

# Assessing the vulnerability of the Karaj aquifer with the upgraded Fuzzy DRASTIC+ model by combining water quality and land use indicators

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## Research Article

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# **Assessing the vulnerability of the Karaj aquifer with the upgraded Fuzzy DRASTIC+ model by combining water quality and land use indicators**

## **Abstract**

Groundwater vulnerability assessment is a key tool for sustainable water resource management, especially in urban and agricultural aquifers under stress. In this study, the Fuzzy DRASTIC+ model was developed for the first time to examine the vulnerability of the Karaj aquifer by combining eleven criteria. These criteria include the main DRASTIC parameters (water table depth, net recharge, aquifer environment, soil texture, slope, unsaturated zone influence, and hydraulic conductivity) and four supplementary criteria (chloride, electrical conductivity, total dissolved solids, and land use). Each layer was standardized using appropriate fuzzy membership functions (linear, small, and large) and the weighting of the criteria was normalized to allow comparison. The results showed that about 45% of the aquifer area is in the high and very high vulnerability classes, which are mainly concentrated in the eastern and northeastern regions of the plain; areas where urban development and intensive agriculture exert the greatest pressure on groundwater quality. The high overlap of these areas with high EC, TDS and chloride concentrations confirms the validity of the model output. Comparison with previous studies (2007) shows that the share of high-risk classes has increased significantly; this change is due to both the intensification of human pressures over the last two decades and the improvement of the sensitivity of the developed model. The findings emphasize that in addition to hydrogeological characteristics, human activities play a direct role in the formation of vulnerability. From a management perspective, the results imply the need to implement urgent measures such as managed artificial aquifer recharge (MAR), control of land use changes and continuous monitoring of groundwater quality. The presented Fuzzy DRASTIC+ framework can be used as a transferable approach for other arid and semi-arid aquifers and can be the basis for scientific decision-making and policy-making in groundwater resource protection.

**Keywords:** Groundwater vulnerability, Fuzzy DRASTIC+, Tehran-Karaj aquifer, EC, TDS, chloride, land use, managed artificial aquifer recharge

## 1-Introduction

Groundwater resources, as one of the most vital natural resources, play a pivotal role in providing drinking water, agriculture, and industry. According to global reports, more than 2 billion people in the world are directly dependent on groundwater, and this resource provides about 40% of the water needed for agriculture (Famiglietti, 2014; Sadeghi et al., 2021). In Iran, which faces semi-arid conditions and a shortage of surface water resources, aquifers cover more than 60% of water needs, but pressures from population growth and economic development threaten the sustainability of these resources (Madani, 2014; Balist et al., 2022). The importance of these resources lies not only in their quantity but also in their quality, as groundwater can often be used without the need for extensive treatment and acts as a natural reservoir against climate change (Balist et al., 2022).

However, the threat of aquifer pollution has become one of the major environmental challenges. Pollutants from human activities such as intensive agriculture, industry, urbanization, and improper waste disposal can rapidly penetrate groundwater layers and lead to a decrease in water quality (Rafiee jolodar et al., 2021; Foster et al., 2020). These pollutants not only endanger public health, but also disrupt groundwater-dependent ecosystems. Therefore, aquifer vulnerability assessment is essential as a preventive tool for identifying high-risk areas and sustainably managing water resources (Zebardast et al., 2023; Vrba & Zaporozec, 1994). These assessments allow for prioritizing conservation measures and reducing environmental risks. The DRASTIC model, as one of the most common methods for assessing aquifer vulnerability, was developed by the United States Environmental Protection Agency (Aller et al., 1987). This model operates based on seven hydrogeological parameters (depth to water table, recharge rate, aquifer medium, soil medium, topography, unsaturated zone influence, and hydraulic conductivity) and generates vulnerability maps using a scoring and weighting system. This approach has been used in several studies due to its simplicity and ability to be integrated with geographic information systems (GIS) (Neshat et al., 2014).

The DRASTIC model assesses inherent vulnerability based on hydrogeological factors that influence contaminant transport (Aller et al., 1987). It assumes that contaminants originate at the surface and move downward with infiltration water, affecting areas larger than 0.4 km<sup>2</sup> (Fannakh & Farsang, 2022). Key principles include attenuation processes in the vadose zone and relative risk assessment rather than absolute prediction (Merchant, 1994). The framework considers ecosystem services dependent on groundwater, such as provisioning (drinking water) and regulating (water purification) services, and relates vulnerability to impacts on these services (Griebler & Avramov, 2015).

The DRASTIC model, developed by the U.S. Environmental Protection Agency (EPA) in collaboration with the National Water Wells Association, provides a standardized approach to assessing the potential for groundwater contamination in various hydrogeological settings (Aller et al., 1987; Patel et al., 2022). Its core theory revolves around the concept of inherent vulnerability,

which refers to the inherent susceptibility of an aquifer to contamination based on its physical and hydrogeological characteristics, independent of the specific contaminants (Fannakh & Farsang, 2022). The model assumes that contaminants originate at the surface, are transported downward by infiltration water (such as rain), and affect areas of at least 0.4 km<sup>2</sup> (Merchant, 1994). It emphasizes factors controlling the time and path of contaminant travel to the water surface, such as infiltration rates and attenuation processes in the vadose zone (Aller et al., 1987). The model is useful for proactive management and identifies high-risk areas for land-use planning and resource conservation (Patel et al., 2022).

While praised for its simplicity and low cost, critics point to its reliance on expert judgment for rankings, ignoring dynamic factors such as climate change and constraints in absolute terms – rendering it a relative tool for screening and prioritizing situations rather than precise predictions (Merchant, 1994; Khosravi et al., 2018).

The optimized methodology integrates the DRASTIC model with geographic information systems (GIS) for spatial mapping, allowing for the overlapping of parameter layers to produce vulnerability indices (Maqsoom et al., 2020; Al-Abadi, 2015). The steps include: (1) collecting and preparing data for seven parameters; (2) assigning a rank (1-10) and a weight (1-5) based on standard ranges; (3) calculating the DRASTIC index (DI) via the formula  $DI = DrDw + RrRw + ArAw + SrSw + TrTw + IrIw + CrCw$ , where  $r$  = rank and  $w$  = weight; (4) classifying the index into vulnerability zones (e.g. low <100, high >160); and (5) validating with field data such as nitrate levels (Yu et al., 2022). Sensitivity analysis is recommended to adjust the weights for local accuracy (Khosravi et al., 2018).

Despite its advantages, the classic DRASTIC model has significant limitations. The fixed weighting of parameters, which is determined based on expert judgment, ignores the inherent uncertainties of the data and may lead to inaccurate assessments (Huan et al., 2020). Furthermore, the model does not consider water quality parameters such as ion concentrations and anthropogenic pressures from land use, which reduces its accuracy in areas affected by anthropogenic activities (Jang et al., 2017). Recent studies show that ignoring these factors can lead to overestimation or underestimation of vulnerability, especially in urban and agricultural aquifers (Sahoo et al., 2016). The DRASTIC model has undergone several versions and developments over the past four decades. Its original version with seven parameters and fixed weights was introduced for vulnerability mapping at large scales (Aller et al., 1987). For special conditions, the DRASTIC-P version with adjusted weights for pesticides in agricultural areas was presented (Banton & Villeneuve, 1989). In recent years, extensions such as DRASTIC-LU with the addition of land use, especially in urban and agricultural areas (Maqsoom et al., 2020) and DRASTICA with the inclusion of a human parameter in industrial areas have been introduced. Also, a modified DRASTIC with local adjustments tailored to the hydrogeological characteristics of each region has been proposed (Assefa & Dinka, 2023). In the area of weighting, the AHP-DRASTIC version using the Analytic Hierarchy Process has been proposed as a multi-criteria approach (Khosravi et al., 2018). Finally, recent developments have included the integration of machine learning methods

with DRASTIC and the development of AI-enhanced models for more accurate and dynamic predictions (Bakhtiarizadeh et al., 2024). The original general version is for general pollutants, while the pesticide version adjusts weights for agricultural chemicals (Saha & Alam, 2014; Banton & Villeneuve, 1989). Enhancements include DRASTIC-LU (adding land use), DRASTICA (human factors), AHP-DRASTIC (objective weighting), and AI-enhanced models (Maqsoom et al., 2020; Bai et al., 2012; Bakhtiarizadeh et al., 2024). Other versions use AHP or machine learning for optimization (Khosravi et al., 2018; Neshat et al., 2014). Regional adaptations such as SINTACS fine-tune the model (Fannakh & Farsang, 2022).

To overcome these limitations, this study introduces an improved model called Fuzzy DRASTIC+. This model increases the accuracy of the assessment by combining fuzzy logic to reduce parameter uncertainties, adding water quality indices (such as TDS, EC, and  $\text{Cl}^-$ ), and considering land use. The main objectives of the study are: 1) applying fuzzy logic to fuzzify the information layers and reduce classification errors; 2) adding water quality indices to reflect the current pollution status; 3) considering land use to assess human pressures; and 4) vulnerability zoning of the Karaj aquifer as a case study, which requires careful management due to its strategic location and development pressures. This innovative approach can serve as a model for similar assessments in semi-arid regions.

## **2-Materials and Methods**

### **Introduction to the Study Area**

The study area is part of the Karaj-Tehran alluvial aquifer, which is located in an area of approximately 508 square kilometers in the Karaj-Tehran plain (Figure 1). This plain is located on the southern edge of the Alborz Mountain range and is limited to foothill units and young alluvial fans from the north and to clay and saline plains from the south. The climate of the region is semi-arid, with an average annual rainfall of about 350 mm and an average annual temperature of 13 °C. The main recharge of the aquifer is provided by atmospheric precipitation and surface flows (Karaj River) from the foothills.

The geology of the area consists mainly of Quaternary alluvium, which is divided into coarse-grained alluvial fans (units 9.1 and 9.2), intermediate alluvium (8.2), and fine-grained and saline plains (units 4.1, 4.2, and 4.3). Exploration and production well log data indicate that the texture of the alluvium varies from clay and silt on the southern margin to sand, gravel, and gravel on the foothills. The depth of the water table is variable, varying from about 9 meters in the western and southern areas to more than 180 meters in the central and eastern parts of the plain.

In terms of exploitation, the area has major agricultural (gardens and agriculture), residential, and industrial uses, and therefore the risk of pollution from anthropogenic activities is significant. Water quality data show that chloride ion concentrations, electrical conductivity (EC), and total

dissolved solids (TDS) have increased relatively in some areas, which could reflect the impact of agricultural and urban uses.

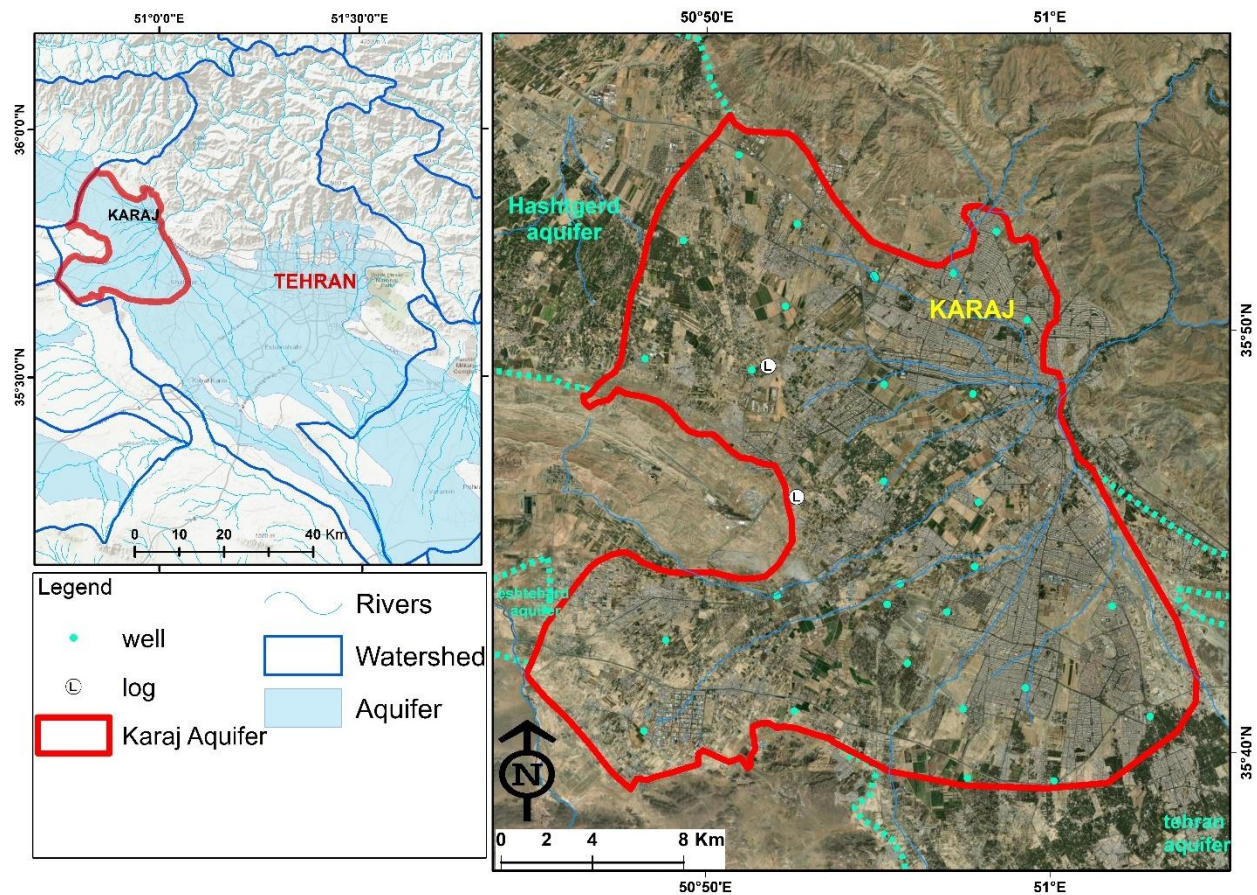


**Figure 1- Location of the study area**

## Methodology

To assess aquifer vulnerability, the Fuzzy DRASTIC+ model was developed. This model is based on the classic version of DRASTIC (Aller et al., 1987) including seven main parameters (depth to water table D, net recharge R, aquifer type A, soil type S, slope or topography T, unsaturated zone influences I, and hydraulic conductivity C). In this study, four additional criteria were also added to the model: total dissolved solids (TDS), electrical conductivity (EC), chloride ion ( $Cl^-$ ), and land use (LU). A total of 11 criteria were used for the final analysis.

The optimal approach is to integrate DRASTIC with geographic information systems (GIS) for spatial mapping (Maqsoom et al., 2020). The steps include data collection, assignment of a rank (1-10), weighting (1-5), calculation of the DRASTIC index ( $DI = \sum \text{rank} \times \text{weight}$ ), classification and validation with pollutants such as nitrate (Yu et al., 2022). Sensitivity analysis adjusts the weights for local accuracy (Khosravi et al., 2018).

## Data collection and preparation

Groundwater depth (D): Obtained from water table data of 30 observation and production wells (1400) and converted into a raster map after interpolation (Kriging). Depth varied in the range of 9 to 183 m.

Net recharge (R): Calculated using precipitation data from meteorological stations and permeability coefficient based on geological and soil studies.

Aquifer type (A): Extracted from a combination of geological map and land units (Land Unit/Source). Coarse-grained units (Qal, alluvial fan) received higher scores, and fine-grained and clayey units received lower scores.

Soil type (S): Classified based on soil map and land units: sandy and sandy loamy soils (high permeability) received higher scores, and clayey and solonchak soils (low permeability) received lower scores.

Topography (T): Calculated from a digital elevation model (DEM) with a resolution of 30 m.

Effect of unsaturated zone (I): Determined using well log data and combined with geological maps. The unsaturated clay and marl layer received lower scores, and the sandy-sandy and gravelly layers received higher scores.

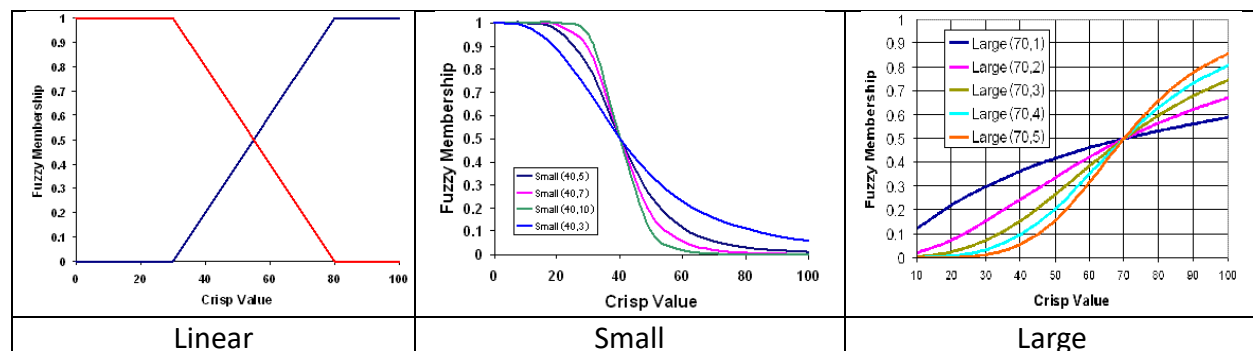
Hydraulic conductivity (C): Estimated based on pumping test data and permeability coefficients.

Water quality indicators (TDS, EC,  $\text{Cl}^-$ ): Extracted from water chemical data of 49 sampling wells (1400). TDS range was recorded between 181–1619 mg/L, EC between 347–2560  $\mu\text{S}/\text{cm}$  and  $\text{Cl}^-$  between 0.3–15.6 mg/L.

Land use (LU): Extracted from the 2023 land use map (satellite images and field classification) including urban lands, agriculture, gardens, wasteland and riverbed.

## Fuzzification and Membership Functions

To reduce uncertainty, all layers were converted to a fuzzy scale (0–1). The membership functions used in ArcGIS were as follows (Figure 2 & Table 1):



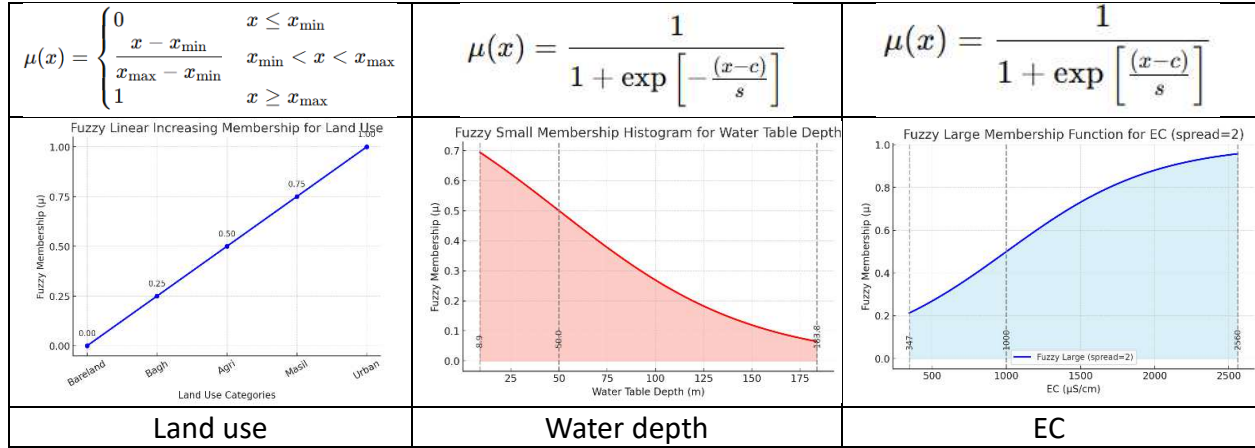


Figure 2 - Fuzzy membership functions

Table 1. Used fuzzy membership for standardizing of the criteria

|    | Criterion                    | Used fuzzy membership  | midpoint | spread | Min | Max |
|----|------------------------------|------------------------|----------|--------|-----|-----|
| 1  | Water level (Depth to water) | Fuzzy Small            | 50       | 1      | 9   | 183 |
| 2  | Recharge rate                | Linear                 |          |        | 0   | 300 |
| 3  | Geology (Aquifer media)      | Linear                 |          |        | 1   | 8   |
| 4  | Soil texture                 | Linear                 |          |        | 1   | 8   |
| 5  | Slope                        | Fuzzy Small            | 15       | 1      | 0   | 25  |
| 6  | Unsaturated zone (Vadose)    | Linear                 |          |        | 1   | 10  |
| 7  | Hydraulic conductivity       | Linear                 |          |        | 0   | 50  |
| 8  | Chloride (Cl <sup>-</sup> )  | Fuzzy Large            | 8        | 1      |     |     |
| 9  | EC                           | Fuzzy Large            | 1000     | 2      |     |     |
| 10 | TDS                          | Fuzzy Large            | 800      | 2      |     |     |
| 11 | Land use                     | Reclass 0–1 membership |          |        | 1   | 5   |

### Weighting of Criteria

The weight of each of the 11 criteria was determined based on scientific and literature importance and then normalized so that their sum equals 1:

$$w_i = \frac{\alpha_i}{\sum_{j=1}^{11} \alpha_j}, \quad \sum_{i=1}^{11} w_i = 1$$

### Overlay and generate vulnerability map

The fuzzy and weighted layers were combined in the ArcGIS environment with the raster calculator and the final vulnerability index was obtained.

$$FD+(x) = \sum_{i=1}^{11} w_i \mu_i(x)$$

### Validation

To validate the map, water quality data (Cl<sup>-</sup>, EC, TDS) and land use were examined with the output of the spatial overlap and correlation model.

### 3-Results

In order to accurately assess the vulnerability of the Karaj aquifer, various hydrogeological and qualitative layers including groundwater depth, land units, land use, and quality indicators such as chloride, TDS, and EC were first extracted and analyzed (Figure 3).

#### Groundwater Depth

The groundwater depth map shows that the western and southwestern areas of the aquifer have shallow depths (about 9 to 40 meters) and are therefore at a higher level of vulnerability, because pollution can reach the water table faster. In contrast, the eastern and northeastern parts have greater depths (up to about 180 meters), which are known as areas more resistant to pollutant intrusion.

#### Land Units

Land units (such as alluvial deposits, clay and sandy plains) play a key role in determining permeability. Areas 9.2 and 4.1, which mainly consist of alluvial sediments with light texture and high permeability, have the highest potential for contaminant transport. In contrast, areas with clay or marl texture (such as 8.2) have lower permeability and act to some extent as a protective layer.

#### Land use

The land use map shows that a large part of the aquifer is dedicated to agricultural and urban uses (especially Karaj and Shahriar). Agricultural use due to the use of chemical fertilizers and pesticides, and urban use due to wastewater discharge and sewage leakage, both play an important role in increasing the risk of aquifer pollution. In contrast, barren and orchard uses play a lesser role in increasing the pollution load.

#### Chloride

The chloride concentration is higher in the southwestern and northwestern parts of the aquifer (up to about 15 mg/L). This indicates the infiltration of pollutants from agricultural wastewater and possibly urban drainage. Lower concentrations are seen in the central and eastern parts.

#### TDS

The TDS map also has a similar pattern to chloride. The southwestern and western parts show the highest risk with higher values (up to about 1600 mg/L). These areas should be monitored more as sensitive areas in terms of water quality.

#### Electrical Conductivity

The EC map also has a high correlation with chloride and TDS, with the highest values observed in the west and southwest (over 2500  $\mu\text{S}/\text{cm}$ ). This indicates that the number of dissolved salts is higher in these areas and the potential for water quality pollution has also increased.

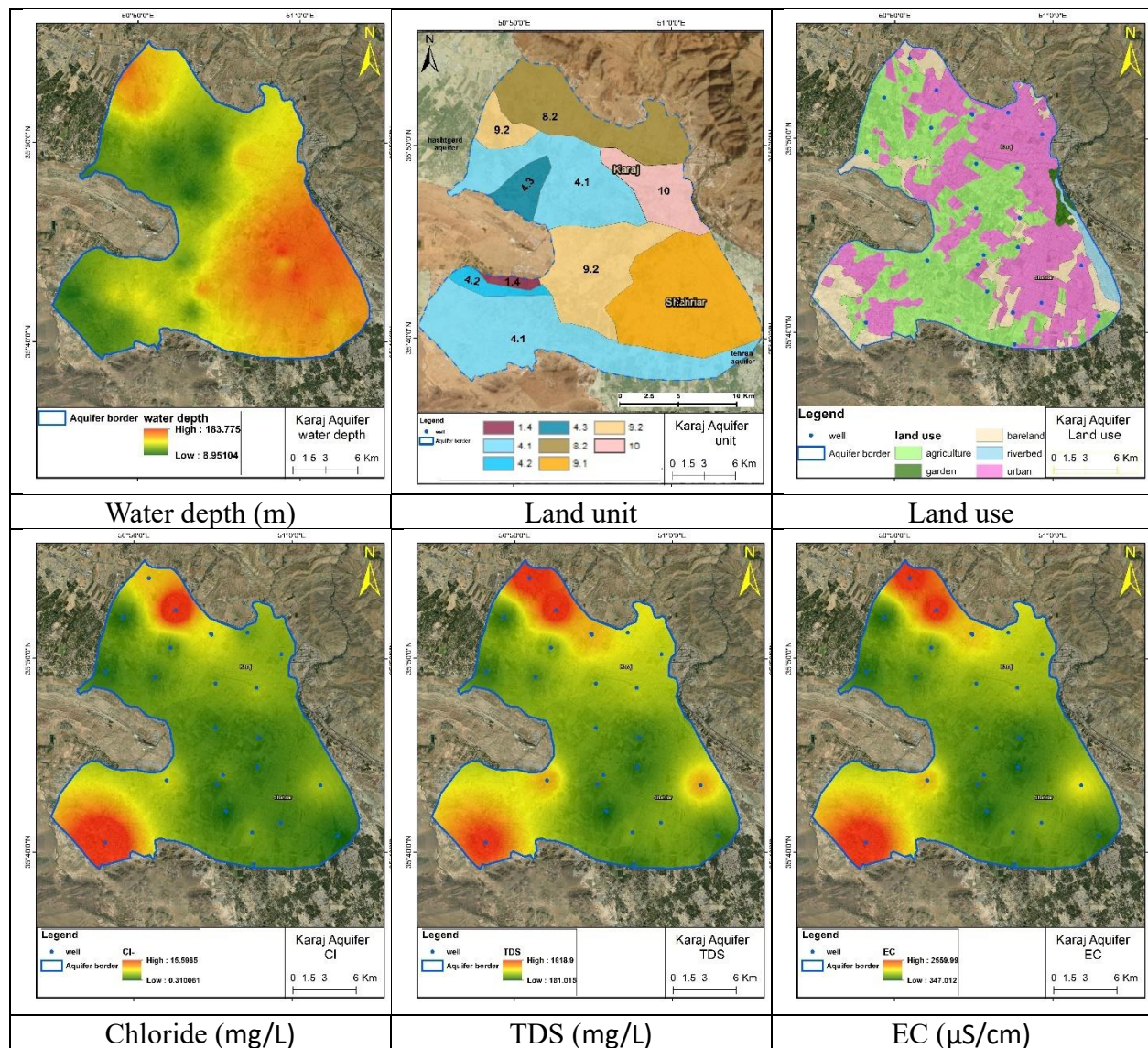


Figure 3. geohydrological characteristics of the Aquifer region

## Standardization of Criteria with Fuzzy Logic

### Water table depth

The groundwater depth map shows that the eastern areas and parts of the central plain have a shallower depth (closer to the ground surface) and therefore have higher vulnerability. In contrast, the western and southwestern areas with deeper groundwater are in a lower vulnerability class. This pattern indicates the key role of shallow depth in facilitating the penetration of contaminants into the aquifer.

### Recharge rate

The recharge rate map indicates a high vulnerability concentration in the eastern and southeastern parts of the plain; where the rate of water recharge and infiltration is higher. These areas have a greater possibility of transferring contaminants to the underground layers due to the presence of highly permeable formations and suitable hydrological conditions.

### *Aquifer media*

The results show that the central and southern parts of the plain, which are composed of alluvial sediments with higher permeability, are more vulnerable. In contrast, areas where clay and marl predominate in the geological composition have a lower level of vulnerability.

### *Soil texture*

The soil texture map shows that areas with lighter soils (sand and sandy loam) are mainly in the high vulnerability category, because these soils have higher permeability and facilitate the passage of pollutants. Clayey and heavier soils in the northern and western areas have a more protective role and are in the lower vulnerability category.

### *Land slope*

The topographic pattern shows that areas with gentle and low slopes (mostly in the center and east of the plain) have a higher vulnerability due to slower runoff and increased infiltration. While areas with steep slopes in the north and west of the plain have a lower vulnerability level due to facilitating surface runoff and reducing the infiltration of pollutants.

### *Unsaturated Zone*

The effect of the unsaturated zone on the relevant map indicates that areas with more permeable sediments and a thinner unsaturated zone (especially in the central and eastern parts of the plain) are in the high vulnerability class. Conversely, areas with thicker and clayier layers in the unsaturated zone play a stronger protective role and are in lower classes.

### *Hydraulic Conductivity*

The hydraulic conductivity map shows that the central and southeastern parts of the plain are more vulnerable. This is due to alluvial sediments with higher permeability, which allows for faster transfer of pollutants to the underground layers. In contrast, the western and northwestern areas with lower hydraulic conductivity values are in the lower vulnerability class.

### *Chloride*

Chloride concentration in groundwater is considered an indicator of the entry of chemical pollutants and salinity. The chloride vulnerability map shows that the northwest and southwest regions have the highest levels and have a relative overlap with the high-risk areas in the overall vulnerability map. This indicates a direct relationship between agricultural use and the intrusion of saline contaminants into the aquifer.

### *Electrical conductivity*

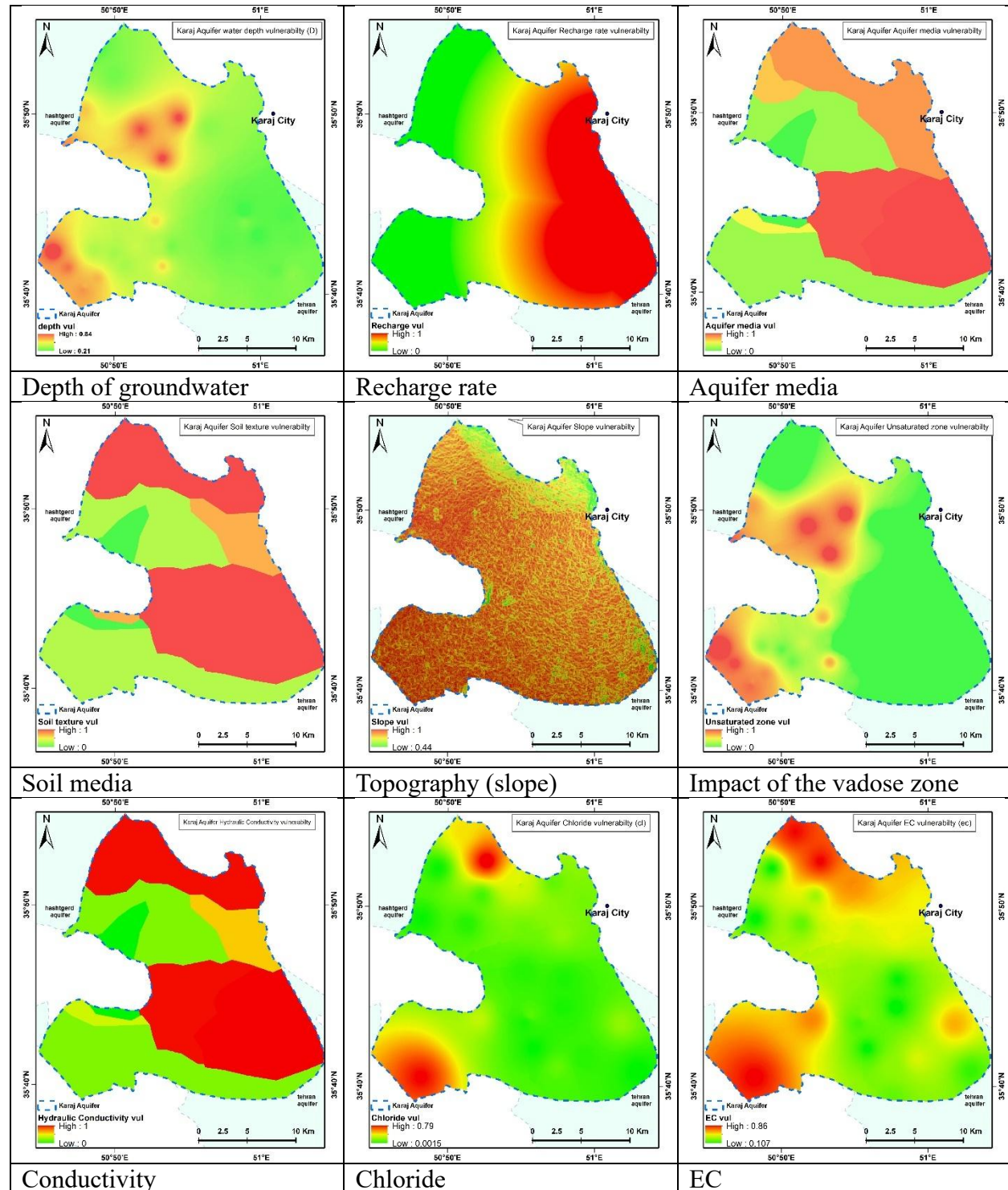
The EC map has a similar pattern to chloride and TDS, showing a high concentration of vulnerability in the south and west of the plain. This pattern indicates an increase in dissolved salts, especially in areas with intensive agricultural activity and inadequate aquifer recharge.

### *Total dissolved solids*

The TDS map shows that the northwest and southwest of the plain have the highest vulnerability. The high TDS in these areas indicates lower groundwater quality and greater susceptibility to surface contamination.

### *Land use*

The land use map shows a high concentration of vulnerability in urban areas and intensive agriculture, especially in the east and southeast of the plain. In contrast, barren areas or barelands are in lower vulnerability classes. This pattern suggests that human factors and land use changes directly contribute to increasing the aquifer's susceptibility to pollution (Figure 4).



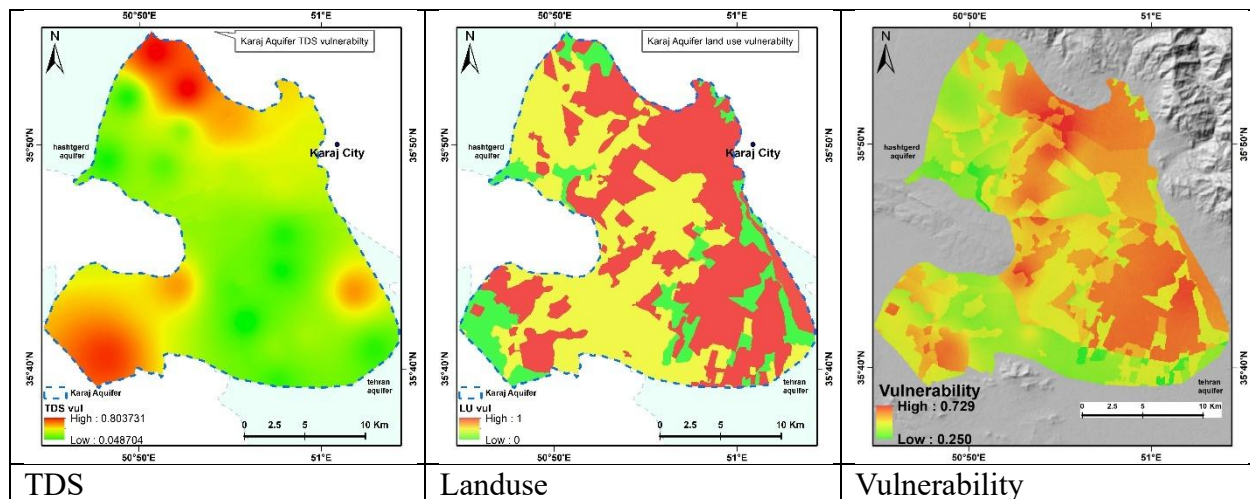


Figure 4. fuzzified criteria maps of F-DRASTIC+ model

In the Fuzzy DRASTIC+ model, the weighting of the criteria plays a fundamental role in determining the contribution of each parameter to the final vulnerability. As the table 2 shows, the highest weight (0.170) is assigned to the two parameter of land use. After that the highest weight (0.143) is assigned to the two parameters of aquifer depth (D) and unsaturated zone (I), which is considered the most logical choice from a hydrogeological perspective; because the depth of the water table determines the speed and probability of contaminants reaching the aquifer, and the unsaturated layer is the first defense barrier against the penetration of contamination into groundwater resources. After that, the recharge rate (R) with a weight of 0.114 is of particular importance, because increased recharge due to precipitation and high permeability can transfer contamination to the aquifer faster. The intermediate criteria including aquifer environment (A), hydraulic conductivity (C), chloride ( $\text{Cl}^-$ ) and land use (Land Use) each with a weight of 0.086 play a complementary and balanced role in the model, indicating that in addition to natural factors, the impact of human activities and water quality indicators is also included in the model. In contrast, slope (S) and TDS with a weight of 0.057, as well as EC and topsoil texture (T) with the lowest weight (0.029), represent secondary but still essential effects in the model. Overall, this fuzzy weighting pattern has caused key criteria such as D, I and R to play the most important role in determining high-risk areas, while other parameters have a supporting and modifying role.

Table 2. fuzzy DRASTIC+ criteria weight

|   | Parameter | Raw weight | Normalized weight |
|---|-----------|------------|-------------------|
| 1 | D         | 5          | 0.143             |
| 2 | R         | 4          | 0.114             |
| 3 | A         | 3          | 0.086             |
| 4 | S         | 2          | 0.057             |
| 5 | T         | 1          | 0.029             |
| 6 | I         | 5          | 0.143             |

|    |                 |    |       |
|----|-----------------|----|-------|
| 7  | C               | 3  | 0.086 |
| 8  | Cl <sup>-</sup> | 3  | 0.086 |
| 9  | TDS             | 2  | 0.057 |
| 10 | EC              | 1  | 0.029 |
| 11 | Land Use        | 3  | 0.170 |
|    | Total           | 35 | 1.000 |

To assess the place of the selected weights in this study’s Fuzzy DRASTIC+, we compared them with authoritative studies. Our weighting pattern—relying on groundwater depth (D) and unsaturated zone effect (I) as the most influential factors—is quite consistent with the classic version of DRASTIC introduced in the original EPA report (raw weights D=5 and I=5; R=4; A=3; S=2; T=1; C=3). Recent reviews also emphasize that in most plains, the model sensitivity is most dependent on D and I, followed by R, A, and C; for example, Berbolescu (2020) summarizes the studies and uses the same classic weighting pattern, showing that D and I factors usually contribute the most to the index. The same trend is observed in objective optimization and weighting approaches: Khosravi et al. (2018) using objective methods (WOE, Shannon entropy, logic tree and Bagging) showed that indices related to aquifer geometry and infiltration path (such as D and I) have the highest resolution in the vulnerability map. In the extended versions, the weighting of anthropogenic variables is more different. In DRASTIC-LU, some studies have considered raw land use weights up to 5 (equivalent to the most important parameters), especially in assessing the risk of pesticide pollution; for example, Kirlas et al. (2023) have used LU=5. In contrast, other studies (such as the CPEC route study by Maqsoom et al., 2020) also emphasize the strong role of anthropogenic factors, although they have adjusted the numerical value of the LU weight to suit local ecosystems. Furthermore, recent work with spatially varying weights shows that the relative importance of parameters can change in space and even within an aquifer, the optimal weight of D or I can shift depending on the formation and feeding regime (VWM model in Yu et al., 2022). Also, in “modified DRASTIC” studies on specific sites, D and I are generally kept in the upper weight categories, and anthropogenic (LU) or qualitative (e.g. nitrate) layers are included as additional parameters with intermediate weights.

In this framework, the normalized weights ( $\sum w=1$ ), which prioritize Land use =170, D=0.143 and I=0.143, and assign intermediate weights to R=0.114 and A, C, Cl<sup>-</sup>, LU=0.086, are consistent with the literature evidence: the main hydrogeological factors contribute the most, while anthropogenic and chemical variables are introduced as moderators and enhancers of the model. Our difference from some versions of DRASTIC-LU (which have a raw weight of LU=5) is that we kept the LU weight at an intermediate level to preserve “inherent vulnerability” and prevent anthropogenic pressure from overwhelming the hydrogeological signal—an approach that is consistent with the recommendations of recent methodological reviews to adjust weights to suit the ecosystem and the purpose of the study.

Figure 5 categorizes the aquifer vulnerability index into five classes from “very low” to “very high” and the accompanying table shows the area and percentage of each class. The total area of

the study area is about 50,799 hectares ( $\approx 508 \text{ km}^2$ ). Of this area, 26.87% or 13,649 hectares is in the very high class and 18.42% or 9,358 hectares is in the high class; This means that a total of  $\approx 45.3\%$  (about 23,007 hectares) of the plain is in a high-risk state. The middle class has a significant share of 28.70% ( $\approx 14,579$  hectares) and can quickly migrate to higher classes with changes in land use or inappropriate management. The low and very low classes together comprise  $\approx 26.01\%$  ( $\approx 13,211$  hectares), which mainly cover the western and southwestern margins and play the role of "refuge areas" of the aquifer.

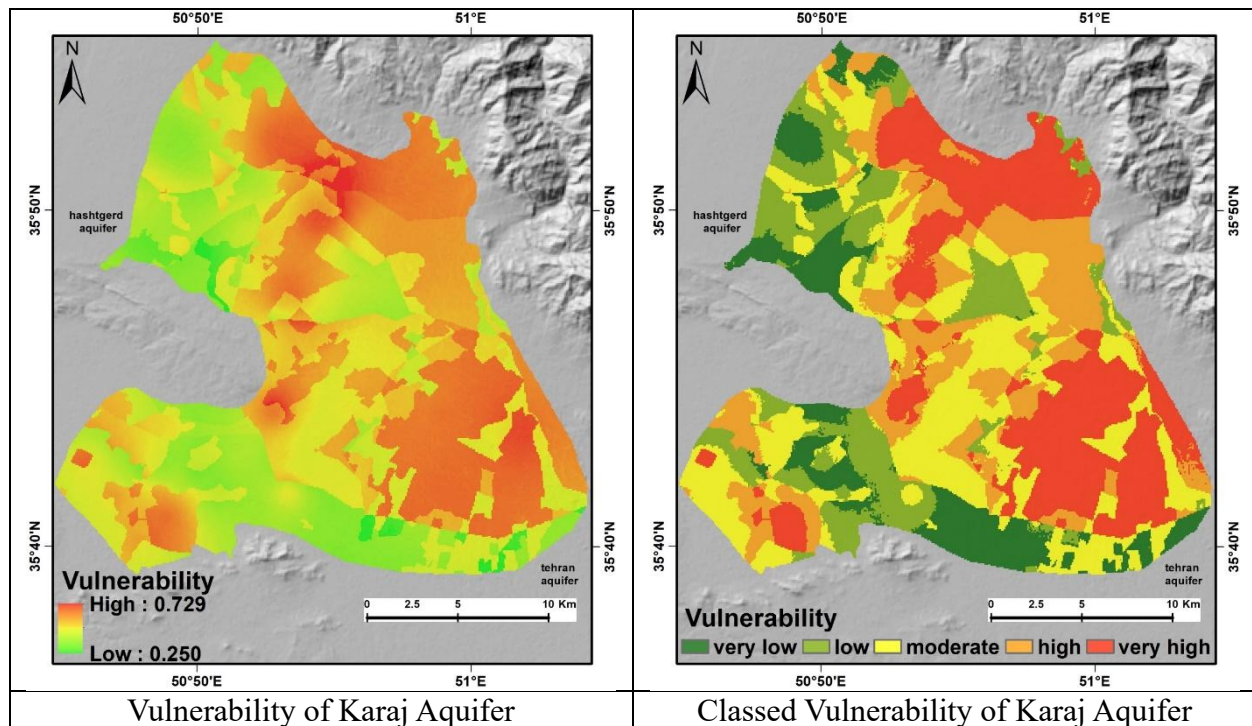


Figure 5. vulnerability of the Karaj aquifer

Spatially, the greatest contiguity of high and very high vulnerability zones is seen in the east and northeast of the plain, where a combination of shallow water table depth, higher recharge rates, more permeable alluvial environment, and human (urban and agricultural) use pressure is present. The yellow to orange bands in the central parts create a transition between the low-risk western and high-risk eastern areas, indicating that these areas are susceptible to upgrading to higher classes with any increase in exploitation intensity. In contrast, the northwest and southwest are predominantly in the low and very low classes, which are consistent with deeper groundwater, finer-grained soils, and slopes that reduce infiltration.

From a management perspective, the concentration of nearly half of the aquifer in the high and very high categories is a serious warning for controlling high-risk uses, managing agricultural runoff and drainage, covering infiltration channels, continuous monitoring of wells, and implementing managed artificial recharge of the aquifer (MAR) with pretreatment. The middle category should be seen as a dynamic buffer zone: any new urban/industrial project or increased

fertilizer and pesticide loads can turn this category into “high.” In the low and very low categories, maintaining the status quo and avoiding abrupt changes in use is the key to sustainability.

Finally, this map provides an integrated picture of the “inherent vulnerability” of the aquifer: where hydrogeological features (D, I, R, A, C) form the main framework, and anthropogenic pressures exacerbate or weaken the patterns. Accordingly, it is proposed to develop a phased conservation plan: (1) focusing stringent measures in the east/northeast, (2) preventive intervention in the central yellow belts, and (3) minimal maintenance and monitoring in the west and southwest. This strategy is both consistent with the current map and reduces the risk of transition from moderate to high-risk areas (table 3).

Table 3. vulnerability classed on the Karaj aquifer

| <b>Value</b> | <b>Vulnerability Class</b> | <b>Percent (%)</b> | <b>Area (ha)</b> |
|--------------|----------------------------|--------------------|------------------|
| 1            | Very Low                   | 5.54               | 2.812            |
| 2            | Low                        | 20.47              | 10.399           |
| 3            | Moderate                   | 28.70              | 14.579           |
| 4            | High                       | 18.42              | 9.358            |
| 5            | Very High                  | 26.87              | 13.649           |

A comparative study of the Karaj aquifer vulnerability map and the land use map show that there is a clear and meaningful spatial relationship between the two. In general, the areas that are located in the very high and high classes in the vulnerability map (red and orange areas) are mainly located in the eastern and southeastern parts of the plain. These areas also correspond to the land use map and show that in these areas, urban use and some agricultural lands are dominant. Such an overlap is expected, because urban development and intensive agricultural activities lead to increased infiltration of pollutants (such as sewage, nitrates from chemical fertilizers, and surface pollutants) into the aquifer, and as a result, the inherent vulnerability of the aquifer also increases. In the medium vulnerability class (yellow), which is mostly scattered in the middle parts of the plain, a high correlation with agricultural lands is observed. In these areas, there is also a risk of aquifer pollution due to the use of fertilizers and chemical pesticides in agricultural land, although the severity is less than in densely populated urban areas. In contrast, the areas with low and very low vulnerability (light and dark green), which are located in the northwest and southwest of the plain, correspond mainly to gardens and barelands. These lands have much less potential for pollutant penetration due to garden vegetation or lack of intense human activity, and therefore the vulnerability index is low. Overall, this analysis shows that the output of the DRASTIC+ fuzzy model has a good spatial agreement with the actual land use pattern, and urban and agricultural areas are correctly identified as higher-risk areas, while gardens and lands with low human activity are placed in lower vulnerability classes. This overlap is actually a kind of spatial validation of the model and shows that the model is able to accurately reflect the impact of human activities on the vulnerability of the aquifer.

The results of the present study are in significant agreement with the findings of studies conducted in other aquifers of Iran and arid and semi-arid regions in terms of the spatial pattern of vulnerability and the simultaneous role of hydrogeological factors and human pressures. In the present study, about 45.3% of the Karaj aquifer area was classified as high and very high vulnerability, and the main concentration of these areas was observed in the eastern and northeastern parts of the aquifer. Spatial analysis of the layers shows that this pattern is the result of the combined effect of hydrogeological features affecting pollutant transport and pressure from urban development and agricultural activities. Such a result shows the importance of going beyond a purely “intrinsic” assessment of vulnerability and introducing variables related to human activities. This finding is consistent with the results of the study by Neshat et al. (2014) in the Kerman Plain. They showed that modifying the DRASTIC structure and adjusting the weights and rankings of parameters according to local conditions can increase the model's ability to identify vulnerable areas compared to the classical model, and validation with nitrate distribution also confirmed the effectiveness of the modified approach. This supports the methodological approach of the present study, because in Fuzzy DRASTIC+, an attempt has been made to reduce the limitation caused by the definitive classification of parameters and to include additional information related to the actual state of the aquifer (Neshat et al., 2014). The prominent role of land use in the results of the Karaj aquifer is also consistent with studies conducted in urban and agricultural aquifers in Iran. In the study of the southern Tehran aquifer, adding a land use layer to the DRASTIC and SINTACS models improved the vulnerability assessment, and sensitivity analysis showed that unsaturated zone and land use were important factors controlling vulnerability. In the optimized model of that study, about 74.8% of the area was in the high and very high categories, indicating the importance of anthropogenic pressures in aquifers located in dense urban and agricultural areas. Although this is higher than the 45.3% contribution obtained for the Karaj aquifer, the difference between the two studies can be attributed to differences in hydrogeological structure, intensity and pattern of land use, the index used for validation, and the way parameters are weighted. However, both studies show that in aquifers under anthropogenic pressure, the use of hydrogeological parameters alone may not provide a complete picture of vulnerability (Noori et al., 2019). The results of the present study are also consistent with the research conducted in the Ajabshir Plain. In that study, adding land use to DRASTIC and then optimizing the model with the Sugeno fuzzy inference system significantly increased the correlation between the vulnerability index and nitrate concentration; such that the correlation increased from about 0.32 in DRASTICL to about 0.80 in the optimized fuzzy model. This result confirms the importance of using fuzzy logic to manage uncertainty and also to include variables related to human pressure (Asghari Moghaddam et al., 2023). This is directly consistent with the logic of developing Fuzzy DRASTIC+ in the present study; with the difference that in addition to land use, the present model has also included three quality indicators EC, TDS and  $\text{Cl}^-$  into the evaluation structure and therefore, in addition to the hydrogeological susceptibility of the aquifer for pollution, information on the observed quality status of groundwater also contributes to determining the final model. The effectiveness of using fuzzy logic has also been reported

previously in the Astaneh-Kuch-Safhan aquifer. In that study, the use of the fuzzy version of DRASTIC increased the correlation of the vulnerability map with nitrate concentration from 0.49 in the standard method to 0.53 in the fuzzy method, and a significant part of the aquifer was also placed in the medium to high and high classes. The researchers attributed this improvement to the ability of the fuzzy method to more continuously display parameter changes and reduce the limitations of the definite boundaries of the DRASTIC classes (Omidi Langrudi et al., 2016). In the Karaj aquifer, the use of fuzzy membership functions instead of completely discrete boundaries allowed for the gradual display of vulnerability changes along hydrogeological and qualitative gradients and could be one of the reasons for the appropriate adaptation of vulnerable areas to the EC, TDS,  $\text{Cl}^-$  and land use patterns. On the other hand, the pattern observed in the Karaj aquifer is also consistent with the results of studies that have emphasized the role of agricultural activities and urban development in exacerbating vulnerability. For example, in the Buindaran aquifer, adding land use to the inherent vulnerability components caused the eastern, southeastern, and parts of the central plain areas that were affected by agricultural activities to be placed in the high and very high vulnerability classes. In that study, shallow groundwater depth and favorable conditions for contaminant transport were also the main factors in creating this pattern, along with land use (Eslamian et al., 2023). Therefore, the concentration of highly vulnerable areas in the urban and agricultural parts of the Karaj aquifer cannot be considered simply the result of a single parameter, but rather the result of the overlap of the aquifer's natural capacity for contaminant transport with anthropogenic pressures and existing signs of water quality decline.

Overall, comparison with previous studies shows that the three main features of the results of the present study – the importance of hydrogeological conditions, the increased resolution of the model using fuzzy logic, and the determining role of land use in aquifers under human pressure – are consistent with the evidence from independent studies. At the same time, the main advantage of Fuzzy DRASTIC+ over many previous versions is the simultaneous integration of hydrogeological factors, land use, and quality indicators EC, TDS, and  $\text{Cl}^-$ . This integration allows the final map to not only reflect the inherent sensitivity of the hydrogeological environment, but also reflect the current conditions of the aquifer under the influence of human pressures and changes in water quality. From this perspective, the overlap of areas with high vulnerability with urban and agricultural areas, as well as areas with higher values of quality indicators, provides support for the application of the developed model in prioritizing areas in need of monitoring and conservation measures.

## **Conclusions**

The findings of this study showed that the use of the Fuzzy DRASTIC+ model, which was developed by adding new criteria including EC, TDS, chloride, and land use, was able to provide a more comprehensive and accurate assessment of the vulnerability of the Karaj aquifer. Combining hydrogeological data (groundwater depth, recharge rate, aquifer media, soil texture,

slope, and unsaturated zone) with qualitative and human indicators created a multidimensional picture of the vulnerability status that is more accurate in reflecting the real conditions of the region than the classic DRASTIC models. The results showed that about 45% of the aquifer area is in the high and very high vulnerability classes, with the highest concentration observed in the eastern and northeastern areas of the plain (near Karaj city and areas with agricultural and urban use). This correlation with the distribution maps of EC, TDS, and chloride, as well as the pattern of urban use expansion, indicates the direct pressure of human activities and overexploitation on groundwater resources.

From a management perspective, these results indicate the need to adopt preventive and corrective strategies. In areas with high vulnerability, implementing managed artificial aquifer recharge (MAR) measures using treated and controlled surface water resources can help reduce pollutant concentrations and increase reserves. In addition, land use management and control of land use changes, especially in the outskirts of Karaj city and high-consumption agricultural areas, should be considered as a priority in regional policies.

Overall, the developed Fuzzy DRASTIC+ model, in addition to providing a scientific framework for quantitative and qualitative assessment of aquifer vulnerability, has high adaptability for similar areas in Iran and other arid and semi-arid regions. The results of this research can be used as a basis for decision-making in sustainable management of groundwater resources and reducing the risk of pollution and destruction of vital aquifer resources.

### **Conflict of Interests**

The authors declare that they have no conflict of interests.

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