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Groundwater quality mapping based on the Wilcox Classification method for agricultural purposes: Qazvin Plain aquifer case

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Abstract

Water quality is an essential component in managing surface and groundwater resources and for various uses; it is considered a necessary principle in planning. This study aims to map the groundwater quality of the Qazvin Plain aquifer in Iran for agricultural use based on the Wilcox classification method. For this purpose, the parameters of electrical conductivity (EC) and sodium adsorption ratio (SAR) of wells in the years 2015-2018 have been used. For interpolation, the inverse distance weighting (IDW) method with optimal power and Kriging geostatistical techniques were used based on spherical, exponential, and Gaussian semicircle algorithms. Electrical conductivity and SAR maps were drawn in the GIS platform after selecting the best interpolation method due to minor errors. The Wilcox method was used to classify the water quality of the studied wells. In most cases, the IDW method with optimal power was selected as the superior interpolation method. During the study, the results obtained from the water quality maps showed that the level attributed to the "high salinity" water class increased from 25.98 to 36.44, and the level attributed to the "slightly salty" water class decreased from 12.54 to 3.14. Finally, the results showed that the quality of underground water for agricultural purpose in the Qazvin Plain aquifer became more unfavourable during the studied period.

1. Introduction

Groundwater is a vital freshwater source for agriculture, drinking water, and various industries. Nearly 30% of the global population relies on it for drinking water, highlighting its crucial role in sustaining human life and economic activity. [1, 2]. Due to a combination of unfavourable climatic conditions, low rainfall, restricted surface water, and growing demand for water, the unsustainable use of groundwater in arid and semi-arid countries is a major concern [3, 4, 5, 6]. Groundwater and surface water sources have become contaminated with nitrogen, heavy metals, and inorganic compounds due to population increase, industrialization, and agricultural practices. Surface and groundwater are severely damaged by a variety of contaminants created by industrial and agricultural activity. It is imperative to maintain groundwater and surface water and prevent contamination [7, 8, 9]. Groundwater quality is greatly impacted by a variety of human activities, such as urbanization, industrial and agricultural processes, and the use of chemical fertilizers and pesticides [10, 11]. Various pollutants are being released into groundwater as a result of these activities, including nitrates, volatile organic compounds, heavy metals, and emerging organic contaminants [12, 13]. Due to the uncontrolled withdrawal of groundwater, Aquifers in Iran are in a critical state [14]. Overexploitation of groundwater has led to severe consequences. Declining water tables, subsidence, and depleted aquifers are common [15]. Due to the imposition of system transfer costs down and thereby increased pumping energy, new problems have arisen such as the drying of water wells, limiting the discharge of rivers and lakes, reducing the quality of water, and increasing the cost per cubic meter of water.

It is, however, difficult and costly to diagnose water pollution and eliminate it. In agriculture and drinking water supplies, it is vital to measure and study changes in water quality [16, 17]. A variety of systems exist for categorizing the quality of surface and groundwater based on the type of water used. The Wilcox method [18] is one of the most commonly used methods for classifying agricultural water. In order to determine water quality using this method, it is necessary to select an appropriate interpolation model and map these parameters. For easier and faster analysis of data, Geographic Information Systems (GIS) software is increasingly used. The use of GIS can connect spatial data with descriptive information and can be applied to a variety of fields, such as mapping [19]. By analyzing the location of the measured points, the relationship between them, and the correlations among different properties, geostatistical methods are generally more efficient in describing spatial variability compared to classical statistical methods [20].

The Wilcox diagram was calculated and plotted by Rahmani [21] using chemical parameters such as magnesium, calcium, electrical conductivity (EC), pH, sodium, and the regional sodium uptake ratio in Hamedan province of Iran. Results indicated that the quality of the water was good and average for the region. Based on geostatistical analysis, Ghafoori [22] found that the co-kriging method simulates better than any other method for all indicators of groundwater quality in Darab Plain in Iran. Using the simple co-kriging method, Sadeghi [23] mapped the quality of agricultural and drinking water in the Malayer Plain in western Iran. Schuler and Wilcox's [24] diagrams also revealed that the drinking water quality situation is classified into three categories: good, acceptable, and unsuitable, while in the agricultural industry, there are two categories: good and average. The Kriging interpolation method was introduced by Alavi [25] to analyze the groundwater quality of the Dez Plain of Iran. Based on Schuler and Wilcox diagrams, the results indicated that the area is suitable for agricultural purposes as well as good for drinking. By using geostatistical methods, Hassen [26] evaluated the quality of plain groundwater in Tunisia in terms of agriculture and drinking and drew the Wilcox and Richards diagrams to illustrate his findings. Water in the area was found to be in excellent condition for agricultural use. Based on the Kriging geostatistical method, Awais [27] analyzed the groundwater quality of the Punjab Plain in Pakistan using EC and sodium adsorption ratio (SAR) parameters. In terms of EC, the semi-exponential model performed the best, and in terms of SAR, the spherical exponential model performed the best. Based on the M5 tree decision model and support vector regression (SVR), Sattari et al. [28] predicted the groundwater level of the Ardabil Plain in Iran over a 17-year period. As a result of the findings, it was found that the M5 tree decision model provided better results than the SVR model. Hosseininia and Hassanzadeh [29] in this study revealed that the groundwater quality in the Rafsanjan plain is largely unsuitable for domestic and agricultural purposes due to high salinity and sodium content. The concentration of major ions decreases from the southeast to the northwest and center of the plain, with most samples falling within the C4S4 and C4S3 classes, indicating a high risk of salinity and sodium hazards for agriculture and crop damage. According to El-Zeiny and Elbeih [30], the groundwater quality of the Dakhla Oases plain in Egypt was evaluated by interpolating the water quality index (WQI) using inverse distance weighted (IDW) methods. According to the results, the quality of the water for agricultural use is excellent. Using 61 samples, Aravinthasamy et al. [31] calculated the WQI by analyzing the parameters of TDS, EC, pH, Ca, Mg, Na, K, HCO_3, and Cl. Additionally, they plotted graphs such as Wilcox and USSL diagrams. The study concluded that 57% of the groundwater in the Shanmuganadhi River Basin in southern India is in poor condition and has poor quality for agricultural use. As part of a ten-year study conducted by Jeon et al. [32], He evaluated the regional groundwater in Korea in terms of agriculture and drinking water. Based on the water quality guidelines of the World Health Organization and the Korean Ministry of Environment, they drew Wilcox and USSL diagrams. According to the results, the water is of good quality for irrigation and drinking. According to Aryafar et al. [33], EC, SAR, Na%, and TDS parameters were used to evaluate the water quality of Birjand Plain in Iran. Results showed that the conventional kriging method was more accurate than the Gaussian variogram. Masmoudi et al. [34], investigated the hydrogeological quality of groundwater in the Western Zab area of Biskra, Algeria. Through the analysis of 35 water samples against the standards set by the World Health Organization and the Algerian authorities, the findings show that the overall water quality is low. Specifically, about 80% of the samples were classified as having poor quality and 17.14% as having very poor quality. Similarly, studies in Rajasthan, India, and Bosaso, Somalia, have found that groundwater in these regions is unsuitable for agriculture or drinking due to high salinity levels [35, 36].

Data mining techniques such as support vector regression, k-nearest neighbour, Hoeffding tree, random forest, random tree, and REP (Reduced Error Pruning) tree were used by Sattari et al. [37] to classify water quality in the Aladag River, Turkey. The REP tree and support vector regression classifier produced the best results, according to the results obtained. Based on a study conducted on the Hableh River in Iran to evaluate drinking and agricultural water quality, Safari et al. [38] determined that the classification of EC and SAR was excellent. The Wilcox chart indicates that the water in the region is suitable for agriculture. The quality of drinking water is reduced by high levels of TDS and EC. Using water quality indexes, Sener et al. [39] examined 31 well samples in the Aksehir region of Turkey. In order to evaluate the quality of drinking water and agricultural water, they developed GIS maps. According to the study, the groundwater in the studied areas is not suitable for drinking and the water quality in the northeastern region is unsuitable for agriculture. Based on Makki et al. [40]'s analysis of drinking and agricultural water quality indices with different parameters such as EC, pH, SAR, and SSP, this result showed that groundwater in central Iraq needs to be repaired and modified for use. The Azarshahr plain in Iran was studied by Ganjei et al. [41] based on Wilcox classification for zoning groundwater in agriculture. A Gaussian variogram was introduced as a superior method for SAR and EC parameters using the Kriging interpolation method. In the central basin of Chabahar and Kenark Iran, Mahmoudizadeh and Esmaeily [42] examined the quality of groundwater resources for agricultural use. While 61% of groundwater is suitable for agriculture according to the Wilcox classification, 39% is considered poor or unusable. Research in Pakistan, using electrical conductivity, sodium absorption ratio, and residual sodium carbonate indices, has indicated changes in groundwater quality in Multan and its surrounding areas [43]. The results showed that groundwater pollution is especially high in terms of EC in Kabirwala region and water quality decreases from northeast to southwest [44]. Othman [45] used a deep learning model called CNN-biLSTM to simulate the complex groundwater system. Data from USGS was used for training and testing. Three models were employed using different algorithms and Bayesian optimization. The CNN model with SGDM showed the best results, effectively simulating time series data. Megahed et al. [46] integrated chemical analysis and geospatial modelling to multi-criteria assess groundwater quality in Egypt in their study. Thirty-one groundwater samples from wells were analysed over three time periods. According to the water quality spatial model, it was found that despite the decreasing trend in rainfall amount, expansion in agricultural areas and population growth, water quality in large areas of the study area is still suitable for human and farmer consumption. In a study by Raheja et al. [47], groundwater quality in Kurukshetra, Haryana, India, was assessed using data from 19 sites. Results showed 5.3% of samples had high limits, 68.42% average limits, and 26.28% low limits for irrigation. The Wilcox plot indicated 78.9% of samples were in the excellent to good category. Principal component analysis (PCA) identified five components explaining 79.23% of the total variance in water quality. Mogaraju [48] used machine learning to analyze groundwater quality, finding RF and KNN models to be optimal. The water quality index assigned values of 1 or 2 to variables exceeding prescribed limits.

A major objective of this study is to investigate the groundwater quality class of the Qazvin plain aquifer for agricultural purposes in Iran using the Wilcox classification method over a four-year period (2015-2018). A sub-objective of this study is to investigate and compare the accuracy of the IDW method with optimal power and kriging statistics based on spherical, exponential, and Gaussian semi-variograms when drawing groundwater quality maps.

2. Material and methods

2.1. Study area

The study area, which covers 3733.68 km^2, is located in the Qazvin Plain of Iran. The Qazvin Plain lies in the range of longitudes 49°25' to 50°35' E and latitudes 35°25' to 36°25' N. The plain consists of wide alluvial plains formed by sediments from surface streams in the mountains that surround around it. During the course of the plain, the height varies between 1150 and 1500 meters, while the height of the mountainous areas varies from 2900 meters in the northeast to 2600 meters in the south. It is generally inclined towards the east, with a slope of 3% in the foothill areas and less than 1% in the plain itself. During the past 10 years, the average annual rainfall in the province of Qazvin has been 306.3 mm and the average annual temperature has been 14.9 °C. Checking the monthly statistics of the stations in the province shows that in these stations, July and August are the hottest months while January and February are the coldest months. According to the annual temperature map of the province, the northeastern and northern elevations of the province, as well as the elevations of Shahr-Auj in the southwest of the province, have lower temperatures than other parts of the province. The lowest average annual temperature is 2 ^{0}C, which is observed in the northeastern peak and the highest average annual temperature is 18 ^{0}C, which can be seen in the low-altitude areas of the northwest around Sefid Rood Dam Lake. In addition, in the plain and inner parts of the province, in the eastern and southern border of Boyin Zahra city, the average temperature is 14.5 ^{0}C. The average annual rainfall in Qazvin province during the last 10 years has been 306.3 mm. Also, the relative humidity is around 51%. This province is affected by Siberian and Mediterranean winds, which are very important factors in controlling the province's climate (Figure 1). According to the De Martonne classification, the region has a semi-arid climate. Climate diversity has provided favourable conditions for the cultivation of tropical crops in different parts of the study area. As a result of its fertile soil and access to sufficient surface and groundwater, Qazvin is renowned for its 33 species of grapes and vineyards. The growth of different plant species that can be seen in Qazvin province is the result of the climate diversity in this province. Most of the area of the province is covered by steppe (mountainous, foothills and desert), where most of its plants are: Milkvetch, Alhagi and Mugworts. Also, the pastures of this province include steppe territory and mountain meadows, which cover about 60% of its area. These pastures, together with the forests of the province, have great economic and environmental value, and it is necessary to preserve them. The province's groundwater resources provide approximately 72% of its agricultural water needs. Qazvin's alluvial soils have a high degree of permeability [49]. Due to the rainfall in the region, some of the wastes on the surface penetrate the ground and contaminate groundwater aquifers.

Over the period of four years (2015-2018), the qualitative parameters of 23 wells, including salinity, EC, and SAR, have been evaluated. The location of the wells is depicted in Figure 1. Also shown in Table 1 are the locations and geographical locations of piezometric wells in the Qazvin plain.

Table 1. Geographical locations of wells in Qazvin plain

No[1]	Stations	UTMx [2]	UTMy [2]
1	Farsjin	354746	3986834
2	Spike	377877	3963817
3	Danesfahan	385627	3961674
4	Kahak	387143	3999591
5	Velazjerd	388360	3984656
6	Dolatabad	394787	4003142
7	Abdul Rab Abad	396260	3980817
8	Shireh Esfahan	397869	4010658
9	Mahmudabadeh	400009	4017886
10	Moin	403118	3994084
11	Jamalabad	408134	4009103
12	Gadimabad	408730	4004349
13	Amirabad	410518	3955940
14	Sagzabad	411041	3962960
15	Mohammadabadkhareh	413461	3986215
16	Papleyvasati	419743	3978907
17	Elhabad	423262	3972676
18	Khakali	425250	4003554
19	Shahrabad	426019	3984227
20	Fathabad	429199	3956289
21	Zageh	440320	3995536
22	Kazanchal	441011	3990831
23	Nodeh	395393	3962940

[1] Number

[2] Universal Transverse Mercator

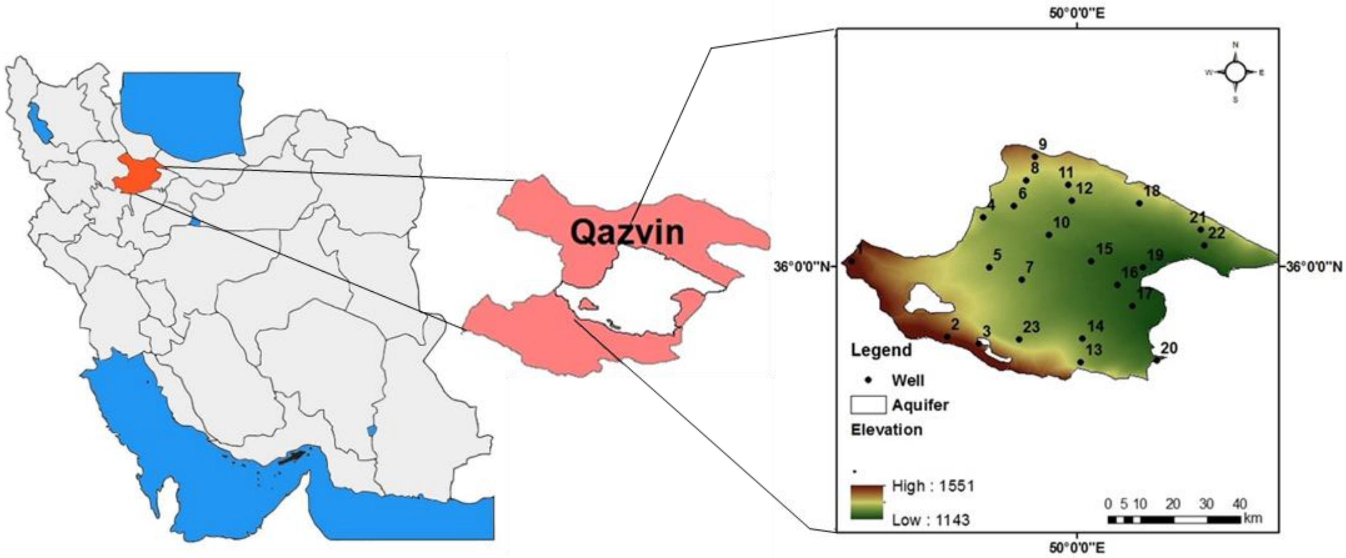

Figure 1. Location of the study area and distribution of selected wells

2.2. Irrigation water classification

Agricultural water quality classes were determined using the Wilcox classification, one of the most widely used classifications in this field. Agricultural water is classified into four groups based on EC and SAR, with excellent, suitable, average, and unsuitable (Table 2) and 16 categories (Table 3) [50]. Annual rainfall time series of Qazvin Plain from 2010 to 2020 are given in Figure 2 (May is the wettest, August is the driest month).

In terms of agricultural water use, salinity and sodium parameters are the most important quality criteria. As well as affecting plant growth, they also determines the quality of irrigation water. In addition, it affects the permeability of the soil. The Wilcox diagram, which consists of two orthogonal axes, is generally used to classify water into different classes for agricultural use. In this diagram, the horizontal axis represents the electrical conductivity in micromhos per centimeter, while the vertical axis represents the SAR. There are 16 regions in the chart that are used to determine the amount of water [51]. There is a direct relationship between the electrical conductivity of groundwater and its total dissolved solids (TDS) and temperature. Due to the increase in these two factors, the salinity increases, and as a result, the quality of the water decreases.

Table 2. Classification criteria in terms of agricultural water quality

Water quality	EC (μS/cm)	Classification	SAR	Classification
Excellent	<250	C_1	<10	S_1
Good	250-750	C_2	10-18	S_2
Average	750-2250	C_3	18-26	S_3
unsuitable	>2250	C_4	>26	S_4

Table 3. Different classification of water and type of quality based on Wilcox classification

No	Water quality type for agricultural use	Classification
1	Clean - completely harmless to agriculture	C_1S_1
2	Slightly salty - almost suitable for agriculture	C_2S_1, C_2S_2, C_1S_2
3	Salinity - for agriculture with the necessary arrangements	C_3S_3, C_3S_2, C_3S_1, C_2S_3, C_1S_3
4	Too salty - harmful to agriculture	C_4S_1, C_4S_2, C_4S_3, C_4S_4, C_3S_4, C_2S_4, C_1S_4

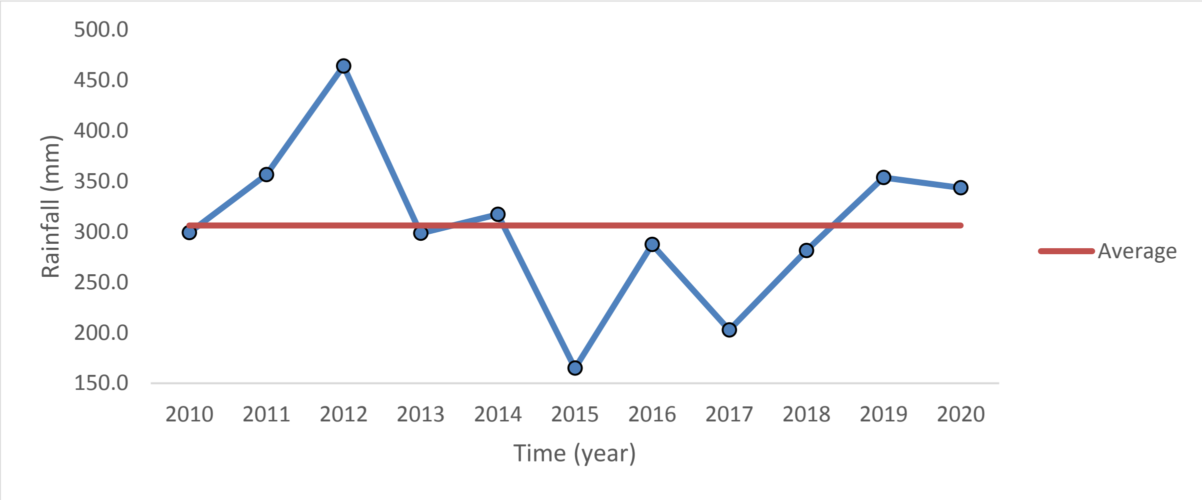

Figure 2. Annual rainfall time series of Qazvin Plain from 2010 to 2020

2.3. GIS and Interpolation

The amount of groundwater quality change at the aquifer level can be determined by mapping the region's groundwater quality with the aid of ESRI ArcGIS 10.4.1 software. These maps were created using interpolation techniques, which also estimated the effective parameters of the Wilcox method for non-sampled points. Existing techniques for interpolation in an Arc Map environment are in two forms deterministic and geostatistical. In specific methods for prediction, mathematical functions are used according to the type of interpolation; however, in geostatistical methods, in addition to mathematical functions, statistics are also used to predict unknown points. In the present study, specific IDW and kriging geostatistical methods were used.

Because stochastic variables are viewed as independent in the analysis of data collected using classical statistics, the effect between neighbouring observations is neglected, but geostatistical methods are of great importance because of the spatial position of the data and their spatial structure. Interpolation and estimation of the desired variables are more accurate [52]. The most common geostatistical technique is kriging, which is based on a weighted moving average. Because it is a probabilistic, expressive method and the best unbiased linear estimator, the estimate's variance should be small and free of systematic errors. The absoluteness of the kriging estimation in interpolating points, and plotting equivalence lines using maximum points with known coordinates, is one of its main advantages [53]. Equation 1 shows the kriging method:

$$Z^* = \sum_{i=1}^{N} \lambda_i \, Z(x_i) \tag{1}$$

Where n is the number of data points, Z* is the estimated spatial data value, $Z(x_i)$ is the observed data at point i, and λi is the sample weight at xi, which indicates the importance of point i in kriging calculations, and the sum of λi coefficients is 1 [54].

The spatial link between random variables is calculated using a semi-variograms. Equation 2 shows the relation of the experimental semi-variogram criterion γ(h).

$$\gamma(h) = \frac{1}{2\,n(h)} \sum_{i=1}^{n(h)} [Z(x_i) - Z(x_{i+h})^2] \tag{2}$$

In which n(h) is the number of points pairs in a particular class of distance and direction, $Z(x_i)$ and $Z(x_{i+h})$ represent the location of Z, and γ(h) shows the values of the semi-experimental exponential change at distances h. In the Kriging interpolation method, it is necessary to replace the experimental discontinuous variogram with a theoretical continuous variogram. In the present study, Gaussian, exponential, and a hemi-spherical (half sphere) model have been used. These models are shown in Equations 3 to 5, respectively:

$$\gamma(h) = c.\left[1 - \exp\left(-\frac{h^2}{a^2}\right)\right. \tag{3}$$

$$\gamma(h) = c.\,Exp\left(\frac{h}{a}\right) = c.\left[1 - \exp\left(-\frac{h}{a}\right)\right. \tag{4}$$

$$\gamma(h) = c.\,Sph\left(\frac{h}{a}\right) = \begin{Bmatrix} c.\left[1.5\frac{h}{a} - 0.5(\frac{h}{a})^3,\ if\,(h \le a)\right. \\ c, if\,(h > a) \end{Bmatrix} \tag{5}$$

In the all above equations, C demonstrates that C is the upper limit of the variogram.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (Z(x_i) - \hat{Z}(x_i))^2} \tag{6}$$

In the above equation, n is the number of points, $Z(x_i)$ is the actual value of the point x_i, $\hat{Z}(x_i)$ Is the estimated value, and s is the variance. For EC and SAR parameters, a variogram with less RMSE is considered the best variogram for each year. The IDW approach assumes that the degree of similarity and correlation between neighbours is inversely proportional to their distance, which can be defined as the distance from any neighbouring point. This method is used when the sample points are sufficiently well distributed at the local scale levels. In this method, each point in the calculation has weight, so the greater the distance, the less effective the known point in estimating the unknown point and the calculation of the mean, so the closer distances gain weight [55]. The formula for the IDW method is as follows [56, 57].

$$Z_0 = \frac{\sum_{i=1}^{N} z_i d_i^{-n}}{\sum_{i=1}^{N} d_i^{-n}} \quad (7)$$

In which Z_0 shows the estimate of the value of the variable z at point i, z_i is the sample value at point i, d_i is the distance of the sample to the estimated point and n is the exponential power parameter that determines weight based on distance.

On the other hand, using power in inverse distance, the influence of the degree of spatial dependence on data can be applied. Many scholars have used inverse power. Interpolation in this method is estimated so that the desired range is converted into a matrix with cells of the same size. The spatial coordinates of this matrix are clear and have a unit of measurement. For example, it has a 50 x 50-meter cell. In this network, the variable's value is known in some cells in other words, it is measured, and in other cells, this amount is unknown. Cells whose value is unknown are estimated using the surrounding cells in a certain radius based on the following formula [58]:

$$\hat{Z}(s_0) = \sum_{i=1}^{N} \lambda_i Z(s_i) \quad (8)$$

Where $Z(s_i)$ is the value measured in the i^{th} position and λ_i is the weight of the value measured in the i^{th} position. S is the predicted position, and N is the number of points measured. λ_i is a function of the distance between them, or in other words, the shorter the distance, the greater the effect of the unknown point, so the inverse of the distances between them is used as a weight in the model.

Appropriate power is closely related to the role of distance in estimating unknown points, in other words, increasing power increases the effect of distance in interpolation. This means that the similarity of the unknown points to the nearer known neighbours rises with increasing power in the model. When the power is zero ($\rho = 0$), the role of the distance becomes the same, and the unknown value is obtained from the average of the neighbouring points [59].

3. Results and discussion

Qualitative studies of the Qazvin plain aquifer have been conducted on 23 wells over a four-year period between 2015 and 2018, which used EC and SAR parameters. IDW and Kriging methods were applied via a GIS platform for the interpolation of EC and SAR parameters. The RMSE metric was used to validate each year, and its values are presented in Table 4. Table 4 indicates that the method with the lowest RMSE is selected as the superior interpolation method.

In Table 4, for all years, the IDW method has optimal capacities in the range of 1.3 to 1.59. Regarding the SAR, in 2016 and 2017, the IDW method had an optimal power of 2.05 and 2.5, respectively; in 2015, the spherical variogram and also in 2018, the exponential variogram were selected as the superior interpolation methods.

Figures 3 and 4 illustrate the interpolation of EC and SAR parameters using superior methods.

Table 4. The parameters and the interpolation techniques results

Parameters	Year	Optimal Power	IDW	Kriging		
				Spherical	Exponential	Gaussian
EC	2015	1.59	1391.84	1478.3	1569.23	1427.68
	2016	1.48	1337.58	1423.68	1442.9	1412.85
	2017	1.37	1595.81	1674.97	1684.14	1654.37
	2018	1.30	1871.07	1941.96	1938.21	1932.91
SAR	2015	2.60	2.14	2.07	2.16	2.13
	2016	2.05	2.19	2.38	2.2	2.35
	2017	2.50	2.14	2.25	2.17	2.23
	2018	1.79	3.13	3.17	3.1	3.21

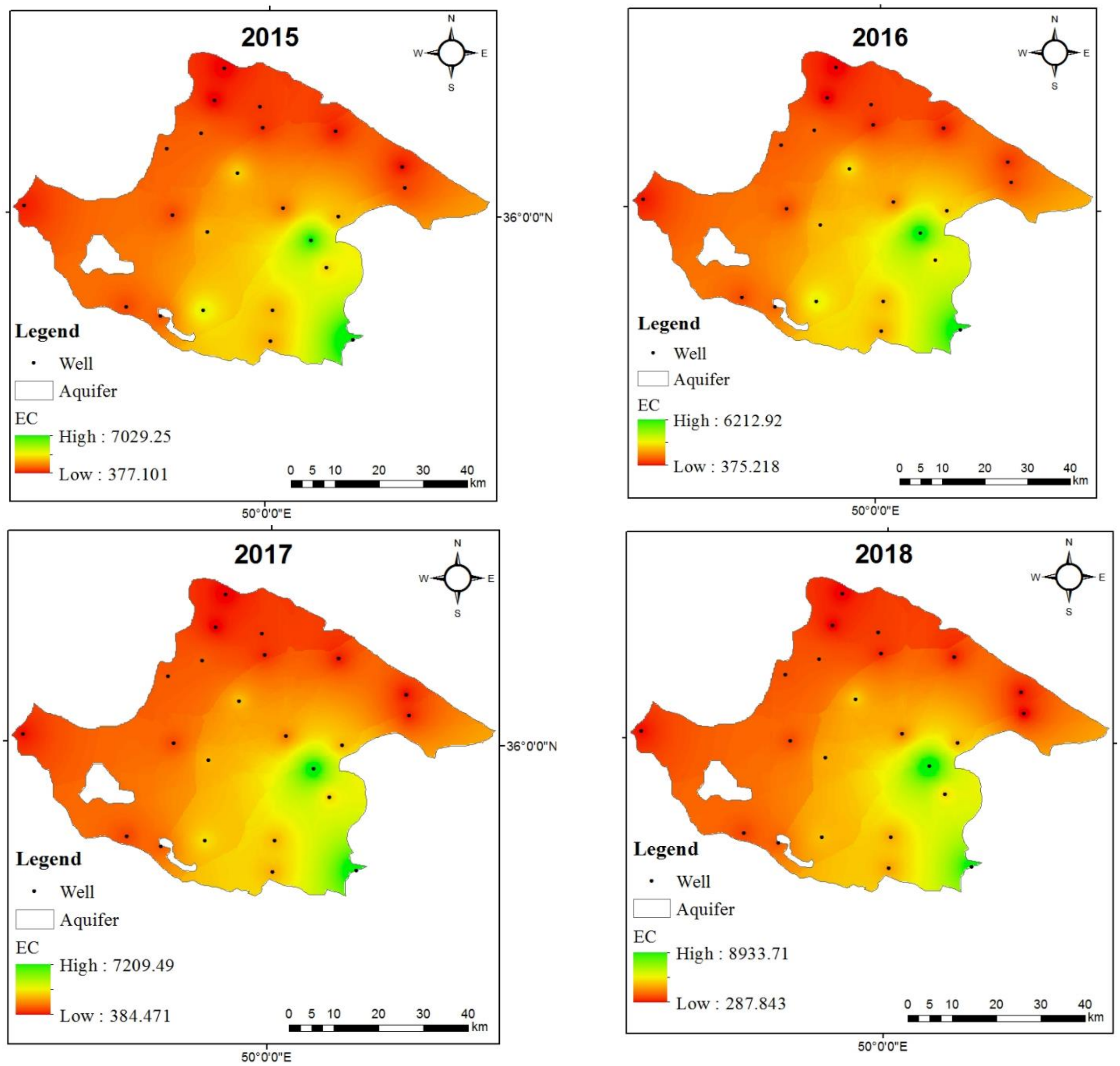

Figure 3. Map of spatial changes of EC in Qazvin Plain in the period of 2015-2018

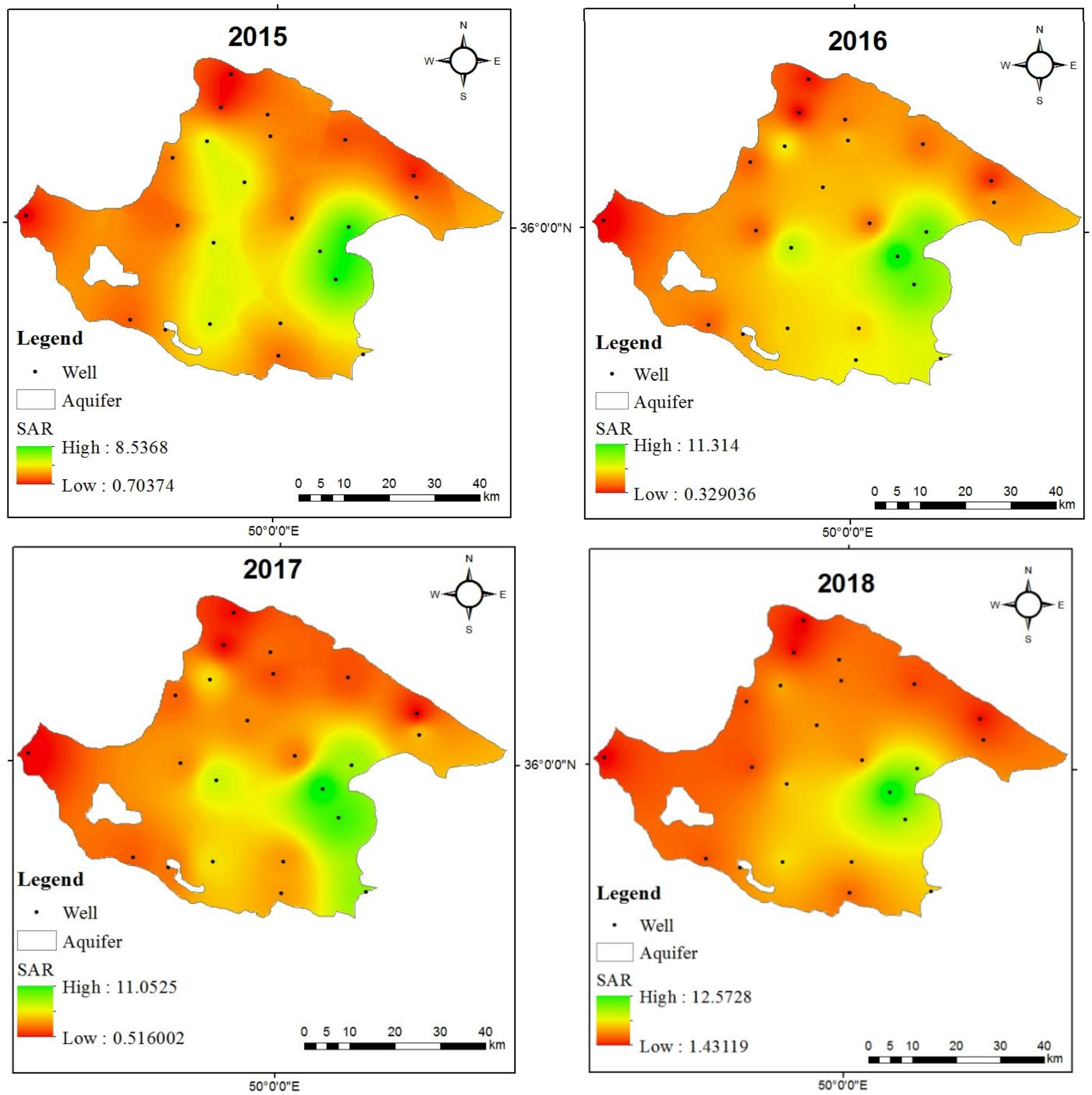

Figure 4. Map of spatial variation of SAR in Qazvin Plain in the period of 2015-2018

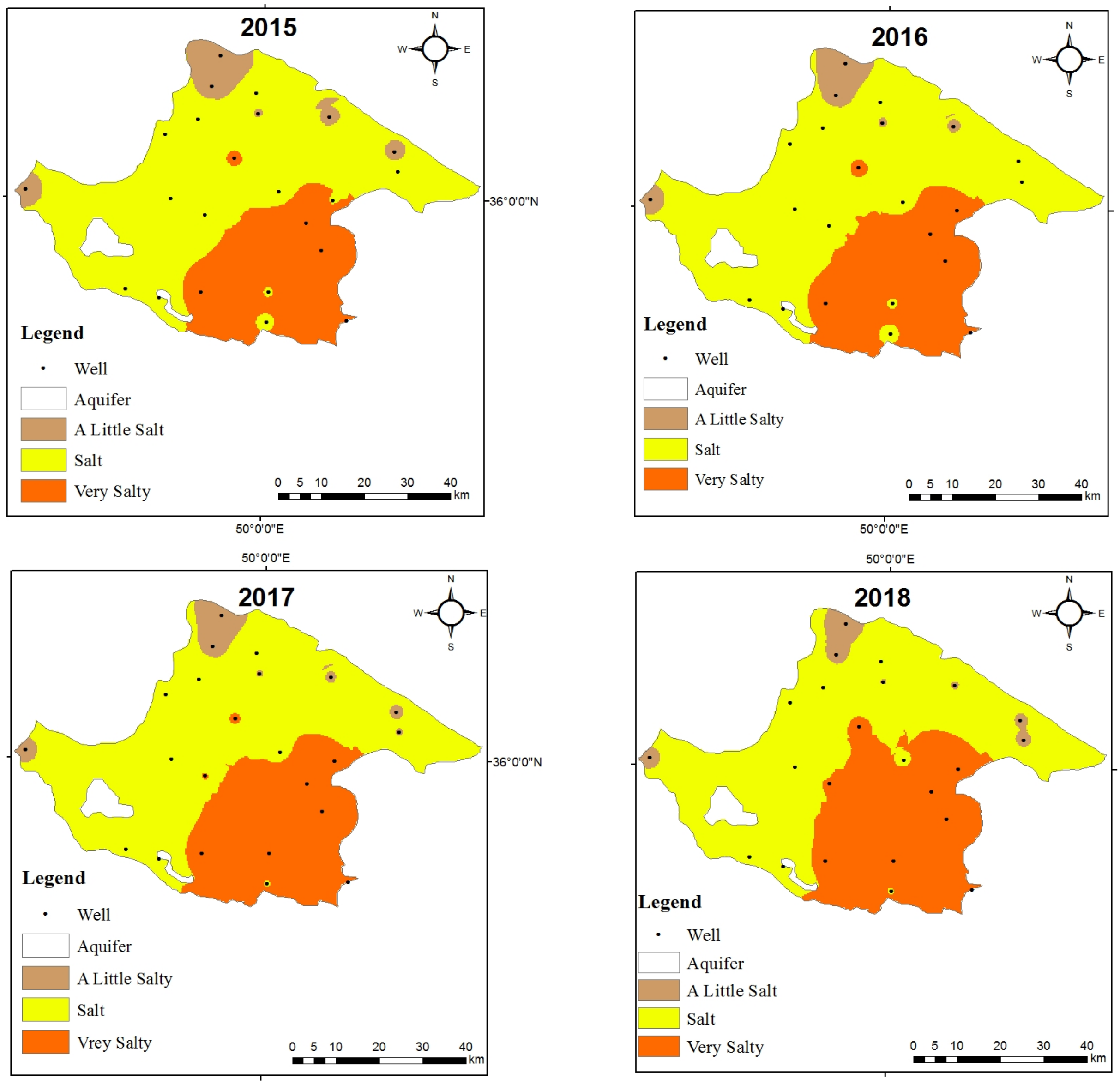

Figure 5. Groundwater quality map for agriculture in Qazvin plain based on Wilcox method

Figure 5 shows the groundwater quality map for agriculture based on the Wilcox method (Tables 2 and 3), which is obtained from the overlap of spatial change maps of groundwater quality criteria based on this method (Figures 3 and 4).

According to Figure 5, a small portion of the north, northeast, and west of the Qazvin Plain in 2015 had slightly saline water and was almost suitable for agriculture. According to Figure 2, the amount of slightly saline water in the region decreased from 2015 to 2018, as a result of the relative increase in rainfall in the region. Groundwater quality can also be improved by reducing the cultivation of irrigated crops. There is highly saline groundwater in the southern and southeastern parts of the aquifer, which is detrimental to agriculture. In 2015, six out of 23 wells were classified as high saline water wells, which increased to nine wells in 2018. In the Qazvin Plain, there is no part that has fresh groundwater that is entirely harmless to agriculture due to a reduction in rainfall compared to the average, and this may be one of the factors contributing to the increase in the amount of high saline water. Over the past four years, the percentage of slightly saline water has decreased, while the percentage of high saline water, which occupies about 40% of the aquifer area, has increased.

As shown in Table 5, different groundwater qualities are assigned to different areas and percentages. According to Table 5, a significant percentage of the aquifer area contains saline water, which can be used for agricultural purposes by changing cultivation patterns and using saline-irrigated crops and plants. Between 2015 and 2018, the percentage of highly saline groundwater increased from 25.98 to 36.44, while the percentage of slightly saline groundwater decreased from 12.54 to 3.14. This has resulted in a reduction in the groundwater quality of the Qazvin aquifer.

4. Conclusions

The EC is an important factor in determining the appropriate quality of water for agricultural use. However, irrigation with high salinity can cause a significant increase in salt levels in the soil, resulting in crop damage. In contrast, high sodium levels in water due to changes in soil properties adversely affect agricultural lands and sensitive crops. The Iranian groundwater resources are exploited in unfavourable conditions, leading to a decline in groundwater levels as a result of improper extraction practices. Aquifer inputs were reduced as a result of improper pollution management.

In contrast, the water quality class is becoming increasingly unsuitable. Based on a 4-year statistical period (2015-2018), EC and SAR parameters were mapped using the kriging geostatistical technique, and the IDW method was selected in the Qazvin plain aquifer. Among the three variograms of the Kriging method and the optimal power of the IDW method, the IDW method was selected for EC, the IDW method for SAR in 2016 and 2017, and semi-spherical and exponential changes in 2015 and 2018, respectively.

Table 5. Area and percent of water quality in the years 2015 to 2018

Year	Quality	Area (km^2)	Percent (%)
2015	Low saline-slightly suitable for agriculture	226.35	12.54
	Saline-suitable for agriculture with special conditions	2460.34	61.48
	High saline-Not suitable for agriculture	1046.84	25.98
2016	Low saline-slightly suitable for agriculture	158.58	4.25
	Saline-suitable for agriculture with special conditions	2457.59	65.82
	High saline-Not suitable for agriculture	1117.36	29.93
2017	Low saline-slightly suitable for agriculture	145.24	3.89
	Saline-suitable for agriculture with special conditions	2425.73	64.97
	High saline-Not suitable for agriculture	1162.56	31.14
2018	Low saline-slightly suitable for agriculture	117.34	3.14
	Saline-suitable for agriculture with special conditions	2255.82	60.42
	High saline-Not suitable for agriculture	1360.37	36.44

With the increase in rainfall from 2015 to 2018, it appears that the amount of slightly saline and saline water has decreased, while the amount of highly saline water has increased. As a result of these findings, it can be concluded that the quality of groundwater in the Qazvin aquifer is declining, with about 40% of the aquifer containing highly salty and harmful water for agriculture. Therefore, it is recommended that in relatively low saline areas, the existing cultivation pattern be changed to saline-friendly plants and irrigation efficiency, be increased, so that less water is drawn from the aquifer, and highly saline and harmful areas are prohibited from harvesting groundwater.

This study's findings, primarily based on the Wilcox diagram, align with previous research within Iran [22, 23, 24], indicating a widespread decline in groundwater quality for both drinking and agricultural purposes across many Iranian plains. Similarly, comparisons with studies outside Iran, such as in Pakistan [26], Southern India [31], Korea [32], and USA [60] reveal that spatiotemporal analysis and geostatistical methods using GIS have been employed to assess groundwater quality in urban areas for drinking and in rural areas for irrigation, yielding comparable results to this study.

In assessing the current quality and contamination risk of groundwater, it is essential to take into account environmental factors as well as agricultural ones [61, 62, 63]. It is essential to note that the findings of this study may not be directly extrapolated to other plains. A comprehensive study encompassing all Iranian plains is recommended. Further investigation into long-term trends in water quality, considering variations in rainfall and groundwater extraction rates, is crucial for a thorough understanding of this issue.

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Author contributions

Mohammad Taghi Sattari: conceptualization, methodology, validation, writing—original draft preparation and supervision phases. **Yasaman Kamrani**: methodology, software, formal analysis, writing—original draft preparation and visualization stages. **Sahar Javidan**: methodology, software, validation, writing—original draft preparation and visualization stages. **Halit Apaydin**: software, validation, data curation and visualization stages. **Nasrin Fathollahzadeh Attar**: conceptualization, writing—review and editing, supervision phases.

Conflicts of interest

The authors declare no conflicts of interest.

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