Ecological Indicators 121 (2021) 107179

Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind

Groundwater suitability analysis for drinking using GIS based fuzzy logic

Santanu Mallik [a,*], Umesh Mishra [a], Niladri Paul [b]

[a] Department of Civil Engineering, National Institute of Technology Agartala, Barjala, Jirania, 799046 Tripura, India
[b] Department of Soil Science & Agricultural Chemistry, College of Agriculture, Tripura, Lembucherra, 799210 Tripura, India

ARTICLE INFO

Keywords:
Geostatistical analysis
Ordinary kriging
Principal Component Analysis
Groundwater quality
Fuzzy MCDM

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 HCO_3^-.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 (Belkhiri and Narany, 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 (Belkhiri and Narany, 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

* Corresponding author.
E-mail address: coolshan02@gmail.com (S. Mallik).

https://doi.org/10.1016/j.ecolind.2020.107179
Received 23 January 2020; Received in revised form 31 October 2020; Accepted 4 November 2020
Available online 23 November 2020

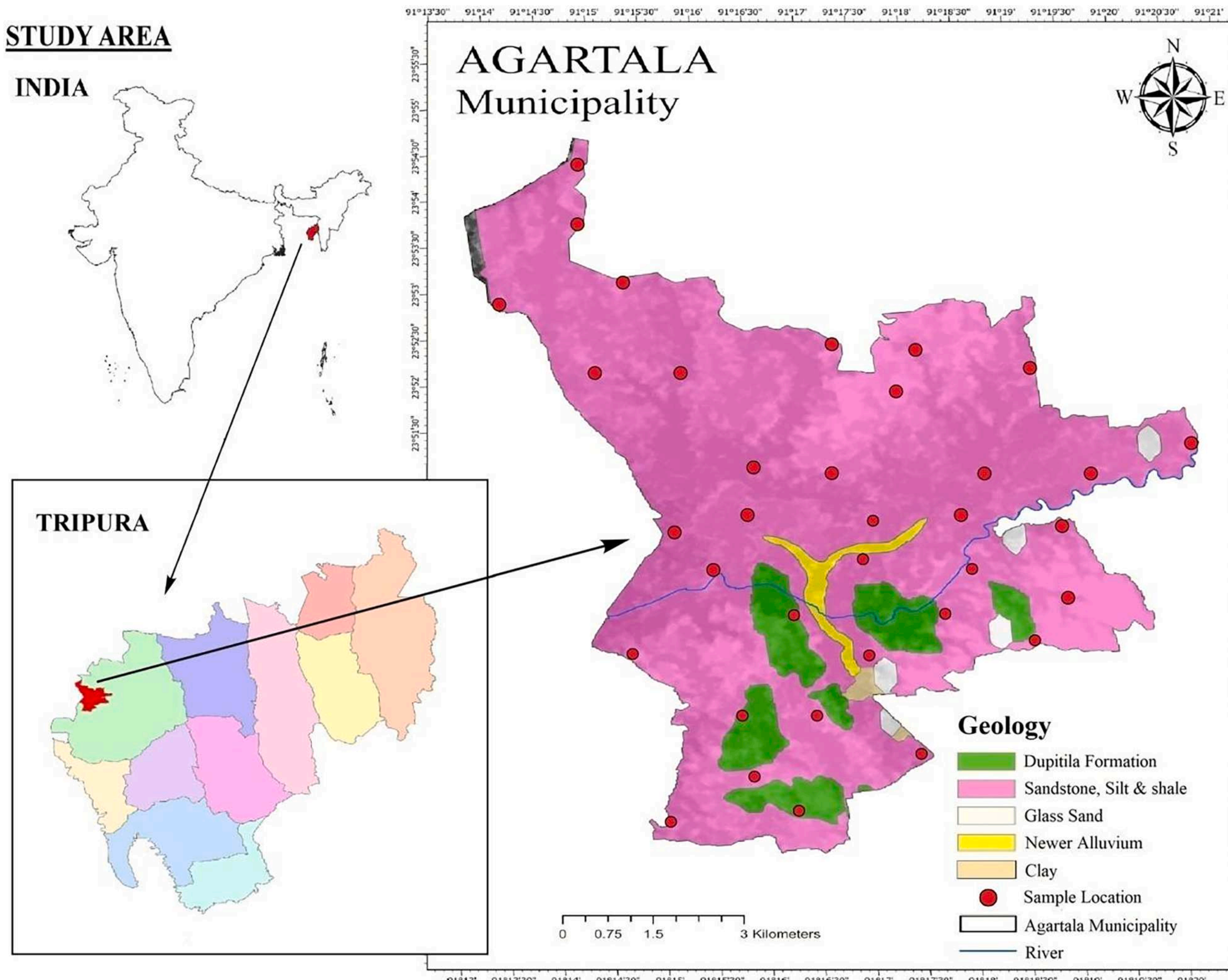

Fig. 1. Study area (Agartala Municipality area).

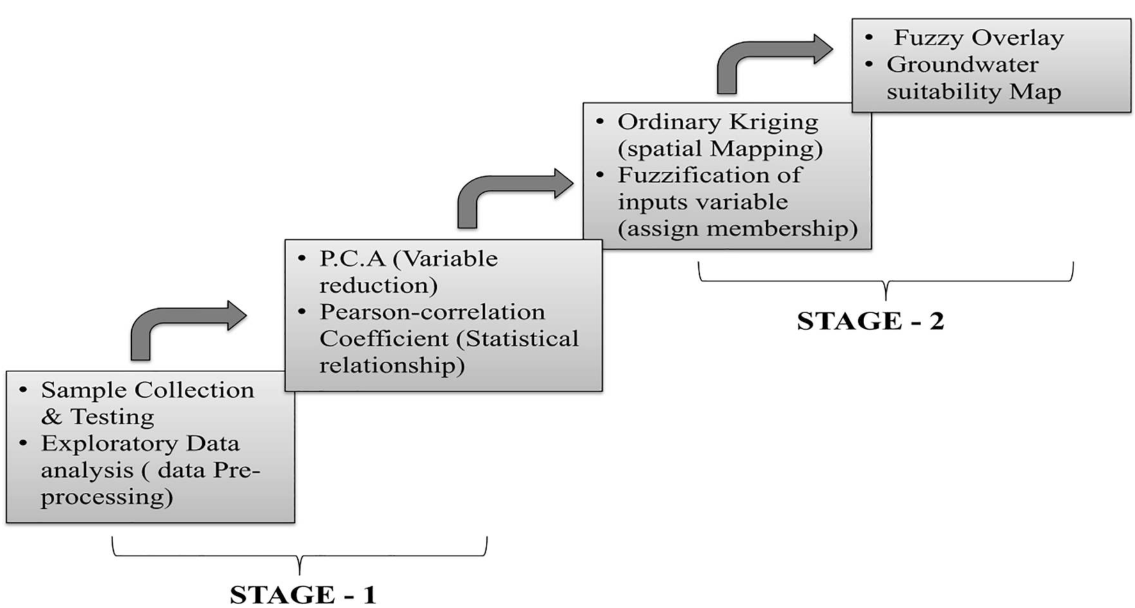

Fig. 2. Schematic structures of stages involve in groundwater suitability analysis.

Table 1
Statistical summary of sampling station data (n = 35) and WQI values.

Variables	Min	Max	Skewness	Mean	SD	B.I.S std	W.H.O Limit
SO_4^{2-} (mg/l)	1.28	9.08	1.05	4.06	1.5	200	250
Fe^{2+} (mg/l)	0.09	7.6	0.08	2.55	2.4	0.3	0.3
NO_3^- (mg/l)	0.22	137.7	3.72	19.49	24.02	45	50
EC (μS/cm)	47.67	1345	3.9	200.68	228.55	1500	1500
Cl^- (mg/l)	0	215	2.77	30.45	48.79	250	250
Mg^{2+} (mg/l)	1.21	24.8	1.08	7.67	5.62	30	150
Ca^{2+} (mg/l)	2	55.65	1.86	15.79	13.1	75	200
pH	4.11	6.59	−0.52	5.69	0.62	6.5–8.5	6.5–8.5
HCO_3^- (mg/l)	10.12	129.17	0.55	51.29	34.88	120	–
WQI	23.03	317	0.68	161.36	95.93	–	–

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^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 metrological 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 Duptila formation group (Geological Survey, 2011). Hydrogeologically the aquifer system of the area is semi confined with a yield of 50–100 m^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) (μS/cm) were measured in the field using portable pocket pH and EC meter (Model HI98129, Hanna India). Various physicochemical parameters such as sulphate (SO_4^{2-}), nitrate (NO_3^-), chloride (Cl^-), bicarbonate (HCO_3^-) magnesium (Mg^{2+}), calcium (Ca^{2+}), and iron (Fe^{2+}) were tested using APHA Standard method (APHA, 2005). $Ca^{2+}$and Mg^{2+} were tested by EDTA titrimetric method. Cl^- was tested using the argentometric titrimetric method and HCO_3^-alkanity was calculated from phenolphthalein (P) and Total (T) alkalinity as $CaCO_3$. SO_4^{2-}, NO_3^-, and Fe^{2+} were determined using a UV–Vis spectrophotometer (HACH DR5000, Hach India) (Abboud, 2017; Belkhiri 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^{2+} 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_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_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 technique 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 (Mallik et al., 2020a, 2020b; Goovaerts et al., 2005; Nas, 2009).

$$z^*(\boldsymbol{u}) = \sum_{\alpha=1}^{n} \lambda_\alpha(\boldsymbol{u}) z(\boldsymbol{u}_\alpha) \tag{1}$$

where $z(\boldsymbol{u}_\alpha)$ is sample value at $\boldsymbol{u}_\alpha$ location, $\lambda_\alpha(\boldsymbol{u})$ is OK weight associated with $z(\boldsymbol{u}_\alpha)$, 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 (Belkhiri 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 (Mallik et al., 2020a, 2020b; Goovaerts et al., 2005; Nas, 2009).

$$\gamma(\boldsymbol{h}) = \frac{1}{2N(\boldsymbol{h})} \sum_{\alpha=1}^{N(h)} [z(\boldsymbol{u}_\alpha) - z(\boldsymbol{u}_\alpha + \boldsymbol{h})] \tag{2}$$

where N(**h**) is the number of data pair, **h** – Lag distance, $z(\boldsymbol{u}_\alpha)$ is sample value at $\boldsymbol{u}_\alpha$ 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 non-linear 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) (Mohebbi Tafreshi et al., 2018; Raines et al., 2010).

$$\text{GaussianMF}\mu(x) = e^{f_1*(X-f_2)} \tag{3}$$

$$\text{SmallMF}\mu(x) = \frac{1}{1+\left(\frac{X}{f_2}\right)^{\frac{1}{2}}} \tag{4}$$

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 product of fuzzy Sum and fuzzy product operators with the power of GAMMA (Ki and Ray, 2014; Lewis et al., 2014; Mohebbi 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 (jenks) 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.

S. No	Eigen Value	Variance (%)	Cumulative Variance (%)	Variables	PC1	PC 2	PC 3
1.	3.0895	0.343	0.343	SO_4^{2-}	0.073	0.295	0.169
2.	2.2933	0.255	0.598	Fe^{2+}	0.378	0.144	0.425
3.	1.1101	0.123	0.721	NO_3^-	−0.355	0.080	0.629
4.	0.9844	0.109	0.831	EC	−0.360	0.370	0.220
5.	0.5990	0.067	0.897	Cl^-	−0.442	0.276	0.259
6.	0.5307	0.059	0.956	Mg^{2+}	−0.241	0.379	0.485
7.	0.1904	0.021	0.977	Ca^{2+}	0.002	0.509	0.195
8	0.1469	0.016	0.994	pH	0.441	0.311	0.056
9.	0.0558	0.006	1.000	HCO_3^-	0.384	0.417	0.058

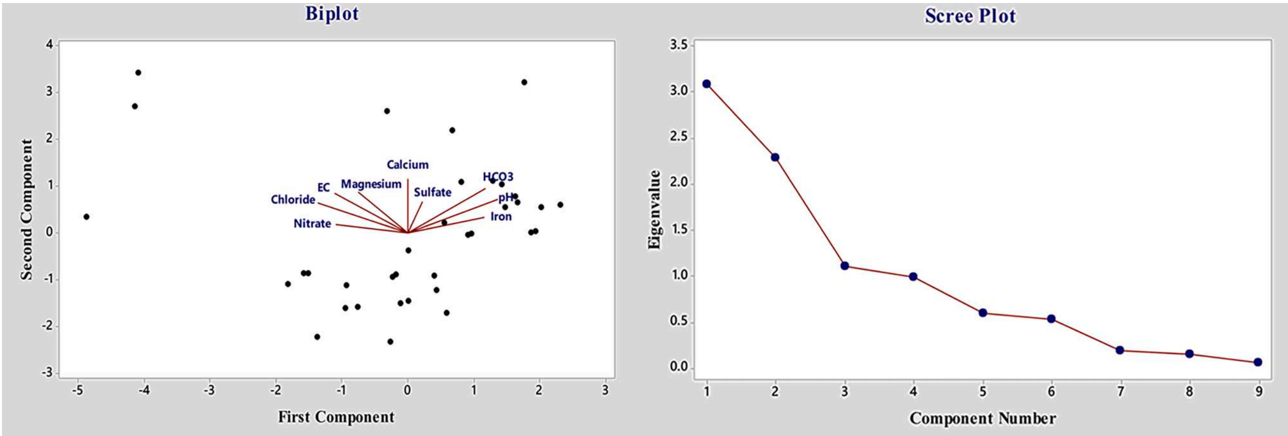

Fig. 3. Bi-plot and scree plot.

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 (Houatmia et al., 2016; Kawo 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 NO_3^-, EC, Mg^{2+} 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 NO_3^-,Ca^{2+}, Fe^{2+}, $^-$ HCO_3^- and Mg^{2+} which indicates the influence of agricultural practices, rock-water interaction and natural mineralization process (Bodrud-Doza et al., 2016; Singh et al., 2013; Ustaoğlu et al., 2019). The variables which are contributing maximum and having a loading rate greater (>0.35) were selected for further analysis. Only SO_4^{2-} 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

Table 3
(a) Geostatistical model properties, (b) Cross validation results.

Variables	Model selected	Transformation	Range	Anistropy	Sill	Lag size	No. of lag
Fe^{2+}	Circular	log	4195.04	False	1.47	600	13
NO_3^-	Exponential	None	2667.95	False	146	482	10
EC	Stable	log	2667.95	False	0.27	290	14
Cl^-	Exponential	None	3960	False	532.8	330	12
Mg^{2+}	Circular	log	2732.62	False	0.627	455	12
Ca^{2+}	Circular	log	2543.79	False	0.711	690	13
pH	Circular	None	3529.36	False	0.471	450	17
HCO_3^-	Exponential	None	4034.03	False	1410.58	415	14
WQI	Spherical	None	4377.44	False	42675.28	540	20

Variables	Model selected	Mean error	RMSE	ASE	RMSSE
Fe^{2+}	Circular	0.01	1.78	2.83	1.09
NO_3^-	Exponential	0.48	14.8	11.84	1.23
EC	Stable	2.62	60.15	62.15	1.02
Cl^-	Exponential	0.57	20.83	20.49	1
Mg^{2+}	Circular	0.32	4.35	6.85	0.9
Ca^{2+}	Circular	−0.98	13.23	15.13	0.946
pH	Circular	−0.01	0.492	0.5	1
HCO_3^-	Exponential	0.29	30.62	33.01	0.93
WQI	Spherical	0.89	160.28	165.18	0.98

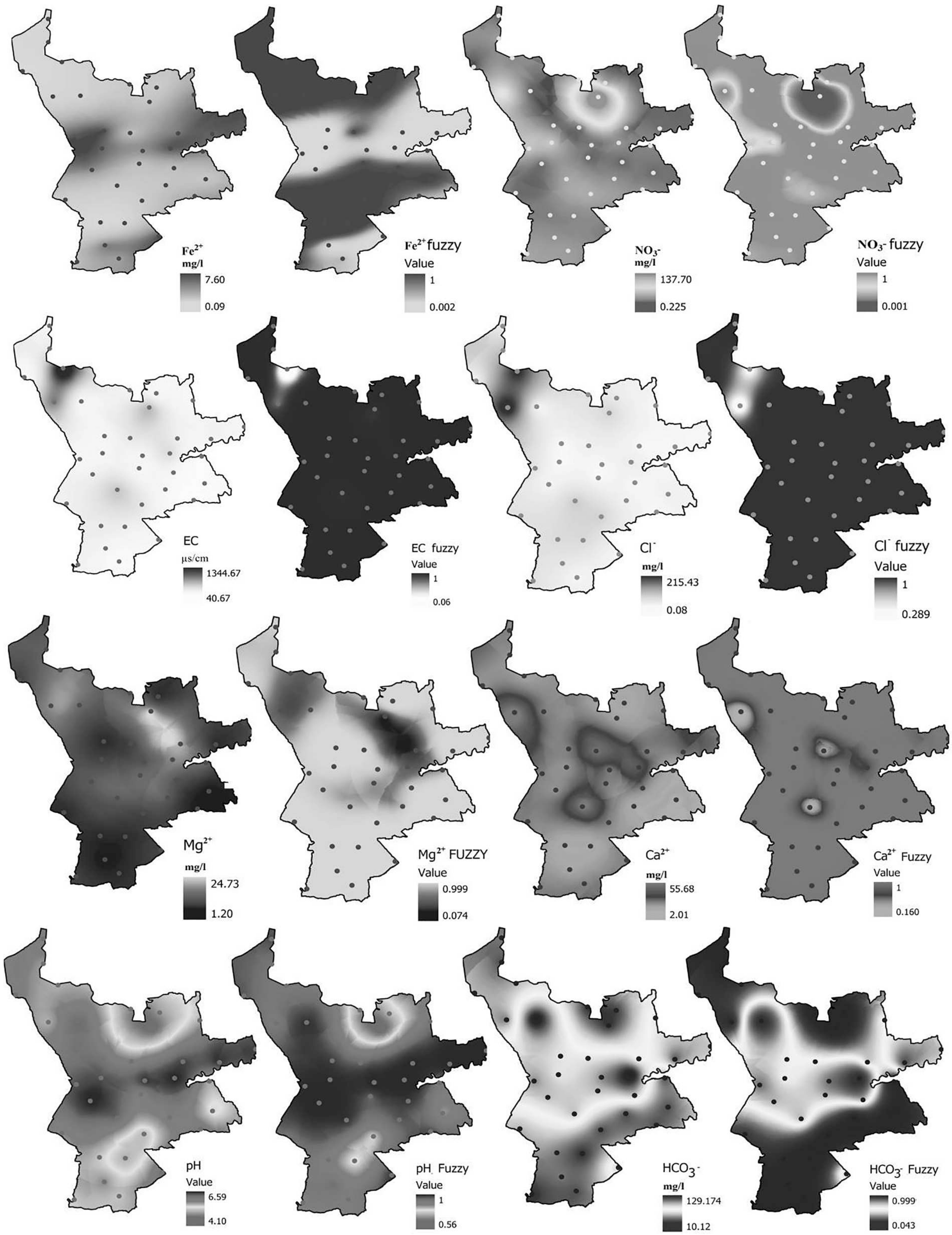

Fig. 4. Mapping of physiochemical parameters & fuzzified output.

results show a high positive correlation between be Cl^- with EC and pH with HCO_3^-, which may be due to higher ionic mobility of Cl^- in compare to other ions and presence of proton on HCO_3^- tends to increase the pH. Moderate positive correlations were observed between Fe^{2+} with pH and HCO_3^-.This can be explained as the presence of Fe^{2+}, which forms a compound with HCO_3^- and do not let the pH of water to get affected. A moderate to low negative correlation is observed between NO_3^- with pH and HCO_3^-. 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).

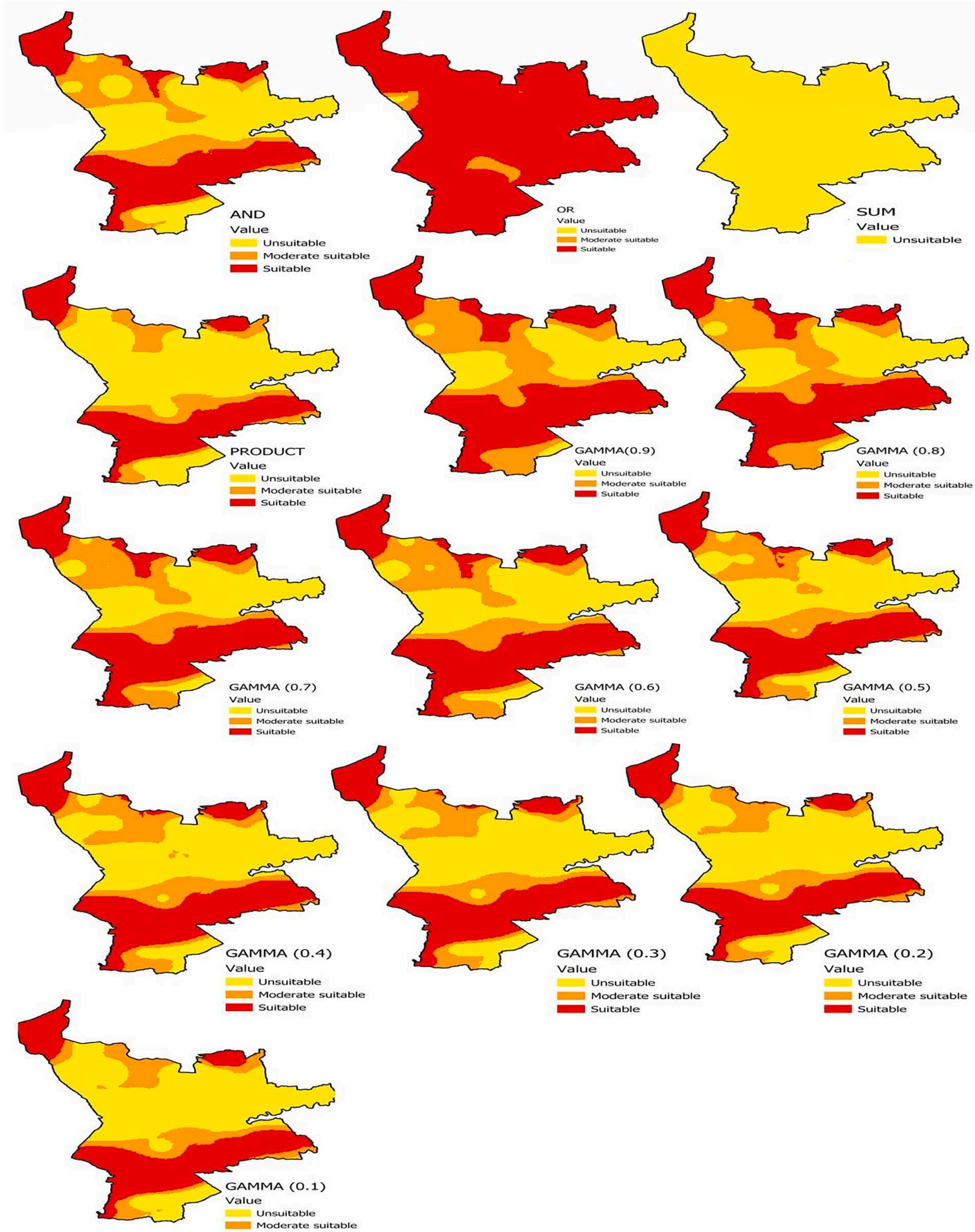

Fig. 5. Overlay maps for groundwater suitability.

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 SO_4^{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 SO_4^{2-}, NO_3^-, Cl^-, and HCO_3^-. Similarly, the circular model was found suitable for Fe^{2+} Mg^{2+}, Ca^{2+}, pH. The stable model was found suitable only for EC. The autocorrelation value ranges between minimum of

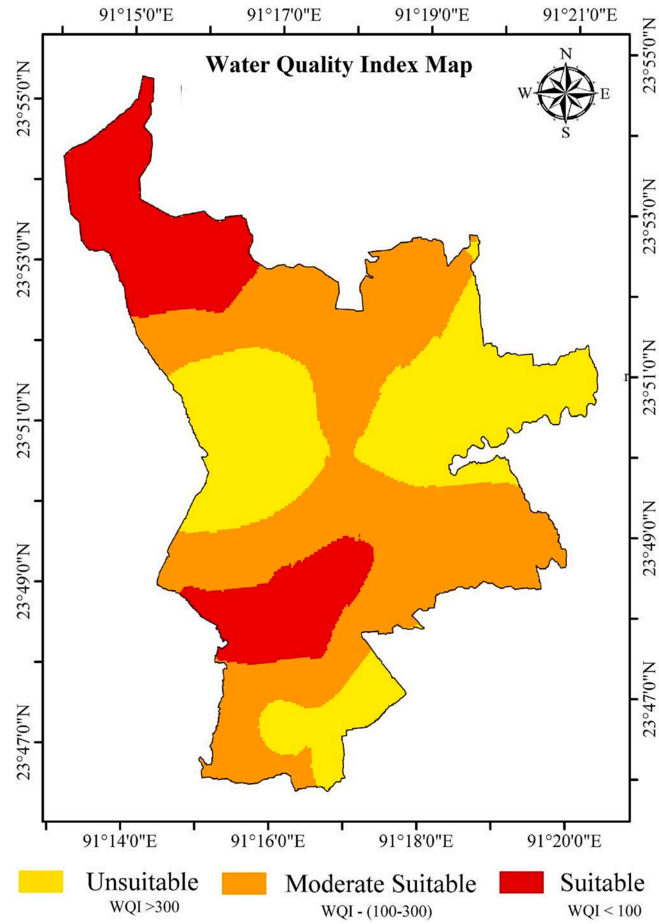

Fig. 6. Water Quality Index (WQI) map.

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 semivariogram 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. 161.36 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 more 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

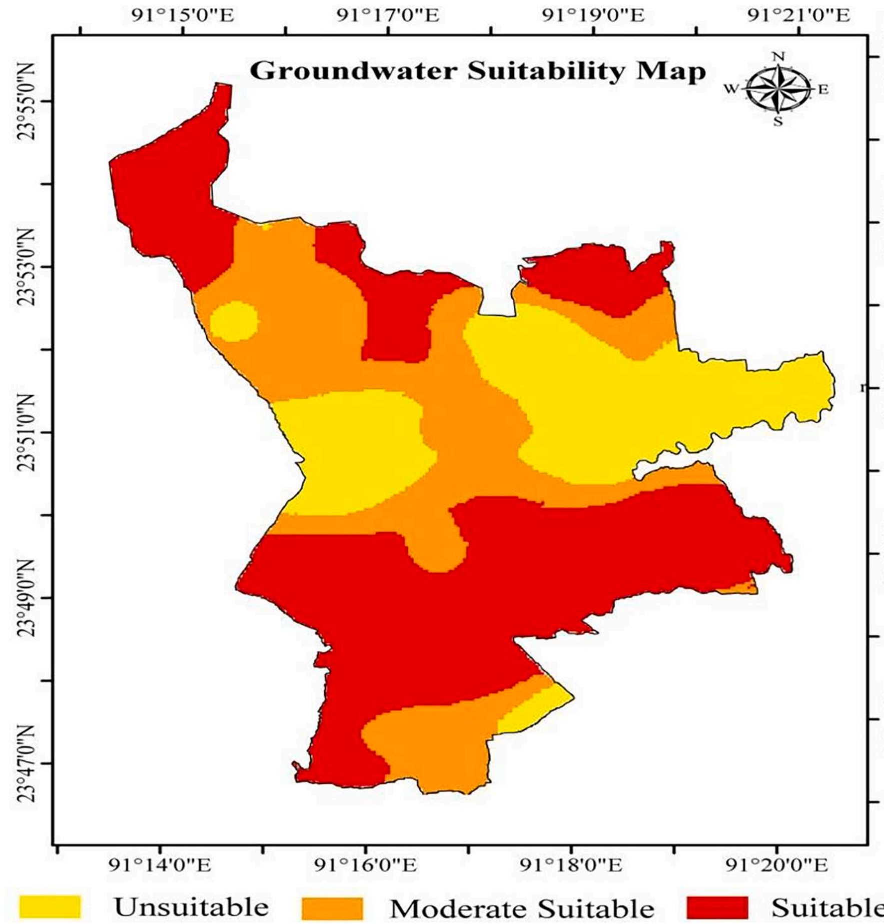

Fig. 7. Groundwater Suitability Map.

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.

Acknowledgement

We would like to thanks Dr. T.K. Mishra, Department of Chemistry, NIT Agartala for providing resources to carry out the lab testing and analysis. The authors are also thankful to the reviewers for their comments that improved the quality of the paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2020.107179.

References

Abboud, I.A., 2017. Geochemistry and quality of groundwater of the Yarmouk basin aquifer, North Jordan. Environ. Geochem. Health 40, 1405–1435. https://doi.org/10.1007/s10653-017-0064-x.

Akbari, M., Neamatollahi, E., Neamatollahi, P., 2019. Evaluating land suitability for spatial planning in arid regions of eastern Iran using fuzzy logic and multi-criteria analysis. Ecol. Indic. 98, 587–598. https://doi.org/10.1016/J.ECOLIND.2018.11.035.

Aouragh, M.H., Essahlaoui, A., El Ouali, A., El Hmaidi, A., Kamel, S., 2017. Groundwater potential of Middle Atlas plateaus, Morocco, using fuzzy logic approach, GIS and remote sensing. Geomatics. Nat. Hazards Risk 8, 194–206. https://doi.org/10.1080/19475705.2016.1181676.

APHA, 2005. Standard Methods for the Examination of Water and Wastewater, 21st ed.; APHA:Washington, DC, USA, 2005. Am. Water Work. Assoc. Public Work. Assoc. Environ. Fed. 552. https://doi.org/10.2105/AJPH.51.6.940-a.

Araya-Muñoz, D., Metzger, M.J., Stuart, N., Wilson, A.M.W., Carvajal, D., 2017. A spatial fuzzy logic approach to urban multi-hazard impact assessment in Concepción, Chile. Sci. Total Environ. 576, 508–519. https://doi.org/10.1016/j.scitotenv.2016.10.077.

ArcGIS pro [WWW Document], n.d. URL https://pro.arcgis.com/en/pro-app/help/analysis/geostatistical-analyst/what-is-geostatistics-.htm (accessed 8.26.19).
Arslan, H., 2017. Determination of temporal and spatial variability of groundwater irrigation quality using geostatistical techniques on the coastal aquifer of Çarşamba Plain, Turkey, from 1990 to 2012. Environ. Earth Sci. 76, 1–12. https://doi.org/10.1007/s12665-016-6375-x.
Awais, M., Arshad, M., Shah, S.H.H., Anwar-ul-Haq, M., 2017. Evaluating groundwater quality for irrigated agriculture: spatio-temporal investigations using GIS and geostatistics in Punjab, Pakistan. Arab. J. Geosci. 10 https://doi.org/10.1007/s12517-017-3280-x.
Batabyal, A.K., Chakraborty, S., 2015. Hydrogeochemistry and water quality index in the assessment of groundwater quality for drinking uses. Water Environ. Res. 87, 607–617. https://doi.org/10.2175/106143015x14212658613956.
Belkhiri, L., Narany, T.S., 2015. Using multivariate statistical analysis, geostatistical techniques and structural equation modeling to identify spatial variability of groundwater quality. Water Resour. Manag. 29, 2073–2089. https://doi.org/10.1007/s11269-015-0929-7.
Bhattacharyya, T., Sarkar, D., Pal, D.K., Mandal, C., Baruah, U., Telpande, B., Vaidya, P. H., 2010. Soil information system for resource management – Tripura as a case study. Curr. Sci. 99, 1208–1217.
Bodrud-Doza, M., Islam, A.R.M.T., Ahmed, F., Das, S., Saha, N., Rahman, M.S., 2016. Characterization of groundwater quality using water evaluation indices, multivariate statistics and geostatistics in central Bangladesh. Water Sci. 30, 19–40. https://doi.org/10.1016/j.wsj.2016.05.001.
Bureau of Indian Standards, 2012. Indian Standard Drinking Water-Specification 1–16.
Foster, S.S.D., Chilton, P.J., 2003. Groundwater: the processes and global significance of aquifer degradation. Philos. Trans. R. Soc. B Biol. Sci. 358, 1957–1972. https://doi.org/10.1098/rstb.2003.1380.
Geological Survey, 2011, 2011. Geology and mineral resources of Manipur, Mizoram, Nagaland and Tripura.
Gharibi, H., Mahvi, A.H., Nabizadeh, R., Arabalibeik, H., Yunesian, M., Sowlat, M.H., 2012. A novel approach in water quality assessment based on fuzzy logic. J. Environ. Manage. 112, 87–95. https://doi.org/10.1016/j.jenvman.2012.07.007.
Ghosh, S., Das, A., 2019. Urban expansion induced vulnerability assessment of East Kolkata Wetland using Fuzzy MCDM method. Remote Sens. Appl. Soc. Environ. 13, 191–203. https://doi.org/10.1016/J.RSASE.2018.10.014.
Goovaerts, P., 1997. Geostatistics for Natural Resources Evaluation. Oxford University Press on Demand.
Goovaerts, P., AvRuskin, G., Meliker, J., Slotnick, M., Jacquez, G., Nriagu, J., 2005. Geostatistical modeling of the spatial variability of arsenic in groundwater of southeast Michigan. Water Resour. Res. 41, 1–19. https://doi.org/10.1029/2004WR003705.
Horton, R.K., 1965. An index number system for rating water quality. J. Water Pollut. Control Fed. 37, 300–306.
Houatmia, F., Azouzi, R., Charef, A., Bédir, M., 2016. Assessment of groundwater quality for irrigation and drinking purposes and identification of hydrogeochemical mechanisms evolution in Northeastern, Tunisia. Environ. Earth Sci. 75 https://doi.org/10.1007/s12665-016-5441-8.
Jha, M.K., Shekhar, A., Jenifer, M.A., 2020. Assessing groundwater quality for drinking water supply using hybrid fuzzy-GIS-based water quality index. Water Res. 179, 115867 https://doi.org/10.1016/j.watres.2020.115867.
Johnston, K., Ver Hoef, J.M., Krivoruchko, K., Lucas, N., 2001. Using ArcGIS geostatistical analyst. Analysis 300, 300.
Kaur, L., Rishi, M.S., 2018. Integrated geospatial, geostatistical, and remote-sensing approach to estimate groundwater level in North-western India. Environ. Earth Sci. 77, 1–13. https://doi.org/10.1007/s12665-018-7971-8.
Kawo, N.S., Karuppannan, S., 2018. Groundwater quality assessment using water quality index and GIS technique in Modjo River Basin, central Ethiopia. J. African Earth Sci. 147, 300–311. https://doi.org/10.1016/j.jafrearsci.2018.06.034.
Ki, S.J., Ray, C., 2014. Using fuzzy logic analysis for siting decisions of infiltration trenches for highway runoff control. Sci. Total Environ. 493, 44–53. https://doi.org/10.1016/j.scitotenv.2014.05.121.
Kovač, Z., Nakić, Z., Pavlić, K., 2017. Influence of groundwater quality indicators on nitrate concentrations in the Zagreb aquifer system. Geol. Croat. 70, 93–103. https://doi.org/10.4154/gc.2017.08.
Lewis, S.M., Fitts, G., Kelly, M., Dale, L., 2014. A fuzzy logic-based spatial suitability model for drought-tolerant switchgrass in the United States. Comput. Electron. Agric. 103, 39–47. https://doi.org/10.1016/j.compag.2014.02.006.
Machiwal, D., Cloutier, V., Güler, C., Kazakis, N., 2018. A review of GIS-integrated statistical techniques for groundwater quality evaluation and protection. Environ. Earth Sci. 77, 1–30. https://doi.org/10.1007/s12665-018-7872-x.
Mallik, S., Bhowmik, T., Mishra, U., Paul, N., 2020a. Mapping and prediction of soil organic carbon by an advanced geostatistical technique using remote sensing and terrain data. Geocarto Int. https://doi.org/10.1080/10106049.2020.1815864.
Mallik, S., Shivam, Mishra, U., 2020. Assessment of Spatial Variations in Groundwater Quality of Agartala, Tripura for Drinking Employing GIS and MCDA Techniques, Lecture Notes in Civil Engineering. https://doi.org/10.1007/978-981-13-7067-0_22.
Mohebbi Tafreshi, A., Mohebbi Tafreshi, G., Bijeh Keshavarzi, M.H., 2018. Qualitative zoning of groundwater to assessment suitable drinking water using fuzzy logic spatial modelling via GIS. Water Environ. J. 32, 607–620.
Morris, B.L., Lawrence, A.R., Chilton, P.J.C., Adams, B., Calow, R.C., Klinck, B.A., 2003. Groundwater and its susceptibility to degradation: a global assessment of the problem and options for management.
Nas, B., 2009. Geostatistical approach to assessment of spatial distribution of groundwater quality. Polish J. Environ. Stud. 18, 1073–1082.
Nas, B., Berktay, A., 2006. Groundwater contamination by nitrates in the city of Konya, (Turkey): a GIS perspective. J. Environ. Manage. 79, 30–37. https://doi.org/10.1016/J.JENVMAN.2005.05.010.
Noori, A.M., Pradhan, B., Ajaj, Q.M., 2019. Dam site suitability assessment at the Greater Zab River in northern Iraq using remote sensing data and GIS. J. Hydrol. 574, 964–979. https://doi.org/10.1016/J.JHYDROL.2019.05.001.
Pilevar, A.R., Matinfar, H.R., Sohrabi, A., Sarmadian, F., 2020. Integrated fuzzy, AHP and GIS techniques for land suitability assessment in semi-arid regions for wheat and maize farming. Ecol. Indic. 110, 105887 https://doi.org/10.1016/J.ECOLIND.2019.105887.
Raines, G.L., Sawatzky, D.L., Bonham-Carter, G.F., 2010. New fuzzy logic tools in ArcGIS 10. ArcUser Spring 8–13.
Rakib, M.A., Sasaki, J., Matsuda, H., Fukunaga, M., 2019. Severe salinity contamination in drinking water and associated human health hazards increase migration risk in the southwestern coastal part of Bangladesh. J. Environ. Manage. 240, 238–248. https://doi.org/10.1016/J.JENVMAN.2019.03.101.
Rattan, R.K., Katyal, J.C., Dwivedi, B.S., Sarkar, A.K., Bhattacharyya, Tapas, Tarafdar, J. C., Kukal, S., 2015. Soil Science: An Introduction, 2015th ed. Indian Society of Soil science.
Reddy, P.S., Nandini, N., 2011. Leachate characterization and assessment of groundwater pollution near municipal solid waste landfill site. Nat. Environ. Pollut. Technol. 10, 415–418. https://doi.org/10.1007/s10661-006-1505-7.
Ross, T.J., 2010. Fuzzy Logic with Engineering Application, third ed., John Wiley & Sons. https://doi.org/10.1002/9781119994374.
Santra, A., Mitra, S., Debbarma, D., 2018. Impact of urbanization on land use changes in Agartala City, India. Res. J. Humanit. Soc. Sci. 9, 407. https://doi.org/10.5958/2321-5828.2018.00070.0.
Semeraro, T., Mastroleo, G., Aretano, R., Facchinetti, G., Zurlini, G., Petrosillo, I., 2016. GIS Fuzzy Expert System for the assessment of ecosystems vulnerability to fire in managing Mediterranean natural protected areas. J. Environ. Manage. 168, 94–103. https://doi.org/10.1016/J.JENVMAN.2015.11.053.
Şener, Ş., Şener, E., Davraz, A., 2017. Evaluation of water quality using water quality index (WQI) method and GIS in Aksu River (SW-Turkey). Sci. Total Environ. 584–585, 131–144. https://doi.org/10.1016/j.scitotenv.2017.01.102.
Singh, A.K., Kumar, S.R., 2015. Quality assessment of groundwater for drinking and irrigation use in semi-urban area of Tripura, India. Ecol. Environ. Conserv. 21, 97–108.
Singh, E.J.K., Gupta, A., Singh, N.R., 2013. Groundwater quality in Imphal West district, Manipur, India, with multivariate statistical analysis of data. Environ. Sci. Pollut. Res. 20, 2421–2434. https://doi.org/10.1007/s11356-012-1127-2.
Talukdar, S., Pal, S., 2019. Wetland habitat vulnerability of lower Punarbhaba river basin of the uplifted Barind Region of Indo-Bangladesh. Geocarto Int. 1–30. https://doi.org/10.1080/10106049.2018.1533594.
Tripathi, M., Singal, S.K., 2019. Use of principal component analysis for parameter selection for development of a novel water quality index: a case study of river Ganga India. Ecol. Indic. 96, 430–436. https://doi.org/10.1016/j.ecolind.2018.09.025.
Ustaoğlu, F., Tepe, Y., Taş, B., 2019. Assessment of stream quality and health risk in a subtropical Turkey river system: a combined approach using statistical analysis and water quality index. Ecol. Indic. 105815 https://doi.org/10.1016/J.ECOLIND.2019.105815.
Vadiati, M., Asghari-Moghaddam, A., Nakhaei, M., Adamowski, J., Akbarzadeh, A.H., 2016. A fuzzy-logic based decision-making approach for identification of groundwater quality based on groundwater quality indices. J. Environ. Manage. 184, 255–270. https://doi.org/10.1016/J.JENVMAN.2016.09.082.
WHO, 2011. Guidelines for Drinking Water Quality, 4th ed.
Wisconsin Department of Natural Resources, 2010. Iron bacteria in Drinking Water [WWW Document]. URL https://www.des.nh.gov/organization/commissioner/pip/factsheets/dwgb/documents/dwgb-3-21.pdf.
Zadeh, L.A., 1965. Fuzzy sets. Inf. Control 8, 338–353. https://doi.org/10.1016/S0019-9958(65)90241-X.
Zeinalzadeh, K., Rezaei, E., 2017. Determining spatial and temporal changes of surface water quality using principal component analysis. J. Hydrol. Reg. Stud. 13, 1–10. https://doi.org/10.1016/j.ejrh.2017.07.002.
Zhang, J., Su, Y., Wu, J., Liang, H., 2015. GIS based land suitability assessment for tobacco production using AHP and fuzzy set in Shandong province of China. Comput. Electron. Agric. 114, 202–211. https://doi.org/10.1016/J.COMPAG.2015.04.004.