, soil map can represent infiltration rates of pollutants. There are some effective factors that determine the potential pollution of soil comprising the type of clay, the grain size and shrink potential of clay. Indeed, less amount of clay, less shrinkage potential and smaller grain size indicate lower vulnerability of aquifer.

### 2.3.5 Topography (T)

Topography refers to slope of land surface and it controls the runoff of contaminants. This factor indicates the probability that contaminant run off or remain on the ground to infiltrate. Therefore, steep slopes increase runoff which contains contaminants and lower chance of infiltration [6]. Digital Elevation Model could be used to prepare topography maps and slope is calculated by GIS tools.

### 2.3.6 Impact of Vadose Zone (I)

The vadose zone also termed unsaturated zone, extends from the top of the ground surface to watertable at which groundwater is at atmospheric pressure. Vertical movement of water in vadose zone is important for pollution transport. The characteristic of unsaturated zone can determine attenuation properties of the media above watertable. A vadose zone map is also prepared using sub-surface geology and lithology characteristics of drilling logs.

### 2.3.7 Hydraulic Conductivity (C)

The ability of an aquifer to transmit water and contaminants is defined as hydraulic conductivity. The results of pumping test and lithology are used for creating a hydraulic conductivity distribution map. Regions with higher hydraulic conductivity indicate more contaminant transmission and distribution. It is also controlled by pore spaces and fractures within aquifer. The equation $k=T/b$ might be used to calculate hydraulic conductivity of aquifer where the hydraulic conductivity of the aquifer is denoted by k (m/d), transmissivity is denoted by T ($m^2$/d) and the thickness of the aquifer is denoted by b (m).

As it was mentioned, DRASTIC approach allocates specific weight and rate for each parameter in order to calculate aquifer vulnerability index. Tables 2.1 and 2.2 present the ranges and colour codes for DRASTIC indices. All the recommended rates and weights are also shown in Table 2.3.

Table 2.1: Criteria of the vulnerability assessment by using DRASTIC method [33]

| Class vulnerability | Low | Average | High | Very High |
|---|---|---|---|---|
| Calculated index value | <101 | 101-140 | 141-200 | >200 |

Table 2.2: Colour codes for DRASTIC Indices introduced by Aller [7]

| Calculated index value | Colour |
|---|---|
| less than 79 | Violet |
| 79-99 | Indigo |
| 100-119 | Blue |
| 120-139 | Dark green |
| 140-159 | Light green |
| 160-179 | Yellow |
| 180-199 | Orange |
| 200 and above | Red |

Table 2.3: Standard DRASTIC weights and rating system [7]

| Depth to water | | Net recharge | | Aquifer media | | Soil media | | Topography | | Impact of vadose zone | | Hydraulic conductivity | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Range (m) | Rating | Range (mm/year) | Rating | Range | Rating | Range | Rating | Range (%) | Rating | Range | Rating | Range (m/day) | Rating |
| 0-1.5 | 10 | <50 | 1 | Massive shale | 2 | Thin or absent, gravel | 10 | 0-2 | 10 | Confining layer | 1 | <4 | 1 |
| 1.5-4.5 | 9 | 50-100 | 3 | Metamorphic /igneous | 3 | Sand | 9 | 2-6 | 9 | Silty/clay | 3 | 4-12 | 2 |
| 4.5-9 | 7 | 100-175 | 6 | Weathered metamorphic /igneous | 4 | Peat | 8 | 6-12 | 5 | Shale | 3 | 12-30 | 4 |
| 9-15 | 5 | 175-250 | 8 | Glacial till | 5 | Shrinking and /or aggregated clay | 7 | 12-18 | 3 | Limestone | 6 | 30-40 | 6 |
| 15-22 | 3 | >250 | 9 | Bedded sandstone, limestone, shale | 6 | Sandy loam | 6 | >18 | 1 | Sandstone, bedded sandstone | 6 | 40-80 | 8 |
| 22-30 | 2 | | | Massive sandstone, Massive limestone | 6 | Loam | 5 | | | Sandstone, shale, sand and gravel | 6 | >80 | 10 |
| >30 | 1 | | | Sand and gravel | 8 | Silty loam | 4 | | | Metamorphic /igneous | 7 | | |
| | | | | Basalt | 9 | Clay loam | 3 | | | Sand and gravel | 8 | | |
| | | | | Karst limestone | 10 | Muck | 2 | | | Basalt | 9 | | |
| | | | | | | Non-shrinking and Non-aggregated clay | 1 | | | Karst limestone | 10 | | |
| DRASTIC weight 5 | | DRASTIC weight 4 | | DRASTIC weight 3 | | DRASTIC weight 2 | | DRASTIC weight 1 | | DRASTIC weight 5 | | DRASTIC weight 3 | |

## 2.4 Modifications on DRASTIC

Despite of simplicity and popularity, there are some weaknesses in vulnerability mapping using DRASTIC technique. The main drawback is its subjectivity and doubts regarding the selection of specific parameters and exclusion of others [82]. In fact, DRASTIC has been criticized on the following points:

- It disregards the effect of regional characteristics by assigning uniform rates and weights to parameters.
- This technique does not use a standard validation method.
- Parameters were selected based on qualitative judgment and not quantitative studies.

Therefore, many researchers have attempted to modify DRASTIC model in order to achieve a more accurate vulnerability assessment. For instance, some researchers correlated DRASTIC index with chemical or contaminant parameters but in many cases they found low correlation. McLay (2001) suggested that models such as DRASTIC with a land management index included, may be useful for predicting areas for more intensive monitoring of groundwater. It was also emphasized that there is a greater need to test the link between measurements of nitrate leaching from a variety of land use activities with measurements of groundwater nitrate concentrations below these activities [65]. Panagopoulos (2006) incorporated the application of simple statistical and geostatistical techniques for the revision of the factor weightings and ratings of all the DRASTIC parameters in a GIS environment. For this modification hydraulic conductivity and soil media were eliminated from the DRASTIC equation, while land use was considered as an additional DRASTIC parameter. The correlation coefficient between groundwater vulnerability index and nitrate concentrations was considerably improved and rose by 33% compared to the standard method [82]. Leone (2009) reported the DRASTIC scores related to groundwater nitrate content. Scores were distributed in two different groups: lower vulnerability (between 60 and 80) with no nitrate content and higher vulnerability (between 110 and 155) with great various nitrate contents from near to 0 to over 160 mg/L [55]. One of the important reasons for this dissimilarity is the need to perform interpolation of sparse field data, which involves error in interpolation. Hence, the results from DRASTIC should be modified according to specification of region and contaminant. For this purpose, numerous techniques have been suggested to develop and modify DRASTIC algorithm.

### 2.4.1 Weight adjustment techniques

In many studies, DRASTIC is subject to modifications, especially for the factor weights, to meet the specifications of the study area. The weight of parameters in DRASTIC could be modified by using different methods that have been discussed in the following sections:

#### 2.4.1.1 Sensitivity Analysis

DRASTIC is implemented using seven hydrogeological layers which some researchers believe it could mitigate the error and uncertainties on the final vulnerability assessment [86]. Other researchers emphasize that more appropriate vulnerability assessment could be obtained by integrating lower number of parameters [17]. Meanwhile, sensitivity analysis could be performed to evaluate the required layers in DRASTIC vulnerability mapping. There are two sensitivity analysis; The map removal sensitivity analysis introduced by Lodwick et al. [58] and the Single Parameter Sensitivity Analysis (SPSA) introduced by Napalitano and Fabbri [72]. The map removal sensitivity analysis determines the sensitivity of vulnerability map to removing one or more layers and is computed by the Eq. 2.2:

$$S = (|V/N - V'/n|/V) \times 100 \tag{2.2}$$

where S is the sensitivity index, V is unperturbed vulnerability index, V´is perturbed vulnerability index, and N and n are the number of data layers used to compute V and V´. The actual vulnerability index obtained using all seven parameters is considered as an unperturbed vulnerability while the vulnerability computed using a lower number of data layers is considered as a perturbed one [14].

The SPSA examines the significance of each layer in vulnerability index. It is also possible to compare the theoretical and effective weight of each parameter. The effective weight of each parameter is computed using the Eq. 2.3:

$$W = ((P_r.P_w) \div V) \times 100 \tag{2.3}$$

where W refers to the 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 [14].

In recent years, many researchers have used sensitivity analysis to modify the weight values recommended in DRASTIC method in order to increase the accuracy and reliability of assessment [2, 18, 49, 73, 75, 79, 87, 90]. Neshat (2014) modified the weights of DRASTIC using SPSA and concluded that modified DRASTIC model performed more efficiently than the traditional method for non-point source pollution. DRASTIC was applied for Kerman plain in Iran and the regression coefficients showed that the relationship between the vulnerability index and the nitrate concentration was 82 % after modification compared to 44 % before modification [75]. Pacheco (2015) applied sensitivity analysis for 26 aquifer systems in Portugal with the modified DRASTIC approach. This resulted in vulnerability indices that on average were 20% lower the original DRASTIC values [80]. Ouedraogo (2016) applied sensitivity analysis in aquifer systems in Africa and indicated that the removal of the impact of vadose zone, the depth to water, the hydraulic conductivity and the net recharge caused a large variation in the mapped vulnerability. He also illustrated that the nitrate concentration data are positively related to the intrinsic vulnerability index with 0.94 as correlation coefficient [79]. Moreover, Abdullah (2016) applied sensitivity analysis in Halabja Saidsadiq Basin located in the northeastern part of Iraq and demonstrated that the modified DRASTIC was dramatically superior to the standard model. Pearson correlation factor showed that there is a good relation between the modified DRASTIC index and nitrate concentration which were 0.69, 0.57, and 0.72 for modified rate (using nitrate concentration), weight (sensitivity analysis), and combined rate-weight methods, respectively [2].

#### 2.4.1.2 Logistic regression

In this method, contaminant of concern as a dependent variable has to be allocated as binary, coded as 0 for regions where the concentration is below a pre-defined threshold and as 1 elsewhere. Then, the equation obtained from Logistic Regression will be written as Eq. 2.4:

$$P = \frac{e^{b_o} + e^{b_1}x_1 + .... + e^{b_p}x_p}{1 + e^{b_o} + e^{b_1}x_1 + .... + e^{b_p}x_p} \tag{2.4}$$

where P is the probability of contaminant concentration being higher than the given threshold, Xj is the rating of factor j and the bj constants are adjustment coefficients. These coefficients are optimized by the Maximum Likelihood Estimation during a run of Logistic Regression [80]. Many researchers have used logistic regression in order to correlate nitrate concentration with hydrogeological factors [77]. Mair and El-Kadi (2013) used logistic regression modeling for groundwater vulnerability assessment in Hawaii, USA [60].

#### 2.4.1.3 Weights of evidence (WoE)

Similar to the Logistic Regression method, Weights of evidence (WoE) is a quantitative statistical method for integrating evidence to test a hypothesis [29]. The application of WoE as a spatial statistical method in groundwater vulnerability assessment, is more recent [1, 15, 63, 80]. This method is based on Bayes theorem which can be used in order to evaluate groundwater vulnerability by establishing correlation between contaminant of concern and hydrogeological layers. The significance of factors and their spatial association to the locations where contamination was observed can be evaluated using WoE method. Abbasi (2013) prepared vulnerability map through statistical analysis of aquifer characteristics and water quality data using WoE approach [1].

#### 2.4.1.4 Correspondence analysis

Vulnerability index calculated using Eq. 2.1 requires independent variables. In case of DRASTIC, variables are usually related to each other, therefore, vulnerability index is calculated with uncertainty. The concomitant error can be identified and neutralized by a weighting technique which Pacheco and Sanches Fernandes (2013) developed based on the application of an eigenvector technique for the factor ratings [81]. Eigenvector methods convert the interrelated variables into vectors so that a major portion of data variation is concentrated on just a few of them, called common vectors. In DRASTIC case where the input data are treated as qualitative and categorical data, the eigenvector technique is called Correspondence Analysis [80]. Pacheco (2013) combined DRASTIC technique with a pioneering approach for feature reduction and adjustment of feature weights to Sordo river basin in Portugal. He also concluded that multivariate statistical method can identify and minimize redundancy between DRASTIC features [81].

#### 2.4.1.5 Analytical Hierarchy Process

Saaty (1980) proposed the Analytical Hierarchy Process (AHP) which is a Multi Criteria Decision Making (MCDM) method. In AHP, various criteria are studied by employing a comparative analysis on a set of pair-wise comparison matrices (PCMs). The rate and weight of the criteria and sub-criteria can be evaluated through AHP according to their significance. In AHP procedure, the first criterion weight is multiplied by the first column of the main PCM and used to define the weighted sum vector. Then, the other criteria are individually multiplied by their respective columns in the original matrix. To calculate a final value, the derived values are added over the rows. The weighted sum vector is divided by the criterion weights to determine the consistency index which is:

$$CI = \lambda_{\max} - n/(n-1) \tag{2.5}$$

Where $\lambda_{\max}$ is the maximum consistency vector and n is the criteria number. Therefore, the consistency ratio, which defines the consistency of each matrix, can be calculated by Eq. 2.6:

$$CR = CI/RI \tag{2.6}$$

Where CR is consistency ratio, ratio of the consistency index (CI) and random index (RI). For a consistent matrix, CR should be less or equal to 0.1. This process is applied to compute the weights of all DRASTIC parameters by modifying the initial weights of factors for determining the vulnerability. The AHP has ability in solving complex decision making problems and many researchers have been applied it in various research areas [3, 102]. Also, a software package AHP-DRASTIC has been developed by Thirumalaivasan (2003) to calculate ratings and weights of modified DRASTIC model parameters to apply in specific aquifer vulnerability assessment. ArcView Geographical Information System (GIS) was integrated with the software in order to model aquifer vulnerability and predict areas which have higher vulnerability than others [94]. In 2013, Sener and Davraz applied AHP for modifying rates of parameters in DRASTIC [89]. Moreover, Neshat (2014), evaluated the validity of the criteria and sub criteria of parameters of the DRASTIC model by AHP and proposed an alternative treatment of the imprecision demands in Kerman plain [74]. Recently, Sahoo (2016) conducted a study for groundwater vulnerability in India by using AHP DRASTIC and Agricultural DRASTIC which considers land use [88]. In addition, Langrudi (2016) applied Fuzzy AHP for vulnerability mapping in Astaneh plain located in Iran [54].

### 2.4.2 Rate adjustment techniques

A more accurate vulnerability assessment depends on validity of the rates [13]. In order to calibrate the rates in DRASTIC, there are some methods that have been discussed in the following sections:

#### 2.4.2.1 Wilcoxon rank sum non-parametric statistical test

Wilcoxon rank sum non-parametric statistical can modify the rates in DRASTIC method by using observed nitrate concentrations as a main factor [98]. In fact, relationship between the vulnerability index and DRASTIC parameters can be statistically analyzed to adjust the rates. In order to optimize the rates of DRASTIC method using contaminant concentrations, the following requirements must be meet [82]:

- Contaminant must be as a result of agricultural activities in the region.

- The distribution of contaminant should be relatively uniform in the area.
- Contaminant reached the groundwater by precipitation.

In brief, the primary land use of the selected region should be agricultural to satisfy all the above conditions.

Many studies have modified DRASTIC using contaminant concentration [48, 49, 75, 82]. Panagopoulos (2006) calibrated the DRASTIC prior to obtaining the correlation coefficient in order to determine the relationship between nitrate concentration and the vulnerability index. Recently, Neshat (2014) implemented Wilcoxon methodology in the Kerman plain in the southeastern region of Iran and revealed that the modified DRASTIC model performed more efficiently than the original method particularly in agricultural areas [75]. Also, Abdullah (2016) modified the rates of DRASTIC using Wilcoxon rank sum nonparametric statistical technique for groundwater vulnerability in Iraq [2]. In addition, Noori (2016) applied Wilcoxon test on Saveh-Nobaran plain in central Iran using chloride concentrations in groundwater and showed that the coefficient of determination between the point data and the relevant vulnerability map increased significantly from 0.52 to 0.78 after modification [87].

#### 2.4.2.2 Probabilistic based statistical model, Frequency ratio

Frequency ratio is considered as a bivariate statistical method which can modify the rates of DRASTIC based on spatial distribution of contaminant concentration and hydrogeological parameters [73]. FR uses the correlation between nitrate samples and seven DRASTIC layers to modify the rates of factors. The FR is computed from the analysis of nitrate association and attributed parameters. Then, the FRs of each factor type or range are calculated from their relationships with the nitrate samples. In this technique, the highest DRASTIC rate is given a higher probability, which is calculated from the FR and the other DRASTIC rates can be obtained by a relation. The processes can also be explained by Eq. 2.7:

$$FR = (A/B)/(C/D) = E/F \tag{2.7}$$

where A is the area of a class or range for each DRASTIC parameters; B is the total area of each parameter; C is the total number of nitrates occurrence in the class of each parameter; D is the number of the total nitrates in the study area; E is the percentage of area in the class of each parameter; F is the percentage of nitrate in the class for each parameter. In defining the FR, the nitrate concentration area ratio is computed in the range of each DRASTIC layer factor; the area ratio for the range of each factor relative to the total area is calculated. Then, the probability for each parameter range is computed by dividing the nitrate concentration ratio by the area ratio; a value of 1 is an average ratio. If the ratio is more than 1, a higher correlation between the factor range and nitrate concentration is indicated. Also, if the ratio is less than 1, a lower correlation is expected [73, 97]. The probabilistic frequency ratio (FR) approach has been used in different aspects such as landslide susceptibility evaluation [30, 70, 101], groundwater potential mapping [43, 71] and many other environmental disciplines. Recently, Neshat (2015) applied this approach for aquifer vulnerability assessment in Kerman plain, Iran [73].

## 2.5 DRASTIC Validation

Nitrate concentration in groundwater sources could rise as a consequence of fertilizer application in agricultural areas [22]. In fact, nitrate is not usually present in groundwater system naturally but since it is highly soluble, it can easily reach both groundwater and surface water after application on the surface [78]. Therefore, nitrate as a main contaminant that human activities introduce into the environment, can be considered as a good indicator of groundwater quality [4]. For this purpose, measured nitrate concentration from monitoring wells can be used to associate and correlate the contaminant in the aquifer to the vulnerability index [18, 24, 34, 47, 75, 90]. Hence, many researchers attempted to validate DRASTIC vulnerability index by using observed nitrate concentrations. For instance, Javadi (2011) demonstrated the applicability of the modified DRASTIC by correlating the pollution potential (nitrate concentrations) in the Astaneh Aquifer to the DRASTIC index. Iqbal (2015) demonstrated GIS based fuzzy pattern recognition model for groundwater vulnerability and compared indices obtained from proposed methodology and DRASTIC model using observed nitrate concentrations [45]. Moreover, Neshat (2015) used nitrate concentrations to indicate that Frequency Ratio approach can be more accurate compared with original DRASTIC vulnerability in Kerman plain [73]. Recently, Barzegar (2016) improved the DRASTIC method for evaluation of groundwater contamination risk using AI methods, such as ANN, SFL, MFL, NF and SCMAI approaches which groundwater nitrate samples were used for training and validation purposes [18]. Furthermore, Sahoo (2016) evaluated Hirakud aquifer vulnerability situated in the western part of Odisha, India and validated DRASTIC map using water quality parameters (EC, $Cl^-$, $Mg^{2+}$ and SAR) [88]. Also, Sinha (2016), replaced hydraulic conductivity parameter to land use and ended up with a good correlation between nitrate samples and modified DRASTIC index [90].

## 2.6 Research gap

Although DRASTIC model has been the most widely used method for vulnerability assessment of groundwater resources but it has many limitations. One major limitation is the need to validate it against field measurements and assess its ability to predict the pollution potential of aquifers. Limited research is available on validation of DRASTIC model and its modification, especially in agricultural areas. In order to demonstrate the applicability of the modification methods and validate the proposed vulnerability map in agricultural areas, nitrate concentrations were used in this research to correlate the pollution in the aquifer to the DRASTIC index. In addition to Pearson's correlation coefficient, DRASTIC maps were tested for measuring significant association with nitrate map. For this purpose, nitrate validation samples were interpolated using spline interpolation method to create nitrate map, then chi-square value was calculated. The modified DRASTIC model were proposed to provide a reliable basis for environmental management in Shahrekord plain as a case study. Apart from that, using two different methods including Inverse Distance Weighting (IDW) and spline, the depth points in the area were interpolated. Thus, impact of interpolation method to create depth raster on vulnerability index in DRASTIC approach was investigated. According to the results obtained from single and multiple map removal sensitivity analysis, a reduced model was proposed for Shahrekord vulnerability evaluation which considers less number of parameters in compared to the original DRASTIC model. Consequently, a simple model with less amount of required input data could be introduced which is reliable and accurate enough in predicting vulnerable areas. Therefore, the contribution of current study was integration of available techniques to modify original DRASTIC model and introduce a more reliable and accurate vulnerability map for Shahrekord aquifer using fewer layers and applying locally adjusted weights.

# Chapter 3

# Material and Methods

## 3.1 Study area

This research was conducted in Chaharmahal-Bakhtiari Province, Shahrekord aquifer, located at southwest Iran. The Shahrekord plain is situated between 32°7′ N and 32°35′ N latitudes and 50°38′ E and 51°10′ E longitudes. Figure 3.1 displays the location and boundary of Shahrekord plain in Chaharmahal-Bakhtiari province.


Figure 3.1: Location and boundry of Shahrekord plain

The Shahrekord aquifer has an area of 270 square kilometers. Majority of the study area is agricultural land with extensive fertilizer application and the rest is urban area, river, and trees. Based on the topographic maps of the region, highest ground elevation in the area is 2502 m, with the lowest point being 2014 m above sea level. The area has a main river flowing from north to south with some seasonal tributaries and remains dry for much of the year. Therefore, Shahrekord aquifer is the primary source of water supply in the region. This aquifer is unconfined and watertable depth varies from 4 m to 33 m and the transmissivity estimated from piezometer tests ranges from 100 to 1500 $m^2/d$. The aquifer thickness increases towards the center of catchment and reaches 167 m below the river channel [69]. The area includes 587 pumping wells with a total annual discharge of $137.22 \times 106$ $m^3$/year which 393 of these wells are used for irrigation, 125 are used for industrial purposes, and 69 wells are dedicated to potable supply [69]. For monitoring purposes, water levels are measured monthly in 25 observation wells. Using pumping tests conducted in the water wells, the hydraulic conductivity of the aquifer was estimated at different locations. The hydraulic conductivity varied from 2.5 to 14 m/day. The higher hydraulic conductivity was estimated for the area close to the geological outcrops and the recharge areas where the aquifer materials were mainly course sand, while lower values were identified in the middle of the plain and also close to the exit end of the aquifer, which consisted of finer materials such as silt and clay [47].

## 3.2 Data and DRASTIC method

Groundwater resources have the potential to be contaminated from non-point sources or distributed point sources of pollution, such as pesticides or nitrates from fertilizers in agricultural areas. Groundwater vulnerability index describes the level of vulnerability which is a dimensionless index and function of hydrogeological factors, contamination sources, and anthropogenic effects [84]. In the current study, ArcGIS 10.3.1 was used to create seven layers of the DRASTIC model and to execute the necessary computations in raster format.

### 3.2.1 Depth to Water

The depths to watertable were measured at 25 observation wells in the study area by Water Organization of Shahrekord. The Geostatistical Analyst extension in ArcGIS was used to interpolate the points and create the raster map with a pixel size of 50 m. Due to lack of enough measured points, Kriging method was not applied as an interpolation method. Thus, Inverse Distance Weighting (IDW) and Spline were used to interpolate depth to water points and the impact of interpolation method was investigated on vulnerability index in DRASTIC approach. Based on the rating system recommended in the original DRASTIC model, maps were rated and divided into different classes. Figure 3.2 displays distribution of the locations used for measured watertable depths in Shahrekord plain, interpolated and rated depth rasters using IDW and spline are presented in Figures 3.3 and 3.4.

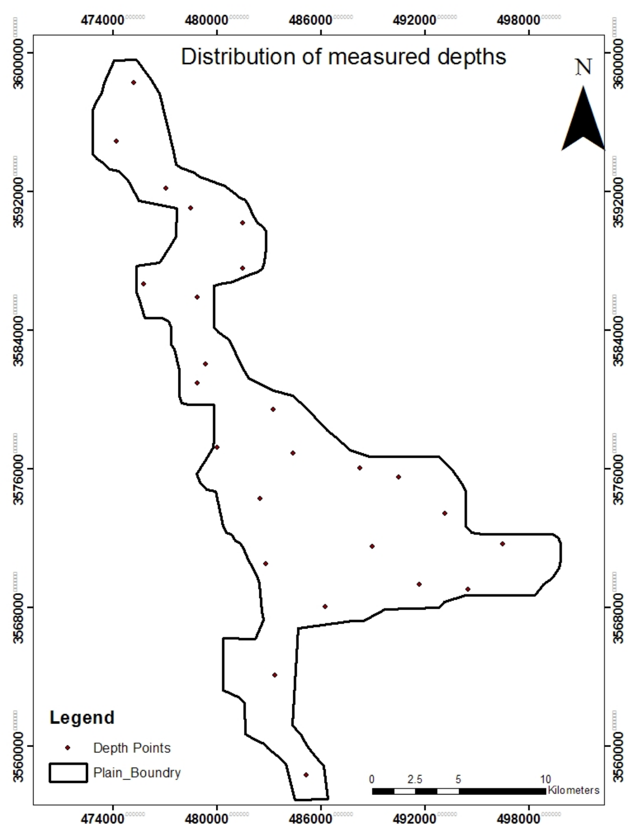



Figure 3.2: Distribution of measured depth points

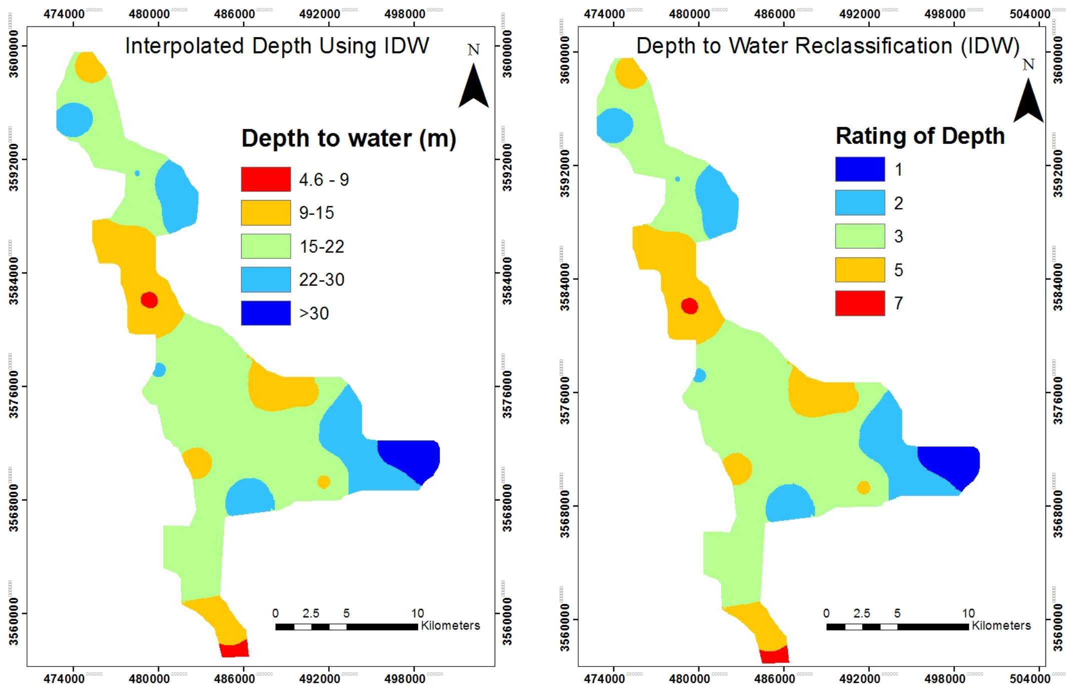



Figure 3.3: Interpolated and rated depth rasters (IDW)

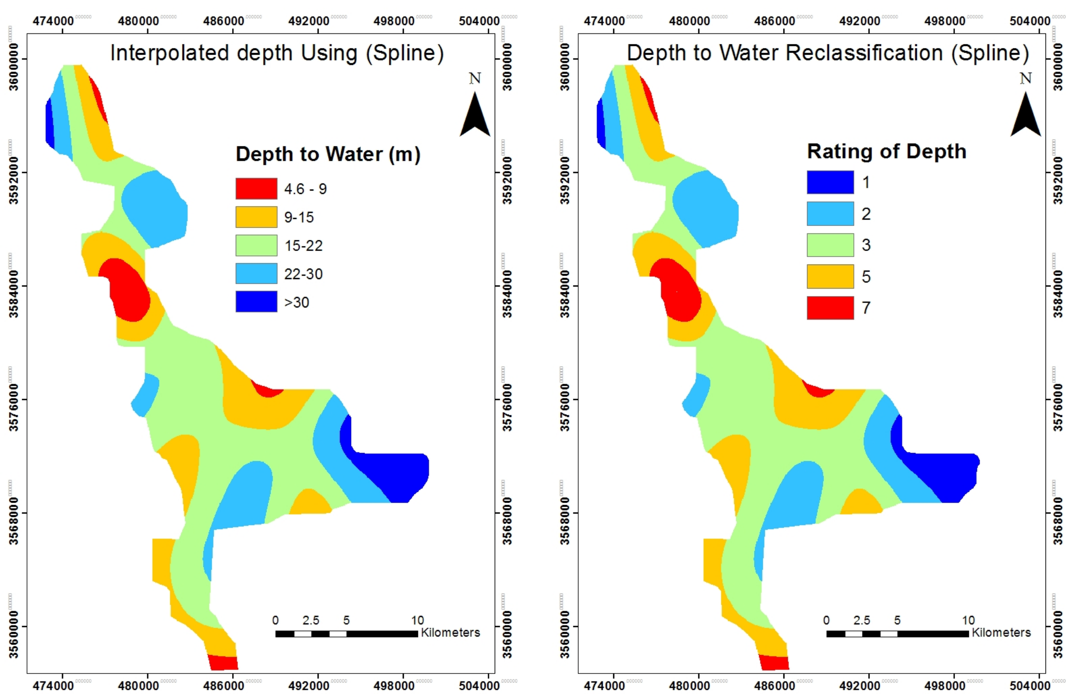



Figure 3.4: Interpolated and rated depth rasters (spline)

The depths to water levels for the Shahrekord plain are classified according the original DRASTIC system, into five classes: 4.6 to 9 m, 9 to 15 m, 15 to 22 m, 22 to 30 m and more than 30 m, with rates ($D_r$) of 7, 5, 3, 2 and 1, respectively.

### 3.2.2 Net Recharge

Precipitation is the main source of groundwater that infiltrates through ground surface to reach watertable. In general, rainfall infiltration, irrigation return flow, and absorption wells are defined as the net recharge [7]. Recharge would facilitate the transportation of pollution to reach watertable thus, the aquifers with more net recharge have higher vulnerability to contamination. Total net recharge in Shahrekord aquifer, was computed by the Provincial Water Authorities in Shahrekord and the raster GIS file was provided to use for the current study [69]. Figure 3.5 shows this layer along with its rated raster in the study area.

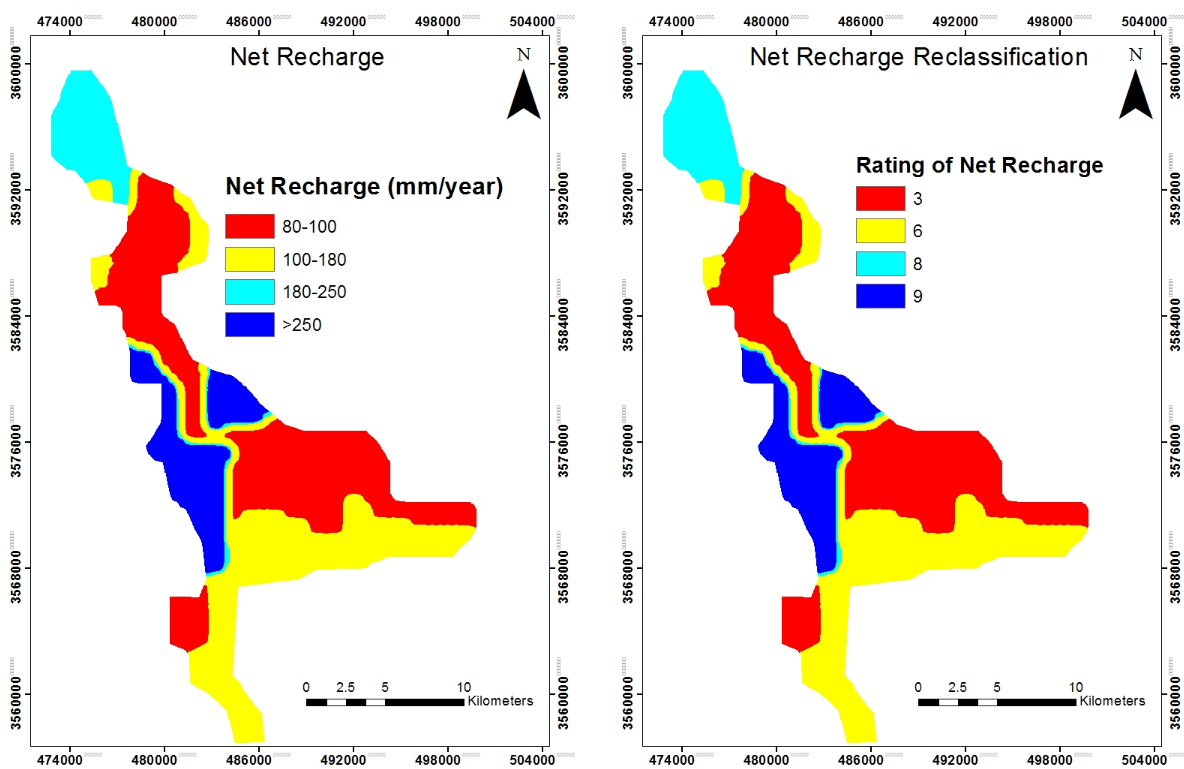



Figure 3.5: Net recharge map and rated raster

Net recharge for the Shahrekord plain are classified according the original DRASTIC system, into four classes: 80 to 100 mm/year, 100 to 180, 180 to 250 mm/year, and more than 250 mm/year, with net recharge rates ($R_r$) of 3, 6, 8, and 9, respectively.

### 3.2.3 Aquifer Media

In this study, classification of aquifer media was determined using a subsurface geology map, geological sections and drilling logs of the Shahrekord aquifer by the Provincial Water Authorities. Aquifer media for the Shahrekord plain is classified according to the original DRASTIC system, into one class which is sand and gravel, with aquifer media rate ($A_r$) of 8. Aquifer media map was also created using ArcGIS which Figure 3.6 displays its raster in the study area.

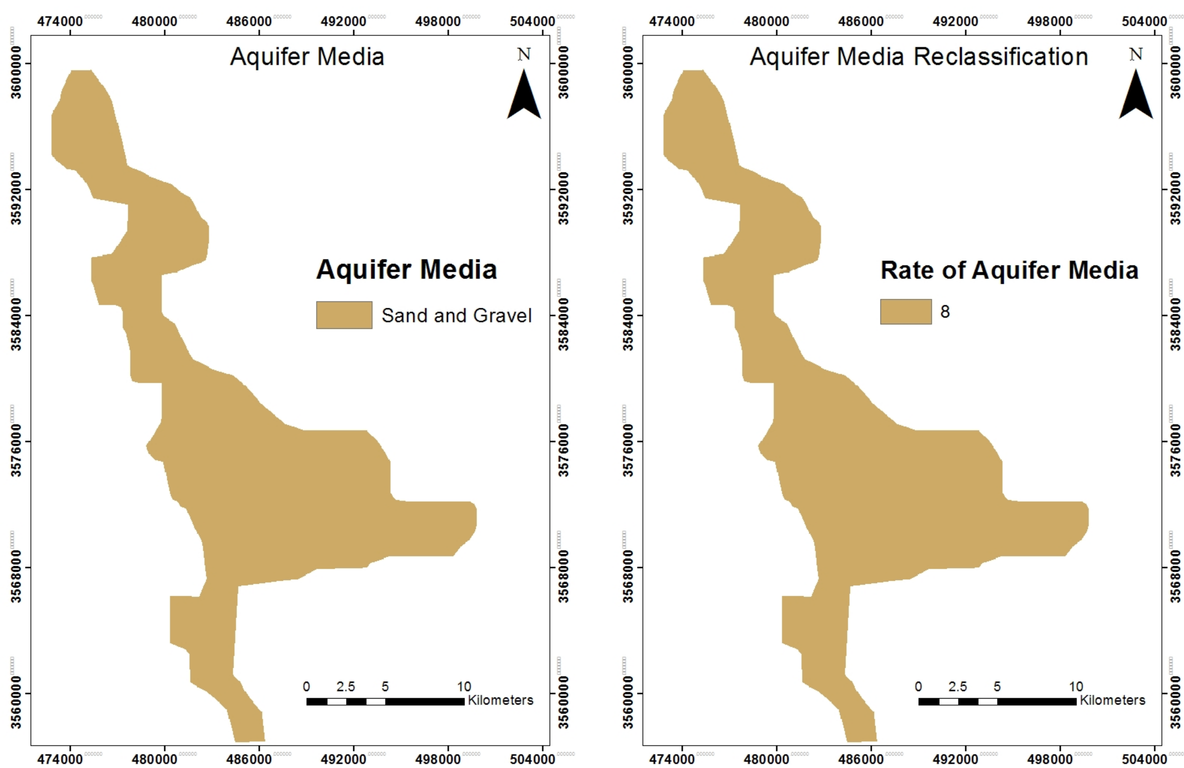



Figure 3.6: Aquifer map and rated raster

### 3.2.4 Soil Media

Soil is considered as the weathered portion above vadose zone which is average 1.8 meter or less [7]. The soil type is important in terms of amount of net recharge which can reach the groundwater system. In fact, pollution potential of soil is mainly affected by the type of clay and grain size of soil. Thus, more clay and smaller grain size implies less amount of pollution potential [7]. The soil map was used from Soil and Water Institute of Shahrekord and ratings were assigned according to the original DRASTIC system. Based on this classification, coarse soil media have high rates in comparison to fine soil media. Soil media for the Shahrekord plain is classified into three classes which is clay loam, sandy loam and peat with soil media rate ($S_r$) of 3, 6 and 8 as displayed in Figure 3.7. It should be noted that Aller in 1987 emphasized that the maximum rate belonged to gravel, sand, and sandy loam. Based on the soil media layer, sandy loam was located in majority of regions in the study area.

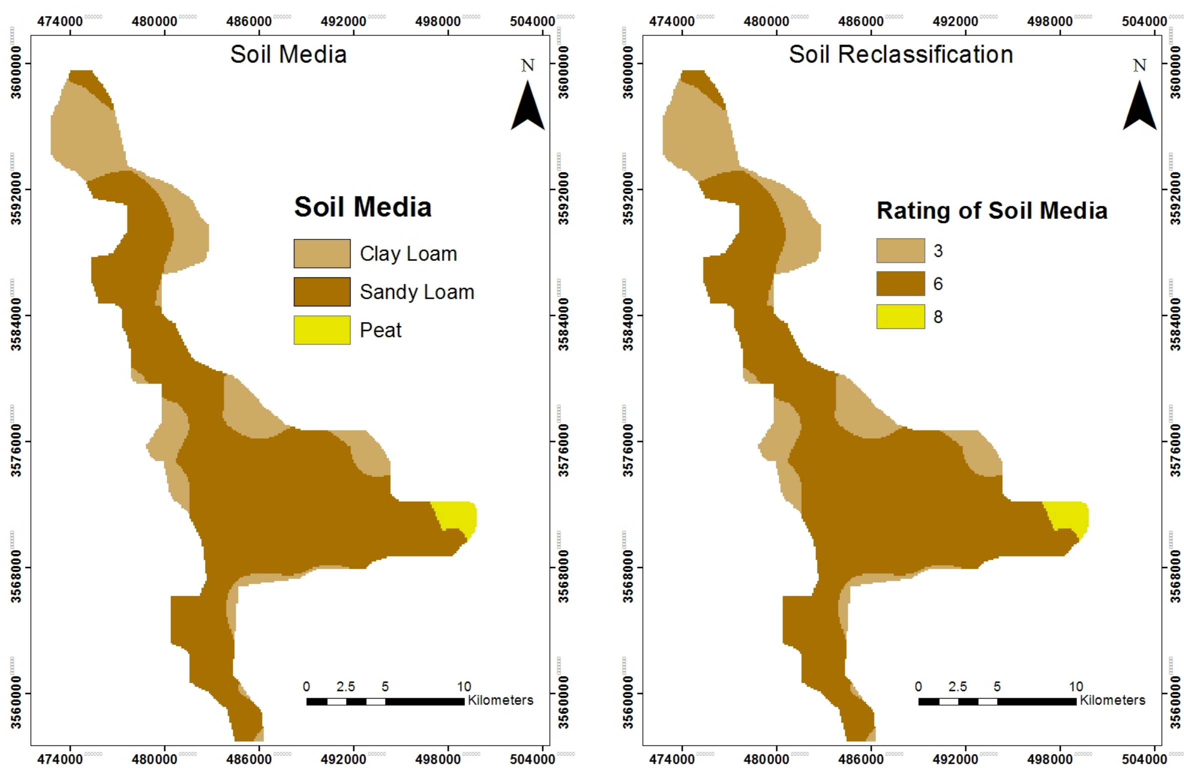



Figure 3.7: Soil map and rated raster

### 3.2.5 Topography

Topography indicates the slope of land which controls the probability that a pollutant will run off or remain on surface to infiltrate [7]. Steeper topographic surfaces are less vulnerable to contamination. The topography was derived from the Digital Elevation Model and slope was computed using Spatial Analyst tools in ArcGIS. Then, the obtained slope map was divided into five classes, which were mostly found in areas with slopes ranging from 0 to 2 percent which seems reasonable since, the area is mostly agricultural regions. The classes are 0 to 2 percent, 2 to 6, 6 to 12, 12 to 18 and higher than 18 percent with slope rate ($T_r$) of 10, 9, 5, 3 and 1. Figures 3.8 and 3.9 display topography and slope maps respectively in Shahrekord plain.

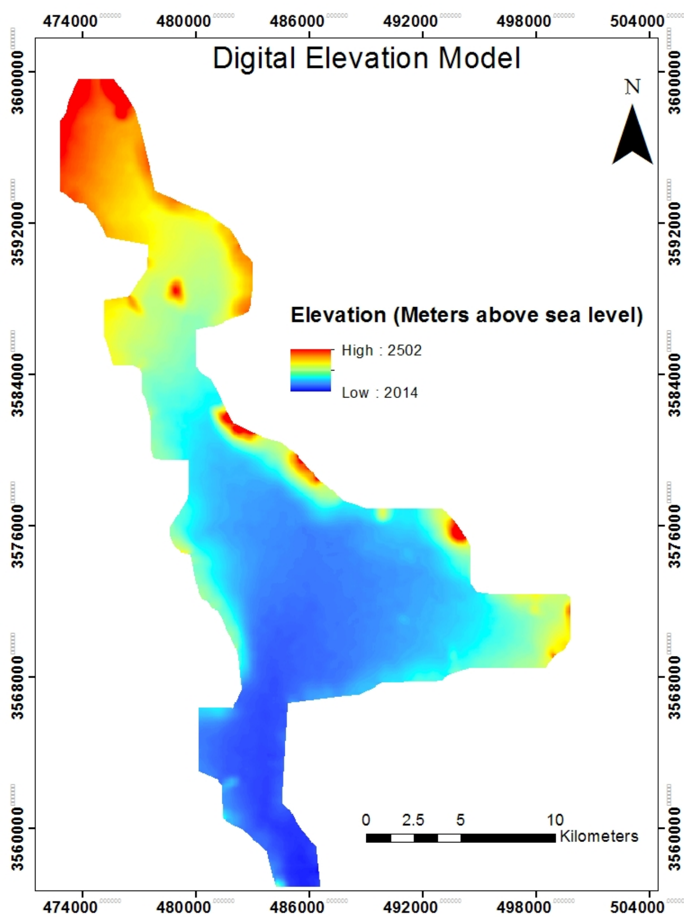



Figure 3.8: Topography map

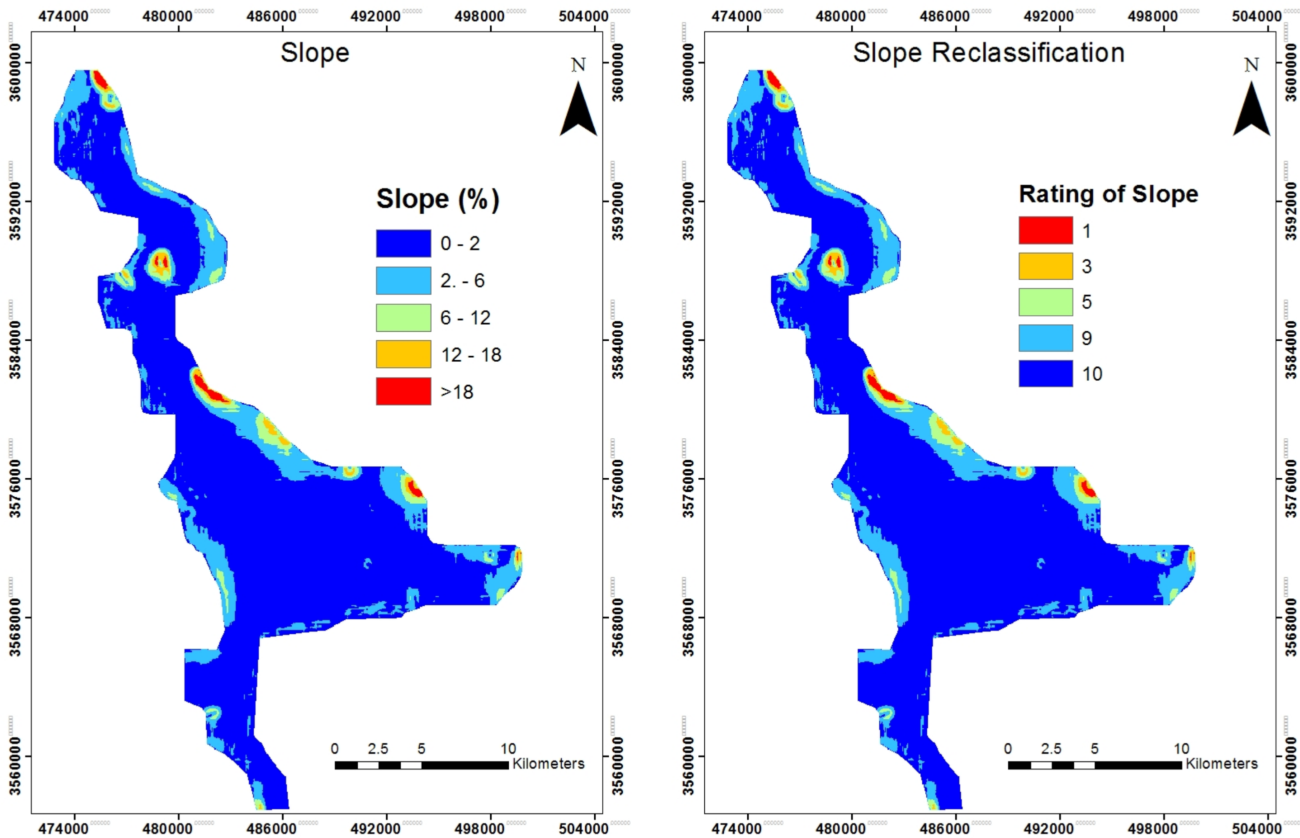



Figure 3.9: Slope map and rated raster

### 3.2.6 Impact of Vadose Zone

Vadose zone is defined as unsaturated zone above watertable [7]. The impact of vadose zone was classified based on the drilling logs in Shahrekord plain by the Provincial Water Authorities. The most significant part of the area included bedded limestone and sandstone. Therefore, impact of vadose zone was divided into one class, which is bedded limestone and sandstone with impact of vadose zone rate ($I_r$) of 6. Figure 3.10 displays impact of vadose zone layer in Shahrekord plain.

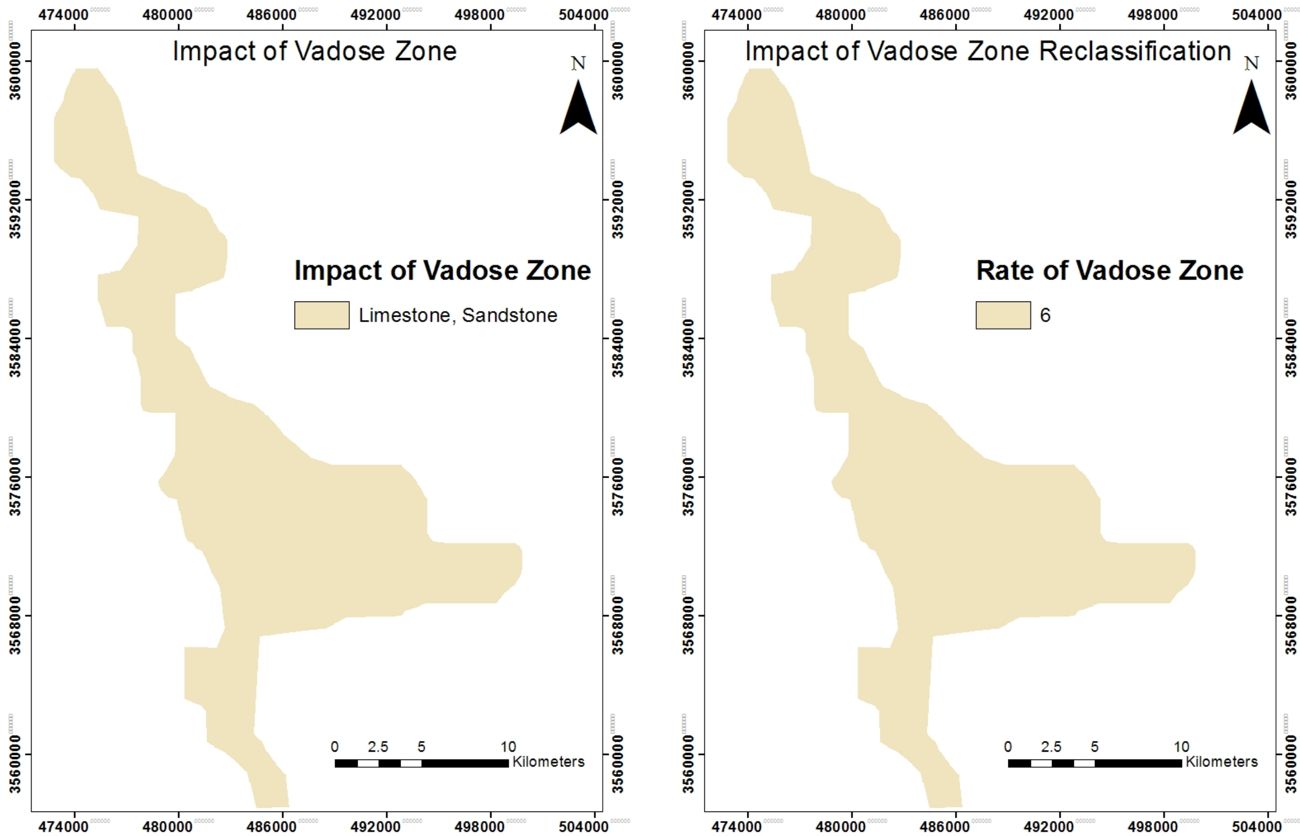



Figure 3.10: Impact of vadose zone map and rated raster

### 3.2.7 Hydraulic Conductivity

In Shahrekord plain, hydraulic conductivity distribution map was generated using pumping test results and a geoelectrical study of the area by Provincial Water Authorities. Areas with high levels of hydraulic conductivity can have higher vulnerability to contamination. Hydraulic conductivity for Shahrekord plain was provided in raster GIS file for using in the current study which were classified according to the original DRASTIC system, into three classes: 2.5 to 5 m/day, 4 to 12, 12 to 14 m/day, with hydraulic conductivity rates ($C_r$) of 1, 2 and 4, respectively. Figure 3.11 displays hydraulic conductivity layer in Shahrekord plain.

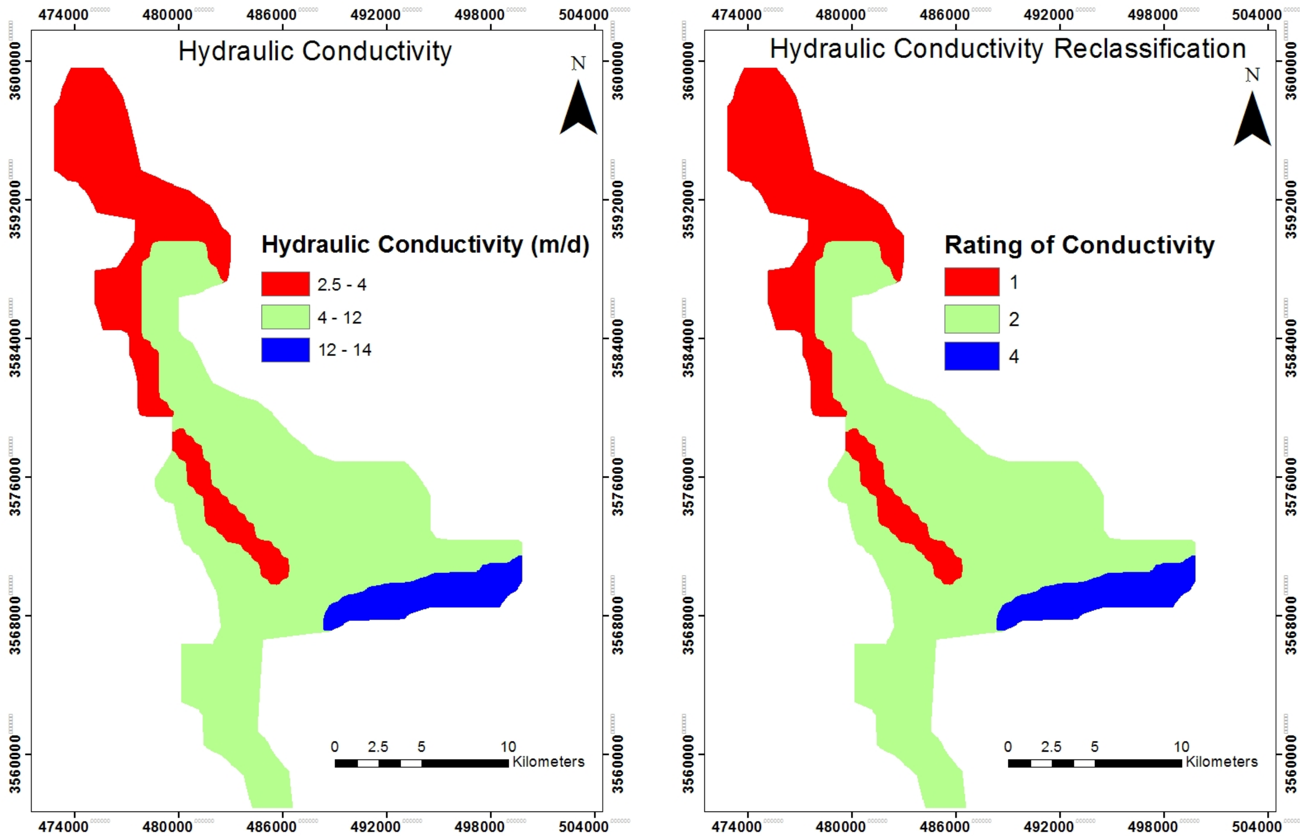



Figure 3.11: Hydraulic conductivity map and rated raster

## 3.3 Nitrate measurements

Since the majority of Shahrekord plain is agricultural with extensive fertilizer application, therefore nitrate concentration was selected as the main parameter representing the extent of aquifer pollution. Nitrate has high solubility and mobility which can easily reach groundwater system even in deep depths. Two monitoring events in 2007 for agricultural wells, were selected for the construction, analysis and assessment of the original and modified DRASTIC models in this study. For using nitrate concentration for adjustment and verification purposes, the result of crop rotation in different years and the effect of applying various levels of nitrate fertilizer for different crops was considered to be averaged and uniform across the study area. The first set of samples, a total of fifteen samples, was obtained in May 2007 and was used for validation purposes and to determine the correlation coefficient between the nitrate concentrations and groundwater vulnerability. The second set of samples was obtained in July 2007 and was used for modification of DRASTIC model which were a total of seventeen samples. The geographic positions of each well was determined using GPS techniques and presented in Figure 3.12.

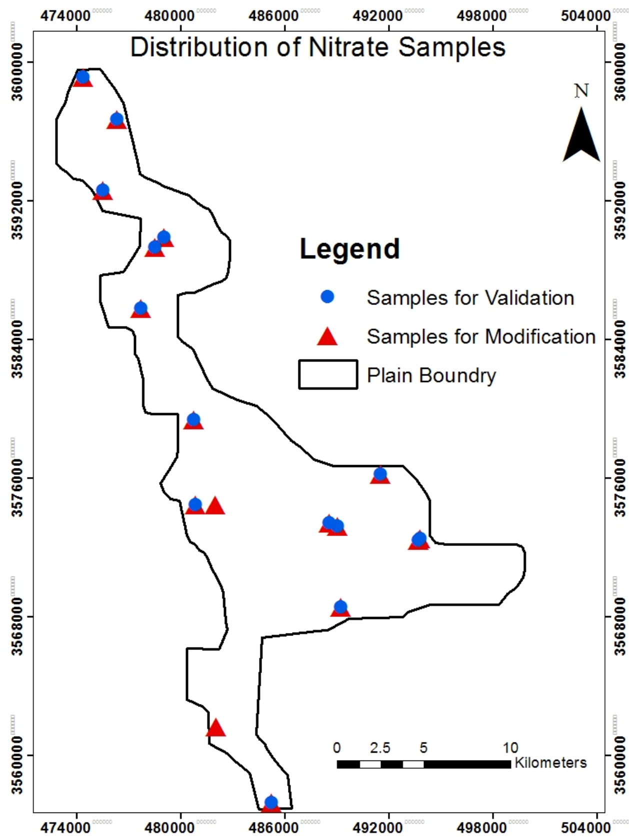



Figure 3.12: Location of nitrate samples

## 3.4 Validation methods

Lack of a standard validation method is one of the common reason to criticize DRASTIC approach. In Shahrekord plain, agriculture is the primary activity and since nitrate does not exist in groundwater naturally, therefore it can be considered as a good indicator of pollution. As it was mentioned above, in the current research, nitrate concentration was measured in 15 monitoring wells in May 2007 in order to verify DRASTIC, modified

DRASTIC and reduced models to show whether the vulnerability maps appropriately represent the actual situation in the study area. This set of data was different from the set used for model modification purpose. Vulnerability index would increase with the increasing nitrate concentration in the region. Two methods were used to validate the obtained models as describe in the below:

### 3.4.1 Pearson's correlation coefficient

Pearson's correlation coefficient (r), as a measure of the linear dependence between two variables, was calculated between vulnerability indices and observed nitrate concentrations.

### 3.4.2 Chi-square value

The association of one map with another can be measured and described quantitatively which is generally useful in a descriptive sense. In the current study, spatial correlation between DRASTIC map and nitrate map was measured as an area cross-tabulation, with classes of one map being the rows, and the classes of the second map being the columns. An area cross-tabulation is a two-dimensional table summarizing the areal overlap of all possible combination of the two input maps. The chi-square statistic is a measure to quantity the degree of association between two maps, the calculations are based on the number from the area cross-tabulation. The area table between map A and map B called matrix T, with elements $T_{ij}$, where there are i=1,2,..,n classes of map B (rows of the table) and j=1,2,..,m classes of map A (columns of the table). The marginal totals of T are defined as $T_{i.}$ for the sum of the i-th row, $T_{.j}$ for the sum of the j-th column, and $T_{..}$ for the grand total summed over rows and columns [19]. The expected area in each overlap category is given by the product of marginal totals, divided by grand total. Thus the expected area $T_{ij*}$ for the i-th row and j-th columns is obtained from Eq. 3.1:

$$T^*_{ij} = \frac{T_{i.}.T_{.j}}{T_{..}} \tag{3.1}$$

Then the chi-square statistic is defined as Eq. 3.2:

$$\chi^2 = \sum_{i=1}^{n} \sum_{j=1}^{m} \frac{(T_{ij} - T^*_{ij})^2}{T^*_{ij}} \tag{3.2}$$

similar to the classical chi$^2$ definition (observed-expected)$^2$/expected expression, which has a lower limit of 0 when the observed areas exactly equal the expected areas and the two maps are completely independent [19]. As the observed areas become increasingly different from the expected areas, chi-square increases in magnitude and has a variable upper limit. The chi-square values can provide an exploratory and descriptive measure of spatial correlation between maps. In this research, chi-square test was not used as a statistical test for the significance of the association of the classes of the maps. The calculated chi-square value was considered only as a relative measure representing the association of the classes of the two maps. The overall chi-square value represents the overall association between nitrate map and vulnerability maps and to investigate if the modified model is improving or degrading the results of DRASTIC in a relative mode, since their efficiency relatively were compared by their chi-square value.

## 3.5 Modification methods

There are numerous methods to adjust standard DRASTIC technique that have already been discussed in literature review chapter. For Shahrekord vulnerability assessment, the rates and weights of original DRASTIC were modified using Wilcoxon rank sum non-parametric statistical test and Single Parameter Sensitivity Analysis (SPSA) respectively. There are some essential requirements in using the Wilcoxon rank sum non-parametric statistical test, as a rate adjustment technique. One of the most important condition is that the region must be agricultural. For rate modification, 17 nitrate samples were measured in July 2007 and the rates of each parameters were rescaled based on average amount of nitrate located in each class of rated raster. The highest rate (10) will be assigned to the class with the highest mean of nitrate and other rates were modified linearly based on this relation. It should be noted that the implementation of the sensitivity analysis requires a well-structured database and a GIS capable of manipulating large tables. Impact of each parameter in DRASTIC index was also evaluated by using Single Parameter Sensitivity Analysis (SPSA). The SPSA was used to modify the weight for each layer and comparison with the original weight in the original DRASTIC.

## 3.6 Map removal sensitivity analysis

Map removal sensitivity analysis was applied only for the modified DRASTIC model that showed the highest correlation and similarity with nitrate concentrations. By removing one or more layers at a time, variation of the vulnerability index were computed. In single map removal, vulnerability variation index was calculated upon removal of only one layer at a time. Then, multiple map removal was applied to calculate variation index upon removal of more than one layer. Based on the obtained results from single map removal, the layers with less variation were preferentially removed. According to the results of map removal sensitivity analysis a reduced model with less number of parameters could be suggested. The reduced model could assess aquifer vulnerability using a fewer parameters in comparison with the original DRASTIC model. It should be noted that the DRASTIC index values of reduced model would be smaller than the values of the full model since it considers fewer parameters. Therefore, in order to compare the reduced and full vulnerability models, the reduced model should be rescaled. The ratio of lowest (highest) vulnerability index in reduced model to the lowest (highest) vulnerability index in the full model were determined. Then the average of calculated ratios were used to rescale of vulnerability indices in the reduced model. It should be noted that, the reduced model was also validated with a different set of observed nitrate concentrations measured in May 2007.

# Chapter 4

# Results and Discussion

## 4.1 Original DRASTIC model

All seven required layers for DRASTIC vulnerability evaluation were created using ArcGIS; each layer was classified and rated using the rating scales based on standard DRASTIC rating system. Among DRASTIC parameters, the depth to water is one of the most important parameter with the weight equal to 5. In order to investigate about the effect of interpolation method used to create this map on the results of vulnerability assessment, two different interpolation methods; Inverse Distance Weighting (IDW) and Spline were used to interpolate the depth to water table measured in 25 wells. DRASTIC map was constructed using both interpolated water depth maps and other six parameters. DRASTIC (IDW) refers to DRASTIC map obtained from interpolated water depth points using IDW and other six parameters. Similarly, DRASTIC (spline) refers to the DRASTIC vulnerability map obtained by interpolated water depth map using spline method along with other six layers. Then, DRASTIC index which is a dimensionless index, was determined by multiplying the rated rasters with the weight factor. Figures 4.1 and 4.2 present GIS models to compute vulnerability index that were created in Model Builder of ArcGIS. Finally, the obtained index was divided into four classes based on the classification introduced by Aller in 1987 [7]. The intrinsic (original) vulnerability indices and the corresponding area percentages for each class are presented in Figures 4.3 and 4.4.

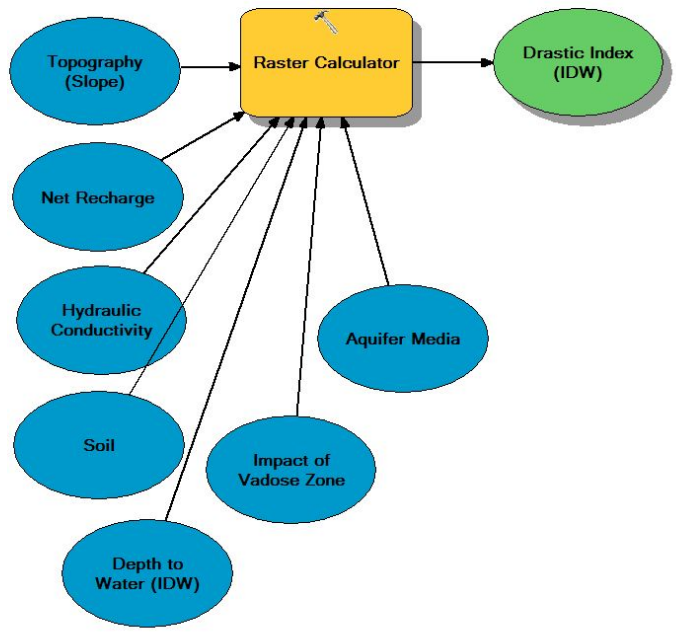



Figure 4.1: GIS model to calculate DRASTIC Index (based on IDW interpolation)

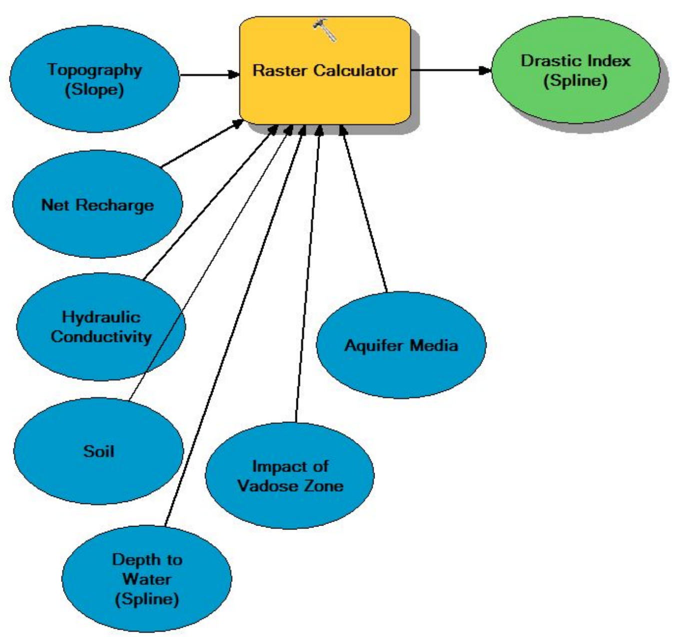



Figure 4.2: GIS model to calculate DRASTIC Index (based on spline interpolation)

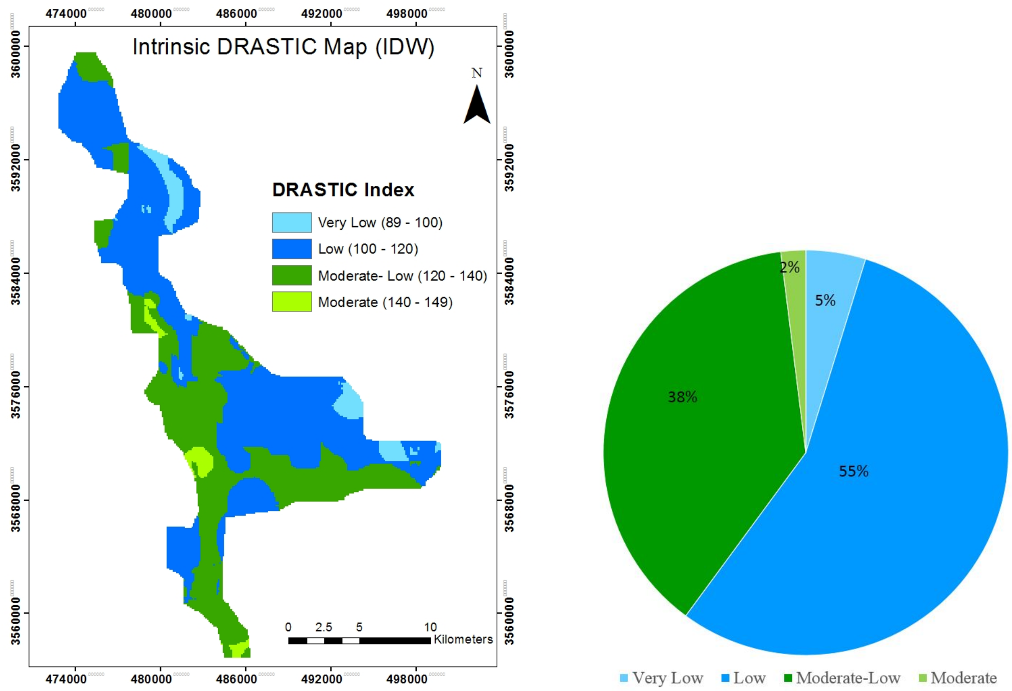



Figure 4.3: Intrinsic vulnerability map and area percentages (IDW)

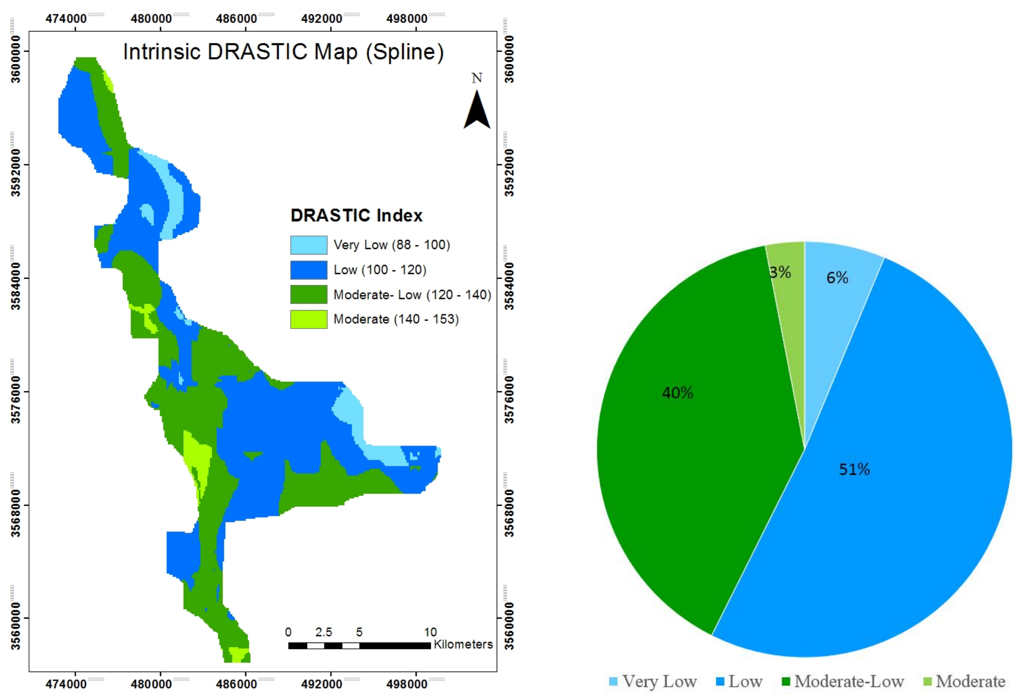



Figure 4.4: Intrinsic vulnerability map and area percentages (spline)

Correlation between original DRASTIC index and nitrate concentrations were used to validate vulnerability map in the study area. For this purpose, the vulnerability index in the location of wells were extracted, then Pearson's correlation was calculated between DRASTIC indices and nitrate concentrations. As Table 4.1, Figures 4.5 and 4.6 display, the Pearson's correlation coefficient for DRASTIC index (IDW) and DRASTIC index (spline) were -0.24 and -0.3, respectively, showing that the original DRASTIC model could not properly represent the pollution potential and the vulnerability of this aquifer.

Table 4.1: Correlation factors between nitrate concentrations and intrinsic DRASTIC index

| Pearson's Correlation Coefficient | Factor |
|---|---|
| -0.24 | DRASTIC Index (IDW) |
| -0.3 | DRASTIC Index (spline) |

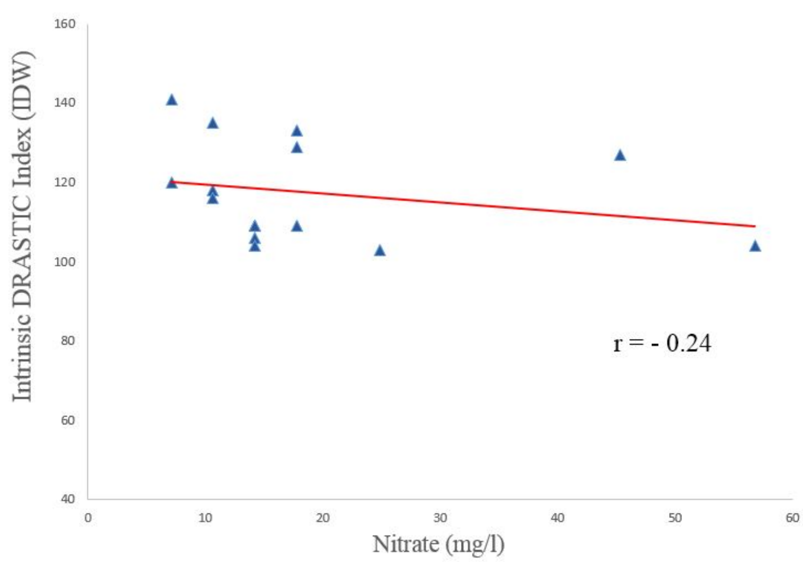



Figure 4.5: Correlation between intrinsic DRASTIC index (IDW) and nitrate

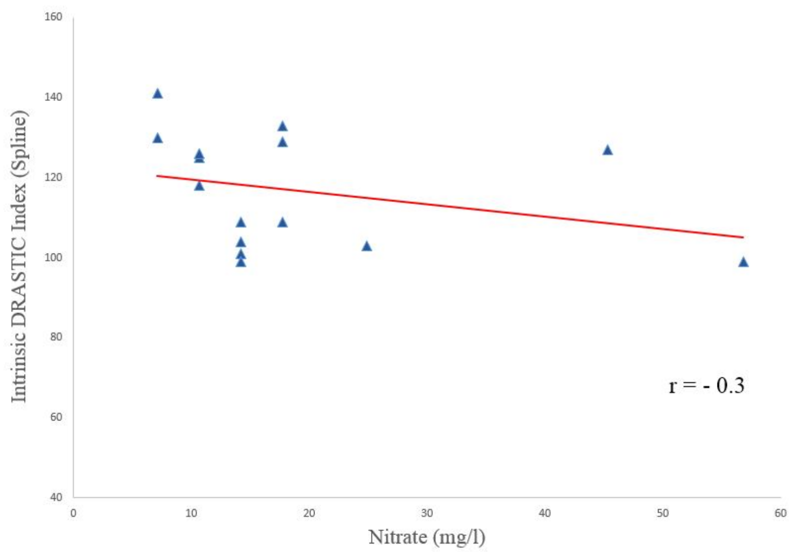



Figure 4.6: Correlation between intrinsic DRASTIC index (spline) and nitrate

In addition to Pearson's correlation, DRASTIC (IDW) and DRASTIC (spline) maps were tested for measuring significant association with nitrate map. For this purpose, nitrate measurements were interpolated using spline interpolation method to create nitrate map, then it was classified based on histogram of nitrate values into eight classes as shown in Figure 4.7.

Moreover, DRASTIC (IDW) and DRASTIC (spline) maps were classified into four classes based on the standard classification introduced by Aller (1987) [7]. The classes include; very low (VL) for vulnerability index (less than 100), low (L) for vulnerability index (100-120), moderate low (ML) for vulnerability index (120-140) and moderate (M) for vulnerability index (140-160). Then, the correlation between DRASTIC (IDW) and DRASTIC (spline) maps with nitrate map were evaluated separately using Spatial Analyst tools (Zonal) in ArcGIS software. The table of area cross-tabulation was the output of correlation analysis in ArcGIS and the table of chi-square values was calculated from the number of area cross-tabulation table using Equation 3.2. Tables 4.3 and 4.5 show the chi-square values calculated from Tables 4.2 and 4.4. The chi-square values for the whole tables were approximately 39.28 and 25.2 for DRASTIC (IDW) and DRASTIC (spline) respectively.

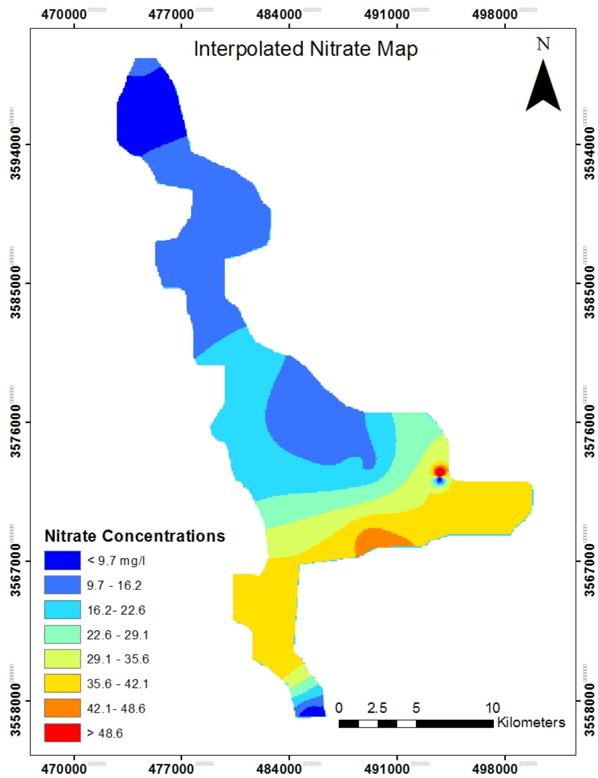



Figure 4.7: Interpolated nitrate map

Table 4.2: Area cross-tabulation between DRASTIC (IDW) and nitrate (km$^2$)

| | Nitrate Class 1 | Nitrate Class 2 | Nitrate Class 3 | Nitrate Class 4 | Nitrate Class 5 | Nitrate Class 6 | Nitrate Class 7 | Nitrate Class 8 | Total |
|---|---|---|---|---|---|---|---|---|---|
| Class VL | 0 | 6.17 | 0.36 | 2.05 | 1.57 | 2.89 | 0 | 0 | 13.05 |
| Class L | 16.26 | 60.31 | 25.45 | 13.44 | 9.4 | 25.6 | 0.35 | 0.3 | 151.13 |
| Class ML | 2.81 | 22.13 | 27.6 | 6.35 | 11.45 | 29.43 | 3.85 | 0 | 103.66 |
| Class M | 0.49 | 1.01 | 1.81 | 2.05 | 0 | 0 | 0 | 0 | 5.38 |
| Total | 19.57 | 89.63 | 55.23 | 23.9 | 22.43 | 57.92 | 4.21 | 0.3 | 273 |

Table 4.3: Chi-square values for DRASTIC (IDW)

| | Nitrate Class 1 | Nitrate Class 2 | Nitrate Class 3 | Nitrate Class 4 | Nitrate Class 5 | Nitrate Class 6 | Nitrate Class 7 | Nitrate Class 8 |
|---|---|---|---|---|---|---|---|---|
| Class VL | 0.93 | 0.83 | 1.96 | 0.73 | 0.23 | 0.005 | 0.2 | 0.01 |
| Class L | 2.72 | 2.32 | 0.84 | 0.003 | 0.72 | 1.29 | 1.68 | 0.1 |
| Class ML | 2.85 | 4.14 | 2.1 | 0.81 | 1.02 | 2.53 | 3.2 | 0.11 |
| Class M | 0.03 | 0.31 | 0.48 | 5.33 | 0.44 | 1.14 | 0.08 | 0.006 |

Table 4.4: Area cross-tabulation between DRASTIC (spline) and nitrate ($km^2$)

| | Nitrate Class 1 | Nitrate Class 2 | Nitrate Class 3 | Nitrate Class 4 | Nitrate Class 5 | Nitrate Class 6 | Nitrate Class 7 | Nitrate Class 8 | Total |
|---|---|---|---|---|---|---|---|---|---|
| Class VL | 0.01 | 7.26 | 0.77 | 2.42 | 2.04 | 4.12 | 0.2 | 0.26 | 17.1 |
| Class L | 12.1 | 47.91 | 25.5 | 14.97 | 11.33 | 27.46 | 0.21 | 0.03 | 139.56 |
| Class ML | 6.47 | 33.06 | 25.43 | 4.51 | 8.67 | 26.14 | 3.78 | 0 | 108.1 |
| Class M | 0.99 | 1.39 | 3.5 | 1.99 | 0.37 | 0 | 0 | 0 | 8.26 |
| Total | 19.57 | 89.63 | 55.23 | 23.9 | 22.43 | 57.74 | 4.21 | 0.3 | 273 |

Table 4.5: Chi-square values for DRASTIC (spline)

| | Nitrate Class 1 | Nitrate Class 2 | Nitrate Class 3 | Nitrate Class 4 | Nitrate Class 5 | Nitrate Class 6 | Nitrate Class 7 | Nitrate Class 8 |
|---|---|---|---|---|---|---|---|---|
| Class VL | 1.2 | 0.48 | 2.08 | 0.56 | 0.29 | 0.07 | 0.01 | 3.22 |
| Class L | 0.43 | 0.09 | 0.26 | 0.62 | 0.001 | 0.14 | 1.73 | 0.09 |
| Class ML | 0.21 | 0.16 | 0.58 | 2.59 | 0.004 | 0.47 | 2.69 | 0.11 |
| Class M | 0.26 | 0.64 | 2.01 | 2.23 | 0.13 | 1.74 | 0.12 | 0.009 |

The larger value of chi-square means that two maps are more spatially dependent. Above results indicated the values of chi-square for DRASTIC (IDW) is larger in comparison with the chi-square calculated for DRASTIC (spline). These values are not helpful in this step because there is no basis for judging how significant these values were but there was a good consistency with the results obtained from Pearson's correlation coefficient.

The comparison between the original DRASTIC values and validation nitrate samples of 15 wells in May 2007 are displayed in Figures 4.8 and 4.9. As the results of correlation showed, the vulnerability mapping for Shahrekord aquifer does not conform to concentrations of nitrate measured in the monitoring wells. This means that the intrinsic vulnerability index calculated by the original DRASTIC model cannot properly represent the pollution potential for this aquifer and must be modified according to specification of study area and nitrate contaminant in order to present a more realistic evaluation of the pollution potential. As the first step, rate modification techniques were applied to calibrate DRASTIC algorithm and then the weights of each parameter were modified using Single Parameter Sensitivity Analysis (SPSA) approach as discussed in the following section.

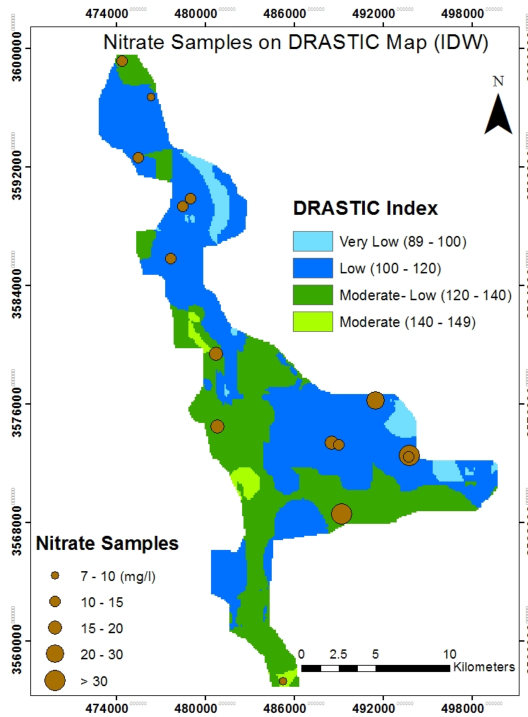



Figure 4.8: Nitrate validation samples on DRASTIC (IDW) map

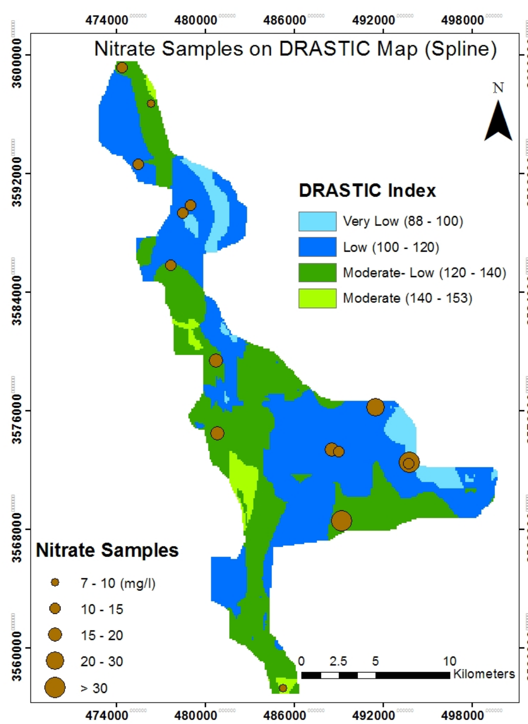



Figure 4.9: Nitrate validation samples on DRASTIC (spline) map

## 4.2 Rate modification using nitrate concentrations

Due to extensive fertilizer application through intense agricultural activities in the region, nitrate concentration is considered as the main source of pollution. The observed nitrate measured at 17 monitoring wells in July 2007 was used to modify the rates of parameters in DRASTIC model. The ranking system derived of Wilcoxon rank sum non-parametric statistical test was used as a rate adjustment technique for vulnerability mapping in the Shahrekord aquifer. The rates of parameters were rescaled based on the average amount of nitrate concentration in each class for each layer, then the highest rate (10) was assigned to the class with the highest mean of nitrate concentration and other rates were modified linearly based on this relation. Aquifer media and impact of vadose zone have only one class in all the region therefore, in the current study, only the rates of the depth to water, net recharge, soil media, topography and hydraulic conductivity were modified based on the mean nitrate concentration. Using 17 samples collected in July 2007, the rates of original DRASTIC were modified. Parameter classes, as well as the corresponding rating of each class, the average nitrate concentrations and the respective modified rating of every class or group of classes are presented in Table 4.6.

Table 4.6: Standard and modified DRASTIC rates based on nitrate concentrations

| Parameter | Range | Standard rate | Mean $NO_3$ (mg/l) | Modified rate |
|---|---|---|---|---|
| Depth to water (Spline) (m) | 4.5-9 | 7 | 17.75 | 5.56 |
| | 9-15 | 5 | 10.65 | 3.33 |
| | 15-22 | 3 | 21.02 | 6.58 |
| | 22-30 | 2 | 15.38 | 4.81 |
| | >30 | 1 | 31.95 | 10 |
| Depth to water (IDW) (m) | 4.5-9 | 7 | 17.75 | 5.88 |
| | 9-15 | 5 | 19.53 | 6.47 |
| | 15-22 | 3 | 17.16 | 5.69 |
| | 22-30 | 2 | 30.18 | 10 |
| | >30 | 1 | No data | 1 |
| Net Recharge (mm) | 80-100 | 3 | 21.3 | 10 |
| | 100-180 | 6 | 17.75 | 8.33 |
| | 180-250 | 8 | 17.75 | 8.33 |
| | >250 | 9 | 14.2 | 6.67 |
| Soil Media | Clay loam | 3 | 22.48 | 10 |
| | Sandy loam | 6 | 18.26 | 8.12 |
| | Peat | 8 | No data | 8 |
| Topography (Slope%) | 0-2 | 10 | 19.64 | 10 |
| | 2-6 | 9 | 14.23 | 7.24 |
| | 6-12 | 5 | No data | 5 |
| | 12-18 | 3 | No data | 3 |
| | >18 | 1 | No data | 1 |
| Conductivity (m/day) | 2.5-4 | 1 | 14.2 | 4 |
| | 4-12 | 2 | 20.24 | 5.7 |
| | 12-14 | 4 | 35.5 | 10 |

In order to compare the rates used to calculate the original and modified-rates DRASTIC index, the statistical summary of rates are provided in Tables 4.7 and 4.8. In original DRASTIC, the highest risk of contamination (mean rates of 8 and 9) of groundwater in Shahrekord aquifer originated from aquifer media and the topography parameters. The soil media, net recharge and impact of vadose zone had moderate risks of contamination (5 and 6) while depth to water and hydraulic conductivity imposed a low risk of aquifer contamination (3 and 1). Depth to water, net recharge and hydraulic conductivity showed moderate variation (CV% are 43, 41 and 39, respectively) while soil media and topography were less variable (CV% are 24 and 14, respectively). In modified-rates DRASTIC, the highest risk of contamination (8 and 9) of groundwater originated from net recharge, aquifer media, soil media and the topography parameters while depth to water, hydraulic conductivity and impact of vadose zone had moderate effect on risk of contamination (5 and 6). Depth to water and hydraulic conductivity were moderately variable (CV% are 30 and 26, respectively) while soil media, net recharge and topography were less variable (CV% are 9, 13 and 17, respectively). Also in both original and modified-rates DRASTIC models, the rate of aquifer media and impact of vadose zone were constant in the whole area.

Table 4.7: Statistical summary of rates in original DRASTIC

| | D (IDW) | D (spline) | R | A | S | T | I | C |
|---|---|---|---|---|---|---|---|---|
| Minimum | 1 | 1 | 3 | 8 | 3 | 1 | 6 | 1 |
| Maximum | 7 | 7 | 9 | 8 | 8 | 10 | 6 | 4 |
| Mean | 3.19 | 3.33 | 5.43 | 8 | 5.32 | 9.51 | 6 | 1.87 |
| SD | 1.11 | 1.44 | 2.25 | - | 1.32 | 1.36 | - | 0.73 |
| CV(%) | 34 | 43 | 41 | - | 24 | 14 | - | 39 |

S.D. stands for standard deviation and CV for coefficient of variation.

Table 4.8: Statistical summary of rates in modified-rates DRASTIC

| | D (IDW) | D (spline) | R | A | S | T | I | C |
|---|---|---|---|---|---|---|---|---|
| Minimum | 1 | 3.33 | 6.67 | 8 | 8 | 1 | 6 | 4 |
| Maximum | 10 | 10 | 10 | 8 | 10 | 10 | 6 | 10 |
| Mean | 6.4 | 5.6 | 8.7 | 8 | 8.56 | 9.19 | 6 | 5.55 |
| SD | 1.87 | 1.7 | 1.15 | - | 0.79 | 1.62 | - | 1.44 |
| CV(%) | 29 | 30 | 13 | - | 9 | 17 | - | 26 |

S.D. stands for standard deviation and CV for coefficient of variation.

All DRASTIC layers except aquifer media and impact of vadose zone were reclassified by ArcGIS, based on new rates which were calculated using nitrate concentrations. The modified-rates DRASTIC (IDW) and modified-rates DRASTIC (spline) indices were calculated and divided into four groups based on Aller's classification. Figures 4.10 and 4.11 display the modified-rates vulnerability maps and their corresponding area percentages. After rate modification and assigning the highest rate (10) to the class with the highest average mount of nitrate, the vulnerability indices increased considerably. It can be justified that vulnerability mapping classes are not absolute and in a relative mode it maps the relative vulnerability of the study area.

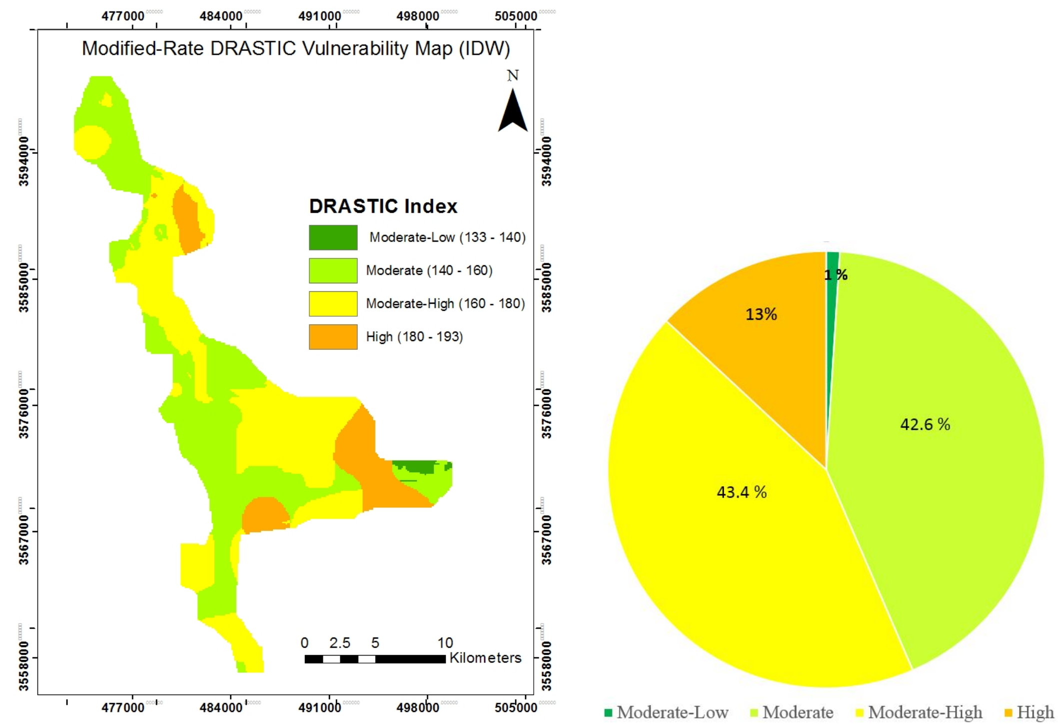



Figure 4.10: Modified-rates DRASTIC (IDW) map and area percentages

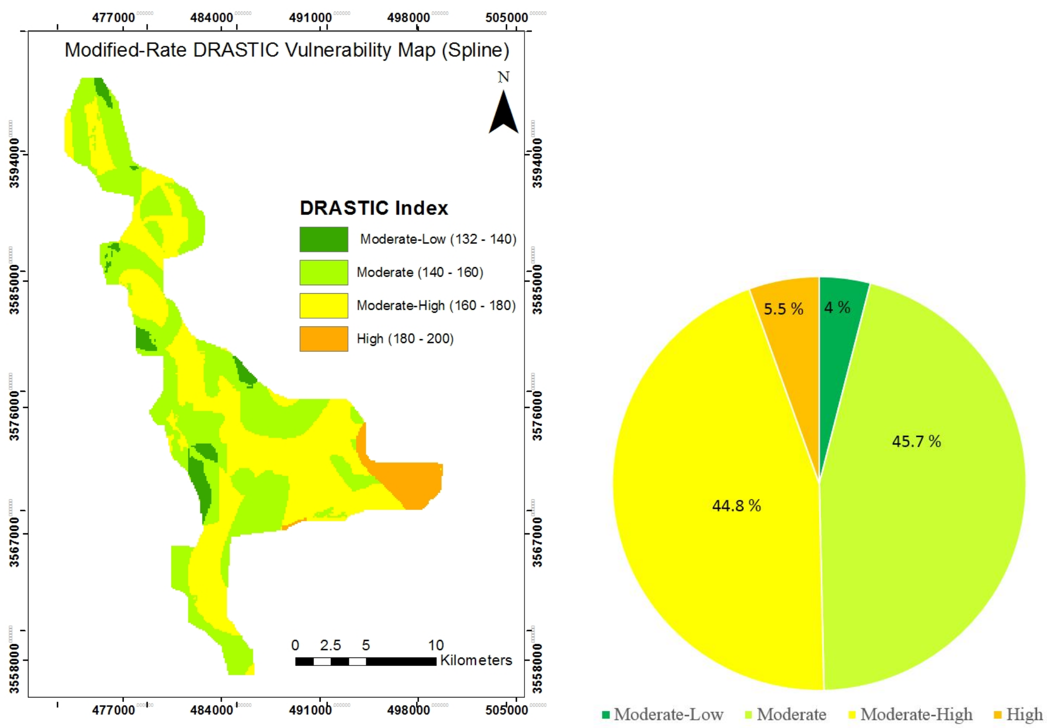



Figure 4.11: Modified-rates DRASTIC (spline) map and area percentages

The modified-rates DRASTIC (IDW) map indicated that 43.4 and 13% of the area belonged to the moderate-high and high vulnerability classes respectively. The percentages for these classes were zero before the rate modification. The percentages for the moderate-low and moderate classes after rate modification were 1 and 42.6 %, respectively, which were 32 and 2% in the original DRASTIC (IDW) model. The same trend was observed when comparing modified-rates DRASTIC (spline) model with original DRASTIC (spline) model.

In order to validate the modified-rates DRASTIC maps, Pearson's correlation between modified-rates DRASTIC index and nitrate concentrations in the 15 monitoring wells were computed. Samples with nitrate values used for this validation are different from the ones applied in DRASTIC modification. The Pearson's correlation for modified-rates DRASTIC index (IDW) and modified-rates DRASTIC index (spline) were computed which increased to 0.64 and 0.84, respectively, as indicated in Table 4.9 and Figures 4.12 and 4.13. The results showed that the modified-rates DRASTIC model now can adequately represent the extent of pollution measured as nitrate concentrations in groundwater. In other words, using modified-rates DRASTIC model, it was possible to obtain a more accurate assessment for groundwater vulnerability in the Shahrekord. Moreover, the results revealed that vulnerability map might vary based on the interpolation method (IDW or spline) used to interpolate depth to water points, since modified-rates DRASTIC (spline) had a higher correlation with nitrate concentrations in compared to modified-rates DRASTIC (IDW) model.

Table 4.9: Correlation factors between nitrate and modified-rates DRASTIC index

| Pearson's Correlation Coefficient | Factor |
|---|---|
| 0.64 | Modified-rates DRASTIC Index (IDW) |
| 0.84 | Modified-rates DRASTIC Index (spline) |

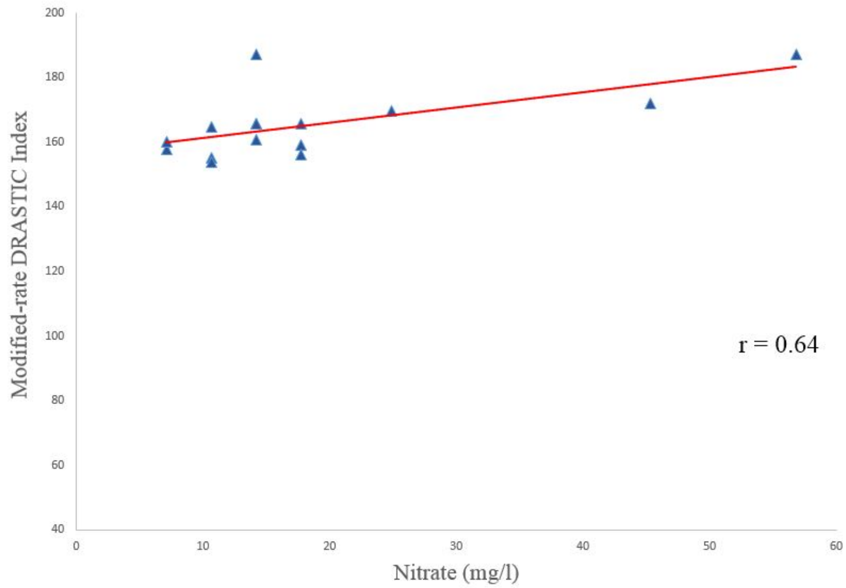



Figure 4.12: Correlation between modified-rates DRASTIC index (IDW) and nitrate

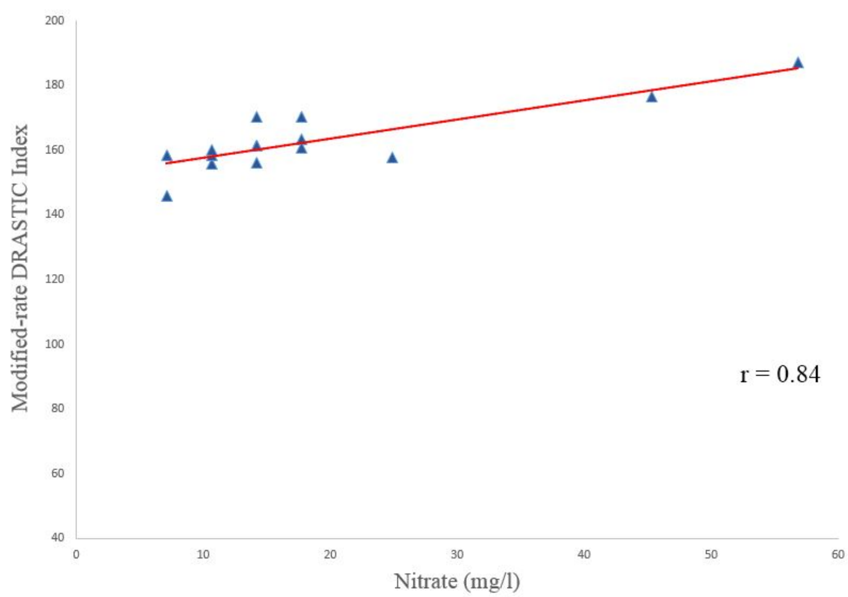



Figure 4.13: Correlation between modified-rates DRASTIC index (spline) and nitrate

To further investigate the accuracy of modified-rates DRASTIC maps, correlation between nitrate map and modified-rates DRASTIC maps were measured. For this purpose, the modified-rates DRASTIC (IDW) and modified-rates DRASTIC (spline) maps were classified based on the standard classification introduced by Aller (1987) into four classes including moderate low (ML) for vulnerability index (120-140), moderate (M) for vulnerability index (140-160), moderate high (MH) for vulnerability index (160-180) and high (H) for vulnerability index (180-200). The classification and creation of nitrate map were discussed in the section of original DRASTIC validation. Tables 4.11 and 4.13 are shown the chi-square values calculated from area cross-tabulation results shown in Tables 4.10 and 4.12. The total chi-square value which is the summation of all values in chi-square table, are approximately 59.04 and 58.34 for modified-rates DRASTIC (IDW) and modified-rates DRASTIC (spline) respectively.

Table 4.10: Area cross-tabulation between modified-rates DRASTIC (IDW) and nitrate ($km^2$)

| | Nitrate Class 1 | Nitrate Class 2 | Nitrate Class 3 | Nitrate Class 4 | Nitrate Class 5 | Nitrate Class 6 | Nitrate Class 7 | Nitrate Class 8 | Total |
|---|---|---|---|---|---|---|---|---|---|
| Class ML | 0 | 0 | 0 | 0 | 0 | 2.75 | 0 | 0 | 2.75 |
| Class M | 13.23 | 31.43 | 29.35 | 9.48 | 10.15 | 22.25 | 0.45 | 0 | 116.37 |
| Class MH | 6.57 | 51.23 | 25.56 | 10.74 | 4.04 | 17.03 | 3.38 | 0 | 118.58 |
| Class H | 0.04 | 6.92 | 0.82 | 3.54 | 8.25 | 15.6 | 0.31 | 0.27 | 35.79 |
| Total | 19.85 | 89.58 | 55.74 | 23.77 | 22.44 | 57.65 | 4.16 | 0.27 | 273 |

Table 4.11: Chi-square values for modified-rates DRASTIC (IDW)

| | Nitrate Class 1 | Nitrate Class 2 | Nitrate Class 3 | Nitrate Class 4 | Nitrate Class 5 | Nitrate Class 6 | Nitrate Class 7 | Nitrate Class 8 |
|---|---|---|---|---|---|---|---|---|
| Class ML | 0.2 | 0.9 | 0.56 | 0.23 | 0.22 | 8.15 | 0.04 | 0.002 |
| Class M | 2.71 | 1.17 | 1.33 | 0.03 | 0.03 | 0.21 | 0.97 | 0.11 |
| Class MH | 0.48 | 3.95 | 0.08 | 0.01 | 3.32 | 2.53 | 1.38 | 0.12 |
| Class H | 2.5 | 1.96 | 5.74 | 0.06 | 9.61 | 8.61 | 0.09 | 1.6 |

Table 4.12: Area cross-tabulation between modified-rates DRASTIC (spline) and nitrate ($km^2$)

| | Nitrate Class 1 | Nitrate Class 2 | Nitrate Class 3 | Nitrate Class 4 | Nitrate Class 5 | Nitrate Class 6 | Nitrate Class 7 | Nitrate Class 8 | Total |
|---|---|---|---|---|---|---|---|---|---|
| Class ML | 0.98 | 3.75 | 3.63 | 1.92 | 0.6 | 0 | 0 | 0 | 10.89 |
| Class M | 12.59 | 49.51 | 27.47 | 7.87 | 9.52 | 17.09 | 0.65 | 0 | 124.73 |
| Class MH | 6.27 | 36.3 | 24.28 | 13.89 | 11.37 | 27.58 | 29.8 | 0.07 | 122.77 |
| Class H | 0 | 0.02 | 0.33 | 0.08 | 0.94 | 12.89 | 0.52 | 0.2 | 15.01 |
| Total | 19.85 | 89.58 | 55.73 | 23.77 | 22.44 | 57.58 | 4.16 | 0.27 | 273 |

Table 4.13: Chi-square values for modified-rates DRASTIC (spline)

| | Nitrate Class 1 | Nitrate Class 2 | Nitrate Class 3 | Nitrate Class 4 | Nitrate Class 5 | Nitrate Class 6 | Nitrate Class 7 | Nitrate Class 8 |
|---|---|---|---|---|---|---|---|---|
| Class ML | 0.04 | 0.009 | 0.89 | 1 | 0.09 | 2.29 | 0.16 | 0.01 |
| Class M | 1.38 | 1.82 | 0.16 | 0.81 | 0.05 | 3.2 | 0.81 | 0.12 |
| Class MH | 0.77 | 0.38 | 0.02 | 0.96 | 0.16 | 0.11 | 0.67 | 0.02 |
| Class H | 1.09 | 4.87 | 2.42 | 1.14 | 0.06 | 29.97 | 0.37 | 2.37 |

As the results of Pearson's correlation coefficient and chi-square value indicated, there was a much higher correlation between modified-rates DRASTIC (IDW) and modified-rates DRASTIC (spline) with nitrate concentrations in comparison with their corresponding correlations in the original DRASTIC models. The correlation coefficient and chi-square value for modified-rates DRASTIC (IDW) were obtained as 0.64 and 59.04 whereas these values were calculated as -0.24 and 39.28 for the original DRASTIC (IDW). Also, for modified-rates DRASTIC (spline), the Pearson's correlation coefficient and chi-square value were calculated as 0.84 and 58.34 whereas these values were -0.3 and 25.2 for the original DRASTIC (spline). The values of chi-square increased after rate modification and it can be concluded that there was more spatial association between modified-rates DRASTIC maps and nitrate map in comparison to the original DRASTIC model. Also, there was a good consistency between the results of Pearson's correlation and chi-square value. As the results demonstrated, the modified-rates DRASTIC model was better able to predict pollutant areas than the original model. Figures 4.14 and 4.15 compare the modified-rates DRASTIC vulnerability maps and the nitrate concentrations visually.

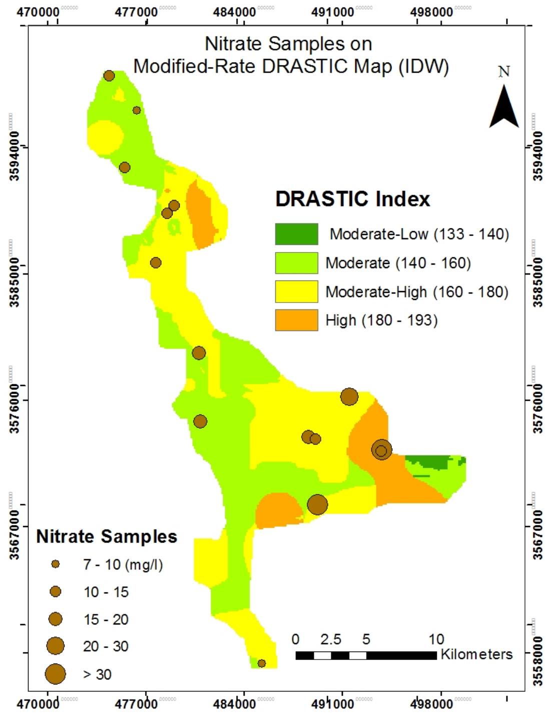



Figure 4.14: Nitrate validation samples on modified-rates DRASTIC (IDW) map

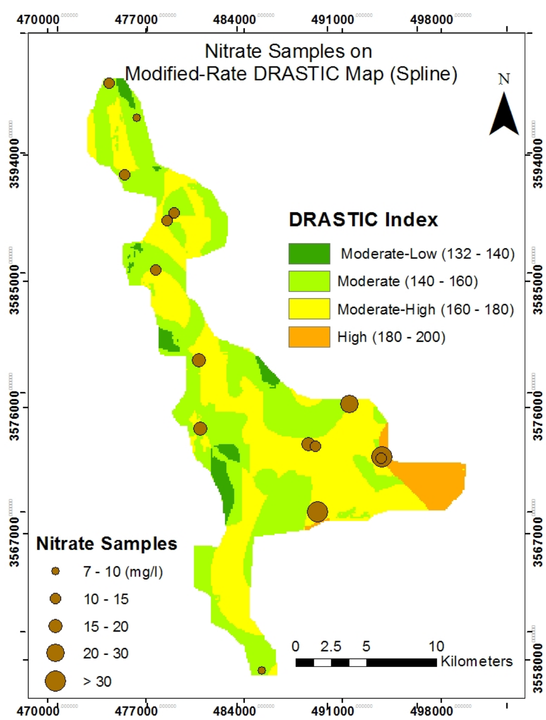



Figure 4.15: Nitrate validation samples on modified-rates DRASTIC (spline) map

## 4.3 Weight modification using SPSA

The weight of each parameter in the original DRASTIC model is assumed constant for whole study area, for instance the weight of depth to water is 5 while it could differ in different parts of study area, depending on the specifications of region. Single Parameter Sensitivity Analysis (SPSA) was applied to compare the modified weight of DRASTIC parameters with their original ones in the original DRASTIC model. As mentioned before, the modified weight is a function of the value of the single parameter with regard to the other six parameters as well as the weight assigned to it by the original DRASTIC model. The modified weights derived from SPSA exhibited some deviation from their original weights as shown in Table 4.14 and 4.15.

Table 4.14: Statistics of SPSA on modified-rates DRASTIC (IDW)

| Parameter | Original weight | Original weight (%) | Modified weight (%) | Modified weight | | | |
|---|---|---|---|---|---|---|---|
| | | | | Mean | Min | Max | S.D. |
| D (IDW) | 5 | 21.74 | 18.2 | 4.42 | 0.79 | 6.25 | 1.04 |
| R | 4 | 17.4 | 20.44 | 4.9 | 4.02 | 5.48 | 0.53 |
| A | 3 | 13.04 | 14.63 | 3.27 | 3.27 | 3.27 | - |
| S | 2 | 8.7 | 11.08 | 2.39 | 2.27 | 2.77 | 0.21 |
| T | 1 | 4.35 | 3.15 | 1.28 | 0.14 | 1.38 | 0.21 |
| I | 5 | 21.74 | 18.28 | 4.2 | 4.2 | 4.2 | - |
| C | 3 | 13.04 | 10.4 | 2.32 | 1.72 | 3.94 | 0.54 |

S.D. refers to the standard deviation.

Table 4.15: Statistics of single parameter analysis on modified-rates DRASTIC (spline)

| Parameter | Original weight | Original weight (%) | Modified weight (%) | Modified weight | | | |
|---|---|---|---|---|---|---|---|
| | | | Mean | Mean | Min | Max | S.D. |
| D (spline) | 5 | 21.74 | 17.33 | 3.97 | 2.58 | 6.1 | 0.98 |
| R | 4 | 17.4 | 21.08 | 5.02 | 4.1 | 5.59 | 0.53 |
| A | 3 | 13.04 | 14.98 | 3.44 | 3.44 | 3.44 | - |
| S | 2 | 8.7 | 10.11 | 2.46 | 1.94 | 2.92 | 0.26 |
| T | 1 | 4.35 | 3.23 | 1.31 | 0.15 | 1.42 | 0.22 |
| I | 5 | 21.74 | 18.72 | 4.3 | 4.3 | 4.3 | - |
| C | 3 | 13.04 | 10.65 | 2.37 | 1.78 | 3.9 | 0.51 |

S.D. refers to the standard deviation.

According to results of weight modification, net recharge had the highest effect in the vulnerability evaluation because it also had the highest mean modified weight among all other parameters. Also, the soil media and aquifer media showed high modified weight (11.08 and 14.63% for DRASTIC (IDW), 10.11 and 14.98% for DRASTIC (spline) that exceeds the original weights assigned by DRASTIC (8.7 and 13.04 %). The rest of the parameters exhibited lower weights compared to the original weights. Using column chart, the value of weights before and after modification can be compared visually as shown in Figures 4.16 and 4.17.

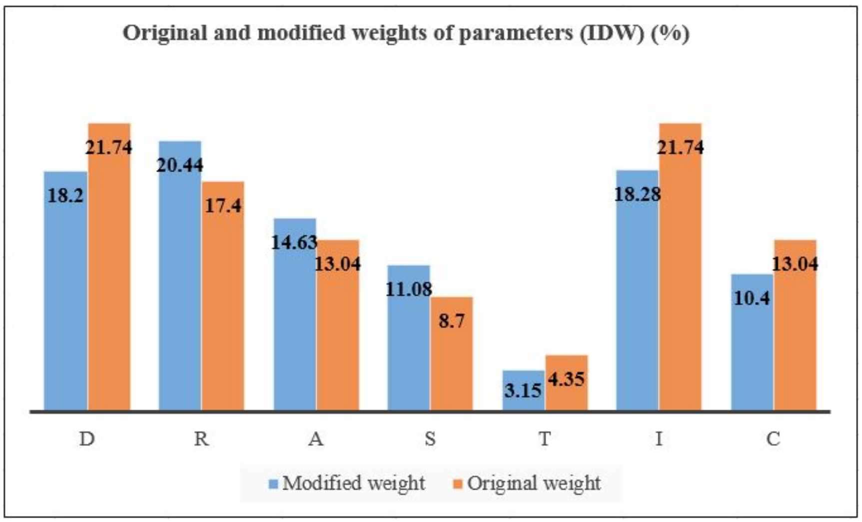



Figure 4.16: Comparison of weights of parameters before and after modification (IDW)

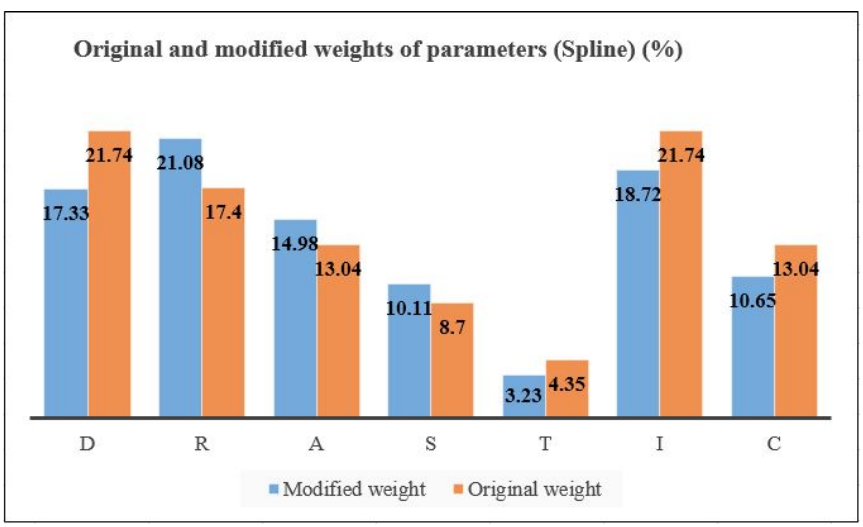



Figure 4.17: Comparison of weights of parameters before and after modification (spline)

All seven DRASTIC parameters were constructed and reclassified based on modified weights in ArcGIS. The modified rate/weight DRASTIC map (MRW DRASTIC) was created using modified rates obtained in previous step and modified weights calculated from SPSA. The MRW DRASTIC (IDW) and MRW DRASTIC (spline) maps were divided into five groups based on Aller's classification as shown in Figures 4.18 and 4.11. The MRW DRASTIC (IDW) and MRW DRASTIC (spline) maps indicated that 11 and 6% of the area belonged to the very high vulnerability class respectively. The percentages for this class was zero in the modified-rates and the original vulnerability maps. Also, the percentages for high class in modified-rates DRASTIC (IDW) and modified-rates DRASTIC (spline) were 13 and 5.5% respectively, while these numbers changed to 15.7 and 20% after weight modification. Moreover, the percentages for moderate and moderate-high classes were declined for MRW DRASTIC (IDW) map to 37 and 25 % respectively. These percentage for MRW DRASTIC (spline) were 35 and 44%, respectively after weight modification.

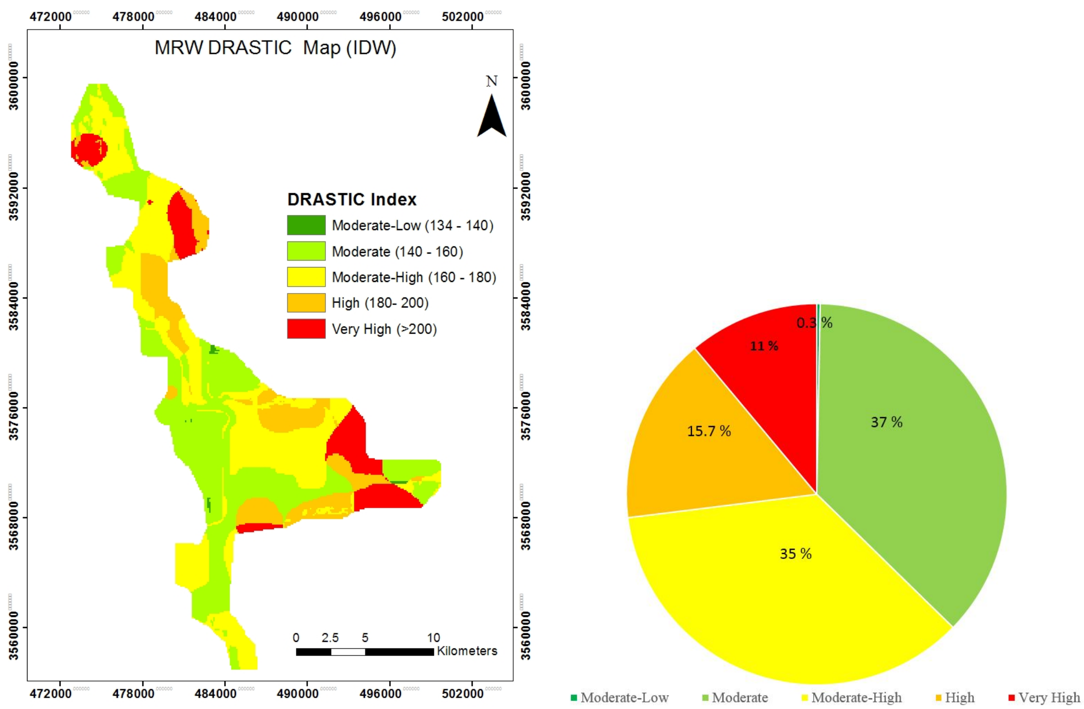



Figure 4.18: MRW DRASTIC map and area percentages (IDW)

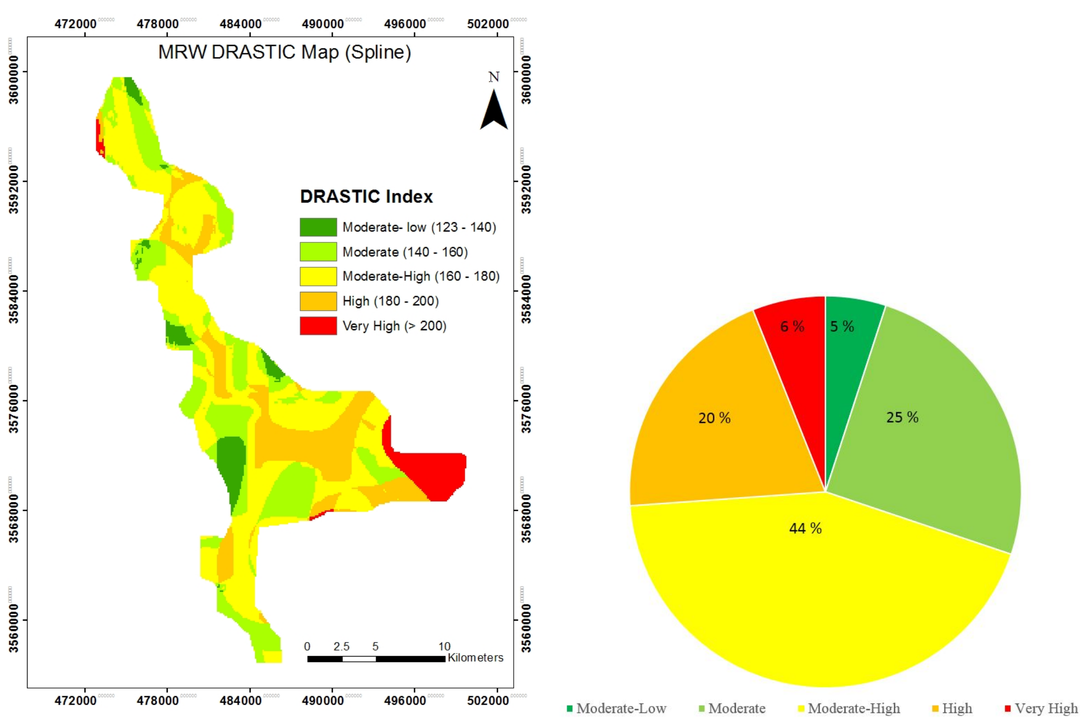



Figure 4.19: MRW DRASTIC map and area percentages (spline)

In order to validate the MRW DRASTIC (IDW) and the MRW DRASTIC (spline) maps, correlation between MRW DRASTIC vulnerability index and 15 nitrate concentrations were computed. Table 4.16 and Figures 4.20 and 4.21 display the results of correlation calculation. The correlation coefficient for both MRW DRASTIC (IDW) and MRW DRASTIC (spline) increased to 0.7 and 0.88, respectively, after weight modification.

Table 4.16: Correlation factors between nitrate and MRW DRASTIC index

| Pearson's Correlation Coefficient | Factor |
|---|---|
| 0.7 | MRW DRASTIC Index (IDW) |
| 0.88 | MRW DRASTIC Index (spline) |

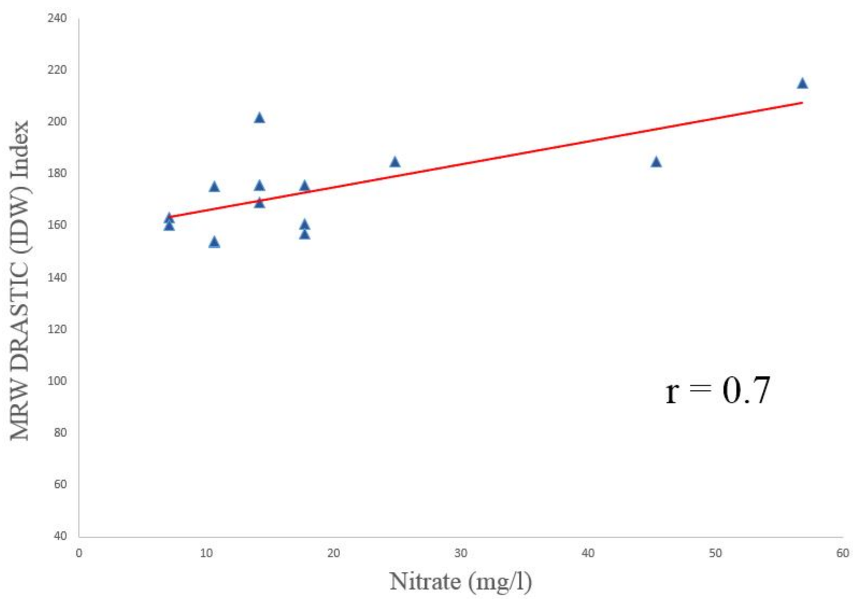



Figure 4.20: Correlation between MRW DRASTIC index and nitrate (IDW)

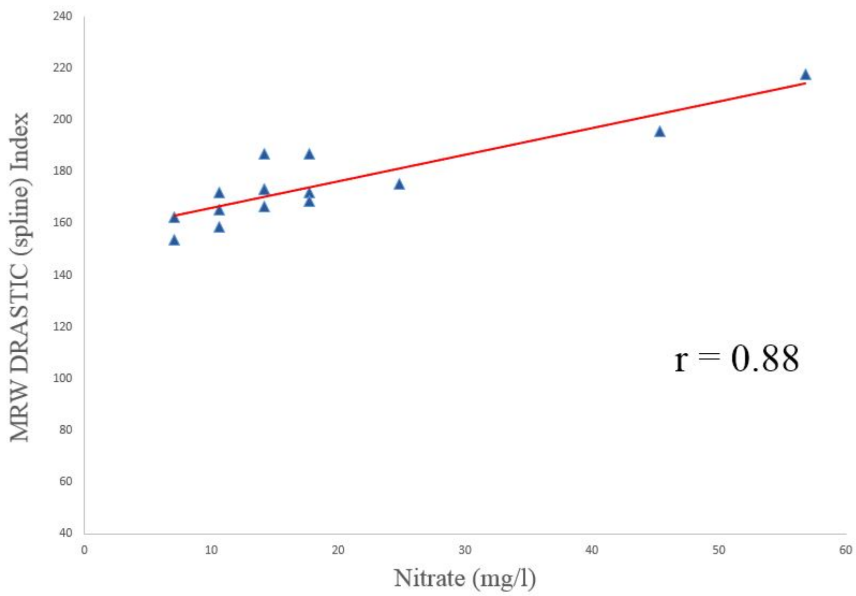



Figure 4.21: Correlation between MRW DRASTIC index and nitrate (spline)

To investigate if there was any improvements in the vulnerability models after weight modification, the models were tested by calculating chi-square for nitrate map with MRW DRASTIC (IDW) and MRW DRASTIC (spline) maps. The MRW DRASTIC (IDW) and MRW DRASTIC (spline) were classified into five classes including; moderate low (ML) for vulnerability index (120-140), moderate (M) for vulnerability index (140-160), moderate high (MH) for vulnerability index (160-180), high (H) for vulnerability index (180-200) and very high (VH) for vulnerability index (above 200). The preparation of nitrate map was the same with previous validation section. Area cross-tabulation table was obtained by using available tools in ArcGIS, then chi-square value table was calculated based on the numbers in cross-tabulation table. Tables 4.18 and 4.20 are shown the chi-square values calculated from Tables 4.17 and 4.19. The chi-square values for the whole tables are approximately 39.38 and 72.93 for MRW DRASTIC (IDW) and MRW DRASTIC (spline) models respectively. The correlation coefficient and chi-square value for MRW DRASTIC (IDW) were obtained as 0.7 and 39.38 whereas these values were calculated as -0.24 and 39.28 for the original DRASTIC (IDW). Also, for MRW DRASTIC (spline), the Pearson's correlation coefficient and chi-square value were calculated as 0.88 and 72.93 whereas these values were -0.3 and 25.2 for the original DRASTIC (spline).

Table 4.17: Area cross-tabulation between MRW DRASTIC (IDW) and nitrate (km$^2$)

| | Nitrate Class 1 | Nitrate Class 2 | Nitrate Class 3 | Nitrate Class 4 | Nitrate Class 5 | Nitrate Class 6 | Nitrate Class 7 | Nitrate Class 8 | Total |
|---|---|---|---|---|---|---|---|---|---|
| Class ML | 0 | 0 | 0.35 | 0.04 | 0.13 | 0.26 | 0 | 0 | 0.79 |
| Class M | 5.05 | 25.3 | 27.7 | 9.36 | 9.43 | 24.3 | 0.6 | 0 | 101.77 |
| Class MH | 9.65 | 37.61 | 21.58 | 9.82 | 4.62 | 14.31 | 0.62 | 0 | 98.25 |
| Class H | 0.7 | 19.94 | 5.49 | 1.29 | 4.27 | 9.09 | 2.61 | 0 | 43.41 |
| Class VH | 4.46 | 6.98 | 0.83 | 3.49 | 3.98 | 10.16 | 0.31 | 0.27 | 30.51 |
| Total | 19.88 | 89.84 | 55.96 | 24.03 | 22.44 | 58.15 | 4.16 | 0.27 | 274 |

Table 4.18: Chi-square values for MRW DRASTIC (IDW)

| | Nitrate Class 1 | Nitrate Class 2 | Nitrate Class 3 | Nitrate Class 4 | Nitrate Class 5 | Nitrate Class 6 | Nitrate Class 7 | Nitrate Class 8 |
|---|---|---|---|---|---|---|---|---|
| Class ML | 0.05 | 0.26 | 0.21 | 0.006 | 0.07 | 0.05 | 0.01 | 0.0008 |
| Class M | 0.72 | 1.91 | 2.34 | 0.02 | 0.15 | 0.35 | 0.56 | 0.1 |
| Class MH | 0.91 | 0.93 | 0.12 | 0.17 | 1.44 | 2.01 | 0.49 | 0.09 |
| Class H | 1.89 | 2.32 | 1.26 | 1.64 | 0.14 | 0.0009 | 5.81 | 0.04 |
| Class VH | 2.3 | 0.9 | 4.65 | 0.25 | 0.88 | 2.12 | 0.04 | 1.98 |

Table 4.19: Area cross-tabulation between MRW DRASTIC (spline) and nitrate (km$^2$)

| | Nitrate Class 1 | Nitrate Class 2 | Nitrate Class 3 | Nitrate Class 4 | Nitrate Class 5 | Nitrate Class 6 | Nitrate Class 7 | Nitrate Class 8 | Total |
|---|---|---|---|---|---|---|---|---|---|
| Class ML | 0.89 | 3.92 | 5.66 | 2.57 | 0.6 | 0.06 | 0 | 0 | 13.72 |
| Class M | 7.28 | 21.11 | 16.86 | 3.9 | 9.15 | 10.6 | 0.18 | 0 | 69.11 |
| Class MH | 10 | 50.75 | 16.62 | 8.51 | 8.8 | 23.67 | 1.56 | 0.07 | 120.03 |
| Class H | 0.68 | 14.02 | 16.46 | 8.94 | 2.92 | 10.3 | 1.89 | 0 | 55.26 |
| Class VH | 1 | 0.02 | 0.32 | 0.08 | 0.94 | 13.43 | 0.52 | 0.2 | 16.54 |
| Total | 19.88 | 89.84 | 55.96 | 24.03 | 22.44 | 58.08 | 4.16 | 0.27 | 274 |

Table 4.20: Chi-square values for MRW DRASTIC (spline)

| | Nitrate Class 1 | Nitrate Class 2 | Nitrate Class 3 | Nitrate Class 4 | Nitrate Class 5 | Nitrate Class 6 | Nitrate Class 7 | Nitrate Class 8 |
|---|---|---|---|---|---|---|---|---|
| Class ML | 0.009 | 0.07 | 2.94 | 1.57 | 0.23 | 2.78 | 0.2 | 0.01 |
| Class M | 1.04 | 0.09 | 0.55 | 0.75 | 2.18 | 1.1 | 0.71 | 0.07 |
| Class MH | 0.2 | 3.36 | 2.5 | 0.37 | 0.1 | 0.11 | 0.03 | 0.01 |
| Class H | 2.73 | 0.9 | 2.41 | 3.48 | 0.55 | 0.16 | 1.34 | 0.05 |
| Class VH | 0.03 | 5.36 | 2.74 | 1.28 | 0.12 | 28.21 | 0.29 | 2.13 |

The larger value of chi-square implies that two maps were more spatially dependent. As the results indicated, the values of chi-square increased after rate and weight modifications. It means that MRW DRASTIC maps can better represent the observed nitrate concentrations in the study area. Both validation results, Pearson's correlation coefficient and chi-square value, demonstrated that MRW DRASTIC (spline) was the best vulnerability map to present contamination situation in the Shahrekord plain. The highest value of Pearson's correlation coefficient (0.88) and chi-square value (72.93) belonged to MRW DRASTIC (spline) map.

The visual comparison between the MRW DRASTIC index values and the nitrate concentrations are displayed in Figures 4.22 and 4.23. The results showed that Pearson's correlation coefficient for the MRW DRASTIC (IDW) increased to 0.7 compared to 0.64 before weight modification. Also, this improvement was remarkable for the MRW DRASTIC (spline), since it increased from 0.84 to 0.88 after weight modification. This values indicated that there are relatively high correlation between obtained modified vulnerability models and nitrate validation samples.

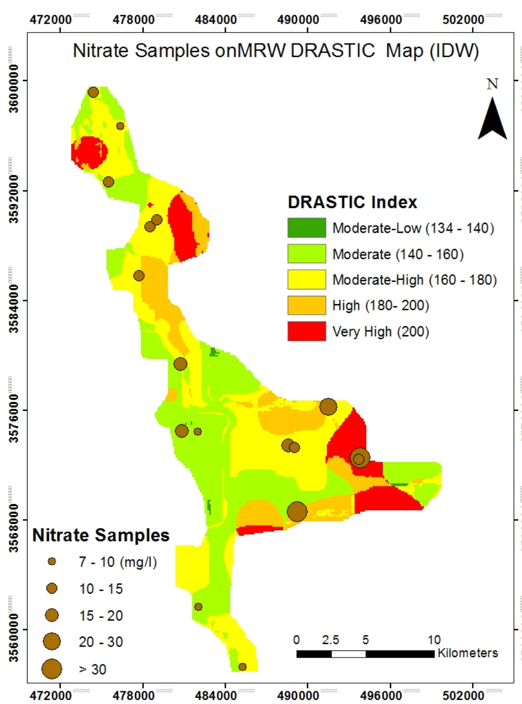



Figure 4.22: Nitrate validation samples on MRW DRASTIC (IDW) map

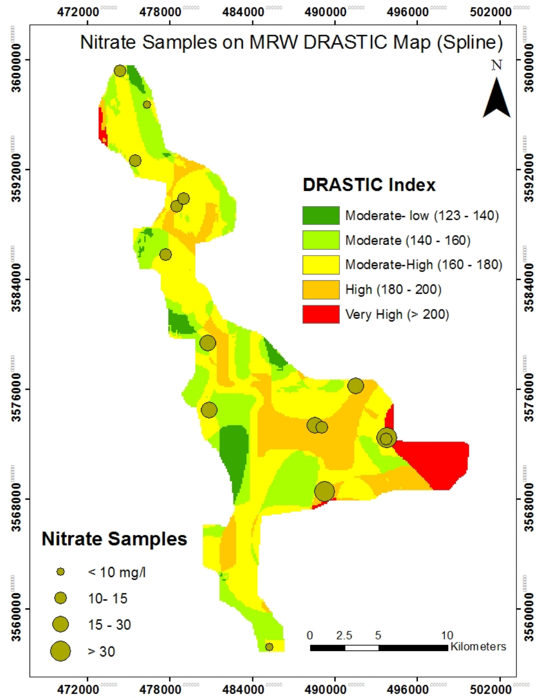



Figure 4.23: Nitrate validation samples on MRW DRASTIC (spline) map

## 4.4 Map removal sensitivity analysis

The map removal sensitivity analysis determines the sensitivity of vulnerability map to remove one or more layers from vulnerability map. This sensitivity can be computed in terms of variation index using the Equation 2.2, as explained in chapter 2. In the current study, the map removal sensitivity analysis were applied for MRW DRASTIC (spline) map which had the best Pearson's correlation coefficient (0.88) and chi-square value (72.93). The results were calculated by removing one or more layers at a time in a stepwise approach. Table 4.21 shows the variation of the vulnerability index as a result of removing only one layer at a time. It is obvious that high variation of the vulnerability index is expected upon the removal of the net recharge parameter from the calculation. This could mainly be attributed to the relatively high modified weight assigned to this layer which was presented in Table 4.15 and the high recharge rate characteristic of the Shahrekord aquifer (mean rating score after rate modification is 8.7).

Table 4.21: Statistics of single map removal sensitivity analysis

| Parameter removed | Variation index(%) | | | |
|---|---|---|---|---|
| | Max | Mean | Min | S.D. |
| Depth to water (D) | 2.83 | 0.86 | 0 | 0.56 |
| Net Recharge (R) | 4.03 | 2 | 0.32 | 0.86 |
| Aquifer Media (A) | 1.35 | 0.39 | 0.02 | 0.25 |
| Soil Media (S) | 4.46 | 0.59 | 0 | 0.38 |
| Topography (T) | 2.36 | 1.15 | 0.54 | 0.35 |
| Impact of Vadose (I) | 1.11 | 0.26 | 0 | 0.2 |
| Hydraulic Conductivity (C) | 1.8 | 1.16 | 0.3 | 0.32 |

In order to apply multiple map removal (removal of more than one layer), the layers were removed based on the results from previous map removal sensitivity measures (Table 4.22). The layers, which had less variation of the final vulnerability index, were preferentially removed. The least average variation index resulted after removing only the impact of vadose zone layer (0.26%). As more layers were excluded from the calculation of the vulnerability index, the mean variation index increased. In general, considerable variation in the vulnerability assessment is expected if a lower number of data layers have been used.

Table 4.22: Statistics of multiple map removal sensitivity analysis

| Parameter used | Variation Index(%) | | | |
|---|---|---|---|---|
| | Max | Mean | Min | S.D. |
| D,R,A,S,T and C | 1.11 | 0.26 | 0 | 0.2 |
| D,R,S,T and C | 2.96 | 0.75 | 0 | 0.57 |
| D,R,T and C | 4.78 | 1.13 | 0 | 0.96 |
| R,T and C | 5.24 | 1.54 | 0 | 1.05 |
| R and C | 9.24 | 3.31 | 0 | 2.18 |
| R | 24.22 | 12 | 1.92 | 5.19 |

After single and multiple map removal, the vulnerability maps were created for all possible cases in ArcGIS. In order to validate the constructed maps, Pearson's correlation coefficients were computed between new vulnerability maps and nitrate concentrations. The results of correlation calculations are displayed in Tables 4.23 and 4.24. The results indicated that removal of aquifer media (A), topography (T) and impact of vadose zone

(I) had the least effect on the correlation coefficient as it expected. It might be concluded that these parameters have less effect than the other layers.

Table 4.23: Correlation between nitrate and vulnerability map obtained from single map removal

| Parameter removed | Pearson's Correlation Coefficient |
|---|---|
| Depth to water (D) | 0.52 |
| Net Recharge (R) | 0.46 |
| Aquifer Media (A) | 0.88 |
| Soil Media (S) | 0.47 |
| Topography (T) | 0.89 |
| Impact of Vadose (I) | 0.88 |
| Hydraulic Conductivity (C) | 0.68 |

Table 4.24: Correlation between nitrate and vulnerability map obtained from multiple map removal

| Parameter(s) removed | Parameter(s) used | Pearson's Correlation Coefficient |
|---|---|---|
| I | D,R,A,S,T and C | 0.88 |
| I and A | D,R,S,T and C | 0.88 |
| I,A and S | D,R,T and C | 0.82 |
| I,A,S and D | R,T and C | 0.52 |
| I,A,S,D and T | R and C | 0.53 |
| I,A,S,D,T and C | R | 0.12 |

Aquifer media (A), Topography (T) and Impact of vadose zone (I) indicated no effect on MRW DRASTIC (spline) index, therefore in order to further investigate the sensitivity of vulnerability map to removing these parameters, MRW DRASTIC (spline) map was constructed only by using Depth to water, Net recharge, Soil media, Hydraulic conductivity layers. Figure 4.24 displays the reduced MRW DRASTIC (spline) map for Shahrekord aquifer which was created by eliminating A, T and I. Comparison of reduced MRW DRASTIC (spline) and full MRW DRASTIC (spline) models in Figure 4.25, it was found that the region of higher vulnerability in both maps was situated in southeastern part of the study area. Nitrate concentration measurements were shown on the same maps for visual comparison.

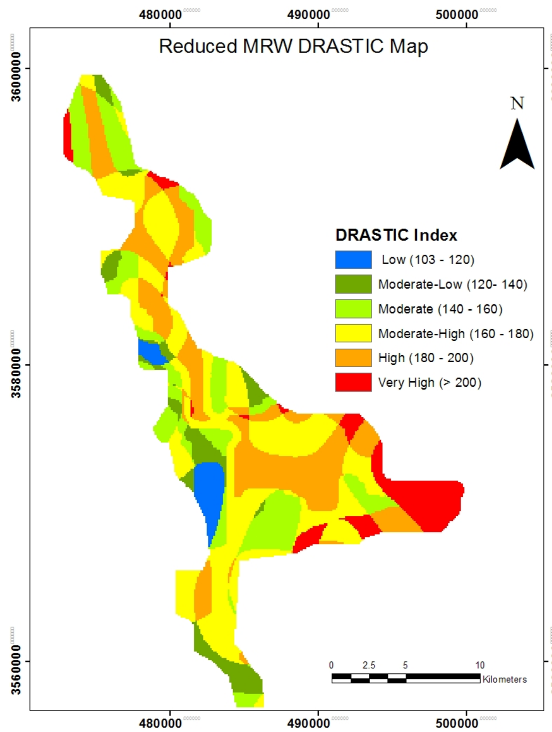
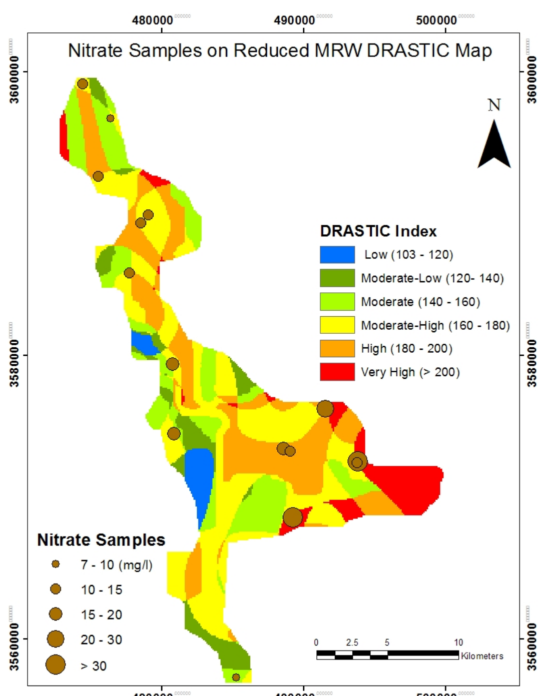



Figure 4.24: Reduced MRW DRASTIC (spline) map



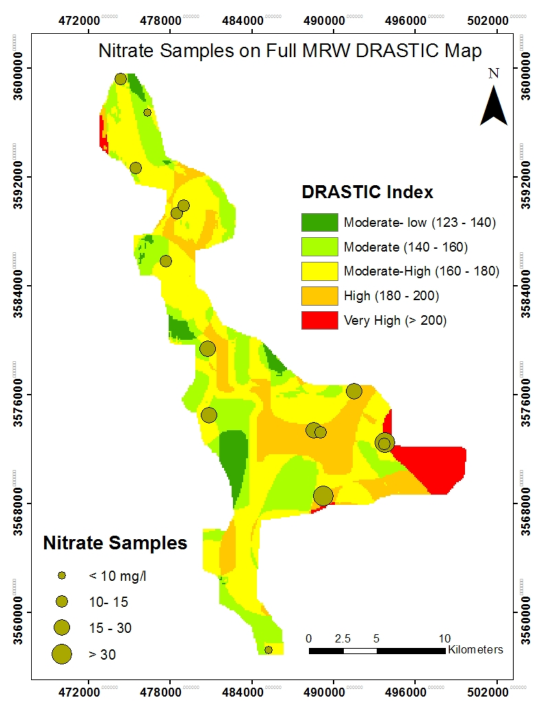




Figure 4.25: Comparison between full and reduced MRW DRASTIC (spline) maps

In order to ensure that the reduced MRW DRASTIC map is reliable enough, it was validated by observed nitrate concentrations. The Pearson's correlation between reduced MRW DRASTIC index and nitrate concentrations demonstrated a high coefficient of 0.88 as displayed in Figure 4.26.

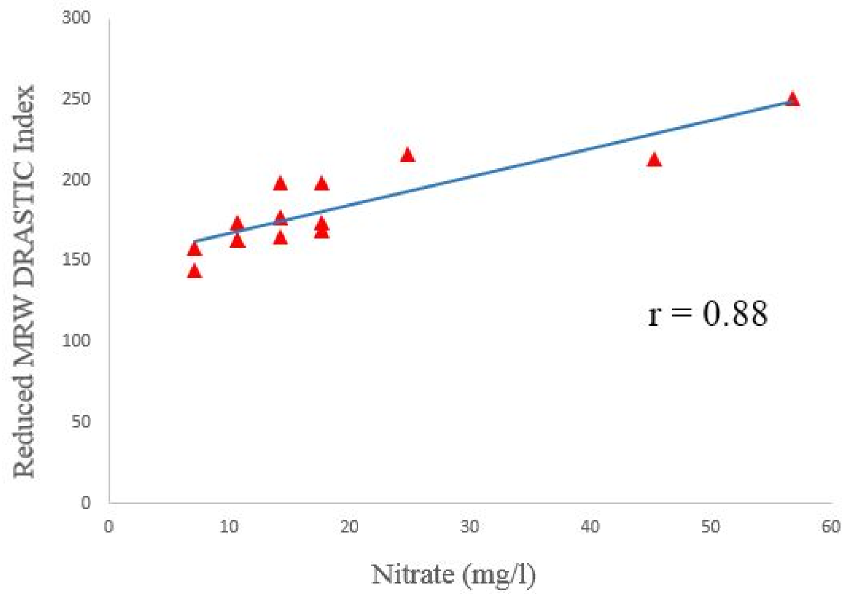



Figure 4.26: Correlation between reduced MRW DRASTIC (spline) index and nitrate

Also, the correlation between nitrate map and reduced MRW DRASTIC map was measured by calculating chi-square value. The relationship between these two maps was apparent as indicated in Tables 4.25 and 4.26. The total chi-square which is the total of values in chi-square table was calculated as 100.38 for reduced MRW DRASTIC model.

Table 4.25: Area cross-tabulation between reduced MRW DRASTIC map and nitrate ($km^2$)

| | Nitrate Class 1 | Nitrate Class 2 | Nitrate Class 3 | Nitrate Class 4 | Nitrate Class 5 | Nitrate Class 6 | Nitrate Class 7 | Nitrate Class 8 | Total |
|---|---|---|---|---|---|---|---|---|---|
| Class L | 0 | 1.08 | 5.58 | 2.49 | 0.61 | 0 | 0 | 0 | 9.76 |
| Class ML | 0.94 | 5.78 | 8.04 | 1.41 | 1.19 | 2.51 | 0 | 0 | 19.87 |
| Class M | 11.2 | 16.1 | 8.61 | 2.57 | 8.09 | 6.7 | 0.16 | 0 | 53.43 |
| Class MH | 0.09 | 38.1 | 15.11 | 6.1 | 7.78 | 24.89 | 1.57 | 0.1 | 94.55 |
| Class H | 5.3 | 28.09 | 17.86 | 9.47 | 3.85 | 8.12 | 0.19 | 0 | 72.88 |
| Class VH | 1.54 | 1.52 | 0.59 | 1.92 | 1.02 | 16.16 | 2.21 | 0.24 | 25.2 |
| Total | 19.88 | 90.67 | 55.79 | 23.96 | 22.54 | 53.38 | 4.13 | 0.34 | 275 |

Table 4.26: Chi-square values for reduced MRW DRASTIC (spline) map

| | Nitrate Class 1 | Nitrate Class 2 | Nitrate Class 3 | Nitrate Class 4 | Nitrate Class 5 | Nitrate Class 6 | Nitrate Class 7 | Nitrate Class 8 |
|---|---|---|---|---|---|---|---|---|
| Class L | 0.7 | 1.41 | 6.57 | 3.17 | 0.04 | 2.06 | 0.14 | 0.01 |
| Class ML | 0.17 | 0.09 | 4.01 | 0.05 | 0.11 | 0.68 | 0.29 | 0.02 |
| Class M | 14.01 | 0.12 | 0.44 | 0.92 | 3.17 | 1.88 | 0.51 | 0.06 |
| Class MH | 5.14 | 1.58 | 0.84 | 0.54 | 0.0003 | 1.88 | 0.01 | 0.002 |
| Class H | 0 | 0.71 | 0.65 | 1.55 | 0.74 | 3.46 | 0.74 | 0.08 |
| Class VH | 0.04 | 5.53 | 3.98 | 0.03 | 0.52 | 21.95 | 8.89 | 1.4 |

According to the validation results, the reduced MRW DRASTIC (spline) model had Pearson's correlation coefficient of 0.88 which was the same with the full MRW DRASTIC spline) model (0.88) and the chi-square value was obtained as 100.38 which was higher than the chi-square value in full model (72.93). The larger value of chi-square indicated a remarkable similarity between the reduced model and nitrate map. Therefore, it can be concluded that the vulnerability map for Shahrekord plain obtained from reduced MRW DRASTIC (spline) model could be considered as reliable as the full MRW DRASTIC (spline) model including all seven layers. Thus, it can be possible to assess Shahrekord vulnerability with fewer parameters in compared to seven parameters in the original DRASTIC model. The advantage of this investigation was the efficiency and capability of vulnerability map obtained from only 4 parameters than seven layers.

## 4.5 Discussion

In the current study, two nitrate data sets were measured during two monitoring events in May and July 2007 were measured for modification and verification purposes. Nitrate concentrations obtained in July 2007 was used to modify the rates of parameters. All modified models were validated by samples from May 2007. Pearson's correlation factor and chi-square value were calculated to quantify the spatial dependency between nitrate map and vulnerability maps. According to results of validation, among all modified DRASTIC models, the MRW DRASTIC (spline) was more reliable map to represent vulnerability conditions in Shahrekord plain.

Map removal sensitivity analysis and SPSA demonstrated that the removal of net recharge caused larger variation in vulnerability index, since this parameter had a relatively high modified weight among other parameters. After single map removal, vulnerability maps were created for all cases, then Pearson's correlation was calculated between new vulnerability index and observed nitrate concentrations. The results indicated that Aquifer media, Topography and Impact of vadose zone had the least effective in Shahrekord vulnerability assessment. Therefore, a reduced model was proposed using only Depth to water, Net recharge, Soil media and Hydraulic conductivity for Shahrekord vulnerability evaluation. The reduced model was also validated using observed nitrate concentrations and the results demonstrated a high Pearson's correlation coefficient and chi-square value. Therefore, it can be concluded that the reduced model is reliable as the full model for Shahrekord vulnerability assessment.

Statistical spatial association between DRASTIC maps (original and modified) and nitrate map were tested using map pair analysis. Chi-square value was calculated as a relative measure to define the spatial dependency between two maps. A larger chi-square value implies higher association and spatial dependency. In this research, this value was considered for comparing the efficiency of modified models to the original ones to see if the new approach is improving or degrading the results of DRASTIC vulnerability assessment.

# Chapter 5

# Conclusion

## 5.1 Summary

The Shahrekord plain is located in a semi-arid region which groundwater is the main water source in the area. Due to extensive cultivation with intense fertilizer application, nitrate concentrations in the groundwater are considered the primary source of pollution. DRASTIC model was applied for aquifer vulnerability evaluation in the study area. All seven required hydrogeological layers comprising Depth to water, net Recharge, Aquifer media, Soil media, Topography, Impact of vadose zone and hydraulic Conductivity (DRASTIC) were created and rated in ArcGIS. The depth to water points which was measured in 25 observation wells, was interpolated using two methods including Inverse Distance Weighting (IDW) and spline. In order to validate the obtained DRASTIC map, the measured nitrate concentrations in agricultural wells were used to correlate the pollution in the aquifer to the DRASTIC index. The Pearson's correlation factor indicated that the original DRASTIC model could not provide a satisfactory intrinsic vulnerability evaluation of groundwater to pollution. Therefore, the original DRASTIC algorithm required modification to obtain a more reliable results. The rates and weights of original DRASTIC model were modified using Wilcoxon rank sum non-parametric statistical test and Single Parameter Sensitivity Analysis (SPSA) respectively. The modified-rates DRASTIC and MRW DRASTIC models were developed and to measure any improvements in new models, the Pearson's correlation coefficient and chi-square value were calculated. The MRW DRASTIC (spline) map showed the best correlation coefficient (0.88) and chi-square value (72.93) among all modified vulnerability maps. For MRW DRASTIC (spline) map, the variation of vulnerability index was tested by single and multiple map removal sensitivity analysis. The results revealed that the removal of net recharge caused larger variation in MRW DRASTIC (spline) index indicating that this parameter had more impact on the DRASTIC vulnerability of the aquifer. Moreover, Aquifer media, Topography and Impact of vadose zone were found not to have a significant effect in assessing Shahrekord aquifer vulnerability. Consequently, a reduced model was introduced with less number of parameters and as a results less amount of required input data for Shahrekord vulnerability mapping containing four parameters; Depth to water, Net Recharge, Soil media, Hydraulic Conductivity. The reduced model was also validated using nitrate concentrations and the results demonstrated the reliability of the proposed model.

## 5.2 Conclusion

Based on studies discussed in this thesis, the following conclusions can be derived:

1- Applying original DRASTIC model in this region did not provide a satisfactory assessment of the intrinsic vulnerability of groundwater to pollution. Thus, it required modification to obtain a more accurate results.

2- The Wilcoxon rank sum non-parametric statistical test and Single Parameter Sensitivity Analysis (SPSA) were used to modify the rates and weights of the original DRASTIC model respectively. These modification techniques significantly improved the ability of the model to predict the aquifer vulnerability.

3- Among all developed modified DRASTIC models, the MRW DRASTIC (spline) map showed the highest Pearson's correlation coefficient with the nitrate concentrations, 0.88 whereas it was -0.3 for the original DRASTIC before modification.

4- Chi-square value was also calculated to measure spatial association between DRASTIC maps and interpolated nitrate map. The chi-square value was 25.2 for the original DRASTIC (spline) map whereas the correlation between nitrate map and MRW DRASTIC (spline) map was computed as 72.93 after rate and weight adjustments.

5- The results obtained from map removal sensitivity analysis revealed that net recharge had the most impact for Shahrekord aquifer vulnerability assessment and its removal caused larger variation in vulnerability index.

6- Aquifer media, Topography and Impact of vadose zone were found not to be important parameters in assessing Shahrekord aquifer vulnerability, thus a reduced model was proposed by eliminating A, I and T for Shahrekord vulnerability assessment.

7- The reduced model showed a high Pearson's correlation coefficient and chi-square value as 0.88 and 100.38 respectively. This results demonstrated that the proposed reduced model could be considered reliable enough to represent vulnerability situation in the study area.

8- All these types of analysis and process modeling require large enough and valid datasets. Otherwise, results and even inputs may not be representative.

## 5.3 Recommendations for future studies

For future studies on aquifer vulnerability assessment the following recommendations can be proposed:

1- For a better prediction of the vulnerable areas, it is suggested to incorporate risk assessment map into the forecast.

2- In DRASTIC model, the seven parameters are treated as independent layers therefore, it is suggested to take into account parameter correlation on further studies.

3- Uncertainty involves intrinsic vulnerability and pollutant exposure thus, uncertainty assessment should be used to improve the vulnerability concept.

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