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Evaluation of Groundwater Electrical Conductivity Regarding Rice Cultivation in Guilan Province, Iran

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Abstract

Considering Sefidrud River discharge decrease in the last decade in Guilan province in the north of Iran, groundwater and surface water resources can meet the water demand of rice cultivation in this area. It is evident that irrigation water quality should be considered in rice cultivation. Electrical conductivity (EC) is one of the essential parameters of assessing the quality of groundwater. The purpose of this research is to identify areas at risk of groundwater EC decrease for rice cultivation. For this purpose, zoning and probabilistic maps were prepared by ArcGIS software. The models were evaluated using ME, RMSE, MSE, RMSSE, and ASE statistical indices. The accuracy of the models was very good; the RMSE values for ordinary kriging were between 0.2674 and 0.4172 dS/m, and for indicator kriging, they ranged from 0.2841 and 0.4087 dS/m. The zoning and probabilistic maps showed an increase in EC of more than 1 dS/m from 2002 to 2015. In addition, the highest EC in Guilan province was in the central and eastern parts of the province, including Rasht, Astaneh, and Lahijan cities. More than 30% of groundwater resources were exposed to excessive salinity exceeding rice's tolerance level. Therefore, to prevent the quality mitigation of groundwater resources in the province and prevent yield penalty related to irrigation water salinity, the regional water companies should take appropriate management measures such as a ban on digging new wells or reducing groundwater extraction in hazardous areas.

Introduction

Groundwater is considered a valuable water source for urban, agricultural, and industrial sectors in all regions. It is evident that groundwater is a crucial component of sustainable agriculture in Iran and globally (Ahmadi & Sedghamiz 2008; Obiefuna & Eslamian, 2019). The quality and quantity of groundwater for use in various consumptions should be considered. Groundwater resource quality, such as surface water, is constantly changing; however, these changes occur much slower than surface water. Human activities, such as using fertilizers on farms, industrial

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processes, and disposal of domestic wastes, can degrade soils and deteriorate groundwater quality, consequently reducing crop yield in many agricultural areas. The most critical factors in groundwater pollution are improper irrigation practices and fertilizer management with adverse soil hydrodynamic conditions (Guimer, 1988). Thus, water quality analysis is an integral part of groundwater assessments.

The zoning quality of groundwater explains the areas that are appropriate for typical usage. Because the polling from all parts of the study area is difficult, interpolation methods are weighed as useful tools for data survey according to spatial structure (Ashrafzadeh et al. 2016). There are different methods for studying zoning and exclusivity of groundwater quality. Choosing appropriate methods depends on local conditions, statistical properties, and the merit of a dataset. Geostatistical are impressive and valid tools for groundwater quality monitoring. ArcGIS is extensively used in the arena of geostatistical analysis and has a range of abilities as follows: (1) the ability to define the space-time manufacture (e.g., analyzing semivariograms), (2) receive trusty for variables in unsampled locations based on scattered observed values, and (3) creating maps and assessing their correctness and accuracy (Goovaerts et al., 2005). Ordinary kriging (OK) and indicator kriging (IK) are used as interpolation methods. In a kriging method, a variogram model should be determined; then, its properties are used to calculate the weights necessary for interpolation. Many studies have been carried out using interpolation methods in groundwater studies. Amiri-Bourkhani et al. (2017) employed the OK interpolation method to analyze the spatial and temporal variations in groundwater salinity in Bafra Plain in Turkey in seven years. The interpolation maps showed a decreasing trend in the groundwater salinity from 2004 to 2010. Aiming to assess the groundwater quality for irrigation and potable uses. Adhikary et al. (2012) employed the OK method to generate the maps of spatial variability of groundwater quality parameters in Najafgarh in India. They found that the southern and east-southern parts of the study area are the most polluted regions, while the best groundwater quality is found in the northern and western parts of the study area. Delgado et al. (2010) used geostatistical analysis and the kriging interpolation method to notice and define the quality of groundwater resources for agricultural use in the state of Yucatán of Mexico. They found that the quality of groundwater concerning salinity and effective salinity in zones I, II, and III, the quality in correlation to possible salinity and chloride in zone II, and the quality in correlation to sulphate in zone III of the study area cannot be recommended for agricultural and potable uses; in zones IV and V, water is of medium quality; in zone VI, water is of good quality for agricultural uses. The IK method in which the interpolation process is carried out based on indicator values is another type of geostatistics technique. Researchers worldwide have employed this technique for different purposes, including generating probability maps of groundwater quality parameters. Samin et al. (2012) used the OK for estimating SAR and chloride in 90 wells in Fars province, Iran. Amiri-Bourkhani et al. (2017) used the IK method for generating probability maps of groundwater salinity in the Bafra Plain in Turkey from 2004 to 2010. They showed that the percentage of the total area in which the probability of exceeding the threshold (0.5 dS/m) is 0.8 to 1.0 varies from 0% in 2004 to 13.6% in 2010. Zaiming et al. (2012) studied some chemical parameters of 130 wells located in Bahayin plain in the northern part of China. The results showed that the best models to fit on TDS, TH, and EC empirical semivariograms respectively were spherical, exponential, and gaussian models. It was determined that, with the zoning maps, the groundwater level dropped from West to East plain, the EC and TDS variations increased, and the highest value of TH was determined to be in the middle of the desert and coastline. Partha et al. (2012) weighed the kriging method as the appropriate method for data interpolation to map groundwater quality parameters such as EC, SAR, and bicarbonate, compared to calcium, nitrate and total hardness. Among the types of kriging, the IK method can be used to qualitatively assess aquifers at risk in different areas. Kuisi et al. (2009) used both OK and IK to analyze the spatial variability of groundwater nitrate and salinity in the Amman-Zarqa Basin. Dash et al. (2010) used OK and IK to produce spatial variability maps in the National Capital Territory of Delhi, India. The salinity level was higher than 2.5 dS/m in 69% of the study area. Jang and Chen (2015) examined the vulnerability of water resources against pollution index. They used IK to determine the vulnerability study area. Juang and Lee (2007) used the multiple IK method to assess hydro-chemical parameters of water quality standards in Taiwan and allotment hydro chemical parameters of groundwater salinity in four main categories of risk: the risk of nitrogen, arsenic risk, and the risk of iron-manganese. The results showed that most aquifers were at high risk of iron-manganese; hence, the combination of iron and manganese in detail with other risks, such as the risk of nitrogen and arsenic risk, was observed in most aquifers.

Numerous researchers have widely used nonparametric trend analysis to detect the trends in water quality and quantity variations. Using Sen's slope estimator and Mann-Kendall methods, Kisi and Ay (2014) assessed the trends in water quality parameters of Kizilirmak River in Turkey. Wahlin and Grimvall (2010) employed the Mann-Kendall method to analyze the trends in groundwater quality parameters in Swedish groundwater in twenty years. They found a decreasing trend in the concentration of sulphate ions and an increasing trend in acid-neutralizing capacity.

Due to the construction of numerous dams on the upstream part of Sepidroud River, which led to the reduction of water entering the Guilan plain and increased salinity, the use of groundwater for irrigation has increased by farmers, which is why this research aims to study and identify areas at risk of salinity. Generating updated maps of groundwater quality variables, such as water salinity, and assessing any observed spatial or temporal variations in groundwater quality can have an effective and efficient role in operating and managing groundwater resources. The present study investigates and analyzes the temporal and spatial variations in groundwater salinity in Guilan Plain, northern Iran, utilizing OK and IK methods and using the Geostatistical Analyst toolbox in the ArcGIS 10.2 software package. IK method can help us to identify areas at risk for rice cultivation. The maps, showing spatial variability of salinity, and the probability maps were generated. A trend analysis of the groundwater salinity data was also conducted using the Mann-Kendall method and Sen's slope estimator. This topic was identified as critical to decision-makers in providing them the necessary background to improve the groundwater management and the sustainability of rice production in Guilan plain.

This study has taken a step toward defining the relationship between groundwater EC and rice yield for one particular rice variety, i.e., Hashemi. Of course, other rice varieties or a different source of irrigation may produce entirely different results. In addition, we acknowledge that methodological and data limitations in the research can limit our interpretations.

Materials and Methods

Guilan province is one of the northern coastal provinces of Iran with an area of 14711 km^2 located in the geographical range of 36° 34' to 38° 27' north latitude and 48° 53' to 50° 34' east longitude. This province has a Mediterranean climate and is covered with rainforest Mountains, including 560,000 ha. The climate of Rasht was determined to be so humid, based on the Köppen method (Zare et al., 2014). The Alborz Mountain has an average height of 3000 m in the west and south of the province. The minimum distance from the Caspian Sea is about 3 km, and the largest distance from the sea is about 50 km. The average annual precipitation of Guilan province is 1359 mm, and the average annual minimum and maximum temperatures are between 3 and 35°C, respectively. The mean annual ET_0 is 2.23 mm/d, according to CropWat 8.0 software, for a long duration period.

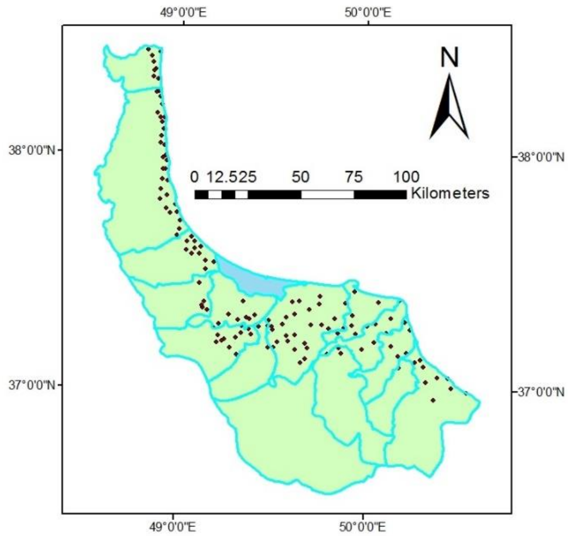

Fig. 1- Location of the study area and position of sampling wells

To evaluate the groundwater quality in Guilan province, salinity data from 2002-2015 were of high significance for assessment; besides, the EC as a statistical sample was detected in more than 100 wells (Fig. 1). Guilan Regional Water Company sampled it. However, due to a large volume of results, only the results obtained in 2002, 2009, 2014, and 2015, respectively the first and last years (the best and worst years), concerning the surface area concerned with high groundwater salinity level were presented.

At first, all data were tested for a normal distribution using the Kolmogorov-Smirnov test by SPSS14 software (Coakes & Steed, 2007). The results indicated that the data distribution is not normal. Thus, by using a polynomial function of grade 6, the data were normalized. The experimental semivariograms in each year were calculated by 11 theoretical models, including circular, spherical, tetraspherical, pentaspherical, gaussian, rational quadratic, effect hole, K-Bessel, J-Bessel, and stables; in addition, the best one was chosen for the estimation stage. For more details, refer to Johnston et al. (2001).

In geostatistics, an experimental semivariogram is a primary tool to examine the spatial structure and correlation among adjacent data. A suitable variogram was selected concerning the lesser RMSE index provided by the ArcGIS software. The experimental semivariogram for discrete sampled locations, defined as half of the arithmetic mean of the squared difference between paired observations, was calculated by the following equation:

$$\gamma(h) = \frac{1}{2N(h)}\sum_{i=1}^{N(h)}[Z(x_i) - Z(x_i + h)]^2 \quad (1)$$

where $Z(x_i)$ and $Z(x_i + h)$ are, respectively, the salinity at locations x_i and $x_i + h$, N (h) represents the pairs with distance h and $\gamma(h)$ is an experimental variogram for distance h.

Ordinary kriging interpolation technique, which can be considered a weighted moving average, was used to interpolate EC values, create estimates for unsampled locations, and construct the prediction maps of annual groundwater EC. The general equation of the ordinary kriging is as follows:

$$Z^*(x_0) = \sum_{i=1}^{n}\lambda_i Z(x_i) \text{ With } \sum_{i=1}^{n}\lambda_i = 1 \quad (2)$$

where $Z^*(x_0)$ is the estimate of salinity in an unsampled location x_0, λ_i is the weight associated with variable Z at location x_i, n is the number of adjacent points, and $Z(x_i)$ is the observed number of the data value of the salinity at the location x_i. Furthermore, to calculate the weights and minimize the variance of error, the following equations should be solved simultaneously (Goovaerts et al. 2005):

$$\begin{cases} \sum_{j=1}^{n} \lambda_j \ \gamma(x_i, x_j) + \mu = \gamma(x_i, x_0) \\ \sum_{j=1}^{n} \lambda_j = 1 \end{cases} \quad i = 1, \dots, n \tag{3}$$

In these equations, $\gamma(x_i, x_j)$ is a semivariogram value for the distance between $x_i$andx_j, μ is the Lagrange parameter for minimizing the variance of kriging estimates, $\gamma(x_i, x_0)$ is a semivariogram value for the distances between the estimated point $x_0$and the ith observed point, and λ_j represents the weights associated with data sampled point x_i. As is clear from Eq. (3), the weights are summed up to one.

The indicator kriging was employed to create the probability maps of groundwater EC. In the indicator kriging method, the probability that the estimated value in an unsampled location could exceed a specified threshold value was estimated using the observed values in adjacent sampled areas. In other words, the indicator values are coded "1" if the measured values of EC are greater than the threshold (EC>1 dS/m); if not, the indicator values are coded "0". The general form of indicator kriging is defined as follows:

$$I(x; z_k) = \mu + \varepsilon(x) \tag{4}$$

$$I(x; z_k) = \begin{cases} 0, & if \ \ Z(\mathrm{x}) \leq Z_k \\ 1, & otherwise \end{cases} \tag{5}$$

where $I(x; z_k)$ is the binary or indicator variable, μ is an unknown constant, $\varepsilon(x)$ is the error associated with location x, Z(x) is the observed salinity value at x, and Z_k is the salinity threshold.

To evaluate and validate the predicted data, five criteria presented in ArcGIS software were used. These five indicators include the mean of the predicted error (ME), the root mean square error (RMSE), the mean standard error (ASE), the standardized mean error (MSE), and the standard root mean square error (RMSSE). The best estimates are achieved when MSE values are close to zero; RMSE, ASE, and ME values are minimum; RMSSE values are close to one. The error measures are defined as follows:

$$ME = \frac{\sum_{i=1}^{n}(Z^*(x_i) - Z(x_i))}{n} \tag{6}$$

$$ASE = \sqrt{\frac{\sum_{i=1}^{n} \sigma(x_i)}{n}} \tag{7}$$

$$MSE = \frac{\sum_{i=1}^{n}(Z^*(x_i) - Z(x_i)/\sigma(x_i)}{n} \tag{8}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Z^*(x_i) - Z(x_i))^2}{n}} \tag{9}$$

$$RMSSE = \sqrt{\frac{\sum_{i=1}^{n}[Z^*(x_i) - Z(x_i))/\sigma(x_i)]^2}{n}} \tag{10}$$

where $Z^*(x_i)$ is the estimate, $Z(x_i)$ is the observed value, $\sigma(x_i)$ is the standard error of estimate at location x_i , and n in the number of observations.

The proportion of the piece effect to the effect threshold is indicative of the spatial structure power of the variables. If this ratio is less than 0.25, a strong spatial correlation is shown. If this ratio ranges from 0.25 to 0.75, a moderate spatial correlation is shown, and if this ratio is greater than 0.75, weak spatial dependence is shown. A strong spatial correlation means that variables can be estimated within the range of influence (Amiri-Bourkhani et al., 2017).

Man-Kendall trend test (Mann 1945; Kendall 1975) was used to detect trends in groundwater EC in Guilan plain. This trend test is generally used to analyze monotonic trends in different time series (Kisi and Ay 2014). The test's null hypothesis is that data are randomized, and no trend present in the dataset is available; the alternative hypothesis states that a trend is present. The necessary condition for using the test is that a meaningful autocorrelation is not present in the time series (Kumar et al., 2009). In the case of no autocorrelation in the time series, the Man-Kendall equations are as follows (Wahlin and Grimvall 2010). In this method, data are ranked first in chronological order, and each data value is compared with all subsequent data values.

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \mathrm{sgn}(x_j - x_i) \tag{11}$$

$$\mathrm{sgn}(x_j - x_i) = \begin{cases} 1\ ; & \text{If } x_j > x_i \\ 0\ ; & \text{If } x_j = x_i \\ -1\ ; & \text{If } x_j < x_i \end{cases} \tag{12}$$

In Eqs. 11 and 12, S is the Mann-Kendall statistics; n is the number of data samples in time series; x_i and x_j are, respectively, the observed values in years i and j. The trend increases if S is positive (S>0) and decreases if S is negative (S<0).

Mann and Kendall showed that when $n \geq 10$, S statistic is normally distributed with mean zero and the following variance:

$$\mathrm{Var}(S) = \frac{n(n-1)(2n+5) - \sum_{i=1}^{P} t_i(t_i-1)(2t_i+5)}{18} \tag{13}$$

where P is the number of series with at least one repeating value, and t_i is the number of similar data in time series. When there are no comparable data in time series, Equation 13 can be irrelevant and, hence, ignored. Furthermore, when $n \leq 10$, the variance is calculated as follows:

$$\mathrm{Var}(S) = \frac{n(n-1)(2n+5)}{18} \tag{14}$$

The standard z statistic is also calculated using the following equation:

$$Z = \begin{cases} \dfrac{S-1}{\sqrt{Var(S)}} & ; \quad \text{If } S > 0 \\ 0 & ; \quad \text{If } S = 0 \\ \dfrac{S+1}{\sqrt{Var(S)}} & ; \quad \text{If } S < 0 \end{cases} \tag{15}$$

The standard z statistic is normally distributed with mean zero and variance one. The null hypothesis (no trend at significance level α is not rejected when $Z_{\frac{\alpha}{2}} \geq |Z|$). The trend increases if the standard z statistic is positive (Z>0) and decreases if z is negative (Z<0). Significance level α is also considered to be 1% or 5%.

When a first-order autocorrelation exists in time series, the Per-whitening method should be used to remove the effect of autocorrelation. Further details are presented in the study of Kumar et al. (2009).

Another nonparametric test for trend analysis is Sen's slope estimator (Sen 1968; Theil 1992). This widely used index in the Mann-Kendall test determines the value of monotonic trend in a series of data as follows:

$$\beta = Median\left(\frac{x_j - x_l}{j - l}\right) \qquad \forall l < j \tag{16}$$

where β is the Sen's slope estimator, and x_j and x_l are, respectively, observed j and l values. Both positive and negative values of β show an increasing trend in the time series dataset.

For these two methods, there are advantages and disadvantages. The Sen slope estimation method can be used to predict the future. These two tests are based on the assumption of static and lack of long-term memory of the data, and the standard deviation of their statistics depends only on the length of the statistical period (Salas, 1992).

Results and Discussion

Since the results are too long to present here, four-year representative results are presented, including 2002, 2009, 2014, and 2015. A statistical summary of groundwater quality parameters in each September of years 2002, 2009, 2014, and 2015 in Guilan province before and after normalization is presented in Tables (1) and (2), respectively. The results show that the average salinity in some years has been increasing and, then, decreasing. The values of skewness and kurtosis show that the data do not have a normal distribution. Kriging methods perform better if data are normally distributed. The results of the Kolmogorov-Smirnov test showed that EC data were not normally distributed; therefore, data were transformed before the semivariogram calculation.

To study the spatial pattern of groundwater EC in Guilan province using OK, the best experimental semivariogram model of EC was determined and fitted for each year among eleven different models. Features of these models are presented in Table (3). Accordingly, the best semivariogram models for groundwater salinity in 2002, 2009, 2014, and 2015 were exponential, exponential, and the hole effect. In a study concerning the groundwater quality in New Delhi, Adhikary et al. (2012) reported that the exhaust model was suitable for EC. The difference in semivariogram results in different years may be due to various climatic conditions such as temperature and rainfall, non-uniform sampling points, different irrigations and drainage practices, land-use change and water level changes in the Caspian Sea, as well as advancement or recession of the seawater (Amiri-Bourkhani et al. 2017).

Accuracy of zoning maps of salinity plotted using OK technique was evaluated using cross-validation (Table 4). For all studied years, the ME and MSE values are negligible and close to zero. In addition, the RMSE and ASE indices are very good. The results of the cross-validation indicate the accuracy of the predictions.

Table 1- Summary statistics of groundwater salinity data (EC in dS/m) in September before normalization

Year	N	min	max	mean	S.D	C.V (%)	Skewness	Kurtosis
2002	171	0.195	1.396	0.695	0.369	53	1.049	1.144
2009	124	0.128	1.196	0.604	0.323	53	0.091	-0.102
2014	126	0.124	1.230	0.590	0.305	52	0.980	0.223
2015	135	0.146	2.00	0.614	0.348	57	0.787	1.166

Table 2- Summary statistics of groundwater salinity data (EC in dS/m) in September after normalization

Water Year	N	min	max	mean	S.D	C.V (%)	Skewness	Kurtosis
2002	171	-0.166	1.090	0.675	0.31	46	-0.603	-0.370
2009	124	-0.129	1.119	0.605	0.324	54	0.092	-0.103
2014	126	-0.216	1.130	0.600	0.308	51	-0.022	-0.216
2015	135	-0.262	1.463	0.621	0.324	52	0.195	-0.473

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Table 3- Characteristics of semivariogram models (ordinary kriging)

Year	Models	Nugget	(Sill)	C0/C0+C	Spatial correlation class	range (km)
2002	exponential	0.09	0.21	0.428571	Average	106.2
2009	exponential	0	0.33	0	Strong	42
2014	Hole Effect	0.07	0.12	0.583333	Average	70.2
2015	J-Bassel	0.04	0.1	0.4	Average	60.8

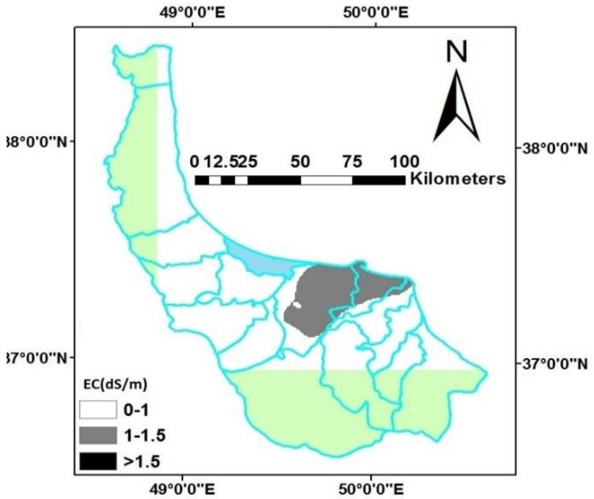
Table 4- Cross-validation between measured and estimated values for groundwater EC (ordinary kriging)

Year	ME (dS/m)	RMSE (dS/m)	MSE (-)	RMSSE (-)	ASE $(dS/m)^{0.5}$
2002	-0.0005	0.37206	0.00044	1.06422	0.34740
2009	-0.0126	0.30528	-0.0202	0.92922	0.30384
2014	0.00322	0.28125	0.01041	0.99065	0.28350
2015	0.00450	0.24367	0.01338	1.02353	0.23612

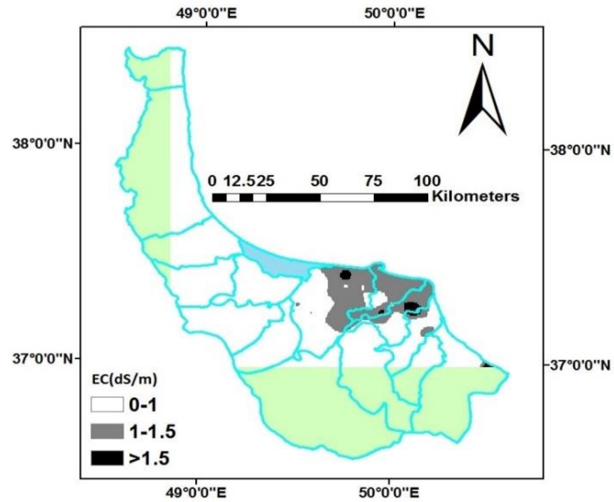
Figure (2) shows zoning maps of groundwater EC in Guilan Plain using OK method for the four years of 2002, 2009, 2014, and 2015. Table (5) shows the area of different EC classes.

Changes in groundwater salinity in Guilan plain may result from the changes in the water level of the Caspian Sea due to increased temperature and decreased rainfall in the region, as well as increased water level and advancement of the seawater in the Caspian Sea until 1994 and recession of the seawater after 1994. Since the recession of the seawater became evident only after 2005, a decrease was observed in areas with 1-2 dS/m salinity. It may be due to excessive exploitation of groundwater resources and overuse of chemical fertilizer.

These maps show that groundwater salinity is generally higher in the central part of the province than in the eastern and western regions. Maximum salinity was observed in the center of the plain in the lowest areas of the province, which could be due to a variety of reasons: the doubling up of the salinity of Sefidroud River water over the last decade, the application of such water for irrigation in the area, vast area of cultivated land in the center of Guilan compared to the west and the east of Guilan province, which led to the flow of drainage water into groundwater sources, high concentration of population, excessive removal and extraction of/from groundwater resources in the region, as well as low elevation of this area compared to the other regions of Guilan. All the reasons mentioned above led to the leaching of salts in farms and upland areas and the accumulation of salts in these areas, which resulted in the salinization of water and soil in this area. Therefore, the management and exploitation of groundwater in this area require special, urgent attention to this considerably important issue.



2002



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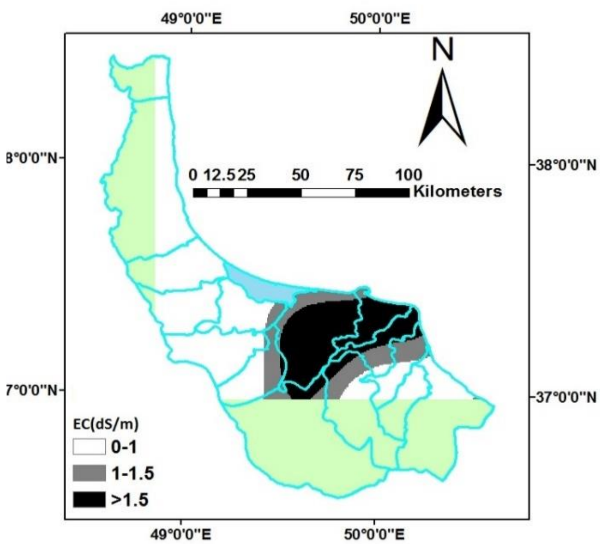
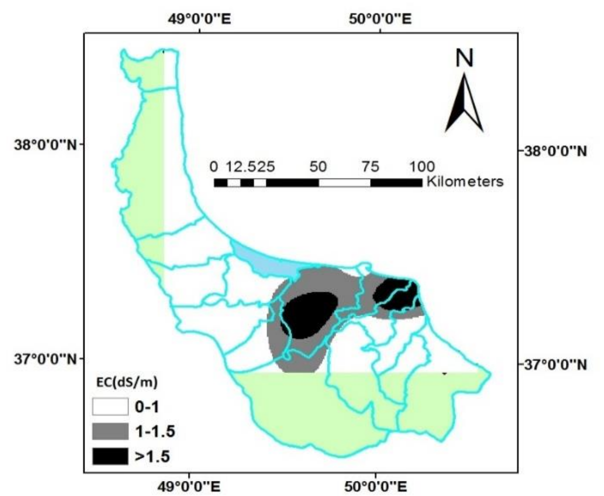


2014



2015

Fig. 2- Electric conductivity zoning maps using ordinary kriging

Table 5- Area of different EC classes (EC in dS/m)

	0<EC<1		1<EC<1.5		EC>1.5		
Year	Area(km^2)	percent	Area(km^2)	percent	Area(km^2)	percent	Conditon
2002	5348.88	68.56	2143.08	27.47	309.96	3.97	First year
2009	6291	80.57	1156.32	17.81	80.64	1.62	Best year
2014	4479.48	59.64	1096.92	14.60	1934.28	25.75	Worst year
2015	5496.12	69.39	1607.04	20.31	816.12	10.30	Last year

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Regarding the area of salinity classes within the studied years of 2014 and 2009, the salinity of more than 1 dS/m in spring (rice cultivation season) was selected as the worst year (2014) and salinity of less than 1 dS/m as the best year (2009). As is clear from the zoning maps, there is no salinity problem in the western part of Guilan province. Thus, due to a large distance from the Sefidroud River, the salinity of the river water has reached and precipitated only into the central and eastern parts of the aquifer, which left the western parts unaffected; hence, better water quality for the western regions has been provided (Ahmadpour et al., 2015). Salinity has expanded to the eastern parts of the regions in the following years; besides, Rasht, Astaneh Ashrafieh, Lahijan, and Langrood have suffered from salinity. Furthermore, increasing salinity can be due to reduced rainfall in those years (Remesan & Panda 2007). Increasing the amount of salinity in 2014-2015 can be due to the low discharge of the Sefidroud River in those years, causing salt accumulation in the soil profile. According to the zoning maps, the highest amount of salinity was detected in the central and eastern parts of Guilan province during the studied years. The Sefidroud basin, which corresponds to the highest EC of the groundwater, is a type of riverine alluvial plain with a lighter texture than the rest of the area. It is also possible that through irrigation of this part of the agricultural land from the irrigation network of Sefidroud and its subsidiary branches, salts and ions along with water percolate deep through these soils and get to the groundwater, and increase EC. Moreover, concerning the degradation of groundwater quality, the increasing number of villages and agricultural lands in the plain district is undoubtedly a warning indication of overexploitation of groundwater resources in this section, which is more than the other areas of the plain.

To generate groundwater EC probability maps, IK method was employed. The threshold value of groundwater salinity was considered as one dS/m due to a decrease in rice yield (Rezaei et al., 2013). In this method, values above one dS/m were assigned as one, and values less than one dS/m were assigned as zero. The best experimental semivariogram model of EC was determined for each year among 11 models for IK. Features of these models are presented in Table (6). One of the advantages of indicator kriging is the use of permissible limits of pollution concerning other interpolation methods, which can describe the probability of passing pollution and characterize the extent of aquifer quality zones (Amiri-Bourkhani et al., 2017). As is clear from Table (7) results, the ME and MSE values are very small and close to zero every year, and the RMSSE value is close to one. The RMSE value is also acceptable. Therefore, it can be concluded that all probabilistic maps have good and proper accuracy. In addition, according to the drawings at the beginning of the study and Table (8), 10.6% of the groundwater resources, with a probability of more than 60% of excessive salinity, were found to have a significant salinity increase during the years 2003-2005 such that, in 2014, 18.7 percent of the resources were on the verge of saltiness.

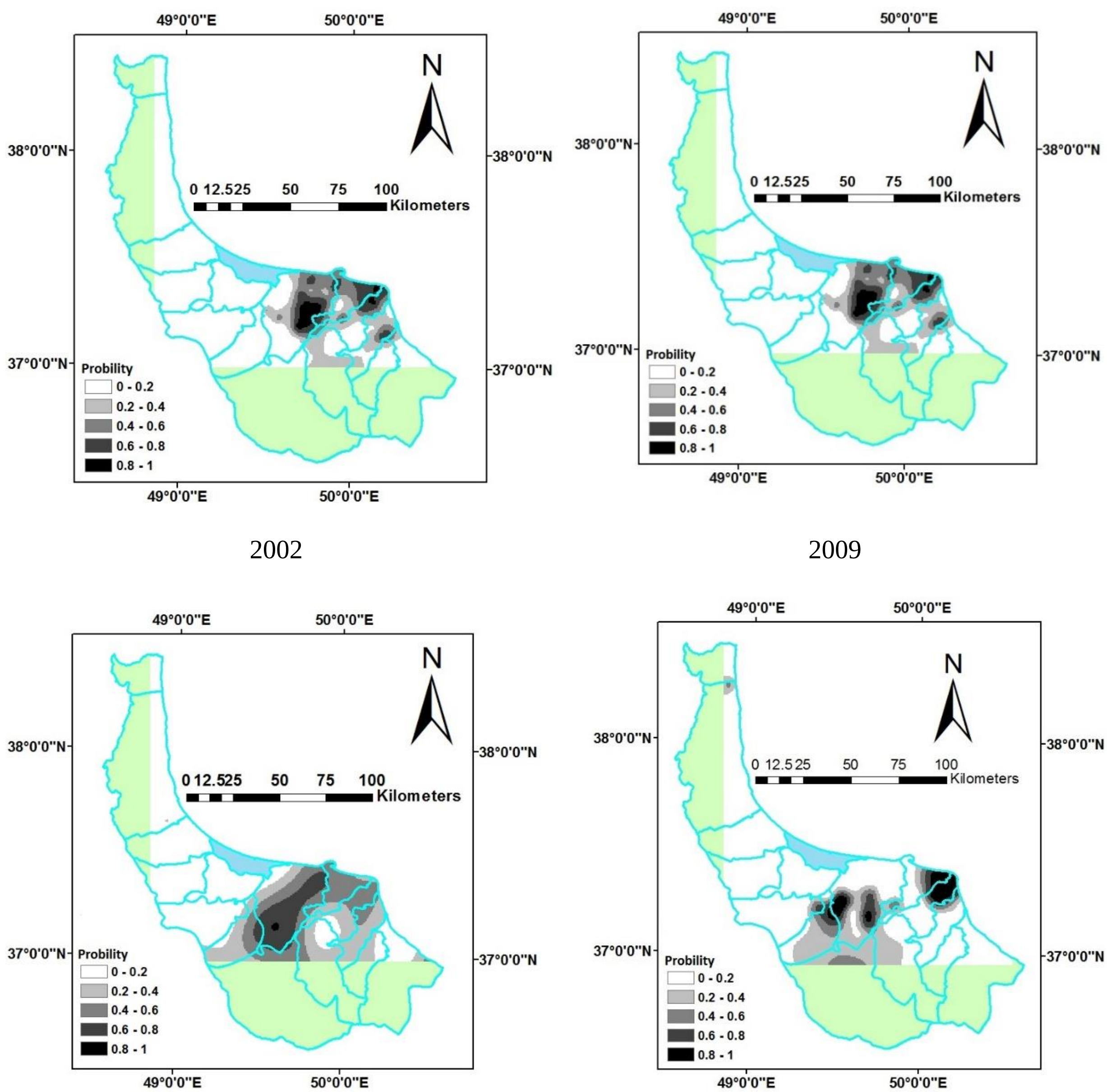
Figure (3) shows probabilistic maps of groundwater salinity in Guilan plain using IK for four years of 2002, 2009, 2014, and 2015.

Table 6- Characteristics of semivariogram models (indicator kriging)

Year	Models	Nugget	(Sill)	C0/C0+C	Spatial correlation class	range (km)
2002	exponential	0.02	0.10	0.20	strong	26.6
2009	exponential	0.03	0.14	0.214286	strong	35.1
2014	Hole Effect	0.08	0.16	0.50	average	38.8
2015	Rational Quadratic	0.05	0.16	0.31	average	28.8

Table 7- Cross-validation between measured and estimated values for groundwater EC (indicator kriging)

Year	ME (dS/m)	RMSE (dS/m)	MSE (-)	RMSSE (-)	ASE $(dS/m)^{0.5}$
2002	-0.00584	0.408738	-0.01344	1.101353	0.364668
2009	0.002844	0.308855	0.007374	1.102066	0.275259
2014	0.001303	0.355879	0.007119	1.031051	0.317386
2015	0.003140	0.279115	0.007336	0.909386	0.308887



2002 2009

2014 2015

Fig. 3- Probabilistic maps of groundwater electrical conductivity

Table 8- Probability ranges of areas exceeding groundwater salinity thresholds, by year (IK) in %

Year	0-0.2	0.2-0.4	0.4-0.6	0.6-0.8	0.8-1	Condition
2002	47.6	21.8	20	10.3	0.3	First year
2009	60.1	17.2	11.9	7.6	3.2	Best year
2014	50.1	22.8	8.4	8.7	10	Worst year
2015	63.4	20.8	6.9	4.3	4.6	Last year

Table 9- The results of Man-Kendall and Sen methods in analyzing the trend of groundwater salinity

	Mann-Kendall trend		Sen's slope estimate	
EC (dS/m)	Test Z	Significant	Q	B
0-1	-0.11	ns	-12.15	5365.49
1-1.5	-1.09	ns	-56.76	2129.04
>1.5	1.09	ns	42.18	27.27
Equation of the Sen's slope estimator	f(year) = Q*(year-first data year) + B			

The Man-Kendall test results Table (9) indicate that the area of zones with groundwater EC of less than 1 dS/m during the statistical period has a negative non-significant trend at a 5% level; further to that, the district area with groundwater EC of more than 1.5 dS/m has a non-significant positive trend at a 5% level, demonstrating a rise in salinity and a decrease in the quality of groundwater resources in Guilan plain over the past fourteen years.

The Sen's slope estimator results are shown in Table (9), in which Q represents slope and B shows a constant in Sen's slope estimator equation. The maximum slope was observed in 1 and 1.5 dS/m EC. The minimum one was observed in 0-1 dS/m salinity, confirming the results of the Man-Kendall test that the quality of groundwater in the region is slightly decreasing.

Figure (4) shows temporal changes in the groundwater EC. As observed, the surface area with EC of lower than 1 dS/m was likely to be stable during the study period, whereas the surface area with 1-1.5 dS/m EC was found to be decreasing; in addition, the surface area with more than 1.5 dS/m EC was found to be increasing in the same period.

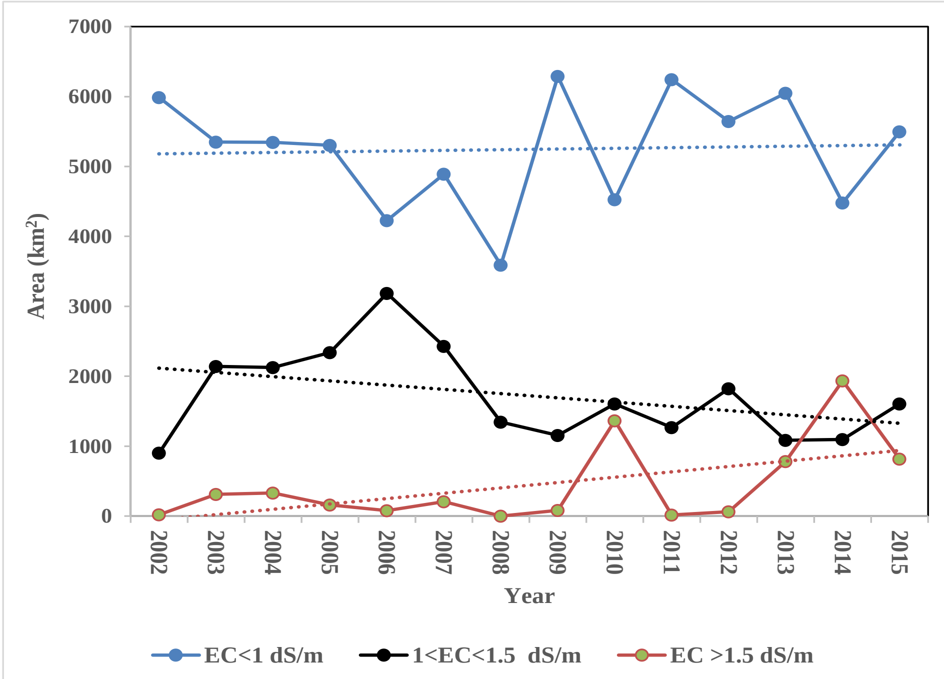


Fig. 4- Temporal changes in surface area for each class of groundwater EC during 2002-2015

Conclusion

In this study, to determine the spatial structure of groundwater (EC) in Guilan province, the best variogram model was selected among the proposed models of the ArcGIS software. The cross-validation results demonstrated good accuracy of the production maps of kriging and indicator kriging methods. In 2003, few areas had a salinity problem; however, then, salinity spread to the east of the province such that, in 2014, the most significant salinity problem was more than 1 dS/m. Furthermore, the produced map in the indicator kriging shows the increasing probability of groundwater salinity in the areas, such that salinity increased from 10.6% in 2002 to more than 18% in 2014. Therefore, to maintain a favorable level of the rice yield, urgent management measures are required to reduce groundwater salinity.

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