Groundwater suitability analysis for drinking using GIS based fuzzy logic

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ABSTRACT
In the last few decades, overexploitation and poor management of groundwater have exposed its resources to undue risk, which makes the assessment of groundwater quality and determining its suitability extremely crucial. The current study has been undertaken with an aim to analyze groundwater suitability for drinking by utilizing fuzzy logic in the geographical Information System (GIS) platform. Water samples were analyzed for various physicochemical parameters collected from different sampling stations of the Agartala Municipality. Principal Component Analysis (PCA) and Ordinary kriging (OK) were used for variable reduction and mapping of the physicochemical parameters. The best fuzzy overlay operator for the groundwater suitability map was determined based on correlation coefficient values between water quality index map and suitability maps. The results of the correlation analysis show a high positive correlation between Cl with EC (Electrical conductivity) and pH with HCO3. The groundwater of the study area is mostly acidic, with elevated iron levels along with pockets of high nitrate concentration. Fuzzy GAMMA (0.9) overlay method was selected as the best overlay operation for suitability analysis. Suitability analysis results revealed that 24.6%, 28.6%, 46.7%, of the total surface area is unsuitable, moderately suitable, and suitable respectively. This study demonstrates the capability of fuzzy logic integrated with the GIS platform to determine the groundwater suitability for drinking. The proposed methodology can be exploited as a comprehensive tool for any other suitability analysis.

1. Introduction

Groundwater is one of the most invaluable natural resources which have become an integral part of millions of individuals due to its usage in various sectors. A continuous and the rapid increase in the demand for groundwater has put immense pressure on groundwater availability and suitability. Consequently, it creates a big concern on groundwater sustainability and ecosystem behavior (Foster and Chilton, 2003). Groundwater contamination is a worldwide problem, and it is getting polluted in numerous different ways that are directly or indirectly affecting the health of the ecosystem (Morris et al., 2003; Nas and Berktay, 2006; Rakib et al., 2019; Reddy and Nandini, 2011).

Globally, various works on groundwater quality have been reported by several researchers using different tools and methods such as geochemical and hydro-chemical approaches, geographic information system (GIS) and geostatistical methods, multi-statistical method, fuzzy logic so more and so forth (Abboud, 2017; Arslan, 2017; Bodrud-Doza et al., 2016; Vadiati et al., 2016). Among all of them GIS based tool is widely used for generating, visualizing, and analyzing groundwater data (Arslan, 2017; Nas and Berktay, 2006; Şener et al., 2017).

Groundwater is complex in nature and inherent uncertainties are associated with it, therefore, geostatistical techniques and multivariate statistical methods have been used to deal with these kinds of problems (Belkhir and Narmy, 2015; Goovaerts, 1997; Goovaerts et al., 2005). Geostatistics helps us to interpolate and predict values at the unsampled location and also measures the uncertainty associated with the predictions (Goovaerts et al., 2005). Multivariate statistical methods such as Principal Component Analysis (PCA) aid in reducing the data set by identifying the possible factors/sources that influence the water quality. Additionally, correlation analysis has been widely used to identify the interrelationship between water quality parameters (Belkhir and Narmy, 2015; Machiwal et al., 2018; Singh et al., 2013; Zeinalzadeh and Rezaei, 2017).

In general, suitability analysis is a multi-criteria decision analysis (MCDA) based problem, and vagueness is associated with the inputs. Fuzzy logic developed by Zadeh (1965) and spatial overlay analysis, a GIS environment tool has been extensively used, for solving different problems related to suitability and vulnerability assessment (Akbari...
Fig. 1. Study area (Agartala Municipality area).

Fig. 2. Schematic structures of stages involve in groundwater suitability analysis.
<table>
<thead>
<tr>
<th>Variables</th>
<th>Min</th>
<th>Max</th>
<th>Skewness</th>
<th>Mean</th>
<th>SD</th>
<th>B.I.S std</th>
<th>W.H.O Limit</th>
</tr>
</thead>
<tbody>
<tr>
<td>SO\textsubscript{2}\textsuperscript{4−} (mg/l)</td>
<td>1.28</td>
<td>9.08</td>
<td>1.05</td>
<td>4.06</td>
<td>1.5</td>
<td>200</td>
<td>250</td>
</tr>
<tr>
<td>Fe\textsuperscript{3+} (mg/l)</td>
<td>0.09</td>
<td>7.6</td>
<td>0.08</td>
<td>2.55</td>
<td>2.4</td>
<td>0.3</td>
<td>0.3</td>
</tr>
<tr>
<td>NO\textsubscript{2} (mg/l)</td>
<td>0.22</td>
<td>137.7</td>
<td>3.72</td>
<td>19.49</td>
<td>24.02</td>
<td>45</td>
<td>50</td>
</tr>
<tr>
<td>EC (\textmu S/cm)</td>
<td>47.67</td>
<td>1345</td>
<td>3.9</td>
<td>200.68</td>
<td>228.55</td>
<td>1500</td>
<td>1500</td>
</tr>
<tr>
<td>Cl\textsuperscript{−} (mg/l)</td>
<td>0</td>
<td>215</td>
<td>2.77</td>
<td>30.45</td>
<td>48.79</td>
<td>250</td>
<td>250</td>
</tr>
<tr>
<td>Mg\textsuperscript{2+} (mg/l)</td>
<td>1.21</td>
<td>24.8</td>
<td>1.08</td>
<td>7.67</td>
<td>5.62</td>
<td>30</td>
<td>150</td>
</tr>
<tr>
<td>Ca\textsuperscript{2+} (mg/l)</td>
<td>2</td>
<td>55.65</td>
<td>1.86</td>
<td>15.79</td>
<td>13.1</td>
<td>75</td>
<td>200</td>
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<tr>
<td>pH</td>
<td>4.11</td>
<td>6.59</td>
<td>−0.52</td>
<td>5.69</td>
<td>0.62</td>
<td>6.5−8.5</td>
<td>6.5−8.5</td>
</tr>
<tr>
<td>HCO\textsubscript{3−} (mg/l)</td>
<td>10.12</td>
<td>129.17</td>
<td>0.65</td>
<td>51.29</td>
<td>34.88</td>
<td>120</td>
<td>–</td>
</tr>
<tr>
<td>WQI</td>
<td>23.03</td>
<td>317</td>
<td>0.68</td>
<td>161.36</td>
<td>95.93</td>
<td>–</td>
<td>–</td>
</tr>
</tbody>
</table>

et al., 2019; Ghosh and Das, 2019; Jha et al., 2020; Noori et al., 2019; Pilevar et al., 2020; Ross, 2010; Semeraro et al., 2016; Zhang et al., 2015). However, certain constraints are associated with spatial overlay analysis such as subjective weights and crisp boundaries based on expert judgment (Gharibi et al., 2012; Ki and Ray, 2014). To address the shortcomings mentioned above this study adopts a GIS based fuzzy overlay analysis. The existing literature establishes the credibility of fuzzy-based suitability work for land suitability analysis. Whereas, the assessment of groundwater suitability using fuzzy-based overlay analysis in GIS environment is not much explored. In addition to this, more research is required to identify the best fuzzy overlay operator in the GIS platform. On the other hand, people of this locality largely depend on tube wells and hand pumps as a source for drinking water, as well as a limited research on groundwater quality and suitability assessment have been documented from this area and thus, all of these have served as a research motivation for this paper.

In this present study effort has been made to (i) assess the physicochemical properties of groundwater (ii) determine the groundwater quality and find the major factors which are affecting it (iii) determine the suitability of groundwater for drinking using fuzzy logic in a GIS environment. This study will help to understand the present status of groundwater quality and the findings of the research will help the local authorities or policymakers to develop a proper plan for groundwater management. This proposed methodology will also help to improve the knowledge based decision making system, which can be used in other regions for determining the suitability of groundwater.

2. Study area

Agartala, the capital city of Tripura, India (23°45′–23°55′N latitude and 91°15′–91°20′E longitude) is situated in the flood plains of the Haora River, with an area of 76.50 km\textsuperscript{2}. The study area map is shown in Fig. 1 with sampling location and geological information. The western part of the study area has an international border with Bangladesh. The climate of Tripura is subtropical, humid, and hot. The average maximum temperature is 29 °C in summer and the average minimum is 10 °C in winter. The annual average rainfall is of the order 2000 to 2500 mm Indian meteorological depth (IMD), Government of India. Alluvial, red sandy and lateritic soils are mostly found in this area. Geologically, the area is classified, under the Tipam sandstone and Duipilla formation group (Geological Survey, 2011). Hydrogeologically the aquifer system of the area is semi confined with a yield of 50–100 m\textsuperscript{3}/h. As per state public works department PWD (DWS), Agartala the depth to the water table of the region varies from 3.96 to 22 m below ground level. The primary land use of most of the study area is agricultural land and built up (Mallik et al., 2020a; Santra et al., 2018).

3. Methodology

The overall methodology of the research is depicted in Fig. 2. The work has been divided into two stages, stage 1 deals with data collection, testing, and multivariate statistical analysis. Whereas, stage 2 deals with GIS based geostatistical mapping and suitability analysis using fuzzy logic.

3.1. Groundwater sampling and analysis

Water samples were collected from 35 different sampling stations shown in Fig. 1 for pre-monsoon (PRM) season. Samples were collected in the month of March from different wards of the Agartala Municipality. Water samples were collected in pretreated polyethylene bottles (500 mL capacity) and stored at 4 °C before analysis. pH and electrical conductivity (EC) (\textmu S/cm) were measured in the field using portable pocket pH and EC meter (Model H198129, Hanna India). Various physicochemical parameters such as sulphate (SO\textsubscript{4}\textsuperscript{2−}), nitrate (NO\textsubscript{3}), chloride (Cl\textsuperscript{−}), bicarbonate (HCO\textsubscript{3}−) magnesium (Mg\textsuperscript{2+}), calcium (Ca\textsuperscript{2+}), and iron (Fe\textsuperscript{3+}) were tested using APHA standard method (APHA, 2005). Ca\textsuperscript{2+} and Mg\textsuperscript{2+} were tested by EDTA titrimetric method. Cl\textsuperscript{−} was tested using the argentometric titrimetric method and HCO\textsubscript{3}−alkalinity was calculated from phenolphthalein (P) and Total (T) alkalinity as CaCO\textsubscript{3}, SO\textsubscript{4}\textsuperscript{2−}, NO\textsubscript{3}, and Fe\textsuperscript{3+} were determined using a UV–Vis spectrophotometer (HACH DR5000, Hach India) (Abbud, 2017; Belikhiri and Narany, 2015). The values obtained were compared with the World Health Organization, WHO, (2011) and B.I.S (IS 10500:2012) standards (Bureau of Indian Standards, 2012; WHO, 2011). The permissible values of B.I.S and W.H.O and the descriptive statistical values of the measured groundwater parameters were summarized given in Table 1.

It is observed from the above table that other than pH all values are positively skewed. The average Fe\textsuperscript{3+} concentration in the study area is about five to eight fold more than the limit stated by B.I.S and W.H.O. It may happen due to the presence of red lateritic parent material (inceptisol) in the soil (Batabyal and Chakraborty, 2015; Rattan et al., 2015). In a few of the locations orange-brown slime in water samples was observed, along with poor odor and taste which may be due to the presence of iron bacteria in the groundwater (Wisconsin Department of Natural Resources, 2010). Elevated levels of NO\textsubscript{3} have been found in very few locations which may due to illegal waste and sewage dump. It may also be due to the injudicious use of nitrogenous fertilizer in agricultural land. The pH values indicate that water in this study area is mostly acidic, which is due to the humid tropical climate of the region making the soils highly leachable and acidic in nature (Bhattacharyya et al., 2010). Similarly, in the case of HCO\textsubscript{3}− only in one particular location the concentration is more than permissible limit as prescribed by B.I.S, which may be due to the presence of landfill site near to that sampling station (Reddy and Nandini, 2011).

3.2. Multivariate statistical analysis

Principal Component Analysis (PCA) was used to reduce the data obtained from the analysis of the physicochemical parameter of groundwater. PCA also helps to find the hidden information about groundwater quality (Singh et al., 2013). Z-score transformation was applied for data standardization. The rotation of principal components (PCs) was carried out by varimax rotation, so that variation explained by
each of the retained PC scan be maximized. PCs having the Eigenvalue greater than one, and contributing maximum (0.35; positive or negative) has been selected for further analysis (Bodrud-Doza et al., 2016; Tripathi and Singal, 2019). A Pearson correlation coefficient matrix was generated after PCA analysis. All the statistical analysis has been carried out using Minitab® 17.1.0 software.

3.3. GIS and geostatistical mapping

The study area was digitized from the existing map of Agartala Municipality. Non-spatial and spatial data, i.e. water quality data along with sample locations were imported to the GIS environment using ArcGIS (v10.3). The spatial mappings of the most significant parameters obtained after PCA analyses were carried out using a geostatistical based kriging approach. Kriging is the best geostatistics interpolation method with minimum mean error to find the best linear unbiased estimate (Awais et al., 2017; Kaur and Rishi, 2018). In this study, Ordinary kriging (OK) was chosen over other kriging interpolation techniques because of its simplicity and prediction accuracy (Bodrud-Doza et al., 2016; Nas, 2009). The OK estimation formula is based on the weighted sum of data which can be defined by the following equation: (Mallick et al., 2020a, 2020b; Goovaerts et al., 2005; Nas, 2009).

\[ z'(u) = \sum_{i=1}^{n} \lambda_i z(u_i) \]

where \( z(u_i) \) is sample value at \( u_i \) location, \( \lambda_i \) is OK weight associated with \( z(u_i) \), \( n \) is number of sample used to estimate the sample value at \( u \) location.

An experimental semivariogram model is to be computed using the field data to assign weights to the OK method (Belkhir and Narany, 2015; Johnston et al., 2001). The experimental semivariogram was obtained by calculating the values of the semivariogram at different lags (distance between data pair) using the expression as shown below (Mallick et al., 2020a, 2020b; Goovaerts et al., 2005; Nas, 2009).

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

where \( N(h) \) is the number of data pair, \( h \) – Lag distance, \( z(u_i) \) is sample value at \( u_i \) location.

The experimental semivariogram obtained is to be fitted with the theoretical semivariogram model. The best-fitted theoretical semivariogram models out of several models (Gaussian, spherical, circular, exponential, stable) were selected based on the trial and error of parameters (Range, nugget, and sill). The range shows the distance at which the semivariogram model first flattens out. Nugget can be explained as a measurement error that may occur due to instrument error or spatial variation of data. Sill is the value in y-axis when a semivariogram attains the range. Performance of the model was checked using cross-validation test which involves minimum mean error (ME), root mean squared error (RMSE) and average squared error (ASE) close to each other and mean square standardized error (RMSSE) near to unity (Awais et al., 2017; Bodrud-Doza et al., 2016; Johnston et al., 2001). Geostatistical analyst extension in ArcGIS (v.10.3) was used for the preparation of the spatial maps of the groundwater parameters.

3.4. Factor standardization and fuzzy overlay

Fuzzification was carried out to transforms the crisp boundaries of inputs into a degree of membership by assigning a value between zero (no membership) and one (full membership) (Aouragh et al., 2017; Zhang et al., 2015) using a fuzzy membership function. The entire fuzzy model was carried out using “Membership fuzzy” and “Fuzzy Overlay” operations available in the Spatial Analyst toolbox of ArcGIS software (Araya-Muñoz et al., 2017; KI and Ray, 2014; Talukdar and Pal, 2019). Midpoint and spread are the two factors associated with the selection of membership function (MF). Expert knowledge and limits suggested by B.I.S (2012) were used for the selection of the MF. Various linear and nonlinear fuzzy MF are available in the membership fuzzy tool such as, large, small, Gaussian, and linear. In this study, a nonlinear MF “small” (large membership value is assigned to a small input raster value) was used for all the parameters except pH. The “Gaussian” (membership values decreased as we move from the midpoint in positive and negative directions) MF was used for pH. The mathematical expression for Gaussian and Small MF is shown below Eqs. (3) and (4) (Mohabbi Tafreshi et al., 2018; Raines et al., 2010).

\[ \text{GaussianMF}(x) = e^{-\left((x-x_m)/s\right)^2} \]

\[ \text{SmallMF}(x) = \frac{1}{1 + \left((x-x_m)/s\right)^2} \]

where \( f_1 \) is spread and \( f_2 \) is midpoint respectively.

Fuzzy overlay technique was used to aggregate all the fuzzified raster inputs. Five different fuzzy combination operators are available in the literatures (fuzzy OR, fuzzy AND, fuzzy Product, fuzzy Sum, and fuzzy Gamma). The fuzzy OR and fuzzy AND operators create the output based on the maximum and minimum membership values of all the inputs layers. The fuzzy product operator multiplies all the membership value together to create the output. The output of the fuzzy sum operator is based on the linear combination of the inputs membership value. The fuzzy GAMMA operator selects the value based on the power of fuzzy Sum and fuzzy product operators with the power of GAMMA (KI and Ray, 2014; Lewis et al., 2014; Mohabbi Tafreshi et al., 2018; Raines et al., 2010).

3.5. Suitability analysis

In this study, all the fuzzy overlay operations were used to determine the groundwater suitability map. Reclassification tool was further used to reclassify the suitability maps into three zones as unsuitable (<0.3), moderate suitable (0.3–0.6), suitable (>0.6) using natural break (jensk) tool in the ArcGIS (v.10.3) software. The best fuzzy overlay operation for suitability map was determined based on correlation coefficient values.

Table 2

(a) Eigen value along with Variance and Cumulative Variance (b) Principal components (PCs) factor loading.

<table>
<thead>
<tr>
<th>S. No</th>
<th>Eigen Value</th>
<th>Variance (%)</th>
<th>Cumulative Variance (%)</th>
<th>Variables</th>
<th>PC1</th>
<th>PC2</th>
<th>PC3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>3.0995</td>
<td>0.343</td>
<td>0.343</td>
<td>SO2</td>
<td>0.073</td>
<td>0.295</td>
<td>0.169</td>
</tr>
<tr>
<td>2.</td>
<td>2.2933</td>
<td>0.235</td>
<td>0.578</td>
<td>Fe2+</td>
<td>0.378</td>
<td>0.144</td>
<td>0.425</td>
</tr>
<tr>
<td>3.</td>
<td>1.1101</td>
<td>0.123</td>
<td>0.721</td>
<td>NO3</td>
<td>-0.355</td>
<td>0.080</td>
<td>0.629</td>
</tr>
<tr>
<td>4.</td>
<td>0.9844</td>
<td>0.109</td>
<td>0.831</td>
<td>EC</td>
<td>-0.360</td>
<td>0.370</td>
<td>0.220</td>
</tr>
<tr>
<td>5.</td>
<td>0.5990</td>
<td>0.067</td>
<td>0.897</td>
<td>Cl</td>
<td>-0.442</td>
<td>0.276</td>
<td>0.259</td>
</tr>
<tr>
<td>6.</td>
<td>0.5307</td>
<td>0.059</td>
<td>0.956</td>
<td>Mg</td>
<td>-0.241</td>
<td>0.379</td>
<td>0.485</td>
</tr>
<tr>
<td>7.</td>
<td>0.1904</td>
<td>0.021</td>
<td>0.977</td>
<td>Ca2+</td>
<td>0.002</td>
<td>0.509</td>
<td>0.195</td>
</tr>
<tr>
<td>8.</td>
<td>0.1469</td>
<td>0.016</td>
<td>0.994</td>
<td>pH</td>
<td>0.441</td>
<td>0.311</td>
<td>0.056</td>
</tr>
<tr>
<td>9.</td>
<td>0.0558</td>
<td>0.006</td>
<td>1.000</td>
<td>HCO3</td>
<td>0.384</td>
<td>0.417</td>
<td>0.058</td>
</tr>
</tbody>
</table>
between water quality index (WQI) map and fuzzy overlay suitability maps. Band collection statistics tools of ArcGIS software has been used to determine the correlation between different fuzzy overlay suitability map and WQI maps. WQI is an effective tool for getting the overall quality of groundwater. The WQI method uses single index value to understand the water quality information, which is calculated using a method proposed by the National Sanitation Foundation (Horton, 1965). This method is based on the principle of ranking and weights that depend on the author’s judgment (Houamia et al., 2016; Kavo and Karuppannan, 2018). The WQI values were calculated for each of the data points and the OK interpolation method was used to prepare the WQI map. The WQI map was further reclassified into three classes (i) unsuitable (WQI > 300) (ii) moderate suitable (WQI 100-300) (iii) suitable (WQI < 100) using natural break (jenks) classification method. The combination which provided the highest correlation coefficient value is selected as the best overlay operation.

4. Result and discussion

4.1. Factor selection using Principal Component Analysis (PCA) and correlation analysis

PCA was performed to reduce the groundwater variables, three PCs were extracted having eigenvalues greater than unity (>1). The three PCs factors extracted have an eigenvalues of 3.08, 2.29, and 1.11 respectively. The eigenvalues and variance of the groundwater variables are presented in Table 2(a). These three PCs, account cumulative 72% total variance of the data. PC 1 explains the highest percentage of total variance of the data i.e. 34.30%. Whereas, PC 2, PC 3 explains about 25.5% and 12.3% of the total variance.

Fig. 3 shows the relationships between the first two PCs, which contribute maximum to the total variance as 2D bi-plot and a scree plot. The scree plot is the graphical representation of the Eigen value for respective PCs. The direction and length of vector in 2D bi-plot indicate the contribution of each variable for the PCs (Tripathi and Singal, 2019). The factor loading of the first two PCs are shown in Table 2(b), it was observed from the table that except NO₂, EC, Mg²⁺ and Cl⁻ all other variable having positive PC 1 loading rate. Whereas, pH and Cl⁻ has strong correlation with PC 1. Although for PC 2 and PC 3 all variables having a positive loading rate. PC 1 factor is not influenced by the effect of agricultural and domestic practices; whereas PC 2 and 3 having highest loading rate for NO₂, Ca²⁺, Fe²⁺, HCO₃⁻ and Mg²⁺ which indicates the influence of agricultural practices, rock-water interaction and natural mineralization process (Bodrud-Doza et al., 2016; Singh et al., 2013; Ustaoglu et al., 2019). The variables which are contributing maximum and having a loading rate greater (>0.35) were selected for further analysis. Only SO₄²⁻ was excluded, as it shows a value of <0.35 for all the PCs.

Fig. 1(S) depicts the Pearson’s correlation coefficient matrix values show the interrelationship among the water quality parameters. The
results show a high positive correlation between be Cl⁻ with EC and pH with HCO₃⁻, which may be due to higher ionic mobility of Cl⁻ in compare to other ions and presence of proton on HCO₃ tends to increase the pH. Moderate positive correlations were observed between Fe²⁺ with pH and HCO₃⁻. This can be explained as the presence of Fe²⁺, which forms a compound with HCO₃ and do not let the pH of water to get affected. A moderate to low negative correlation is observed between NO₃ with pH and HCO₃⁻. This may be due to increase in nitrification rate at surface soil followed by leaching, which leads to increase nitrate concentration and also reduce pH and alkalinity in water (Kovač et al., 2017).
4.2. Geostatistical analysis and mapping

Exploratory data analysis and data transformation was applied to the data set before applying geostatistical analysis. Based on the result obtained from PCA the semivariogram was computed for eight parameters by excluding \( \text{SO}_2 \). The empirical model for the semivariogram was selected using numerous trial & error (Bodrud-Doza et al., 2016). Ordinary kriging was used in our study and based on the results of cross validation best model was selected. The details of the empirical model and cross validation results are shown in Table 3(a), (b). It can be observed from the table that, an exponential model was found suitable for \( \text{SO}_2^- \), \( \text{NO}_3^- \), \( \text{Cl}^- \), and \( \text{HCO}_3^- \). Similarly, the circular model was found suitable for \( \text{Fe}^{2+} \), \( \text{Mg}^{2+} \), \( \text{Ca}^{2+} \), pH. The stable model was found suitable only for EC. The autocorrelation value ranges between minimum of
2543.79 m for Ca$^{2+}$ to 4195.04 m for Fe$^{2+}$. The directional influence of autocorrelation i.e. anisotropy was not considered for all the models because no significant support was found for any directional influence factor such as geological structure or groundwater flow direction in the study area. The cross validation result indicates how well the models predict the unknown values. It can be seen from Table 3(b) that the entire models selected have the least mean error (ME), and mean square standardized error (RMSSE) near to unity, which indicated an accurate and unbiased prediction.

Fig. 4 shows the spatially interpolated map for selected eight parameters. It can be seen from the figure that the central part of the study area is mostly affected due to high concentration of Fe$^{2+}$. Whereas, EC and Cl$^{-}$ have uniform distribution across the study area except for two sampling stations. Few pockets in the northern part of the study area are highly affected due to the elevated concentration of NO$_3^-$, HCO$_3^-$ along with low pH. An inverse relationship can be seen between NO$_3^-$ with pH and HCO$_3^-$ this may be due to increase in nitrification rate at surface soil followed by leaching. It is observed that as per the limit suggest by BIS and WHO the overall quality of groundwater in most of the study area is good.

4.3. Fuzzy analysis and groundwater suitability description

All the raster maps of groundwater physicochemical parameters were further converted into fuzzified input using fuzzy MF. Fig. 4 also shows the fuzzified maps obtained by using various MF along with the respective maps of physicochemical parameters. In each of the fuzzy maps the value closer to zero and one shows the unsuitable and suitable zones respectively on a continuous scale. Fig. 5 illustrates the fuzzy overlay maps using various overlay functions, all these overlay functions displays the quantity of interaction among all the maps of physicochemical parameters. It can be seen from the figure that mostly the central part of the sampling area is recorded to be unsuitable and the suitability increases while moving away from the center. It is clear from the figure that the fuzzy OR and fuzzy SUM overlay function fails to create different zones of groundwater suitability. It is because the fuzzy OR aggregation technique uses the maximum membership value and makes the entire zone suitable, although fuzzy SUM combine membership value linearly makes entire zone unsuitable.

OK interpolation method used for the preparation of WQI map and the details associated with it i.e. empirical model and cross validation result are also included Table 3(a), (b). The spherical model is selected to be the best fitted empirical variogram model for the preparation of WQI map shown in Fig. 6. To determine the WQI the highest and lowest weight was assigned based on parameters concentration and its effects on human bodies. Generation of WQI map also help in understanding the spatial variation of the quantitative groundwater quality of the study area. It can be seen from the figure that the larger part of study area i.e. central part of Agartala Municipality having WQI > 300, indicates a poor water quality and some parts of the northern and southern west having good water quality with WQI < 100. The average WQI value i.e. 1.61.36 and WQI map indicates that most of the groundwater of the study area is suitable for drinking. The WQI map obtained is used to assess the best fuzzy overlay method for determining the groundwater suitability for drinking purposes. Table 1(S) shows the correlations between the WQI map and fuzzy overlay maps. The dependency between the layers is quantified using the correlation value. The maximum value correlation coefficient i.e. 0.752 was obtained for GAMMA (0.9) overlay operator with WQI map. Based on the result, fuzzy GAMMA (0.9) overlay method was selected as best overlay operation for suitability analysis.

WQI provides a simple, quick and concise overview of overall water quality and it is acceptable worldwide. So, using WQI map for determining the best fuzzy overlay operator could be a reliable method over optimum index factor or equalized histogram technique as used by Lewis et al. (2014), Mohebbi Tafreshi et al. (2018). The suitability of the groundwater was measured on a scale between 0 and 1; values near to zero suggest the unsuitable area whereas values more closer to one is suitable. Fig. 7 illustrates the suitability of the groundwater for the study area. The surface area of respective groundwater suitability zones i.e. unsuitable, moderate suitable and suitable are observed in 24.6%, 28.6%, 46.7% of the total surface area.

Primarily, the presence of iron mostly affects the suitability of the groundwater of the study area as well as the nitrate and low pH concentration. This observation reaffirms the finding made by Singh and Kumar (2015), Mallik et al. (2020b) on groundwater characterization of the study area. Iron removing plant can be installed in the study area or low cost portable water treatment system can be provided to the household of this region. The methodology developed in this study for the assessment of the suitability of groundwater will be quite significant for the GIS users due to its simplicity. The capability to integrate data from the various GIS layers along with performing the fuzzy analysis in a single platform makes this method much robust. Moreover, different MCDM methods can also be incorporated to develop various hybrid methods.

5. Conclusion

The present study investigated the groundwater quality of Agartala city and evaluated its suitability for drinking purposes. The observation reveals that most of the groundwater quality in the study area is suitable for drinking. It is observed from the PCA analysis that, the groundwater quality of Agartala city is mainly deteriorated due to agricultural activities, rock-water interaction and natural mineralization process. The results indicate that the Fuzzy GAMMA overlay operator is the best overlay operator then compared to other fuzzy overlay operators. The
groundwater of study area is found to be mostly acidic with elevated iron level along with few pockets of high nitrate level. In addition to it, periodic testing of groundwater samples and human risk assessment due to high level of iron can be investigated for the study area. Further studies could help to find the origin, fate and, transport of nitrate in the study area and also a machine learning model can be used to predict the suitability of groundwater.

In comparison with traditional methods used for determining groundwater suitability in GIS environment such as different overlay, hybrid and statistical methods, the methodology developed in this study is flexible with number of parameters and their associated weights. Thus, it makes this method more reliable. Finally, we believe that similar approach can also be adopted for determining the suitability as well as vulnerability of land and groundwater for various purposes. This research provides a procedure to assess the suitability of groundwater, which can improve the decision making framework. It can also help the local authorities in the proper planning and management of groundwater.

CRediT authorship contribution statement

Santanu Mallik: Methodology, Software, Formal analysis, Validation, Writing - original draft, Writing - review & editing. Umesh Mishra: Supervision, Resources, Conceptualization. Niladri Paul: Methodology, Investigation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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References


