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Original Research

Geostatistical Approach to Assessment of Spatial Distribution of Groundwater Quality

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Abstract

A large portion of the water requirements of Konya, Turkey, is supplied by 200 groundwater wells. The quality of this groundwater was determined by taking samples from 156 of the wells within a study area of 427.5 km^2. The locations of the wells were obtained using a hand-held global positioning system (GPS) receiver. The purposes of this investigation were to provide an overview of current groundwater quality and to determine spatial distribution of groundwater quality parameters in the study area. The geostatistical analyst extension module of ArcGIS was used for exploratory data analysis, semivariogram model selection, cross-validation, and development of a distribution pattern of groundwater quality parameters such as pH, electrical conductivity, Cl^-, SO_4^{-2}, hardness, and NO_3^- concentrations. The ordinary Kriging (OK) method was used to produce the spatial patterns of water quality over the study area. The result of OK interpolation showed that higher chloride, sulfate, conductivity and hardness concentrations are clearly situated in the northeast of the study area. Concentrations of groundwater quality parameters were compared with World Health Organization, U.S. Environment Protection Agency, and Turkish Standards Institute drinking water guidelines.

Keywords: geographic information system, geostatistics, groundwater, Kriging

Introduction

The usage of groundwater has gradually increased due to of the increase of water demand and the shortage of surface water during the growth of population and rapid industrialization. Groundwater can become contaminated from numerous types of human activities such as residential, municipal, commercial, industrial, and agricultural usage.

Natural resources and environmental concerns, including groundwater, have benefited greatly from the use of GIS. ArcGIS geostatistical analyst effectively bridges the gap between geostatistics and GIS analysis [1]. Geostatistical analysis has been useful to determine water variables in space and time [2, 3]. Many studies have successfully used interpolation techniques with and without the use of the ArcGIS Geostatistical tool [1, 4-11]. Methyl-tert-butyl-ether (MTBE) concentrations were assessed in the groundwater of the city of Temecula, California, using geostatistical analysis by He and Jia [4]. The MTBE concentration values were predicted using the simple Kriging interpolation technique. The soil heavy metal concentrations (Cu, Zn, Pb, Cr, and Cd) in paddy fields were estimated for the sites with no sampling data. Ordinary Kriging (OK) and lognormal Kriging were used to produce the spatial patterns of heavy metals and disjunctive Kriging was applied to quantify the probability of heavy metal concentrations higher than their guide values [5]. Sarangi et al. [6], employed the OK and co-Kriging techniques of geostatistics using the ArcGIS and GS+ tools to generate the rainfall spatial variability map of St Lucia. They were able to map the rainfall variability accurately over these mountainous regions with very low sampling density (i.e. 40 raingauges spread over 616 km^2 area of St Lucia). In another study by Sarangi et al. [7], the spatial

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variability map of soil phosphorous saturation (Psat) percentage was developed over the St-Espirit watershed in Quebec, Canada, using GS+ software and the geostatistical analyst module of ArcGIS. In the study conducted by Hu et al. [8], spatial variability of grounwater quality and risk of NO_3 pollution in groundwater in the central North China Plain were determined using the OK method. Zimmerman et al. [12] evaluated and compared the accuracy of OK, universal Kriging and IDW methods based on an analysis of synthetic data from a computational experiment. Geostatistical methods, Kriging and co-Kriging, were applied to estimate the sodium adsorption ratio (SAR) in a 3,375 ha agricultural field [13]. Zhu et al. [14, 15] produced a radon distribution map using the Kriging and GIS techniques in Belgium. The spatial distribution of nitrate concentration in the aquifer of central Italy (about 110 km^2) was investigated and co-Kriging and OK techniques were compared in another study by D'Agostino et al. [16]. OK is most commonly adopted for environmental studies [4-8, 10-12, 14-16].

The main aims of this investigation are to provide an overview of present groundwater quality for parameters such as pH, electrical conductivity, chloride, sulfate, hardness, and nitrate concentrations, and to determine the spatial distribution of groundwater quality parameters in the study area using GIS and geostatistics techniques.

Study Area and Data Collection

The city of Konya is located in the middle of Anatolia, 260 km from Ankara, the capital of Turkey. The population of the city is about 850,000 and it is the largest city in Turkey, with a surface area of 38,183 km^2. Fig. 1 shows the location of the city of Konya. The study area is about 17.1 km wide from east to west and 25 km long from north to south, which yields a total area of 427.5 km^2. Average rainfall is 326 mm and the average temperature is 11.5°C. Average temperature varies from 0°C in January to 23°C in July.

A large proportion of water requirements for the city of Konya are supplied from 200 groundwater wells. In 1995, a drinking water treatment plant was put into operation. The treatment plant was constructed to treat water of the Altınapa Dam and to supply 43% of the total water requirement of the city. Presently, new deep wells are still being drilled and operated by the Water Authority of Konya City Municipality (WAKCM), as the water requirements of the city constantly increase. Depth of the wells varies between 25 m (minimum) and 206 m (maximum), with an average of 128 m. Fig. 2 shows the location of wells within the study area.

Water samples were taken directly from 156 wells in December 2003 by the WAKCM. The wells were pumped until temperature, conductivity, and pH stabilized. Glass containers were used for the collection of water samples for analyses, and delivered to the WAKCM laboratory within 2 hours. Analyses were normally carried out as soon as the samples reach the laboratory. Water quality parameters (chloride, sulfate, hardness) were then analyzed in the laboratory according to the methods given in Standard Methods [17]. Sample pH was measured using a glass electrode pH meter. Electrical conductivity was measured using a platinum electrode conductivity meter. Nitrate (NO_3^-) concentrations were measured with a UV-VIS spectrophotometer by Brucine colorimetric method [18].

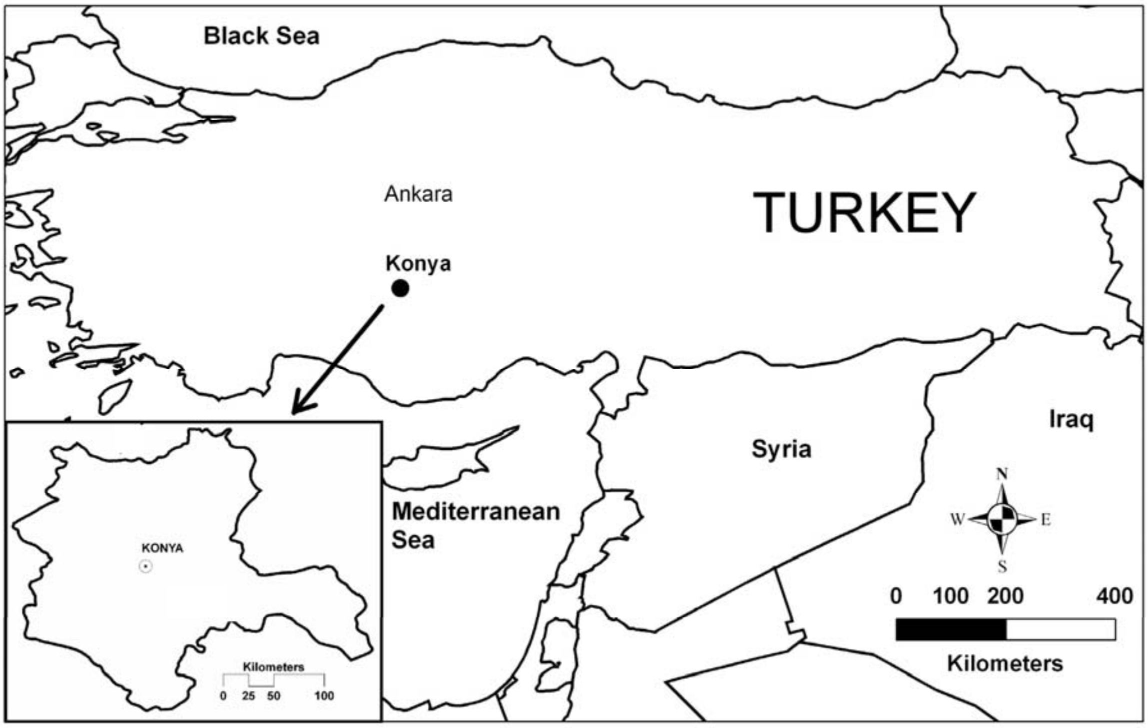

Fig. 1. Location of the study area.

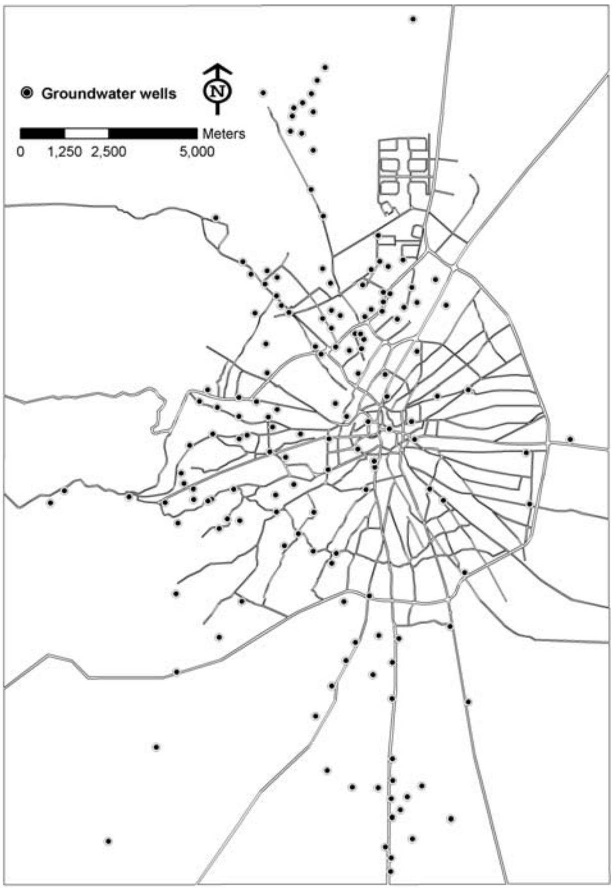

Fig. 2. Location of wells in the city of Konya.

Methods

The paper map of Konya City is a 1/25,000 scale and was digitized to the UTM coordinate system (6º section width) by applying the on-screen digitizing method. The well locations were obtained for 156 wells spreading all over the region using a Magellan Spor Trak hand-held global positioning system (GPS) receiver. A GIS software package ArcGIS 8.3 and ArcGIS Geostatistical Analyst extension were used for the ordinary Kriging estimations in this study. This section briefly deals with the procedures of data analysis using ArcGIS and ArcGIS Geostatistical Analyst extension and the Kriging methods of interpolation.

Kriging, which is the geostatistical term for optimal linear prediction of spatial processes, is widely used in geology, hydrology, environmental monitoring and other fields to interpolate spatial data [19]. Interpolation procedures can be simple mathematical models such as inverse distance weighting, trend surface analysis, Thiessen polygon etc., or more complex models of geostatistical methods, such as Kriging and thin plate splines [20].

Geostatistical interpolation techniques (e.g., Kriging) utilize both the mathematical and the statistical properties of the measured points. The geostatistical techniques quantify the spatial autocorrelation among measured points and account for the spatial configuration of the sample points around the prediction location. Kriging is a stochastic interpolation technique for prediction of spatial surface. It is flexible and permits investigation of spatial autocorrelation of the data, because it uses statistical models. The basic assumption in Kriging is that the data comes from a stationary stochastic process and some methods require that the data be normally distributed. Kriging is divided into two distinct tasks: viz. quantifying the spatial structure of the data and producing a predicted surface. In order to predict an unknown value for a specific location, Kriging will use the fitted model from variography, the spatial data configuration, and the values of the measured sample points around the prediction location [7]. Because Kriging uses statistical models, it allows a variety of map outputs, including predictions, prediction standard errors, probability, and quantile maps. With the recent advances in computation facilities and the availability of geostatistical software, the use of Kriging in the spatial analysis of environmental data is increasingly popular. Today, a number of variants of Kriging are in general use, these are: simple Kriging, ordinary Kriging, universal Kriging, block Kriging, co-Kriging and disjunctive Kriging. Among the various forms of Kriging, ordinary Kriging has been used widely as a reliable estimation method [21].

Mathematical Functions for Ordinary Kriging (OK)

Kriging relates the semivariogram, half the expected squared difference between paired data values $z(x)$ and $z(x+h)$ to the distance lag h, by which locations are separated:

$$\gamma(h) = \frac{1}{2} E\left[z(x) - z(x+h)\right]^2 \tag{1}$$

For discrete sampling sites the function is written in the form:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \left[z(x_i) - z(x_i + h)\right]^2 \tag{2}$$

...where $z(x_i)$ is the value of the variable Z at location of x_i, h is the lag, and $N(h)$ is the number of pairs of sample points separated by h. For irregular sampling, it is rare for the distance between the sample pairs to be exactly equal to h. Therefore h is often represented by a distance interval.

A semivariogram plot is obtained by calculating values of the semivariogram at different lags. These values are then usually fitted with a theoretical model: spherical, exponential, or Gaussian. The models provide information about the spatial structure as well as the input parameters for the Kriging interpolation. Kriging is regarded as an optimal spatial interpolation method, which is a type of weighted moving average:

$$\hat{z}(x_0) = \sum_{i=1}^{n} \lambda_i z(x_i) \tag{3}$$

...where: $\hat{z}(x_0)$ is the value to be estimated at the location of x_0; $z(x_i)$ is the known value at sampling site x_i, and λ_i is weight.

Table 1. Statistical evaluation of groundwater quality parameters in Konya city (n=156).

pH	n	Conductivity (μS/cm)	n	Chloride (mg/L)	n	Sulfate (mg/L)	n	Hardness (ºF)	n	Nitrate (mg/L)	n
< 7	2	< 1000	145	< 50	135	< 50	101	< 30	55	< 10	86
7-8	148	1000-2000	11	50-100	17	50-100	43	30-50	90	10-50	67
> 8	6	> 2000	0	> 100	4	> 100	12	> 50	11	> 50	3

Parameter	Minimum	Maximum	Mean	Median	Standard deviations	Skewness	Kurtosis
pH	6.81	9.51	7.51	7.5	0.31	1.962	13.687
Conductivity (μS/cm)	304	1480	646.65	604.5	224.63	1.196	4.630
Chloride (mg/L)	5	132	29.71	22.0	21.77	2.237	8.275
Sulfate (mg/L)	5	200	50.67	45.0	35.63	2.159	8.008
Hardness (ºF)	12	71	34.49	33.0	10.82	0.814	3.696
Nitrate (mg/L)	1.2	142	13.23	9.0	15.70	5.119	37.65

n=number of studied samples.

There are *n* sites within the search neighborhood around x_0 used for the estimation, and the magnitude of *n* will depend on the size of the moving search window and user definition. Kriging differs from other methods (such as IDW), in which the weight function λ_i is no longer arbitrary, being calculated from the parameters of the fitted semivariogram model under the conditions of unbiasedness and minimized estimation variance for the interpolation. Thus, Kriging is regarded as a best linear unbiased estimation (BLUE). A more detailed explanation of the method is given by [2, 19, 21, 22]. Out of different Kriging techniques, the ordinary Kriging (OK) method was used in the present study because of its simplicity and prediction accuracy in comparison to other Kriging methods [2].

Interpolation Procedures

The preliminary step of geostatistical analysis is exploratory data analysis (EDA), in which the histogram, normality, trend of data, voroni mapping, semivariogram cloud and cross covariance cloud of the raw data were observed [7, 23]. Kriging methods work best if the data is approximately normally distributed [23]. Transformations were used to make the data normally distributed and satisfy the assumption of equal variability for the data. In ArcGIS Geostatistial Analyst, the histogram and normal QQPlots were used to see what transformations, if any, are needed to make the data more normally distributed. The Trend tool raises the points above a plot of the study site to the height of the values of the attribute of interest in a three dimensional plot of the study area. The points are then projected in two directions onto planes that are perpendicular to the map plane. A polynomial curve is fit to each projection. If the curve through the projected points is flat, no trend exists. For each water quality parameter, an analysis trend was made. Directional influences (anisotropy) are critical to the accurate estimation of water quality surface. The directional search tool was used to remove the directional influences from the groundwater quality data.

In this study, the semivariogram models were tested for each parameter data set. Prediction performances were assessed by cross validation. Cross validation allows determination of which model provides the best predictions. For a model that provides accurate predictions, the standardized mean error should be close to 0, the root-mean-square error and average standard error should be as small as possible (this is useful when comparing models), and the root-mean square standardized error should be close to 1 [23].

Results and Discussion

Water samples were taken from 156 wells in the study area. Statistical evaluation of groundwater quality parameters can be seen in Table 1.

In this study, the data has been checked by a histogram tool and normal QQPlots to see if it shows a normal distribution pattern. Normal QQPlots provide an indication of univariate normality. If the data is asymmetric (i.e., far from normal), the points will deviate from the line. Histogram and normal QQPlot analysis were applied for each water quality parameter and it was found that only the pH parameter showed normal distribution. It was determined that electrical conductivity, chloride, sulfate, hardness and nitrate concentrations do not show normal distributions. For those parameters, a log transformation has been applied to make the distribution closer to normal. For each water quality parameter, an analysis trend was made and it was determined that there is no global trend for all parameters.

Table 2. Cross validation results of nitrate parameters.

Models	Prediction Errors				
	Mean	Root Mean Square	Average Standard Error	Mean Standardized	Root Mean Square Standardized
Circular	0.441	12.85	16.51	0.0235	0.715
Spherical	0.471	12.71	16.47	0.0223	0.718
Tetraspherical	0.489	12.63	16.38	0.0259	0.712
Pentaspherical	0.486	12.59	16.31	0.0264	0.708
Exponential	0.578	12.41	17.14	0.0326	0.663
Gaussian	0.472	12.53	16.50	0.0225	0.704
Rational Quadratic	0.685	12.09	16.60	0.0403	0.666
Hole Effect	**0.4148**	**13.04**	**14.72**	**0.0200**	**0.792**
K-Bessel	0.4705	12.54	17.16	0.0258	0.683
J-Bessel	0.4367	12.53	15.61	0.0269	0.727
Stable	0.4710	12.62	17.32	0.0259	0.682

In this study, the semivariogram models (circular, spherical, tetraspherical, pentaspherical, exponential, gaussian, rational quadratic, hole effect, K-Bessel, J-Bessel, and stable) were tested for each parameter data set. Prediction performances were assessed by cross validation, which examines the accuracy of the generated surfaces. Table 2 lists cross validation results to examine the validity of the fitting models and parameters of semivariograms for nitrate parameters. All of the water quality parameters were assessed by cross validation and given nitrate parameter as an example. For the nitrate sample, the standardized mean range is from 0.02 to 0.0326 and the RMSS range is from 0.663 to 0.792.

In this case, for the nitrate parameter the best fit is the Hole Effect model with a 0.02 standardized mean error. It is closest to zero, and the 0.792 RMSS value is closest to 1. When the average estimated prediction standard errors are close to the root-mean-square prediction errors from cross-validation, then you can be confident that the prediction standard errors are appropriate [23]. For the nitrate sample, average estimated prediction standard errors are close to the root-mean-square prediction errors as 14.72 and 13.04 in the hole effect model, respectively. This result proves that the hole effect model is the best one.

After applying different models for each water quality parameter examined in this study, the error was calculated using cross validation and models giving best results were determined. Table 3 shows the most suitable models and their prediction error values for each parameter. Table 3 also shows that for different parameters different models may give better results. For water quality parameters, RMSS range from 0.79 to 1.11.

The groundwater quality prediction maps showing the concentration distribution generated from the surface map developed from the cross validation process discussed above. Fig. 3 shows the spatial distribution of pH, conductivity, chloride, sulfate, hardness, and nitrate concentrations in the study area, respectively.

pH

The maximum contaminant level (MCL) for pH in drinking water is given as to be 6.5-8.5 by the World Health Organization, the European Community and the U.S. Environmental Protection Agency, but 6.5-9.2 by the TSE. In addition, Turkish Standards recommend 6.5-8.5 for pH [24-26].

The minimum and maximum values of pH were measured as 6.81 and 9.51, respectively. There was a well (No. 35) in which pH exceeds the MCL of 9.2 given in Turkish Standards. Spatial distributions of pH concentrations are shown in Fig. 3a. It is shown that the low pH concentrations (< 7.4) occur within the city center.

Conductivity

Electrical conductivity (EC) is a parameter related to total dissolved solids (TDS). EC is actually a measure of solution in terms of its capacity to transmit current. The importance of EC and TDS lies in their effect on the corrosivity of a water sample and in their effect on the solubility of slightly soluble compounds such as $CaCO_3$. In general, as TDS and EC increase, the corrosivity of the water increases.

For the EC, a value of 400 µS/cm is the recommended European Community Standard but there is no indication for the MCL. However, in Turkish Standards the value of 400 µS/cm is recommended with the MCL of 2,000 µS/cm.

In the study area, electrical conductivity ranged from 304 µS/cm to 1480 µS/cm with a mean value of 666.65 µS/cm.

Table 3. Fitted parameters of the theoretical variogram model for groundwater quality parameters.

Parameters	Models	Prediction Errors				
		Mean	Root Mean Square	Average Standard Error	Mean Standardized	Root Mean Square Standardized
pH	Circular	-0.0002	0.256	0.224	0.0053	1.11
Conductivity	Rational Quadratic	-4.903	187	190.9	-0.0187	0.94
Chloride	Rational Quadratic	-0.853	19.36	18.36	-0.0304	0.95
Sulfate	Pentaspherical	-1.193	31.12	31.52	-0.0722	1.06
Hardness	Stable	-0.022	8.20	9.11	-0.0010	0.90
Nitrate	Hole Effect	0.415	13.04	14.72	0.0200	0.79

The recommended value of 400 µS/cm can be obtained from 10 out of 156 wells. There was no water well in which the EC exceeds the MCL of 2,000 µS/cm given in Turkish Standards. As shown in Fig. 3b, the value decreases southwest of the city area.

Chloride

Chlorides occur in all natural waters in widely varying concentration. The chloride content normally increases as mineral content increases [27]. There are several potential human-related sources of chloride and sulfate to aquifers. These include agricultural activity, household sewage, landfill leachate, industrial effluent and road salting [28, 29]. The chloride ion occurs in natural waters in fairly low concentrations, usually less than 100 mg/L, unless the water is brackish or saline [29]. Chloride concentrations above 250 mg/L could affect the taste of drinking water and above 150 mg/L are toxic to crops and generally unsuitable for irrigation. Water containing more than 350 mg/L chloride is unsuitable for most industrial uses [28].

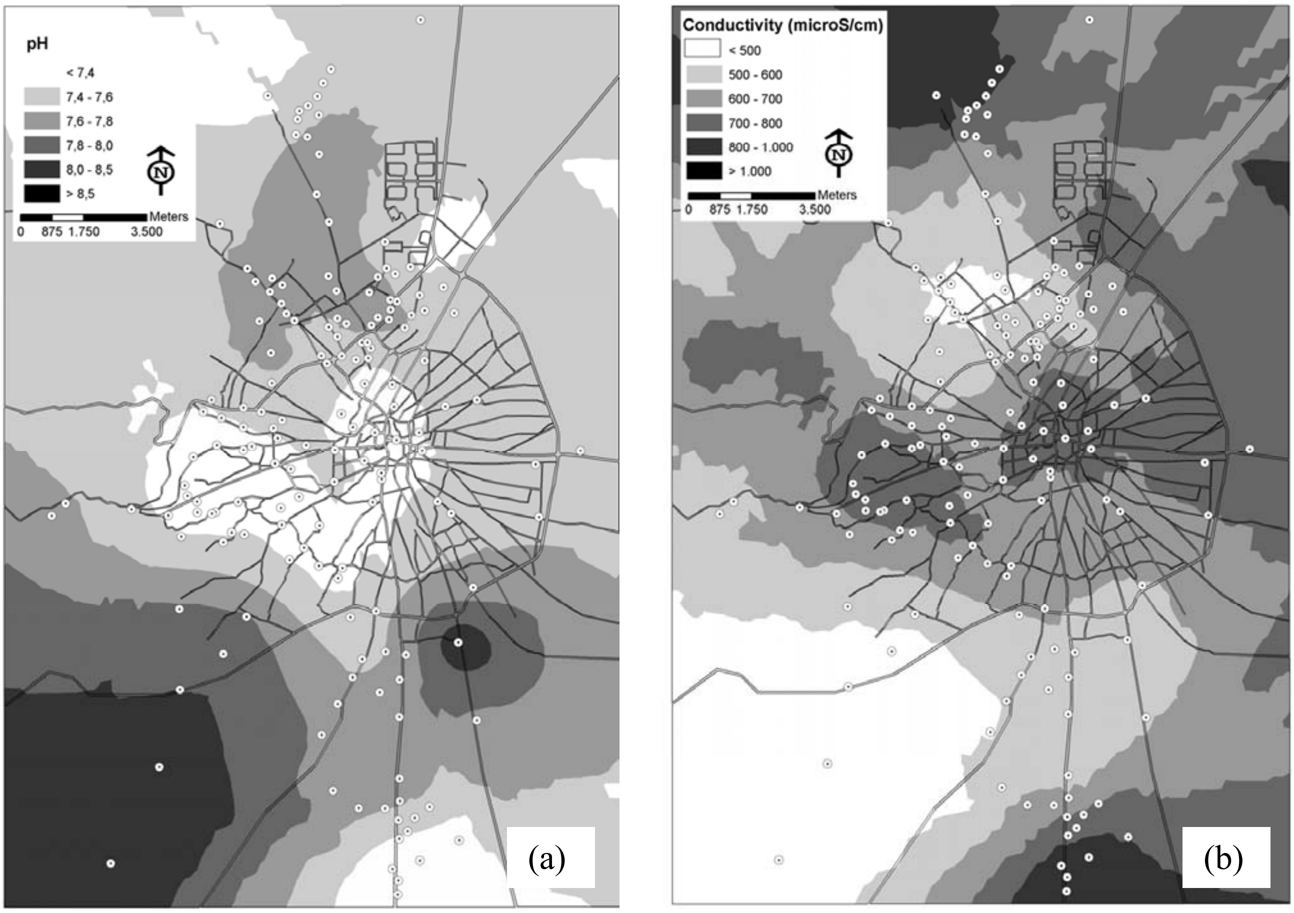

Fig. 3. Spatial distribution of a) pH, b) electrical conductivity.

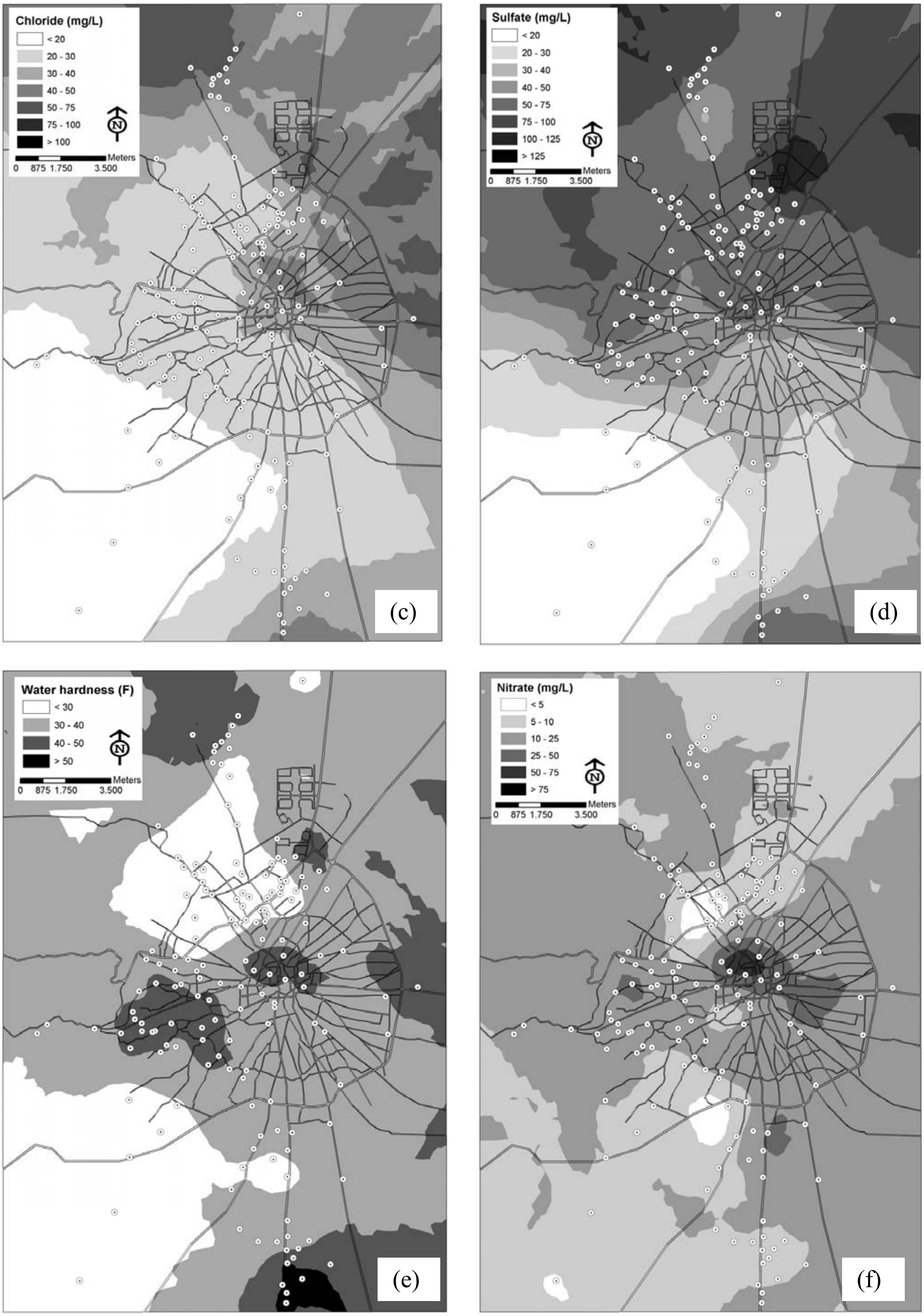

Fig. 3. Continued. Spatial distribution of c) chloride, d) sulfate, e) hardness, and f) nitrate concentrations in the study area.

The MCL for chloride in drinking water is given as to be 250 mg/L by WHO and the EPA, but 600 mg/L by the TSE. On the other hand, there is no indication in EC standards about the MCL for chloride. In addition, Turkish and EC standards recommend 25 mg/L for chloride [24-26].

The minimum and maximum concentrations of chloride were measured as 5 mg/L in the No. 82 well in the southwest and 132 mg/L in the No. 93 well east of the study area. The mean concentration of chloride was about 29.71 mg/L. Chloride concentration complied with the value of 25 mg/L for 55 out of 156 wells. There was no water well in which the chloride concentration exceeds the MCL given in Turkish Standards. As indicated by Fig. 3c, chloride concentration increased from southwest to northeast. In a wide area around the southwest part of the city, less than 20 mg/l chloride concentration occurs.

Sulfate

Sulfate is a substance that occurs naturally in drinking water. Generally, sulfate is considered beneficial in irrigation water, especially in the presence of calcium. However, high levels of sulfate with calcium forms a hard scale in steam boilers. High sulfate and chloride concentrations also affect the taste of water [28]. For irrigation waters with sulfate above 500 mg/L, plant life may be harmed [30]. Water in igneous or metamorphic rocks generally contains less than 100 mg/L sulfate but sedimentary rocks can contain much higher levels [28]. There are few scientific reports that address sulfate concentration in drinking water and the effects it may have on the health of those individuals who are exposed. The EPA [30] examined the association between consumption of tap water containing high levels of sulfate and reports of osmotic diarrhea in susceptible populations (infants and transients). In experimental trials with adult volunteers, the EPA [30] did not find an association between acute exposure to sodium sulfate in tap water (up to 1,200 mg/L) and reports of diarrhea. Whereas Sawyer and McCarty [27] indicated diarrhea when it is present in excessive amounts. Hudak [28] reported that sulfate concentrations above 500 mg/L could have a laxative effect on humans.

TSE, WHO, EPA and EC indicate the MCL of 250 mg/L for sulfate, a concentration of 25 mg/L is recommended in both EC and Turkish Standards. The minimum and maximum values of sulfate were measured as 5 mg/L in well No. 38 and 200 mg/L in well No. 122, respectively. The mean concentration of sulfate was calculated at about 50.67 mg/L. The sulfate concentration of 25 mg/L can be seen in 133 of the 156 wells. There was no water well in which the sulfate concentration exceeds the MCL given in Turkish Standards. It can be seen in Fig. 3d that the sulfate concentration (same as chloride) increases from the southwest to the northeast of the city area.

Hardness

The hardness of water is generally considered to be those waters that require considerable amounts of soap to produce foam or lather and that also produce stains in hot water pipes, heaters, and boilers [27]. Other adverse effects of water hardness include bathtub rings, deterioration of fabrics and, in some cases, stains. While high water hardness levels pose several problems, extremely low values can lead to inadequate uptake of essential nutrients, principally calcium and magnesium. Calcium contributes to healthy bones and teeth. Hard water may also improve cardiovascular health [31]. The principal hardness-causing cations are calcium, magnesium, strontium, ferrous iron, and manganous ions. The hardness of water reflects the nature of the geological formations with which it has been in contact [27].

There is no limitation of water hardness by EPA, Turkish and EC standards, but WHO gives a value of 50ºF as the maximum value for water hardness. There is no water hardness value at all between 0-7.5ºF, which are classified as “soft” water in the study area.

The minimum, maximum and mean values of hardness were 12ºF, 71ºF and 34.49ºF, respectively. North of the study area is an aquifer lithology of limestone (Mesozoic) and the hardness value in this area reaches up to 40ºF. Insoluble bicarbonates are converted to soluble carbonates because of the existence of carbon dioxide in the soil. Since limestone is not pure carbonate but includes impurities such as sulfates and chlorides, these materials become exposed to the solvent action of the water as the carbonates are dissolved, and they pass into solution, too. Therefore, chloride and sulfate concentrations as well as water hardness are very high in such areas.

South of the study area (Alakova region) has sandy, gravelly (Plio-Quaternary) and sandy clay (Plio-Quaternary) aquifer lithology, and the hardness value in this area were observed to be between 20-40ºF. From north of the Alakova region to southwest, west and northwest of the city, water hardness was estimated to be less than 30ºF. The value of water hardness increases from the south to the northeast of the city area (Fig. 3e)

Nitrate

Groundwater contamination by nitrates is a worldwide problem, mainly related to the important use of fertilizers in intensive agriculture [32, 33]. Nitrate is a frequently occurring contaminant in groundwater. Because of its solubility and its anionic form, nitrate is very mobile in groundwater [34]. Previous studies have shown that rural land uses, especially agricultural practices, can contribute nitrate to groundwater. Non-agricultural sources of nitrogen, such as septic systems and leaking municipal sewers, are generally less significant regionally but may affect groundwater locally [29]. During recent years, the problem of groundwater contamination by nitrates has been studied thoroughly all over the world [16, 34-37]. Several studies document adverse effects of higher nitrate levels, most notably methemoglobinemia and non-Hodgkin’s lymphoma [36].

For TSE, WHO and EC, the MCL of nitrate is given to be 50 mg/L, with 44.27 mg/L from the EPA for drinking water. On the other hand, both the TSE and EC describe the limit concentration of nitrate as 25 mg/L.

Spatial distributions of nitrate concentrations are shown in Fig. 3f. It is shown that the high nitrate concentrations (>50 mg/l) occur within the city center. It can be seen in Table 3 that the minimum and maximum nitrate concentrations were observed to be 1.2 mg/L and 142 mg/L, with the average value of 13.23 mg/L in the 156 wells. The nitrate concentrations of 105 mg/L and 142 mg/L were measured in well Nos. 69, and 41, respectively. Nitrate concentrations for these 2 wells exceed the MCL of 50 mg/L indicated in TSE. Well No. 41 is placed at a park in the city center where fertilizers were often applied to the lawns. Fertilizers may cause this high level of nitrate concentration. This groundwater well was also taken out of operation. Nitrate content for 14 groundwater wells does not meet the standard of 25 mg/L indicated by TSE.

Conclusions

Groundwater is an essential water source in the city of Konya, Turkey. Approximately 75% of the city's water consumption has been supplied from groundwater wells for the last six years. The primary objective of this study was to map and evaluate the groundwater quality in Konya. Spatial distribution of groundwater quality parameters such as pH, chloride, sulfate, hardness, electrical conductivity, and nitrate concentrations were carried out through GIS and geostatistical techniques.

Ordinary Kriging was used to obtain the spatial distribution of groundwater quality parameters over the area. The groundwater quality data have been checked by a histogram tool and normal QQPlots to see if it shows a normal distribution pattern, and it was found that only the pH parameter showed normal distribution. It was determined that electrical conductivity, chloride, sulfate, hardness and nitrate concentrations do not show normal distributions. For each water quality parameter, an analysis trend was made, and it was determined that there is no global trend for all parameters. The eleven different semivariogram models were tested for each parameter data set. Prediction performances were assessed by cross validation.

According to the groundwater quality parameters distribution map, (Fig. 3) the southwest of the city has optimum groundwater quality and, in general, the groundwater quality decreases from southwest to northeast of the city. On the other hand, south of the city are a low-density residential area and mainly an agricultural area. Residential areas are located at the city center.

In order to manage groundwater effectively, a systematic control program and the building of GIS is recommended. It is also important to use a GIS-linked monitoring system in order for the Water authorities to determine the water quality parameters easier and faster. Prior to drilling new wells, groundwater quality maps produced as a result of this research should be taken into account by WAKCM as a decision support system.

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