Geostatistical evaluation of groundwater quality distribution of Tonk district, Rajasthan
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ABSTRACT
Groundwater is an important source of drinking water in the semi-arid region of Rajasthan, India. Therefore, it becomes important to assess the groundwater quality. The groundwater chemical data of conductivity, total dissolved solids, total hardness, fluoride, nitrate and chloride of 112 wells were taken from Ground Water Board. Since it is not feasible to collect the data from all the locations in the study area; so, geo-statistical analyst extension of ArcGIS was used to generate the spatial distribution maps of the water quality parameters using the data collected. This tool was used for exploratory data analysis, selection of the best semivariogram model, and cross-validation. The best fit semivariogram model was selected on the basis of root-mean-square standardized error (RMSS), mean square error (MSE), root mean square error (RMSE), and average standard error (ASE). The spatial distribution maps of all the given parameters are prepared by applying the ordinary kriging interpolation method.

Keywords: Groundwater quality, Geostatistical analyst, Kriging, Semivariogram, Root mean square standardized error.

1. Introduction
Water is one of the most important natural resource for survival of human life. There has been a continuous increase in demand of water due to increase in population. Due to increasing urbanization leading to increasing demand for water, qualitative deterioration is also happening very fast. This has rendered water unfit for use by human beings.

With the increasing population and simultaneous decrease of surface water resources due to various reasons, groundwater resources have become more important. Groundwater resources have much more importance in India because of mostly rural set up, most of the villages still not connected with surface water supply system. The importance of groundwater resources increases many fold for semi-arid tracts of Rajasthan.

These studies will provide the decision makers/planners with accurate and reliable scientific database regarding the quality of water, type of contamination, source of contamination, affected population etc. In view of the importance of a scientific and organized database on all the aspects of groundwater resources, this work has been undertaken, mainly to assess the current status of groundwater quality in Tonk district, Rajasthan.

ArcGIS Geo-statistical Analyst tool plays an efficient role in creating a continuous surface map from measured sample points that are stored in a point layer. The data stored in the point layer can be depth to the water table or water table elevation or water quality data. Geo-
statistical Analyst provides a variety of tools for generating the surfaces. These tools can be used to visualize, analyze, and understand spatial phenomena.

The spatial distribution of groundwater constituents shows some heterogeneity and it is not feasible to collect the data of every possible location in the specified area. This infeasibility is due to the time and the cost involved in data collection. Therefore, only alternative is to predict the values at unknown locations by making use of values of known locations. To perform this prediction, the geo-statistical methods such as kriging can be used.

The basic assumption in using geo-statistics is that the properties in the earth have some spatial continuity up to a certain lag distance. Kriging method considers the spatial correlation between the sample points (Ella et al, 2001). Kriging is distinguished from IDW and other interpolation methods by taking into consideration the variance of estimated parameters (Buttner et al, 1998).

Many researchers applied geostatistical techniques for spatial distribution of groundwater parameters. Barca et al. (2008) used Disjunctive kriging and simulation methods to prepare nitrate hazard map in Modena plain of Italy. Their results showed that the applied method is the suitable one to study the declining quality of Groundwater. Delgado et al. (2010) applied kriging method to prepare groundwater quality maps for various parameters in Yukatan, Mexico. On the basis of these maps, they classified the study area into different zones and demarcated the suitable zones for agriculture purpose. Adhikary et al. (2010) assessed the groundwater pollution in West Delhi, India and analyzed spatial variability of groundwater quality. They made use of indicator kriging to generate the probability maps of groundwater contaminants. Houshmand et al. (2011) applied kriging and cokriging methods for spatial analysis of SAR and Cl- concentration in groundwater. They found Gaussian model, the best semi-variogram model, among all the available models. Rawat et al. (2012) have also used Kriging methods to predict spatial variability of some groundwater quality parameters in Mathura district, Uttar Pradesh, India. Gorai et al (2013) made a study on the groundwater quality in Ranchi Municipal Corporation area. They tested various semi-variogram models for ordinary Kriging to identify the best fitted model. The best model was selected on the basis of mean square error (MSE), root mean square error (RMSE), average standard error (ASE), and root mean square standardized error (RMSSE).

Thus, it can be said that researchers have applied distinct interpolation method for their specific problem. A single method for specific region cannot be generalized to others. The main objective of the research paper is to assess the accuracy of different geostatistical interpolation methods for spatial distribution of Groundwater quality parameters in Tonk district, Rajasthan.

2. Study area

The area covered in this study is Tonk District, Rajasthan, which is located in North - Eastern part of the state between 75° 07’ 00” to 76° 19’00” East longitude and 25° 41’ 00” to 26° 34’00” North Latitude (figure 1). The total area covered by the district is 7194 sq kms. The area is having generally flat to undulating topography. The Banas River is major one running through Tonk district. It enters at Negaria in Deoli tehsil and leaves the district at Sureli near Barawara station, covering 135 kms in the district.
The pre-monsoon groundwater quality data of the year 2014 were taken from Ground Water Board, Jaipur, Rajasthan. This data of 112 wells pertain to physico-chemical parameters such as conductivity, total dissolved solids, total hardness, fluoride, nitrate and chloride.

3. Methodology

The software tool Geostatistical Analyst in ArcGIS 10.2 is used for interpolating the surfaces in this study. Geostatistical Analyst provides two categories of interpolation techniques: deterministic and geostatistical (stochastic). Deterministic methods provide no assessment of errors with predicted values, whereas stochastic methods offer assessment of prediction errors.

Both the interpolation techniques make use of the weights of nearby known values to predict values at unknown locations. The stochastic techniques being statistical models are more flexible and allow examination of spatial autocorrelation of the data. Kriging gives the efficient results if the data is normally distributed. Kriging process is performed in two stages, first it compute the spatial structure of the data and then generate a predicted surface. To estimate an unknown value for a particular location, Kriging method makes use of the fitted...
model of semivariogram, the spatial data relationship, and the values of the known points around the predicted location (Sarangi et al., 2005).

Kriging generates a variety of maps as compared to IDW. The final output maps produced by kriging are prediction map, probability map, prediction standard error map, and quantile map. Kriging method is becoming more popular in the spatial analysis of environmental data with the current progression in computation services and more powerful geostatistical software packages. A variety of Kriging methods are provided by the geostatistical software such as simple, ordinary, universal, block, co-Kriging and disjunctive Kriging. Among these forms, ordinary Kriging has been used widely by many researchers as a reliable estimator (Yamamoto J.K., 2000).

3.1 Ordinary Kriging

The spatial variation in kriging consists of three components: a spatially correlated component; a structure representing a trend; and an error term.

To compute the spatially correlated component, Kriging uses the semivariance. This component is also called spatial autocorrelation or spatial dependence. The semivariance can be calculated by the following equation (1):

\[ \gamma(h) = \frac{1}{2} [z(x_i) - z(x_j)]^2 \]  

where \( \gamma(h) \) represents the semivariance between known points, \( x_i \) and \( x_j \), separated by the distance \( h \); and \( z \) is the attribute value.

The next step is to compute the average semivariance by using equation (2):

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

where \( \gamma(h) \) is the average semivariance between the sample points separated by lag \( h \); \( z(x_i) \) is the value of \( z \) at location \( x_i \), \( z(x_i + h) \) is the value of \( z \) at location \( x_i + h \), \( h \) is the lag distance, and \( N(h) \) is the number of pairs of sample points separated by a lag distance \( h \).

A semivariogram plots the average semivariance against the average distance. A semivariogram may be used alone as a measure of spatial autocorrelation in the data set. But to be used as an interpolator in kriging, the semivariogram must be fitted with a mathematical function or model. The fitted semivariogram can then be used for estimating the semivariance at any given distance.

Fitting a model to a semivariogram is a difficult task. One reason for the difficulty is the number of models to choose from, since Geostatistical Analyst offers 11 models. These models provide information about the input parameters and the spatial structure for the Kriging method. Kriging is a weighted moving average method, considered an optimal spatial interpolation method, and is calculated as follows:
\[ \tilde{z}(x_0) = \sum_{i=1}^{n} w_i z(x_i) \]  

(3)

where: \( \tilde{z}(x_0) \) is the value to be calculated at the location \( x_0 \); \( z(x_i) \) is the actual value at sampling location \( x_i \); \( w_i \) is the weight of the \( i^{th} \) point; \( n \) is the number of known points used in prediction.

The weights can be obtained by solving a set of simultaneous equations. For example, the following equations are needed for a point (0) to be estimated from three known points (1, 2, and 3) (Chang K.T., 2008):

\[ W_1 \gamma(h_{11}) + W_2 \gamma(h_{12}) + W_3 \gamma(h_{13}) + \lambda = \gamma(h_{01}) \]  

(4)

\[ W_1 \gamma(h_{21}) + W_2 \gamma(h_{22}) + W_3 \gamma(h_{23}) + \lambda = \gamma(h_{02}) \]  

(5)

\[ W_1 \gamma(h_{31}) + W_2 \gamma(h_{32}) + W_3 \gamma(h_{33}) + \lambda = \gamma(h_{03}) \]  

(6)

\[ W_1 + W_2 + W_3 + 0 = 1.0 \]  

(7)

where \( \gamma(h_{ij}) \) is the semivariance between known points \( i \) and \( j \), \( \gamma(h_{i0}) \) is the semivariance between the \( i^{th} \) known point and the point to be estimated, and \( \lambda \) is a Lagrange multiplier, which is added to ensure the minimum possible estimation error. Once the weights are solved, the equation (2) can be used to estimate \( z_0 \)

\[ z_0 = z_1 W_1 + z_2 W_2 + z_3 W_3 \]  

(8)

The preceding example shows that weights used in kriging involve not only the semivariances between the point to be estimated and the known points but also those between the known points. This differs from the IDW method, which uses only weights applicable to the point to be estimated and the known points.

The weight function \( w_i \) in kriging is calculated from the parameters of the fitted semivariogram model. The ordinary Kriging method was used in the present study because of prediction accuracy and the simplicity of ordinary kriging as compared to other Kriging methods (Isaaks E.H., 1989).

### 3.2 Interpolation procedure

Firstly, all the required layers are added in the ArcMap. Exploratory Spatial Data Analysis tools are used to explore the distribution of the data, looking for the global and local outliers, looking for the global trends and examining the spatial autocorrelation. The methodology adopted for generating the spatial distribution maps is shown in figure 2.

### 3.3 Model comparison and surface prediction

The results of the different surfaces produced by different models are compared here and that model is selected for prediction which provides a best solution on the basis of the root-mean-
square error, the mean prediction error, the root-mean-square standardized error, and average standard error. (Johnston K. et al, 2001).

Figure 2: Flowchart of geostatistical analysis and selection of best model for surface generation

The various error terms are calculated using the following formulas:

Mean Prediction error:

\[ \frac{1}{n} \sum_{i=1}^{n} (\hat{z}(s_i) - z(s_i)) \]

Root-mean-square prediction error:

\[ \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\hat{z}(s_i) - z(s_i))^2} \]

Average standard error:

\[ \sqrt{\frac{1}{n} \sum_{i=1}^{n} \hat{\sigma}(s_i)} \]

Mean standardized prediction error:

\[ \frac{1}{n} \sum_{i=1}^{n} \frac{(\hat{z}(s_i) - z(s_i))/\hat{\sigma}(s_i)} \]

Root-mean-square standardized prediction error:

\[ \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left[ (\hat{z}(s_i) - z(s_i))/\hat{\sigma}(s_i) \right]^2} \]
where $\hat{Z}(s_i)$ is the predicted value obtained from cross-validation, $z(s_i)$ is the observed value and $\hat{\sigma}(s_i)$ is the prediction standard error for location $s_i$.

4. Results and discussion

The statistical evaluation of groundwater samples is calculated, as shown in Table 1, using the data collected from the ground water board. Before generating the spatial distribution maps of various water quality parameters, it is better to check the data normality. The tools available in Geostatistical Analyst such as Histogram and normal QQPlot are used for this purpose. There are some other measures through which data normality can be checked. The data may be normally distributed if:

1. The mean and median are approximately the same.
2. The coefficient of skewness is near to zero. (It is used to determine the symmetry of a distribution)
3. The kurtosis of a normal distribution is near to 3. (It is based on the size of the tails of a distribution)

It was determined that none of the parameters show the normal distribution. So, to make the data normally distributed, a log-transformation has been applied. It can be easily verified from Table 1 that the mean and median are nearly the same, skewness is close to 0 and kurtosis is close to 3 after applying the log-transformation for all the parameters.

All the parameters were also examined for the global trend and it was determined that total hardness (TH) did not show any global trend; nitrate (NO$_3$) and fluoride (F) show a linear trend; conductivity (EC) and chloride (Cl$^-$) show a parabolic trend; and TDS show a stronger parabolic trend.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>Median</th>
<th>Std Dev.</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>Trend Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>EC</td>
<td>520</td>
<td>8200</td>
<td>2247.9</td>
<td>1850</td>
<td>1527</td>
<td>1.4703</td>
<td>5.3282</td>
<td></td>
</tr>
<tr>
<td>EC*</td>
<td>6.2538</td>
<td>9.0119</td>
<td>7.5052</td>
<td>7.5229</td>
<td>0.6660</td>
<td>-0.0699</td>
<td>2.419</td>
<td>Smooth Parabola</td>
</tr>
<tr>
<td>TDS</td>
<td>171.79</td>
<td>2908.1</td>
<td>833.2</td>
<td>682.92</td>
<td>543.51</td>
<td>1.4712</td>
<td>5.0111</td>
<td></td>
</tr>
<tr>
<td>TDS*</td>
<td>5.1463</td>
<td>7.9753</td>
<td>6.5421</td>
<td>6.5263</td>
<td>0.6013</td>
<td>0.2048</td>
<td>2.4742</td>
<td>Stronger parabola</td>
</tr>
<tr>
<td>Cl-$^-$</td>
<td>14.18</td>
<td>1559.8</td>
<td>302.01</td>
<td>173.7</td>
<td>323.51</td>
<td>1.8125</td>
<td>5.8291</td>
<td></td>
</tr>
<tr>
<td>Cl-$^*$</td>
<td>2.6518</td>
<td>7.3523</td>
<td>5.1942</td>
<td>5.1572</td>
<td>1.0563</td>
<td>-0.0448</td>
<td>2.4168</td>
<td>Smooth Parabola</td>
</tr>
<tr>
<td>NO$_3$</td>
<td>1.24</td>
<td>176.08</td>
<td>43.465</td>
<td>24.8</td>
<td>44.014</td>
<td>1.4941</td>
<td>4.2709</td>
<td></td>
</tr>
<tr>
<td>NO$_3^*$</td>
<td>0.2151</td>
<td>5.1709</td>
<td>3.2355</td>
<td>3.2108</td>
<td>1.15</td>
<td>-0.5473</td>
<td>3.2078</td>
<td>Linear</td>
</tr>
<tr>
<td>F-$^-$</td>
<td>0.08</td>
<td>8.04</td>
<td>1.9877</td>
<td>1.67</td>
<td>1.5875</td>
<td>1.3146</td>
<td>4.6934</td>
<td></td>
</tr>
<tr>
<td>F-$^*$</td>
<td>2.5257</td>
<td>2.0844</td>
<td>0.3235</td>
<td>0.5128</td>
<td>0.9552</td>
<td>-0.743</td>
<td>3.4569</td>
<td>Linear</td>
</tr>
<tr>
<td>TH</td>
<td>70</td>
<td>1455</td>
<td>275.58</td>
<td>240</td>
<td>179.87</td>
<td>3.2436</td>
<td>19.129</td>
<td></td>
</tr>
<tr>
<td>TH*</td>
<td>4.2485</td>
<td>7.2828</td>
<td>5.4739</td>
<td>5.4806</td>
<td>0.5211</td>
<td>0.3329</td>
<td>3.7272</td>
<td>No</td>
</tr>
</tbody>
</table>

*After applying log-transformation

All the parameters are measured in mg/L except EC (micros/cm)
There are various semivariogram models available such as exponential, circular, Gaussian, spherical, tetraspherical, K-Bessel, J-Bessel, pentaspherical, hole effect, rational quadratic and stable. Each model is selected for prediction purpose.

Cross-validation is used to ensure “how well” the model predicts the unknown values. Cross-validation leave out a point sequentially, predicts its value using the rest of the data, and then the predicted and measured values are compared. The difference between the predicted and measured value is termed as the prediction error. This process is repeated for all the points.

Table 2 lists the cross-validation results of total hardness. The best fit model for total harness is found to be exponential model. Its mean standardized value (-0.072) is nearest to 0, root mean square standardized error (1.0573) is nearest to 1 among all the models.

<table>
<thead>
<tr>
<th>Models</th>
<th>Mean</th>
<th>Root Mean Square</th>
<th>Average Standard Error</th>
<th>Mean Standardized</th>
<th>Root Mean Square Standardized</th>
</tr>
</thead>
<tbody>
<tr>
<td>Circular</td>
<td>3.4099</td>
<td>189.953</td>
<td>184.6948</td>
<td>-0.0734</td>
<td>1.0625</td>
</tr>
<tr>
<td>Spherical</td>
<td>3.4165</td>
<td>189.9585</td>
<td>184.7405</td>
<td>-0.0734</td>
<td>1.0626</td>
</tr>
<tr>
<td>Tetraspherical</td>
<td>3.4343</td>
<td>189.9627</td>
<td>184.8353</td>
<td>-0.0733</td>
<td>1.0622</td>
</tr>
<tr>
<td>Pentaspherical</td>
<td>3.4431</td>
<td>189.9652</td>
<td>184.8834</td>
<td>-0.0733</td>
<td>1.0621</td>
</tr>
<tr>
<td>Exponential</td>
<td>3.6499</td>
<td>190.0078</td>
<td>185.9358</td>
<td>-0.072</td>
<td>1.0573</td>
</tr>
<tr>
<td>Gaussian</td>
<td>3.437</td>
<td>189.9333</td>
<td>184.8136</td>
<td>-0.0727</td>
<td>1.0595</td>
</tr>
<tr>
<td>Rational Quadratic</td>
<td>3.4268</td>
<td>189.963</td>
<td>184.8213</td>
<td>-0.0737</td>
<td>1.0633</td>
</tr>
<tr>
<td>Hole Effect</td>
<td>3.1676</td>
<td>189.9016</td>
<td>183.4038</td>
<td>-0.0747</td>
<td>1.0677</td>
</tr>
<tr>
<td>K-Bessel</td>
<td>3.4582</td>
<td>189.9358</td>
<td>184.9283</td>
<td>-0.0726</td>
<td>1.0589</td>
</tr>
<tr>
<td>J-Bessel</td>
<td>3.0171</td>
<td>189.9006</td>
<td>183.4065</td>
<td>-0.0747</td>
<td>1.0676</td>
</tr>
<tr>
<td>Stable</td>
<td>3.4371</td>
<td>189.9333</td>
<td>184.8136</td>
<td>-0.0727</td>
<td>1.0595</td>
</tr>
</tbody>
</table>

On the basis of the calculated prediction errors, following observations can be made:

1. If the mean prediction error is close to 0, then the predictions are unbiased.
2. If the root-mean-square standardized prediction error is close to 1, then the standard errors are accurate.
3. If the root-mean-square error and average standard error are small, then the predictions do not deviate much from the measured values.

Table 3 shows the most suitable models and values of all the types of errors for each water quality parameter. It was determined earlier that chloride, conductivity, fluoride, nitrate and TDS show some global trend. For all these parameters, the RMSS value is better in cases where the trend was removed in comparison to when the trend was not removed. All the semivariogram models except J-Bessel perform well in predicting the surfaces of these parameters.
Table 3: Fitted parameters of the semi-variogram models for groundwater quality parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Models</th>
<th>Trend Removal</th>
<th>Prediction Errors</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Mean</td>
<td>Root Mean Square</td>
<td>Average Standard Error</td>
<td>Mean Standardized</td>
<td>Root Mean Square Standardized</td>
</tr>
<tr>
<td>Chloride</td>
<td>Rational Quadratic</td>
<td>NO</td>
<td>20.242</td>
<td>1 320.4807</td>
<td>525.145</td>
<td>8</td>
<td>0.009</td>
</tr>
<tr>
<td>Chloride</td>
<td>All Methods (except J-Bessel)</td>
<td>Yes (second Order)</td>
<td>14.120</td>
<td>6 322.3453</td>
<td>380.791</td>
<td>-0.0877</td>
<td>1.0044</td>
</tr>
<tr>
<td>EC</td>
<td>J-Bessel</td>
<td>NO</td>
<td>38.962</td>
<td>5 1516.993</td>
<td>1730.10</td>
<td>3</td>
<td>-0.0024</td>
</tr>
<tr>
<td>EC</td>
<td>All Methods (except J-Bessel)</td>
<td>Yes (second Order)</td>
<td>43.531</td>
<td>1 1514.773</td>
<td>1506.82</td>
<td>-0.0682</td>
<td>1.0772</td>
</tr>
<tr>
<td>F-</td>
<td>Hole Effect</td>
<td>NO</td>
<td>0.1782</td>
<td>1.5752</td>
<td>2.7565</td>
<td>0.025</td>
<td>0.6296</td>
</tr>
<tr>
<td>F-</td>
<td>All Methods (except J-Bessel)</td>
<td>Yes (First Order)</td>
<td>0.0532</td>
<td>1.7267</td>
<td>2.1644</td>
<td>-0.1099</td>
<td>1.0026</td>
</tr>
<tr>
<td>NO3</td>
<td>Rational Quadratic</td>
<td>NO</td>
<td>4.9966</td>
<td>44.9101</td>
<td>85.4558</td>
<td>0.0243</td>
<td>0.5909</td>
</tr>
<tr>
<td>NO3</td>
<td>All Methods (except J-Bessel)</td>
<td>Yes (First Order)</td>
<td>-0.1679</td>
<td>48.1782</td>
<td>65.7014</td>
<td>-0.1289</td>
<td>0.9963</td>
</tr>
<tr>
<td>TDS</td>
<td>J-Bessel</td>
<td>NO</td>
<td>1.9442</td>
<td>528.4838</td>
<td>572.975</td>
<td>2</td>
<td>-0.0059</td>
</tr>
<tr>
<td>TDS</td>
<td>All Methods (except J-Bessel)</td>
<td>Yes (First Order)</td>
<td>20.205</td>
<td>9 527.0971</td>
<td>513.671</td>
<td>-0.0667</td>
<td>1.0356</td>
</tr>
<tr>
<td>TH</td>
<td>Exponential</td>
<td>NO</td>
<td>3.6499</td>
<td>190.0078</td>
<td>185.935</td>
<td>8</td>
<td>-0.072</td>
</tr>
</tbody>
</table>

Once the best models are selected, then spatial distribution maps of these parameters are generated considering the required parameters and the best selected model. The spatial distribution maps of Conductivity and TDS are shown in figure 3(a) and 3(b). The desirable and permissible limits recommended for EC (IS 10500:2012) are 1500 microS/cm and 3000 microS/cm respectively. In the study area, a small part in northern side shows the EC values exceeding the permissible limits. As shown in figure 3(a), the value of EC decreases as we move from north to south. The desirable and permissible values recommended for TDS (IS 10500:2012) are 500 mg/L and 2000 mg/L respectively. In the study area, all the values of TDS fall under the prescribed limits, as shown in figure 3(b).

The spatial distribution maps of Total Hardness and Nitrate are shown in figure 4(a) and 4(b). The desirable and permissible limits recommended for TH (IS 10500:2012) are 200 mg/L and 600 mg/L respectively. There is no such part of the study area which is having the exceeding limits of 600 mg/L for TH. But some areas in northern and southern parts of the study area have the TH values above the desirable limits. The desirable values recommended for nitrate (IS 10500:2012) are 45 mg/L, but there is no relaxation in the permissible values. In the study area, almost all the values of nitrate fall under the prescribed limits except small part in north-east and western part, as shown in figure 4(b).
The spatial distribution maps of Fluoride and Chloride are shown in figure 5(a) and 5(b). The desirable and permissible limits recommended for Fluoride (IS 10500:2012) are 1.0 mg/L and 1.5 mg/L respectively. A major part of the study area in north and extending towards south show the exceeding values of fluoride above 1.5 mg/L. The desirable and permissible limits recommended for Chloride (IS 10500:2012) are 250 mg/L and 1000 mg/L respectively. In the study area, all the values of Chloride fall under the prescribed limits, as shown in figure 5(b).
5. Conclusion

The main objective of the present work was to evaluate and map the groundwater quality of Tonk district. Ordinary krigging was used to generate the spatial distribution maps of EC, TDS, TH, nitrate, fluoride and chloride. It was determined that none of the parameters show the normal distribution. So, all the data are log-transformed to make the data normally distributed. All the parameters were also examined for the global trend and it was determined that total hardness (TH) did not show any global trend; nitrate (NO₃⁻) and fluoride (F⁻) show a linear trend; conductivity (EC) and chloride (Cl⁻) show a parabolic trend; and TDS show a stronger parabolic trend. The eleven different semivariogram models were tested for each water quality parameter. Cross-validation method was used to assess the prediction performances by these models.

According to the spatial distribution maps of various water quality parameters, it was concluded that northern part of the study area has a poor water quality, since this part has exceeding limits of fluoride. Small part in north-east and western part of the study area have exceeding the limits of nitrate; it may be due to heavy use of fertilizers. The south-eastern and south-western part of the study area is suitable for drinking purpose. Some special measures must be taken by the authorities to solve the water quality problems in the affected areas of the district.

6. References


