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ORIGINAL PAPER

# Evaluation of heavy metal contamination and pollution indices through geostatistical methods in groundwater in Bafra Plain, Turkey

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## Abstract
Groundwaters are continuously polluted by various factors, including industry, excessive fertilizer, and pesticide use. In this study, ten heavy metals (Pb, Zn, Cr, Mn, Fe, Cu, Cd, Ni, Al, and As) were analyzed in groundwater samples collected from Bafra Plain, and groundwater quality was assessed through heavy metal pollution index (HPI), heavy metal evaluation index (HEI) and degree of contamination (Cdeg) indices. Geostatistical analyses and ordinary kriging methods were used to determine the spatial distribution of heavy metals and pollution indices. The present findings revealed that Al, As, Fe, and Mn concentrations in some sections of the study area were above the limits set for drinking waters. In terms of pollution indices, 21.97% of the study were found to be highly polluted with HPI, 16.27% with HEI, and 36.08% with Cdeg. Geostatistical analyses revealed that Al, Mn, HPI, HEI, and $C_{deg}$ exhibited moderate spatial dependence, and As and Fe exhibited strong spatial dependence. In some parts of the research area, groundwater iron levels were above the limits set for drip irrigation. Less heavy metal pollution levels were encountered in western parts of the research area. It was thought that pesticide and fertilizer used over the agricultural lands and geological structures were effective in groundwater pollution. It was concluded based on the present findings that groundwater quality should continuously be monitored, and fertilizer and pesticide use should be minimized to reduce groundwater pollution levels. Geostatistical methods should also be used in the management and development of groundwater resources.

**Keywords** Groundwater · Water quality · Spatial analysis · Pollution indices · Human health

## Introduction

Surface and groundwater resources are largely allocated for agricultural, domestic, and industrial uses. Thus, water quality should continuously be monitored (Maskoni et al. 2020; Mthembu et al. 2021). Water resources pollution can be natural or anthropogenic (Ravindra and Mor 2019; Zhai et al. 2019). Anthropogenic pollutants include agrochemicals, fertilizers, industrial pollution, or domestic pollution. There have been recent increases in metal pollution of surface and groundwater (Arslan and Ayyıldız Turan 2013; Long et al. 2020). High metal concentrations in drinking waters pose severe threats to human health (Tirkey et al. 2017). High heavy metal contents may result in an ulcer or cancer-like diseases; besides, heavy metals may influence the brain and liver (Khalid et al. 2020; Singh et al. 2018).

There are several studies conducted in various parts of the world about heavy metal contents of surface and groundwater and potential risks exerted on human health (Bhuyan et al. 2017; Gokalp and Mohammed 2019; Mthembu et al. 2020; Wen et al. 2019). Mukherjee et al. (2020) determined heavy metal (Fe, Sr, Ni, Zn, Cr, Pb, and Cu) contents of groundwater in Eastern India and reported that Fe and Pb values exceeded allowable limits. Qiao et al. (2020) took

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samples from 130 groundwater wells in the Guanzhong plain region of China and conducted a risk assessment study using 13 heavy metal parameters.

Instead of assessing the health risks of heavy metals in waters separately, water quality indices considering all heavy metals together have recently been employed (Chaturvedi et al. 2018; Rezaei et al. 2017). Water quality indices or pollution indices are simple and efficient methods developed to identify pollution levels of water resources or sources of pollution, and these methods offer a reliable tool for water management planners (Afonne et al. 2020; Rahman et al. 2020; Singh et al. 2017). HEI, HPI, and $C_{deg}$ have been used to investigate heavy metal pollution levels of the waters and potential use of water resources as drinking water (Dippong et al. 2019; Paul et al. 2019; Singha et al. 2020). Gharaat et al. (2020) used HPI, HEI, and $C_{deg}$ indices to examine heavy metal pollution of groundwater in southern Iran and identified quite a high pollution problem in some sections of the research site. Singaraja et al. (2015) assessed groundwater heavy metal pollution in India using HPI, HEI and $C_{deg}$ indices and indicated potential effects of chemical wastes and domestic leakages on pollution.

Geostatistical methods are commonly used to estimate pollution values at unsampled locations. These methods also facilitate identifying pollution sources and water resources management practices (Bodrum-Doza et al. 2019). Ordinary kriging method is commonly used to assess the spatial distribution of groundwater quality traits between the geostatistical methods. (Arslan 2017; Ashrafzadeh 2016; Karami et al. 2018). Islam et al. (2017) used the ordinary kriging method to assess spatial distribution maps for groundwater heavy metals in the Rangpur region of Bangladesh. Fallah et al. (2019) investigated heavy metal pollution of groundwater in Canada using HPI, HEI, and $C_{deg}$ indices. Researchers initially determined the best semivariograms model for each parameter and used ordinary kriging for spatial distribution.

Bafra Plain is among the largest irrigation districts of Turkey, and groundwater of the plain plays a great role in irrigation and domestic uses. Besides, in recent years, excessive quantities of chemical fertilizers and pesticides are used in agricultural practices. This study was conducted (1) to assess heavy metals contents of groundwater in terms of drinking water quality, (2) to determine heavy metal pollution of groundwater with the use of HPI, HEI, and $C_{deg}$ indices, (3) to generate spatial distribution maps with the use of kriging method through geostatistical modeling of heavy metal contents, HPI, HEI, and $C_{deg}$ values, and (4) to identify the sections of the plain with potential heavy metal pollution.

## Materials and methods

### Study site

This research was laid out in the Middle Black Sea Region in the north of Turkey. The study area is located between 41–36´–41–44´ north latitudes and 35–48´–36–1´ east longitudes, covering about 134 $km^2$ land area and 14 villages (Fig. 1). The altitude of the study area varies between 2 and 28 m, and the average slope is around 1%. The study area has a temperate climate with annual average precipitation of 775 mm and a temperature of 18 ºC.

Bafra Plain is considered to be young geologically (about 2000 years) and composed of smooth alluvial terrains (Demirci et al. 2020). Besides, the upper sections of the plain are also composed of volcanic rocks, sandstone, and claystone deposits (Fig. 2). The aquifer of the study area is unconfined, and groundwater well depths vary between 5 and 20 m. Groundwaters are generally used as irrigation or drinking water. Soil depth is around 1.5 m, and soil texture is clay-loam. Soil average pH is around 8.0, and organic matter content is high. Paddy, maize, wheat, pepper, and watermelon are the primary crops cultivated in the Bafra Plain. Intensive pesticide, insecticide, and fertilizer are practiced in agricultural production activities. There are agricultural industry, textile, and machinery production factories in some parts of the area.

### Groundwater sampling and analysis

The water samples were taken from 44 different groundwater wells in September 2016, and coordinates of groundwater wells were determined using Global Positioning Systems (Magellan Spor Trak Pro). Before water sampling, pumps were operated for 15 min, and water samples were collected in polyethylene bottles of 1 L. The samples were acidified using $HNO_3$ acid and preserved at 4 ºC until the analyses.

Water samples were subjected to ten different heavy metals (lead (Pb), zinc (Zn), chromium (Cr), manganese, (Mn), iron (Fe), copper (Cu), cadmium (Cd), nickel (Ni), aluminum (Al), and arsenic (As)) analyses with the use of Agilent 7500a inductively coupled plasma mass spectrometry (ICP-MS) device following EPA 200.8 guidelines in General Directorate of State Hydraulic Works.

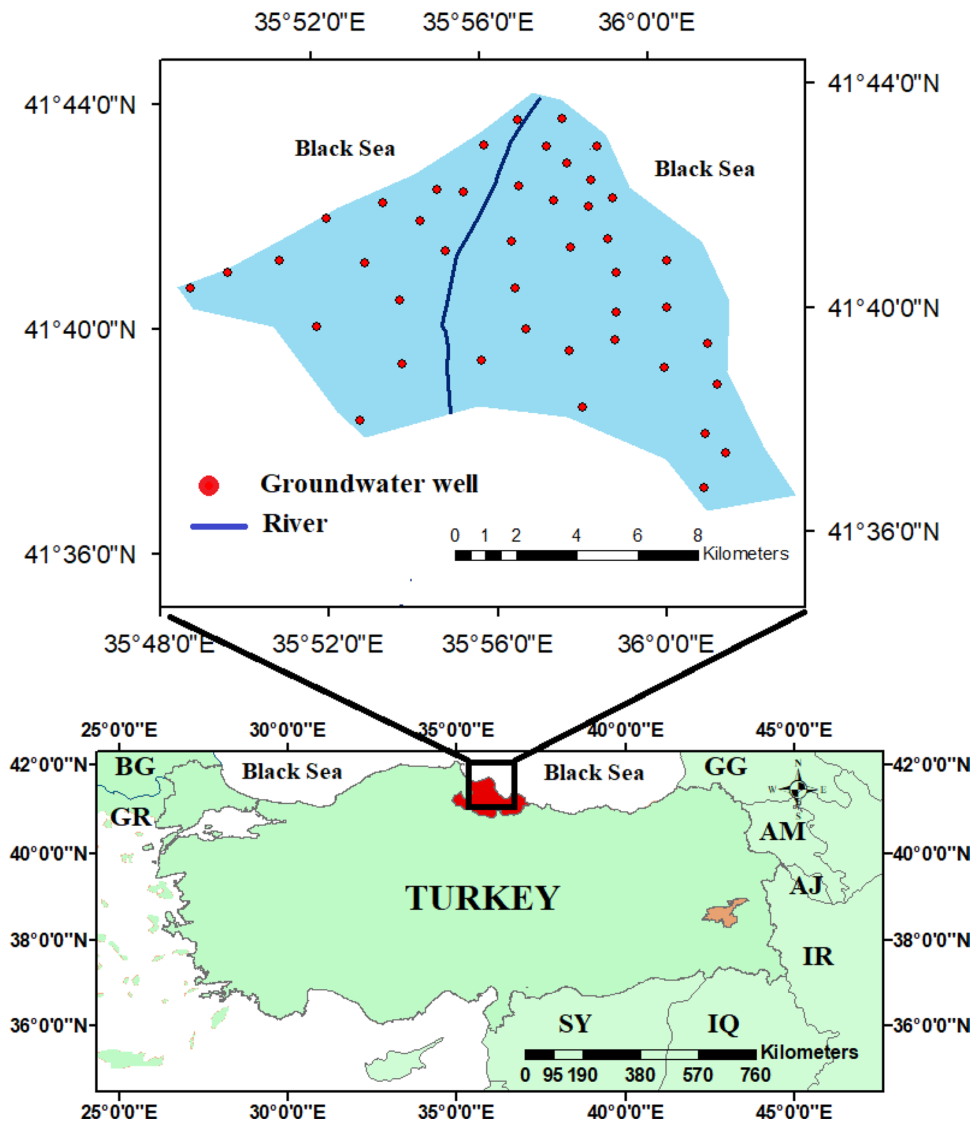


**Fig. 1** Study area and sampling sites

## Pollution assessment indices

The pollution assessment indices of HPI, HEI, and Cdeg were used to efficiently evaluate the heavy metal pollution levels of the groundwaters using ten parameters (Pb, Zn, Cr, Mn, Fe, Cu, Cd, Ni, Al, and As).

### Heavy metal pollution index (HPI)

The heavy metal pollution index (HPI) was developed by Mohan et al. (1996) to evaluate the combined effect of heavy metals in water and employed by researchers to determine pollution levels of waters (Shil and Singh 2019; Hossain and Patra 2020). HPI was calculated with the use of Eq. (1) and Eq. (2):

$$\mathrm{HPI} = \frac{\sum_{i=1}^{n} W_{\mathrm{i}} Q_{\mathrm{i}}}{W_{\mathrm{i}}} \tag{1}$$

$$Q = \sum_{i=1}^{n} \frac{\left|M_{\mathrm{i}} - I_{\mathrm{i}}\right|}{S_{\mathrm{i}} - I_{\mathrm{i}}} \times 100 \tag{2}$$

where $W_i$ is the unit weight of the ith parameter, $Q_i$ is the sub-index of the ith parameter, and n is the number of heavy metals measured. $M_i$, $I_i$ and $S_i$ are the monitored values of heavy metals, ideal and standard values of the $i^{th}$ parameter, respectively.

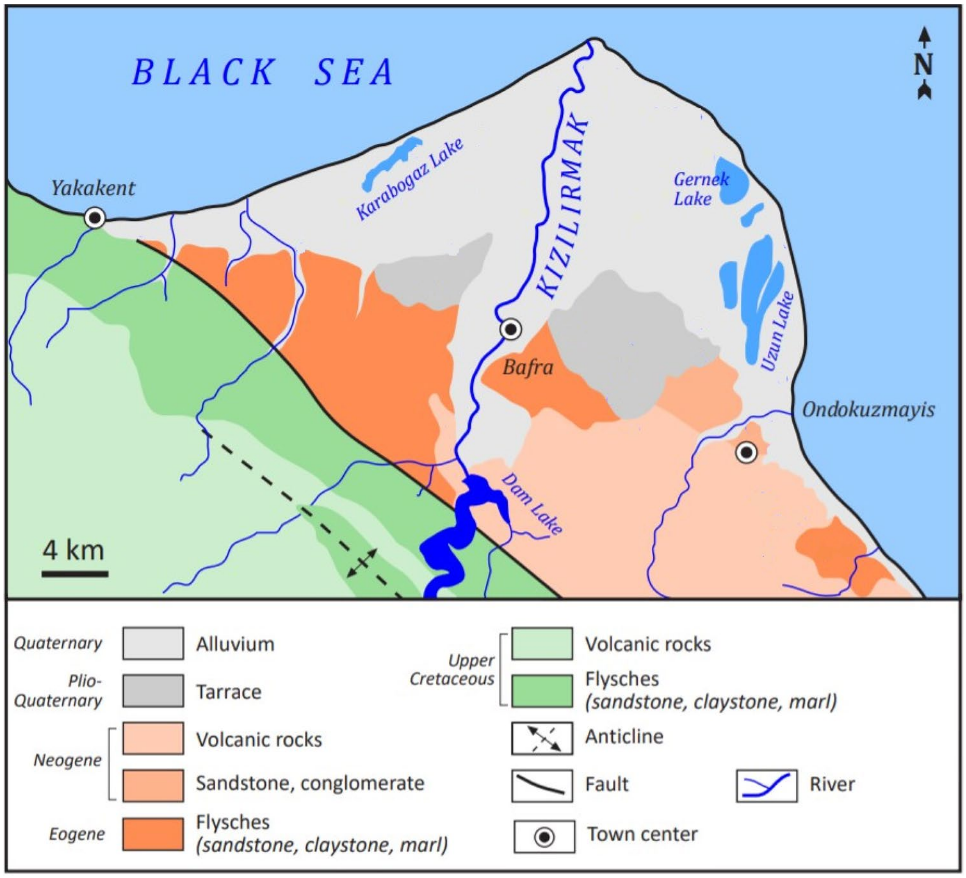


**Fig. 2** Geological setting of Bafra District

### Heavy metal evaluation index (HEI)

The heavy metal evaluation index (HEI) was developed by Edet and Offiong (2002) to identify the availability of waters to be used as drinking water. HEI is calculated with the use of Eq. (3):

$$\mathrm{HEI} = \sum_{i=1}^{n} \frac{H_c}{\mathrm{Hmac}} \tag{3}$$

where $H_c$ *and Hmac* are the measured concentrations and maximum admissible value of the ith parameter, respectively.

### Degree of contamination ($C_{deg}$)

The degree of contamination ($C_{\mathrm{deg}}$) takes combined effects of different water quality criteria into account and is calculated with the use of the following equations (Backman et al. 1998):

$$C_{\mathrm{deg}} = \sum_{i=1}^{n} C_{\mathrm{fi}} \tag{4}$$

$$C_{\mathrm{fi}} = \frac{M_{\mathrm{i}}}{MAC_{\mathrm{i}}} - 1 \tag{5}$$

where $C_{fi}$ is the contamination factor, $M_i$ is the measured value of the i[th] parameter, and $MAC_i$ is allowable concentration.

## Geostatistical modeling and spatial distribution maps

Geographical information systems and geostatistical methods were used to assess the spatial distribution of heavy metal characteristics and different pollution indices. The geostatistical software package ArcGIS (version 10.1) was used to prepare spatial distribution maps and semivariogram models. In geostatistical modeling, data on groundwater characteristics and pollution indices were subjected to a normality test using the Kolmogorov–Smirnov test. The second phase determined minimum, maximum, mean, standard deviation, skewness, and kurtosis-like basic descriptive statistics of heavy metal characteristics. Then, 11 semivariogram models (circular, spherical, tetra-spherical, pentaspherical, exponential, Gaussian, rational quadratic, hole effect, K-Bessel, J-Bessel, and stable) were tested to identify the best models for each parameter. The models with the highest coefficient of determination ($R^2$) were determined as the best models. Finally, the best semivariogram models identified for each trait were used in the kriging method to generate spatial distribution maps and estimated values of unsampled locations.

Cross-validation was used to identify the estimation performance of the models. Mean error (ME), root-mean-square error (RMSE), average standard error (ASE), mean standardized error (MSE), and root-mean-square standardized error (RMSSE) were estimated in order to identify the best-fit of the theoretical models (Arslan, 2013). For accurate estimation of the model, MSE should be close to 0; RMSE and ASE values should be small as much as possible, and RMSSE should be close to 1. These values were calculated with the use of the following equations (ESRI, 2008):

$$\mathrm{ME} = \sum (Z - Z_{\mathrm{i}}) \tag{6}$$

$$RMSE = \sqrt{\frac{\sum (Z - Z_i)^2}{n}} \tag{7}$$

$$\mathrm{ASE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left[ Z_{\mathrm{i}} - \frac{\sum_{i=1}^{n} Z_{\mathrm{i}}}{n} \right]^2} \tag{8}$$

$$\mathrm{MSE} = \frac{1}{n} \sum_{i=1}^{n} (Z - Z_{\mathrm{i}})^2 \tag{9}$$

$$\mathrm{RMSSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (Z - Z_{\mathrm{i}})^2} \tag{10}$$

where $Z_i$ is predicted value, $Z$ is measured value, and $n$ is the number of observations.

## Results and discussion

### Heavy metal properties and pollution indices of groundwater

The primary descriptive statistics for groundwater heavy metal characteristics are given in Table 1. Lead (Pb) values were varied between 0.0009 and 0.00983 mg/L with a mean value of 0.00178 mg/L. Zinc (Zn) values varied between 0.017 and 0.82 mg/L, and chrome (Cr) values varied from between 0.001 to 0.021 mg/L. Copper (Cu) concentrations ranged between 0.012 and 0.055 mg/L, and nickel (Ni) concentrations varied between 0.008 and 0.051 mg/L with a mean value of 0.015 mg/L. Cadmium (Cd) concentrations varied between 0.001 and 0.019 mg/L. Pb, Zn, Cr, Cu, Cd, and Ni values over the entire research area were below the standards set by WHO (2011) for drinking waters, and therefore, it could be stated that there was no problem in drinking.

Manganese (Mn) values varied from 0.027 to 1.072 mg/L (mean, 0.333 mg/L), and values of some wells were greater than the limiting value of 0.1 mg/L set by WHO (2011). Groundwater iron (Fe) values varied among 0.129—5.57 mg/L, and the values of some wells were far above the limiting value of 0.3 mg/L set

**Table 1** Descriptive statistics for heavy metal concentrations and pollution indices

| Parameter | Min | Max | Mean | S.D | C.V | WHO guideline value | Skewness | Kurtosis | Transformation |
|---|---|---|---|---|---|---|---|---|---|
| Pb (mg/L) | 0.0009 | 0.00983 | 0.00178 | 0.0014 | 78.65 | 0.010 | 4.822 | 28.47 | Log-normal |
| Zn (mg/L) | 0.017 | 0.279 | 0.082 | 0.057 | 69.51 | 5.000 | 1.40 | 4.88 | Log-normal |
| Cr (mg/L) | 0.001 | 0.021 | 0.0023 | 0.0043 | 186.96 | 0.050 | 2.81 | 10.98 | Log-normal |
| Mn (mg/L)) | 0.027 | 1.072 | 0.333 | 0.243 | 72.97 | 0.100 | 0.93 | 3.41 | Log-normal |
| Fe (mg/L) | 0.129 | 5.57 | 1.93 | 1.739 | 90.10 | 0.300 | 0.726 | 2.10 | Log-normal |
| Cu (mg/L) | 0.012 | 0.055 | 0.030 | 0.01 | 33.33 | 2.000 | 0.139 | 2.064 | Normal |
| Cd (mg/L) | 0.001 | 0.0019 | 0.00188 | 0.0001 | 5.32 | 0.003 | 0.109 | 2.62 | Normal |
| Ni (mg/L) | 0.0008 | 0.051 | 0.015 | 0.0108 | 72.00 | 0.070 | 1.177 | 4.58 | Log-normal |
| Al (mg/L) | 0.005 | 3.937 | 0.306 | 0.715 | 233.66 | 0.200 | 3.564 | 16.16 | Log-normal |
| As (mg/L) | 0.0001 | 0.185 | 0.021 | 0.043 | 204.76 | 0.100 | 2.518 | 8.363 | Log-normal |
| HEI | 4.044 | 138.53 | 23.124 | 26.61 | 115.08 | – | 2.72 | 10.665 | Log-normal |
| HPI | 40.18 | 356.64 | 85.224 | 73.16 | 85.84 | – | 2.455 | 8.108 | Log-normal |
| $C_{deg}$ | -7.81 | 56.394 | 5.973 | 13.099 | 219.30 | – | 1.948 | 7.299 | Normal |

na number of samples, SDa standard deviation, CVa coefficients of variation for drinking waters. Aluminum (Al) concentrations varied between 0.005 and 3.937 (mean 0.306 mg/L) with some groundwater wells exceeding WHO (2011) limit of 0.200 mg/L. Arsenic (As) concentrations varied between 0.0001 and 0.185 mg/L with a mean value of 0.021 mg/L, and some wells had greater values than the limiting value of 0.1 mg/L set by WHO (2011) for drinking waters.

The HPI, HEI, and $C_{deg}$ indices were used to assess heavy metal pollution of groundwater. The HEI values varied between 4.044 and 138.5, with a mean value of 23.124. The HPI values varied from 40.18 to 356.64, with a mean value of 85.224. The degree of contamination (Cd) results varied from -7.81 to 56.394, with an average of 5.973.

## Spatial distribution of heavy metals and pollution indices

In kriging method, data were initially subjected to a normality test to minimize the errors (Xie et al. 2011). Kolmogorov–Smirnov test was applied to present data, and while copper, cadmium, and degree of contamination exhibited normal distribution, the other parameters exhibited log-normal distribution (Table 1).

The coefficient of variation (CV) is used to determine the variability of the investigated traits. The CV values of ≤ 15 indicate low variability, CV values between 15 and 35 indicate moderate variability, and CV values of > 35 indicate high variability (Wilding 1985). Based on CV values of original data, $C_{deg}$ exhibited low variability, Cu exhibited moderate variability, and the other parameters exhibited high variability (Table 1).

In the present study, ten different heavy metals were investigated in groundwaters, and three different pollution indices were calculated using these values. Geostatistical modeling and spatial distribution maps were conducted for four heavy metals (Al, As, Mn, and Fe) posing problems in terms of drinking and domestic uses and HPI, HEI, and Cdeg pollution indices.

For each trait, 11 different semivariogram models were compared, and the best model was identified for each trait. The best semivariograms model was identified as Gaussian for As and HEI; exponential for Fe and HPI; hole effect for Al and $C_{deg}$; and J-Bessel for Mn (Table 2). Different semivariograms for different traits may be attributed to different sources of pollution. Fallah et al. (2019) reported the best model as penta-spherical for Mn, tetra-spherical for Fe and HEI, circular for HPI, and Gaussian for $_{Cdeg.}$

Nugget (Co)/Sill (Co + C) ratio reveals spatial dependence, and the ratios of < 25% indicate strong dependence, ratios between 25–75% indicate moderate dependence, and

**Table 2** Semivariogram model parameters for heavy metals and pollution indices

| Parameter | Models | Nugget ($C_0$) | Sill ($C_0$ + C) | Range (m) | Nugget ratio |
|---|---|---|---|---|---|
| Al | Hole Effect | 1.671 | 2.843 | 18,697 | 58.78 |
| As | Gaussian | 7.39 | 8.11 | 7745 | 91.12 |
| Fe | Exponential | 1.2517 | 1.4279 | 5082 | 87.66 |
| Mn | J-Bessel | 0.4517 | 0.8636 | 14,825 | 52.30 |
| HPI | Exponential | 0.4517 | 0.9558 | 20,819 | 47.26 |
| HEI | Gaussian | 0.5960 | 0.8827 | 21,668 | 67.52 |
| $C_{deg}$ | Hole Effect | 126.52 | 204.99 | 21,668 | 61.72 |

**Table 3** Cross-validation between observed and predicted values for heavy metals and pollution indices

| Parameter | Prediction errors | | | | |
|---|---|---|---|---|---|
| | Mean | Root-Mean-Square | Mean Standardized | Root-Mean-Square Standardized | Average Standard |
| Al | − 0.0869 | 0.7197 | − 0.1701 | 1.1805 | 0.7641 |
| As | 0.0012 | 0.0726 | 0.0032 | 0.0171 | 7.5253 |
| Fe | 0.2958 | 1.885 | 0.0225 | 0.464 | 4.7175 |
| Mn | − 0.0071 | 0.2431 | − 0.0904 | 0.9385 | 0.2904 |
| HPI | 0.0019 | 0.2496 | − 0.0663 | 0.8608 | 0.3257 |
| HEI | − 1.7277 | 26.075 | − 0.0898 | 1.0943 | 22.0178 |
| $C_{deg}$ | − 0.1453 | 13.0374 | − 0.0138 | 1.0942 | 11.9102 |

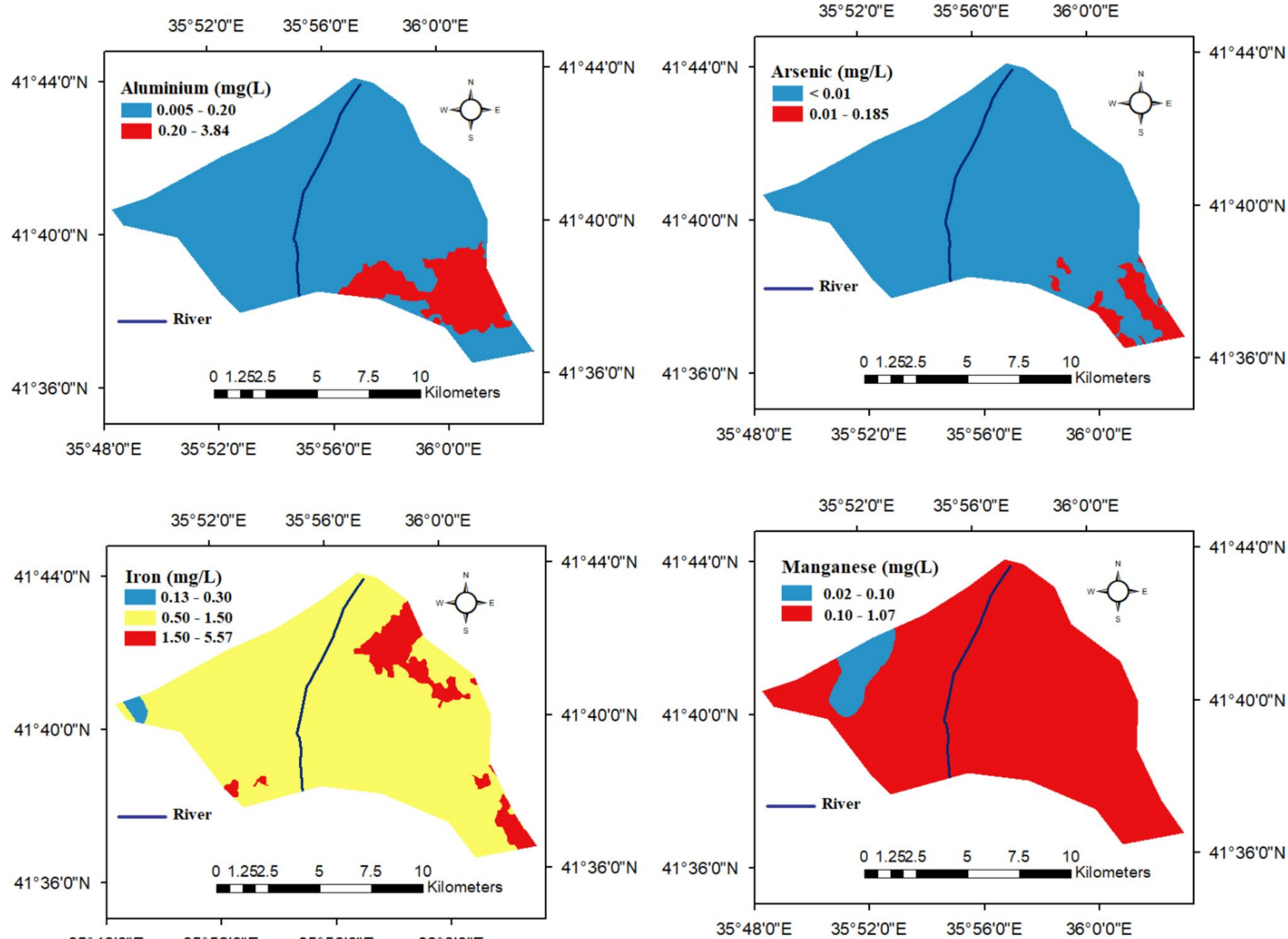


**Fig. 3** Spatial distribution of Al, As, Fe, and Mn in groundwater

ratios of > 75% indicate weak dependence (Cambrella et al. 1994). In terms of nugget ratios of groundwater traits, Al, Mn, HPI, HEI, and Cdeg exhibited moderate, while As and Fe exhibited strong dependence. Geostatistical range values varied between 5082 and 21,668 (Table 2).

According to cross-validation results for investigated traits, ME values varied between -1.7277 and 0.2958, and RMSE values varied between 0.0726 and 26.075 (Table 3).

High arsenic (As) contents of groundwater pose serious risks to human health, and long-term use of such waters may result in liver, lung, and skin cancers (Chowdhury et al. 2010). As the content of drinking waters should be lower than 0.1 mg/L. The spatial distribution of As is shown in Fig. 3, and about 4.73% of the study area had problems in terms of drinking water (Table 4). The problematic sites are mostly located in southern parts of the study area. High As levels may either be geogenic-originated or may be resulted from anthropogenic factors including fertilizer, pesticide uses, metal and alloy manufacture, oil refinery, and fossil fuels (Ayotte et al. 2003; Zhang et al. 2019). Agricultural activities, especially paddy cultivation, are intensively practiced in the study area, and high As might have resulted from fertilizers and As-containing pesticides used over the agricultural lands.

Iron plays an important role in groundwater to be used for both irrigation and drinking, and iron sources are mostly anthropogenic (Li and Zhang 2010). In terms of irrigation and drinking water quality, iron was mapped in three different categories (Fig. 4). In drinking waters, iron concentrations should be below 0.3 mg/L; about 99.3% of the study area had problems in terms of drinking water, and iron concentrations reached quite high levels in some parts of the study area (Table 4). Iron concentrations of irrigation waters should not exceed 5 mg/L, but iron values above 1.5 mg/L may result in plugging of drippers (FAO 1994). Iron concentrations were greater than 1.5 mg/L in 7.64% of the study area, and in the case of drip irrigation in these sections, dripper plugging may be encountered. Therefore, sprinkler or furrow irrigation should be practiced in these parts of the study area instead of drip irrigation. Besides, iron levels of

**Table 4** Spatial distribution of selected heavy metals and pollution indices

| Characteristics | Range | Area (ha) | % |
|---|---|---|---|
| Al | 0.0–0.20 | 11,744 | 87.74 |
| | 0.20 < | 1641 | 12.26 |
| As | 0.0–0.01 | 12,752 | 95.27 |
| | 0.01 < | 633 | 4.73 |
| Fe | 0.0–0.30 | 93 | 0.7 |
| | 0.30–1.50 | 12,269 | 91.66 |
| | 1.50 < | 1023 | 7.64 |
| Mn | 0.0–0.10 | 645 | 4.82 |
| | 0.10 < | 12,740 | 95.18 |
| HPI | 0–100 (Low) | 10,386 | 77.6 |
| | 100–200 (Medium) | 2941 | 21.97 |
| | 200 < (High) | 58 | 0.43 |
| HEI | 0–10 (Low) | 35 | 0.26 |
| | 10–20 (Medium) | 11,172 | 83.47 |
| | 20 < (High) | 2178 | 16.27 |
| $C_{deg}$ | 0–3.0 (Low) | 2756 | 20.59 |
| | 3.0–6.0 (Medium) | 5800 | 43.33 |
| | 6.0 < (High) | 4829 | 36.08 |

three wells were above 5 mg/L. Thus, these waters should not be used in irrigations.

The spatial distribution of aluminum is shown in Fig. 3. Al concentration of drinking waters should be less than 0.2 mg/L, and Al concentrations were greater than the drinking water quality criterion in 12.26% of the study area (Table 4). Problematic sites are located in southern parts of the research area, and geological structure could be the primary source of Al in groundwaters. Buragohain et al. (2010) explained that the high aluminum in groundwater might be caused by its dissolution from clays and other alumino-silicate minerals in soils and sediments.

High manganese (Mn) concentrations may lead to Alzheimer-like diseases and influence the intellectual functions of the children (Wasserman et al. 2006; Tirkey et al. 2017). High Mn concentrations of waters may be originated from industrial activities and intrusions from sediment and rocks into groundwaters (Demirel 2007). Mn concentrations of greater than 0.1 mg/L in drinking waters may pose some risks to human health. In terms of Mn concentrations, 95.18% of the present study area was found to be unsuitable for drinking, and only five wells were found to be suitable for drinking.

HPI is commonly used to assess heavy metal pollution of water resources (Sobhanardakani 2018). For HPI, the critical value is 100. Waters with HPI values of < 100 have low pollution levels and do not pose any risks on human health. On the other hand, waters with HPI values of > 100 are considered as highly polluted waters (Ghaderpoori et al. 2018). High pollution problem was encountered in 22.40% of the present study area, and these sites are located in three different sections of the study area. Correlation analysis was conducted to investigate the relationships between HPI and measured heavy metals, to determine the heavy metals effective in HPI and to identify sources of pollution (Table 5). There were significant correlations between HPI and As ($r = 0.993$) at 1% level. Such a case revealed that high HPI might have resulted from pesticides and fertilizers.

The waters with HEI values of < 10 are classified as low polluted, HEI values of between 10 and 20 are classified as medium polluted, and HEI values of > 20 are classified as highly polluted waters. About 0.26% of the present study area exhibited low pollution, 83.47% medium pollution, and 16.27% high pollution. In terms of HEI, highly polluted sites are located in southeast sections of

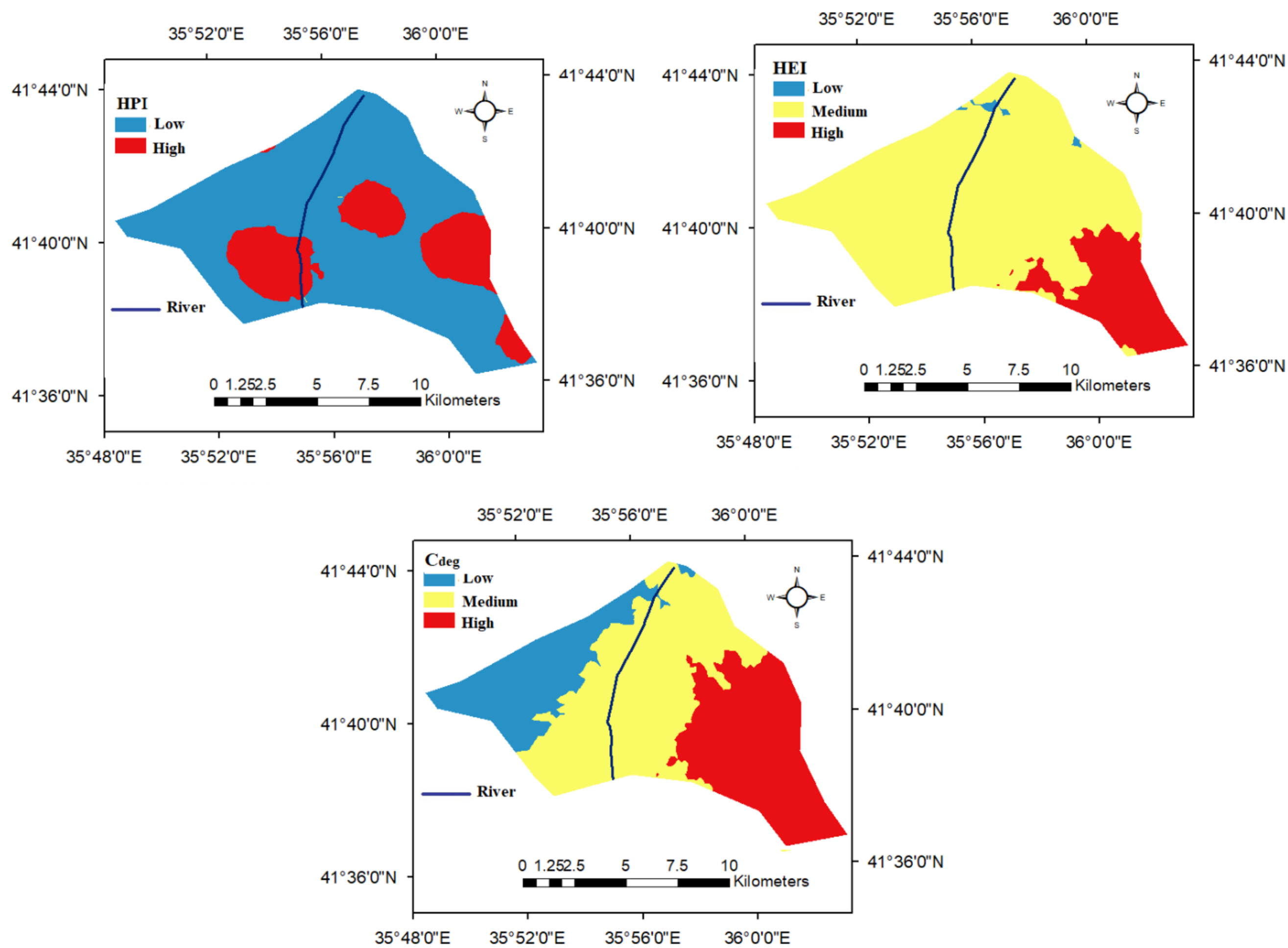


**Fig. 4** Spatial distribution of HPI, HEI, and $C_{deg}$ in groundwater

**Table 5** Correlation coefficients for pollution indices and heavy metal concentrations

| | Pb | Zn | Cr | Mn | Fe | Cu | Cd | Ni | Al | As | $C_{deg}$ | HEI | HPI |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $C_{deg}$ | 0.632** | 0.068 | 0.692** | 0.181 | 0.587** | 0.125 | – 0.175 | 0.595** | 0.823** | 0.280 | 1 | | |
| HEI | 0.739** | 0.104 | 0.867** | 0.183 | 0.457** | 0.234 | – 0.143 | 0.701** | 0.958** | 0.089 | 0.937** | 1 | |
| HPI | – 0.018 | – 0.046 | – 0.075 | – 0.172 | 0.220 | – 0.082 | – 0.208 | – 0.170 | 0.006 | 0.993** | 0.385** | 0.198 | 1 |

the study area. HEI had significant correlations with Pb, Cr, Fe, Ni, and Al at 1% level. High Pb concentrations of groundwaters mostly result from fertilizers and pesticides (Hossain and Patra 2020). It was thought that fertilizer and pesticide-like anthropogenic polluters had significant effects on HEI.

The waters with Cdeg values of < 3 are considered to have low heavy metal pollution, Cdeg values between 3–6 are considered to have medium heavy metal pollution, and Cdeg values of > 6 are considered to have high heavy metal pollution (Fallah et al. 2020). About 20.59% of the present study area had low pollution, 43.33% had medium pollution, and 36.08% had high pollution. Western sections of the study area had low pollution, and pollution levels increased toward the study area's eastern sections. The Cdeg values had significant correlations with Pb, Cr, Fe, Ni, and Al at 1% level. High Cdeg values might have resulted from agricultural pollutants and geological structure.

## Conclusion

In this study, concentrations of ten heavy metals (Pb, Zn, Cr, Mn, Fe, Cu, Cd, Ni, Al, and As) were determined in the groundwater of the Bafra plain. The heavy metal pollution of the plain was assessed through the HPI, HEI and $C_{deg}$ pollution indices and geostatistical methods. The ordinary kriging method was used to generate spatial distribution maps of heavy metals and pollution indices. Al values were above the permissible limits set for drinking waters in 12.16% of the study area, As in 4.73%, Fe in 99.3%, and Mn in 95.18% of the study area. About 21.97% exhibited high pollution in terms of HPI, 16.27% in terms of HEI and 36.08% in terms of Cdeg. Greater pollution levels were encountered in southeastern sections of the study area. Groundwater pollution was mostly anthropogenic and partially geogenic-originated. Heavy metal pollution of groundwater is a significant issue in terms of both drinking and irrigation purposes. In order to reduce heavy metal pollution in groundwater, the use of pesticides and fertilizers should be reduced, and industrial facilities should be controlled. New industrial facilities should not be allowed to be established in areas with high pollution.

Therefore, the quality of water resources should continuously be monitored, and different pollution indices should be used to determine current pollution levels. Geographical information systems and geostatistical methods should also be used in water resources management.

**Author's contributions** Hakan ARSLAN, Kadir Ersin TEMİZEL, Mehmet Sait KİREMİT, and Alper GÜNGÖR collected data. Nazlı AYYILDIZ TURAN, Ayşe KULEYİN, and Hava YILDIZ ÖZGÜL analyzed the experimental data. Hakan ARSLAN drew the figures and wrote the manuscript. Nazlı Ayyıldız TURAN designed the experiment and reviewed and revised the manuscript.

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**Data availability** All data generated or analyzed during this study are included in this published article. This manuscript has not been published and is not under consideration for publication elsewhere. All authors have approved of and have agreed to submit the manuscript to this journal.

### Declarations

**Conflict of interests** The authors reported no potential conflict of interest.

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