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Assessing groundwater quality for drinking water supply using hybrid fuzzy-GIS-based water quality index

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ABSTRACT

Groundwater is a vital source of freshwater in both urban and rural regions of the world. However, its injudicious abstraction and rapidly increasing contamination are posing a severe threat for sustainable water supply worldwide. Geographical Information System (GIS)-based groundwater quality evaluation using Groundwater Quality Index (GQI) has been proved to be a cost-effective tool for assessing groundwater quality and its variability at a larger scale. However, the conventional GQI approach is unable to deal with uncertainties involved in the assessment of environmental problems. To overcome this limitation, a novel hybrid framework integrating Fuzzy Logic with the GIS-based GQI is proposed in this study for assessing groundwater quality and its spatial variability. The proposed hybrid framework is demonstrated through a case study in a hard-rock terrain of Southern India using ten prominent groundwater-quality parameters measured during *pre-monsoon* and *post-monsoon* seasons. Two conventional GIS-based GQI models GQI-10 (using all the ten groundwater-quality parameters) and GQI-7 (using seven 'concerned/critical' groundwater-quality parameters) as well as hybrid Fuzzy-GIS-based GQI (FGQI) models (using seven critical parameters) were developed for the two seasons and the results were compared. The Trapezoidal membership functions classified the model input parameters into *'desirable'*, *'acceptable'* and *'unacceptable'* classes based on the experts' knowledge and water quality standards for drinking purposes. The concentrations of Ca^{2+}, Mg^{2+}, and SO_4^{2-} in groundwater were found within the WHO desirable limits for drinking water throughout the year, while the concentrations of seven parameters (TDS, NO_3^--N, Na^+, Cl^-, K^+, F^- and Hardness) exceed their permissible limits during *pre-monsoon* and *post-monsoon* seasons. A comparative evaluation of GQI models revealed that the FGQI model predicts groundwater quality better than the conventional GQI-10 and GQI-7 models. GQI modeling results suggest that the groundwater of most of eastern and southern parts (~60% in *pre-monsoon* season; ~90% in *post-monsoon* season) of the study area is unsuitable for drinking. Further, the groundwater quality deteriorates during *post-monsoon* seasons compared to *pre-monsoon* seasons, which indicates an increased influx of contaminants from different industries, mining areas, waste disposal sites and agricultural fields during monsoon seasons. This finding calls for the strict enforcement of regulations for proper handling of effluents from various contamination sources in the study area. It is concluded that the fuzzy logic-based decision-making approach (FGQI) is more reliable and pragmatic for groundwater-quality assessment and analysis at a larger scale. It can serve as a useful tool for the water planners and decision makers in efficiently monitoring and managing groundwater quality at watershed or basin scales.

1. Introduction

Water quality is inherently linked with human health, poverty reduction, gender equality, food security, livelihoods and the preservation of ecosystems, as well as economic growth and social development of our societies (IAH, 2008; UNESCO, 2015). Increase

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in urbanization, industrialization and agricultural activities have adversely affected the quality of both surface water and groundwater across the globe. Groundwater being more reliable source of freshwater is under enormous pressure to fulfill water demands for increasing global population, especially in developing countries including India. According to World Bank (2010), India is the largest consumer of groundwater in the world, with an estimated annual groundwater use of about 230 km^3. India is facing groundwater crisis in the 21st century due to its overexploitation (CGWB, 2017) as well as growing contamination from point and non-point sources of pollution (SoE, 2009). Contrary to surface water contamination, groundwater contamination is difficult to detect because of being hidden and once contaminated, the groundwater can remain so for decades or even for hundreds of years due to relatively slow movement of water and contaminants in the subsurface environment. Therefore, there is an urgent need to develop efficient management strategies for the sustainable utilization and protection of vital groundwater resources. To this end, it is imperative to have a suitable tool/technique for effective monitoring and assessment of groundwater quality at a larger scale, which in turn can serve as an effective tool for improved management and development of vital groundwater resources.

One possible management alternative is through the development of water quality indices to provide a comprehensive assessment of surface water and groundwater quality. Water Quality Indices (WQI) is a simple mathematical tool that can provide a distinct picture of overall water quality status over an area based on important water quality parameters (Abbasi and Abbasi, 2012). The WQI-based maps are easily understandable and aid in creating public awareness on groundwater/surface water pollution as well as in enforcing regulations for proper managements of wastes released from various sources and imposing restrictions on groundwater extraction, which in turn can help formulate effective management strategies for protecting aquifers from contamination (e.g., Saeedi et al., 2010; Vadiati et al., 2016). In past few decades, the WQI approach was followed by many researchers worldwide (e.g., Bolton et al., 1978; Babiker et al., 2007; Nasiri et al., 2007; Machiwal et al., 2011; Vicente et al., 2011; Zhao et al., 2013; Jasmin and Mallikarjuna, 2014; Boateng et al., 2016; Selvaganapathi et al., 2017). Lumb et al. (2011) provided a comprehensive review on the evolution of WQI over the years and highlighted major limitations embedded in the process of index development and provided recommendations to overcome the drawbacks.

Many of the past researches on WQI focused particularly on surface water with very limited number of studies dealing with groundwater. It is important to mention that biological properties (bacteria, algae, etc.) and physico-chemical properties (temperature, turbidity, color, dissolved oxygen, pH, etc.) are important parameters for surface water quality evaluation, whereas hydrochemical properties (major cations and anions) are important parameters for groundwater quality evaluation (Vadiati et al., 2016). Thus, a variety of water-quality parameters are involved in the evaluation of groundwater quality and data constraints often impede the process of Groundwater Quality Index (GQI) development. Probably, Tiwari and Mishra (1985) were the first to formulate a methodology for drinking water suitability using surface water quality index (Lumb et al., 2011; Vadiati et al., 2016). Adopting their procedure, several studies were carried out dealing with GQI development in different parts of the world (Lumb et al., 2011). In the recent past, several researchers have also employed GIS-based GQI to evaluate groundwater quality and analyze spatial variability of groundwater-quality parameters. Babiker et al. (2007) was pioneer in proposing the development of GIS-based GQI using a statistical procedure to calculate an index based on the World Health Organization (WHO) standards for drinking water. This methodology has been widely employed by subsequent researchers to assess groundwater quality and its spatial variability (e.g., Nas and Ali, 2010; Machiwal et al., 2011; El-Fadel et al., 2014; Vadiati et al., 2016). Apart from analyzing the drinking water suitability using GQI, a few studies have also been carried out for assessing irrigation water suitability using GQI. For example, Soltan (1999) evaluated groundwater quality of artesian wells in Egypt for irrigation water suitability based on GQI, whereas Stigter et al. (2006) used groundwater GQI as an assessment tool for the agricultural regions of Portugal.

Groundwater Quality Index (GQI) is easy to calculate using the threshold values of different groundwater quality parameters and the results are very convenient to interpret. However, one of the major issues with the traditional WQIs (for both surface water and groundwater) is that they fail to deal with the uncertainty and subjectivity that are inherent in the assessment of environmental problems (Silvert, 2000), especially while classifying water quality near the parameter-threshold boundary (Chang et al., 2001). To overcome this subjectivity and to incorporate environmental uncertainty in the groundwater quality evaluation process, the application of Artificial Intelligence (AI) based computational methods are highly recommended (Maiti et al., 2013; Araghinejad, 2013; Patki et al., 2015; Bagherzadeh et al., 2018; Salari et al., 2018). The available AI methods can be classified into two broad categories: (a) Symbolic AI, and (b) Computational AI. The former mainly deals with the development of knowledge-based system, while the latter deals with the development of behavior-based system (Chau, 2006). The computational AI includes Neural Networks, Genetic Algorithm, Fuzzy systems, etc. Among various computational AI methods, Fuzzy Logic (FL) is extensively used to deal with complex water-related environmental problems (McKone and Deshpande, 2005; Ghosh and Mujumdar, 2006; Chau, 2006; Mohebbi Tafreshi et al., 2018), owing to its capability to deal with non-linearity and uncertainty involved in environmental systems (Chanapathi et al., 2019). In addition to this, FL serves as an effective tool for conveying the results to the public and beneficiaries in a much understandable linguistic format (Li et al., 2018). The Fuzzy Logic was introduced by Zadeh (1965) and is based on 'fuzzy' set-theory in contrast to the classical mathematics which is based on the 'crisp' set-theory. Ocampo-Duque et al. (2006) first used fuzzy inference system (FIS) to evaluate river water quality in Spain and identified the fuzzy WQI to be more robust compared to the traditional WQI. A few studies have used Fuzzy Logic to evaluate groundwater quality (Dahiya et al., 2007; Jinturkar et al., 2010; Hosseini-Moghari et al., 2015; Mohamed et al., 2019) and it has been recommended for the evaluation of complex water quality problems. All of these studies implemented Fuzzy Logic based GQI for point-based groundwater samples collected from open/bore wells (Dahiya et al., 2007; Hosseini-Moghari et al., 2015; Gorai et al., 2016; Vadiati et al., 2016; Agoubi et al., 2016; Mohamed et al., 2019) or from hand pumps (Jinturkar et al., 2010) and did not map the spatial variation of groundwater quality. Furthermore, a general difficulty has been reported in validating Fuzzy-based GQI owing to the linguistic subjectivity involved in the construction of Fuzzy-based indices (Ocampo-Duque et al., 2013).

It is evident from the review of literature presented above that the application of Fuzzy Logic for developing GIS-based GQI is in its infancy and little attention has been given to employ Fuzzy Logic to address the non-linearity and uncertainty involved in the spatial mapping of GQI (Machiwal et al., 2018). Also, the issue involved in the validation of Fuzzy-based GQI has not been addressed to date. Considering these research gaps and the need for an efficient methodology for evaluating groundwater quality at larger scales, the goal of this study is to develop a novel hybrid framework by integrating Fuzzy Logic with the GIS-based GQI to assess groundwater quality and its spatial variability at larger scales. This hybrid framework is named Fuzzy-GIS-based Groundwater Quality Index (henceforth called "FGQI"), and its efficacy and applicability are demonstrated through a case study in a hard-rock terrain of Tamil Nadu state, South India. Also, for the first time, the issue concerning validation of the developed FGQI has been addressed in this study. Two recent studies conducted in a few parts of Tiruchirappalli District (Selvakumar et al., 2017; Rajendran et al., 2019) deal with the basic geochemical analysis of groundwater at limited locations using statistical and/or graphical methods, which also indicate the necessity for an efficient methodology to assess groundwater quality at a larger scale.

2. Materials and methods

2.1. Overview of study area

2.1.1. Location and climate

The study area selected for this study is Tiruchirappalli district (also known as 'Trichy), which is situated in the central position of Tamil Nadu state in the southern part of India (Fig. 1). It is located between 10°16′ and 11°22′ North latitude and 78°15′ and 79°16′ East longitude and encompasses an area of approximately 4403.83 km^2. It is sub-divided into 14 administrative units (known as 'blocks') namely, Anthanallur, Lalgudi, Manachanallur, Manapparai, Manikandam, Marungapuri, Musiri, Pullambadi, Tattayangarpettai, Tiruverumbur, Thottiyam, Thuraiyur, Uppliyapuram and Vaiyampatti (Fig. 1). The main source of surface water is the Cauvery River and its tributaries (Ayyar, Uppar and Koraiyar rivers) which flow through the center of the study area.

The area is characterized by 'Tropical wet and dry climate' with hot and dry summer from March to May, normal to moderate monsoon rainfall from June to December, followed by mild cold and moist winter during January and February. The monsoon season in the study area occurs in two phases: June to September from the Southwest Monsoon and October to December from the Northeast Monsoon, with the former contributing 32% to the annual rainfall and the latter being the major rainy season contributing 48%. Owing to the Cauvery River dispute, the surface water reserves are not sufficient during the non-monsoon season, resulting in heavy dependency on groundwater reserves for drinking and irrigation purposes. This situation calls for proper groundwater management in the river basin.

2.1.2. Hydrogeology and land characteristics

The study area predominantly consists of three geological groups: (i) the Bhavani group of formations comprising of Fissile hornblende gneiss of Archaean age in the North covering 30% of the study area, (ii) the Migmatite complexes made up of Hornblende biotite gneiss of Archaean age extending in the South occupying about 37% of the study area, and (iii) the Quaternary formations of Alluvium belonging to the Cainozoic age underlying the Cauvery River in the central region covering 10% of the area (Fig. S1). Additionally, patches of limestone of the Trichinopoly group and sandstone of the Gondwana group of Mesozoic age are confined to the East of the study area (Jenifer and Jha, 2017). A massive stretch of Charnockite of Charnockite group is found in the extreme North and South of the study area. Granite prevailing in the Central and Western portions of the study area is mostly hard and easily weathered. The Anorthosite (intrusive igneous rocks) of the Sathayamangalam group are exposed in the southwestern part of the study area are mainly comprised of calcium-rich coarse crystals.

The hard-rocks in the study area possess negligible primary porosity but are rendered porous and permeable due to secondary porosity by fracturing and weathering. Groundwater yields from granite and gneiss formation are better than charnockite formations. Shale, sandstone, clay and alluvium act as unconfined or leaky confined aquifers in some parts of the study area. The aquifer is highly heterogeneous due to changes in the lithology, texture and structural features within a short span of distance. Groundwater in the study area is usually found at depths of 2–20 m below the ground in the weathered formations (unconfined aquifers) and it is tapped mostly through dug wells. Deeper fractured formations (leaky confined or confined aquifers) occur at depths of 20–40 m which are tapped through bore wells or dug-cum-bore wells (CGWB, 2008).

The land use/land cover map of the study area is shown in Fig. 2(a). Major portion of the study area (66.53%) has agricultural land wherein crops like paddy, cereals, fruits, vegetables, oil seeds, and fiber crops such as cotton, sugarcane and pulses are grown. Fallow land covers 11.45%, forest 9.98%, water bodies 6.34% and settlement covers 3.62%. Mining activities are limited to about 2% of the study area, mostly concentrated near the Cauvery River where sand and sandstone mining is prevalent. A few mining sites are also located in the eastern and southern parts of the study area where predominantly limestone is excavated. On the other hand, a variety of industries and some gasoline stations are present in different parts of the study area [Fig. 2(b)], with the cluster of industries located in the central portion of the study area. These industries and gasoline stations coupled with mining and agricultural activities constitute potential sources of contamination for surface water bodies and groundwater (Jenifer, 2018; Jenifer and Jha, 2018).

2.1.3. Data acquisition

For the groundwater-quality assessment of the unconfined aquifer system underlying the study area, groundwater-quality data of 24 observation wells during *pre-monsoon* season (July 2013) and 37 observation wells during *post-monsoon* season (January 2014) (Fig. 1) were obtained from Institute of Water Studies, Chennai, Tamil Nadu. Both the *pre-monsoon* and *post-monsoon* seasons' groundwater-quality data were used in this study to investigate seasonal variation in the groundwater quality and the influence of the rainfall on the quality of groundwater. The obtained groundwater quality parameters consisted of major anions and cations including Total dissolved solids (TDS), Nitrate-Nitrogen (NO_3^--N), Calcium (Ca^{2+}), Magnesium (Mg^{2+}), Sodium (Na^+), Chloride (Cl^-), Potassium (K^+), Fluoride (F^-), Sulphate (SO_4^{2-}) and Hardness (measured as $CaCO_3$). These ten groundwater-quality parameters were employed for developing GQI for assessing the suitability of groundwater for drinking water supply in the study area. In this study, only prominent water-quality parameters were considered based on their importance in affecting groundwater quality as reported in the earlier studies conducted in some parts of Tiruchirappalli district (e.g., Jameel and Sirajudeen, 2006; Venkatesan et al., 2013; Selvakumar et al., 2017; Rajendran et al., 2019), and their impacts on human health. Also, another reason for considering only important water-quality parameters is due to the fact that the inclusion of more parameters (less prominent water-quality parameters) in the groundwater-quality model unnecessarily increases uncertainty. Thus, the consideration of less important/unimportant water-quality parameters is neither technically sound nor practically useful/significant.

2.2. Development of GIS-based groundwater quality index (GQI) models

The hybrid framework adopted in this study for developing Fuzzy-GIS-based Groundwater Quality index (FGQI) is illustrated in Fig. 3. The complete procedure can be segregated into three major steps viz., geostatistical analysis, development of traditional GIS-

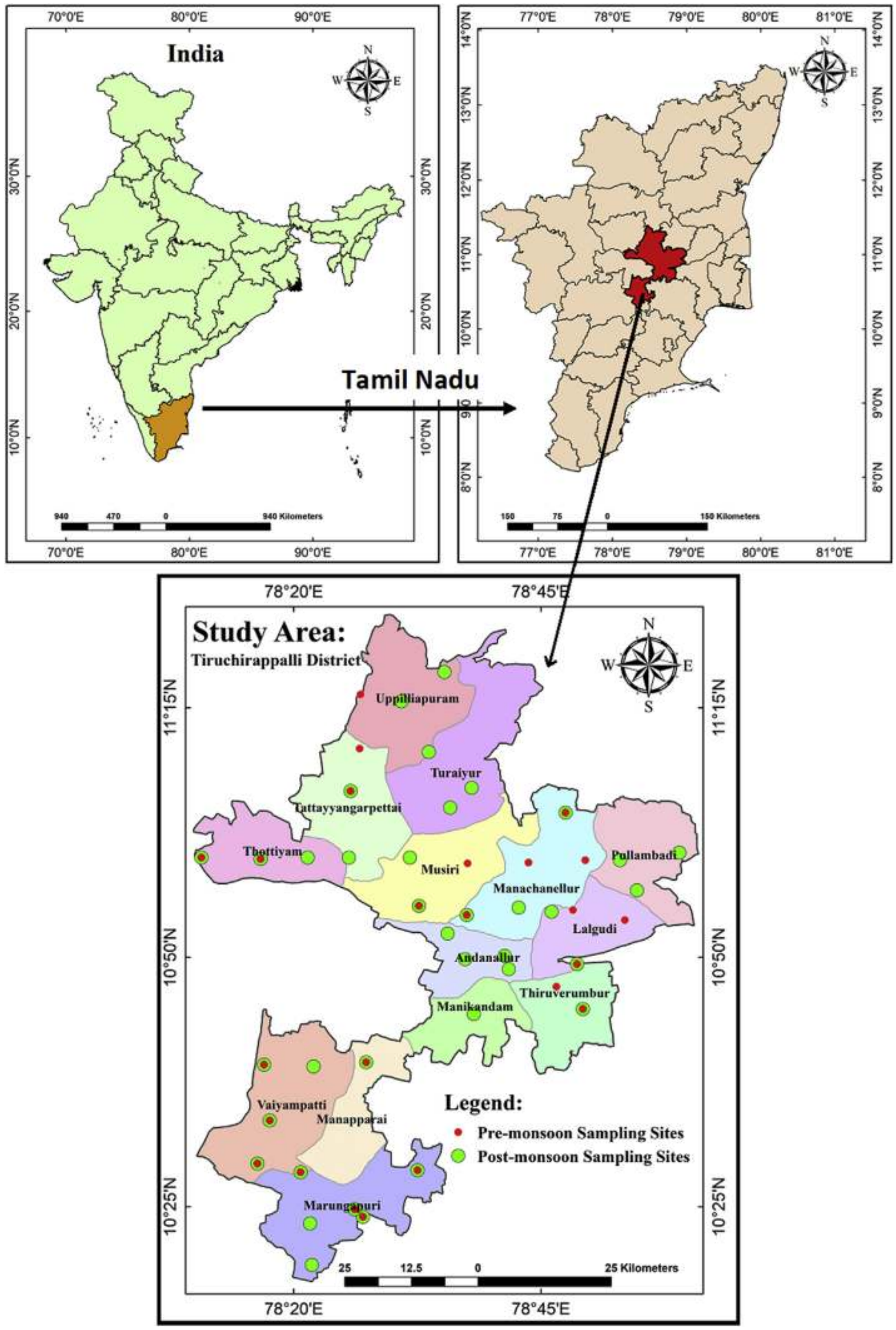

Fig. 1. Location map of the study area with the location of groundwater sampling sites.

based GQI models and development of Fuzzy-GIS-based GQI (FGQI) models.

2.2.1. Geostatistical analysis

Geostatistical analysis, especially spatial interpolation of point data is the first and foremost step for developing GQI, because further model development depends heavily on it. Since it is nearly impossible to obtain field data for each point throughout the study area, spatial interpolation techniques were used to estimate the data at un-sampled points using the data from sampled points. Inverse distance weighting (IDW), Kriging and Co-kriging are most widely used spatial interpolation methods. IDW is a deterministic interpolation technique that estimates value at unmeasured points on the basis of its closeness to the measured points. On other hand, Kriging is a geostatistical interpolation technique which uses spatial statistics of the measured points to estimate values at unmeasured points, whereas Co-Kriging is an extension of Kriging in which an auxiliary variable is used to help the Kriging estimator. The auxiliary variable is the one which is highly correlated with the primary variable.

Kriging/Co-Kriging performs better than the IDW method when the data are near normally distributed (Kerry and Oliver, 2007a) and have no extreme values (Kerry and Oliver, 2007b). Among the Kriging and Co-Kriging methods, Co-Kriging is found to be superior

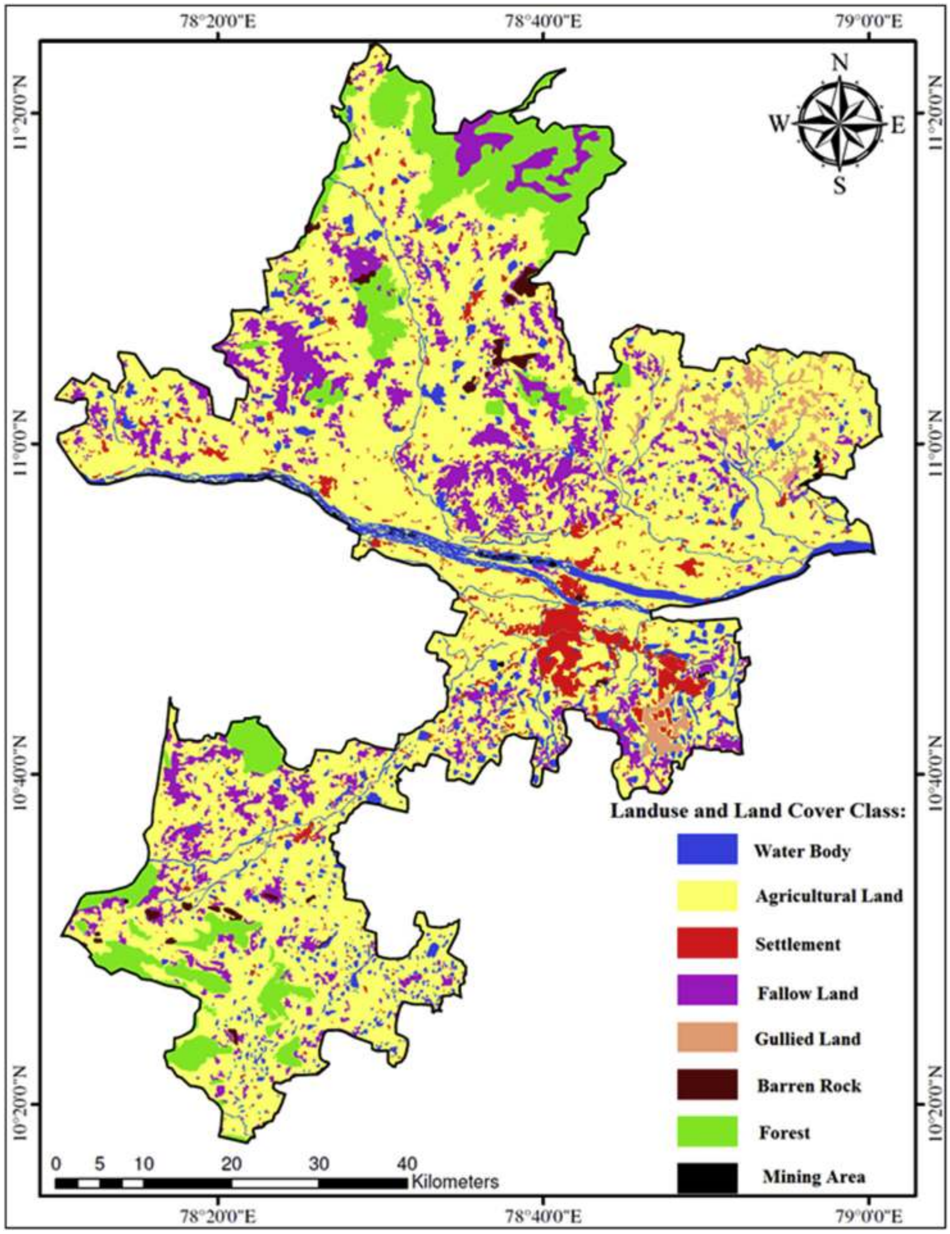

Fig. 2a. Land Use/Land Cover in the study area (modified from Jenifer and Jha, 2018).

when the correlation coefficient between the primary and auxiliary variable is more than 0.5 (Yates and Warrick, 1987). Tables S1 and S2 show correlation between all the ten groundwater-quality parameters during *pre-monsoon* season and *post-monsoon* season, respectively. Finally, groundwater-quality parameters following near-normal distribution were interpolated by employing Kriging/Co-Kriging considering correlation coefficient values of the parameters (Tables S1 and S2). The choice between Kriging and Co-Kriging was finally decided based on the least value of root mean square error (RMSE). On the other hand, the groundwater-quality parameters having no near-normal distribution were interpolated using IDW, which efficiently captures the extreme values that are most likely in case of groundwater-quality data (Mueller et al., 2004). Thus, the interpolation methods used to prepare concentration maps of individual groundwater-quality parameters for *pre-monsoon* and *post-monsoon* seasons are shown in Table 1. Using suitable interpolation methods, concentration maps of 50 m × 50 m pixel size were prepared using GIS for all the groundwater-quality parameters for both the seasons and a summary of the basic statistics of the concentrations of individual parameters during *pre-monsoon* and *post-monsoon* seasons is presented in Table 1. Further, these maps were used for analyzing spatial variability of the concentration of individual groundwater-quality parameters.

2.2.2. Traditional GIS-based groundwater quality index (GQI) models

The concentration maps were employed to compute GIS-based GQI following the procedure proposed by Babiker et al. (2007). Firstly, the concentration maps of each parameter were used to create normalized maps, also known as Concentration Index maps (CI), by comparing the parameter concentration value (X) with its

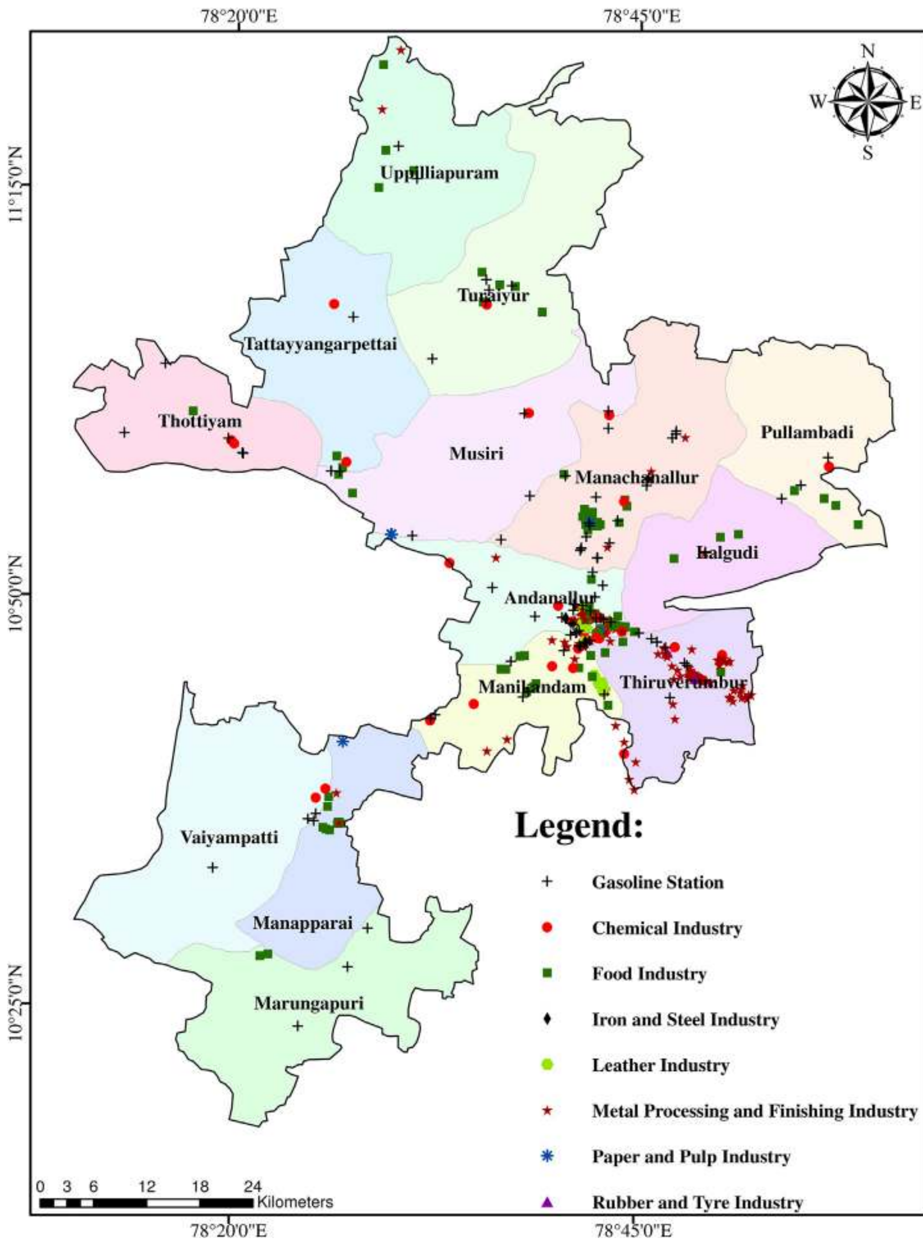

Fig. 2b. Distribution of different industries and gasoline stations over the study area.

standard threshold (T) using Eqn. (1). The WHO Standards for drinking water (WHO, 2004) and the Indian Standards (IS) for drinking water provided by the Bureau of Indian Standards (BIS, 2012) were used as shown in Table 1. Thereafter, the rank (R) maps of all the parameters were generated using Eqn. (2).

$$CI = \frac{X - T}{X + T} \tag{1}$$

$$R = 0.5{*}CI^2 + 4.5{*}CI + 5 \tag{2}$$

$$W = \begin{cases} mean(R); \;\; for \;\; TDS, Ca^{2+}, Mg^{2+}, \, SO_4^{2-}, \, K^+, \, F^-, \, Hardness \\ \qquad\qquad mean(R) + 2; \; for \;\; NO_3^- - N, Na^+, Cl^- \end{cases} \tag{3}$$

$$GQI = 100 - \frac{R_1{*}W_1 + R_2{*}W_2 + ... + R_n{*}W_n}{n} \tag{4}$$

Furthermore, the weights (W) for each parameter were determined as mean of the respective rank values. However, as suggested by Babiker et al. (2007), the potential parameters were given higher weights as shown in Eqn. (3). In this study, Nitrate-Nitrogen (NO_3^--N), Sodium (Na^+) and Chloride (Cl^-) were identified as potential health-risk parameters for the study area. Excess levels of Nitrate are known to cause 'blue baby' syndrome, whereas excess Chloride levels are known to increase colon cancer risk (Aieta and Berg, 1986). Although higher sodium levels do not pose a serious threat to the human health, it creates a risk to the people under low sodium diet which is usually recommended for hypertension (high blood pressure) and congestive heart failure patients. Finally, the GQI values were calculated using Eqn. (4), which lie between 0 and

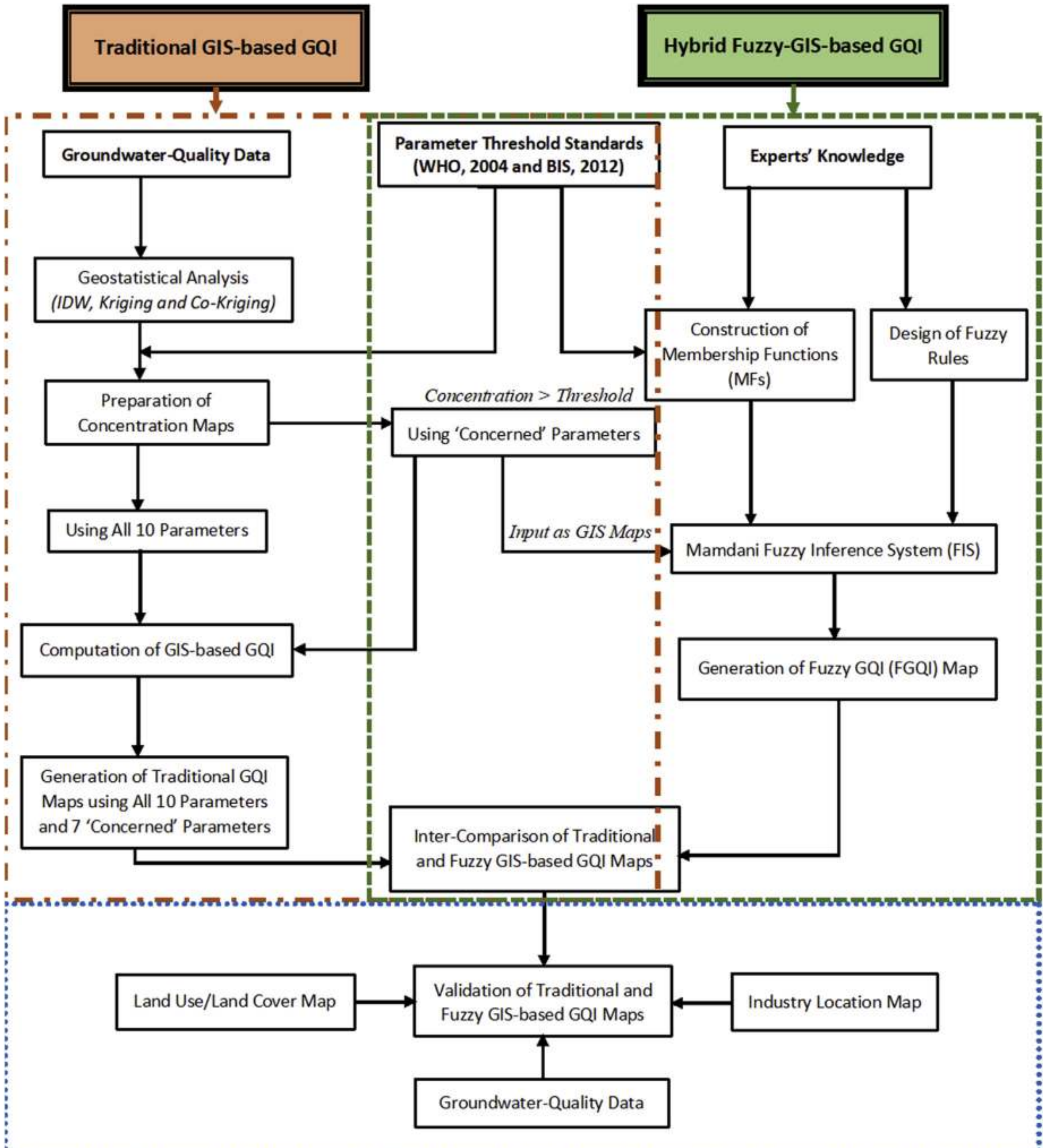

Fig. 3. Flowchart depicting the methodology for developing traditional and Fuzzy GIS-based GQI models.

100. Two traditional/conventional GQI models of the study area for *pre-monsoon* and *post-monsoon* seasons were prepared using all the ten groundwater-quality parameters, and are denoted as GQI-10 models [using total dissolved solids (TDS), Nitrate-Nitrogen (NO_3^--N)), Calcium (Ca^{2+}), Magnesium (Mg^{2+}), Sodium (Na^+), Chloride (Cl^-), Potassium (K^+), Fluoride (F^-), Sulphate (SO_4^{2-}) and Hardness (measured as $CaCO_3$)]. Similarly, two more traditional GQI maps were prepared for *pre-monsoon* and *post-monsoon* seasons using only the parameters whose concentration values exceed their permissible limits (henceforth called 'concerned/critical parameters' in this study), and are denoted as GQI-7 models [using seven 'concerned/critical parameters' namely total dissolved solids (TDS), Nitrate-Nitrogen (NO_3^--N), Sodium (Na^+), Chloride (Cl^-), Potassium (K^+), Fluoride (F^-), and Hardness]. The computed index values in each case were categorized into suitable classes to generate four traditional GQI maps based on the classification scheme proposed by Babiker et al. (2007).

2.2.3. *Fuzzy-GIS-based groundwater quality index (FGQI) model*

Since its inception by Zadeh (1965), Fuzzy Logic (FL) has helped researchers to induce human knowledge and experience to deal with the uncertainty and vagueness involved while assessing natural systems. Fuzzy Logic maps input to output using Fuzzy Inference System (FIS) that combines FL and experts' knowledge via four main components viz., fuzzification, fuzzy inference rules, aggregation and defuzzification. Two most important fuzzy inference systems are Mamdani FIS (Mamdani, 1976) and Sugeno FIS (Sugeno, 1985). Mamdani FIS is most widely used for environmental

Table 1
Basic statistics of seasonal groundwater quality, threshold values of water quality parameters, and interpolation method used for concentration mapping.

Groundwater Quality Parameter	Threshold Concentration (mg/L)	*Pre-monsoon* Season (July 2013)					*Post-monsoon* Season (January 2014)				
		Interpolation Method Used	Minimum (mg/L)	Maximum (mg/L)	Mean (mg/L)	SD (mg/L)	Minimum (mg/L)	Maximum (mg/L)	Mean (mg/L)	SD (mg/L)	Interpolation Method Used
Total Dissolved Solids	500*	Co-Kriging	157.1	3202.7	793.6	385.5	190.0	3028.0	911.8	337.7	IDW
Nitrate-N	10#	IDW	0.1	126.0	15.9	13.9	1.0	105.0	16.4	10.2	IDW
Calcium	300#	Co-Kriging	22.0	67.2	39.9	7.5	32.9	65.5	43.3	5.5	Co-Kriging
Magnesium	300#	Co-Kriging	21.9	120.0	53.2	13.3	35.6	119.3	71.5	17.8	Co-Kriging
Sodium	200#	Co-Kriging	15.7	875.6	157.3	97.2	14.0	640.0	178.6	79.5	IDW
Chloride	250*	Co-Kriging	35.2	1304.7	263.3	176.1	32.0	1347.0	305.4	166.9	IDW
Potassium	12#	IDW	0.1	74.0	16.5	11.1	0.3	60.5	19.5	9.5	Kriging
Fluoride	1*	IDW	0.1	1.9	0.6	0.3	0.1	2.4	0.6	0.4	IDW
Sulphate	250#	Kriging	10.5	199.9	69.0	23.0	5.0	237.5	79.8	41.5	Kriging
Hardness	150+	IDW	95.0	880.0	314.7	108.8	150.0	1500.0	397.8	169.4	IDW

Note: * Threshold/Desirable Concentration based on BIS; # Threshold Concentration based on WHO; + Threshold Concentration based on BIS and WHO; Shaded rows indicate the groundwater-quality parameters having concentrations within their desirable limits for drinking water.

applications due to its simplicity and practical application (Icaga, 2007; Scannapieco et al., 2012) and it has been employed in this study for the development of FGQI.

2.2.3.1. Fuzzification. The fuzzification of the input and output is done by constructing Membership Functions (MFs). Membership Function (MF) is a curve which shows the degree of belongingness (membership value) of the data to a particular class. The membership value was determined using experts' knowledge and drinking water quality standards of WHO (WHO, 2004) and BIS (BIS, 2012) as shown in Table 1 and S3. Fig. 4(a-h) show the chosen MFs for the input and output variables. Trapezoidal MFs were adopted in this study as they are the most commonly used functions in many studies (Kosko, 1993). The inputs to the FIS were the concentration maps of the 'concerned parameters' similar to the traditional GQI-7 map so as to reduce the uncertainty. The trapezoidal membership functions of all the seven groundwater-quality parameters and FGQI were constructed using following equation (Hosseini-Moghari et al., 2015):

$$f(x;a,b,c,d)=\begin{cases}0 & x<a \ \text{or} \ d<x\\ \dfrac{a-x}{a-b} & a\le x\le b\\ 1 & b\le x\le c\\ \dfrac{d-x}{d-c} & c\le x\le d\end{cases} \tag{5}$$

Where, x is the parameter to be fuzzified and *'a', 'b', 'c'*, and *'d'* are the linguistic variables used to divide the parameters into different classes (Table S4). The input parameters were divided into three classes: *'desirable'* (concentration value less than or equal to the desirable limit), *'acceptable'* (concentration value between desirable and permissible limits), and *'unacceptable'* (concentration value more than the permissible limit) based on the WHO and BIS standards for drinking water [Fig. 4(a-g) and Table S4]. The outputs (values of FGQI) were classified into five classes namely *'unacceptable'*, *'poor'*, *'moderate'*, *'good'* and *'excellent'* [Fig. 4(h) and Table S5].

2.2.3.2. Fuzzy inference rules. The fuzzy inference rules are in the form of *'if-then'* format. They map the input class categories to the output class categories. The '*if*' part is called an antecedent and the '*then*' part is called a consequent. For example, '*If* the concentration of a parameter (e.g., TDS) is desirable, *then* the water quality (FGQI) is excellent'. Fuzzy rules for the study area were designed by using experts' knowledge and carefully considering the parameters having potential health risk (i.e., NO_3^--N, Cl^- and Na^+). An outline showing the design of fuzzy inference rules is depicted in Fig. 5. The main premise while designing the fuzzy inference rules was: *"even if one water-quality parameter exceeds the permissible limit for drinking water, then the water is not suitable for direct consumption by the people".* All the fuzzy inference rules were designed keeping this main premise in mind. Moreover, while designing the fuzzy inference rules, three potential health risk parameters NO_3^--N, Cl^- and Na^+ were also taken into special consideration. This main premise ensures the practicality of the developed water quality index in judging drinking water suitability. This is important to emphasize here as this knowledge helps to inculcate human understanding in the Fuzzy Logic assessment of groundwater quality.

2.2.3.3. Aggregation of fuzzy rules. Once the fuzzy inference rules were designed, the next step was combining all the designed fuzzy inference rules. The aggregation of the consequent part of the fuzzy inference rules is needed to calculate a single fuzzy output, which is FGQI in this study. Maximum method (Ross, 2004) was used as an aggregation procedure in this study, which applies *union* operation on all the truncated output fuzzy sets.

2.2.3.4. Defuzzification. Finally, defuzzifying the aggregated output value was carried out to convert the fuzzy sets to a numeric value. The final numeric score obtained is "Fuzzy Groundwater Quality Index (FGQI)". The most commonly used Centroid of Area (COA) method (Ross, 2004) was employed for defuzzification of the fuzzy sets. The detailed description of all the fuzzy set operations and FIS can be found in Ross (2004). All the FL operations were carried out in Matlab R2014a (Mathworks, 2014), whereas the GIS operations were carried out in ArcGIS 10.2.2 (ESRI, 2014). Thus, Fuzzy-GIS-based Groundwater Quality Index (FGQI) maps of the study area were prepared for *pre-monsoon* and *post-monsoon* seasons using seven 'concerned parameters'.

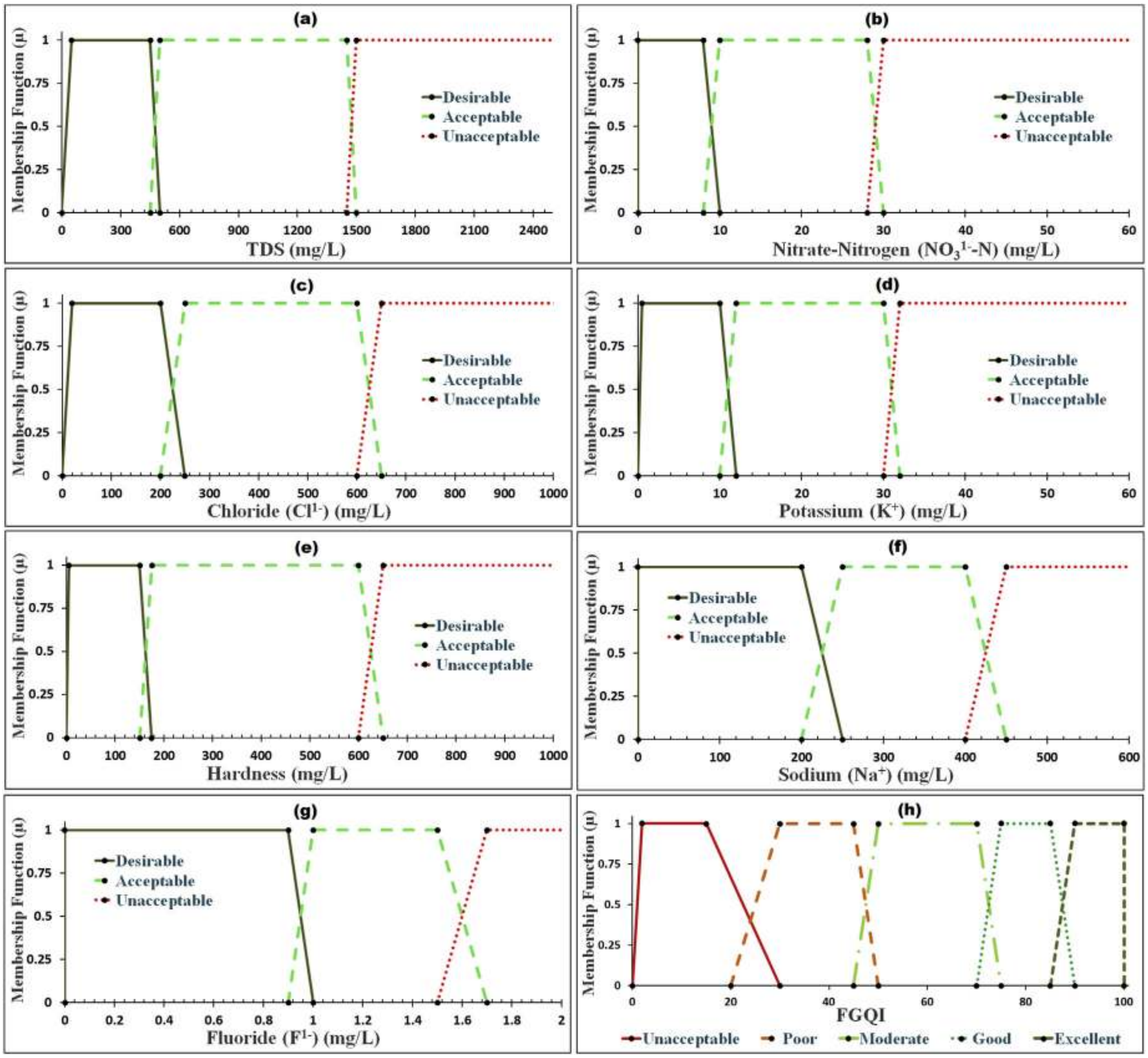

Fig. 4. (a–h). Fuzzy Membership Functions (MFs) of the input and output variables: (a) TDS; (b) Nitrate-Nitrogen; (c) Chloride; (d) Potassium; (e) Hardness; (f) Sodium; (g) Fluoride; (h) FGQI.

2.3. *Validation of the developed GQI models*

For the first time, the validation of FGQI has been attempted in this study because it is a difficult task. It is important to emphasize that FGQI is developed based on linguistic terminology in the form of fuzzy rules. Equations are only used to map the parameters which reduce the non-linearity of the fuzzy model. The best method to validate an index is to use impact factors or indicators (Ocampo-Duque et al., 2006). However, relating an impact factor to groundwater quality is furthermore challenging and it is not possible in some situations. In this study, the FGQI and traditional GQI models developed for *pre-monsoon* and *post-monsoon* seasons were validated qualitatively using land use/land cover and industry location maps [Fig. 2(a and b)] as well as quantitatively using site-specific groundwater-quality data obtained from the analysis of groundwater samples collected from different observation wells over the study area; these water-quality data indicate the status of groundwater quality with minimum uncertainty. Since unacceptable concentration of even one parameter renders the water unsuitable for drinking and other domestic proposes, the score of a given groundwater quality index was examined for the observation well with respect to its number of unsafe parameters (parameters exceeding their acceptable/permissible limits).

3. Results and discussion

3.1. *Variability of groundwater-quality parameter concentration in the study area*

The concentration maps created using spatial interpolation of the point values of the concentrations of ten groundwater-quality parameters for *pre-monsoon* and *post-monsoon* seasons are shown in Fig. 6(a and b). The concentration maps are categorized into three classes on the basis of the desirable and permissible limits of WHO and BIS for drinking water (Table S3). As it can be seen from Fig. 6(a and b) that Calcium, Magnesium and Sulphate are the *'safe parameters'* as they are well within the desirable limits throughout the study area during both *pre-monsoon* and *post-monsoon* seasons. However, the remaining 7 parameters, i.e., TDS, NO_3^--N, Na^+, Cl^-, K^+, F^- and Hardness exceed their permissible limits in some parts

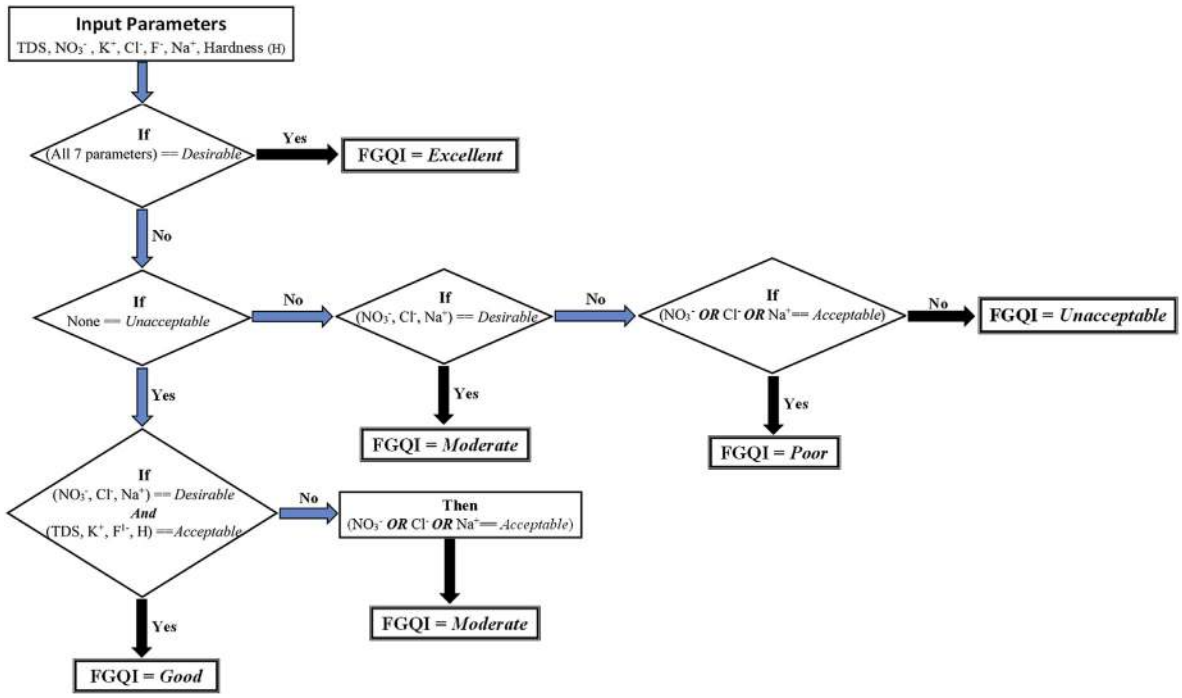

Fig. 5. Methodology for designing Fuzzy inference rules to evaluate groundwater quality based on FGQI.

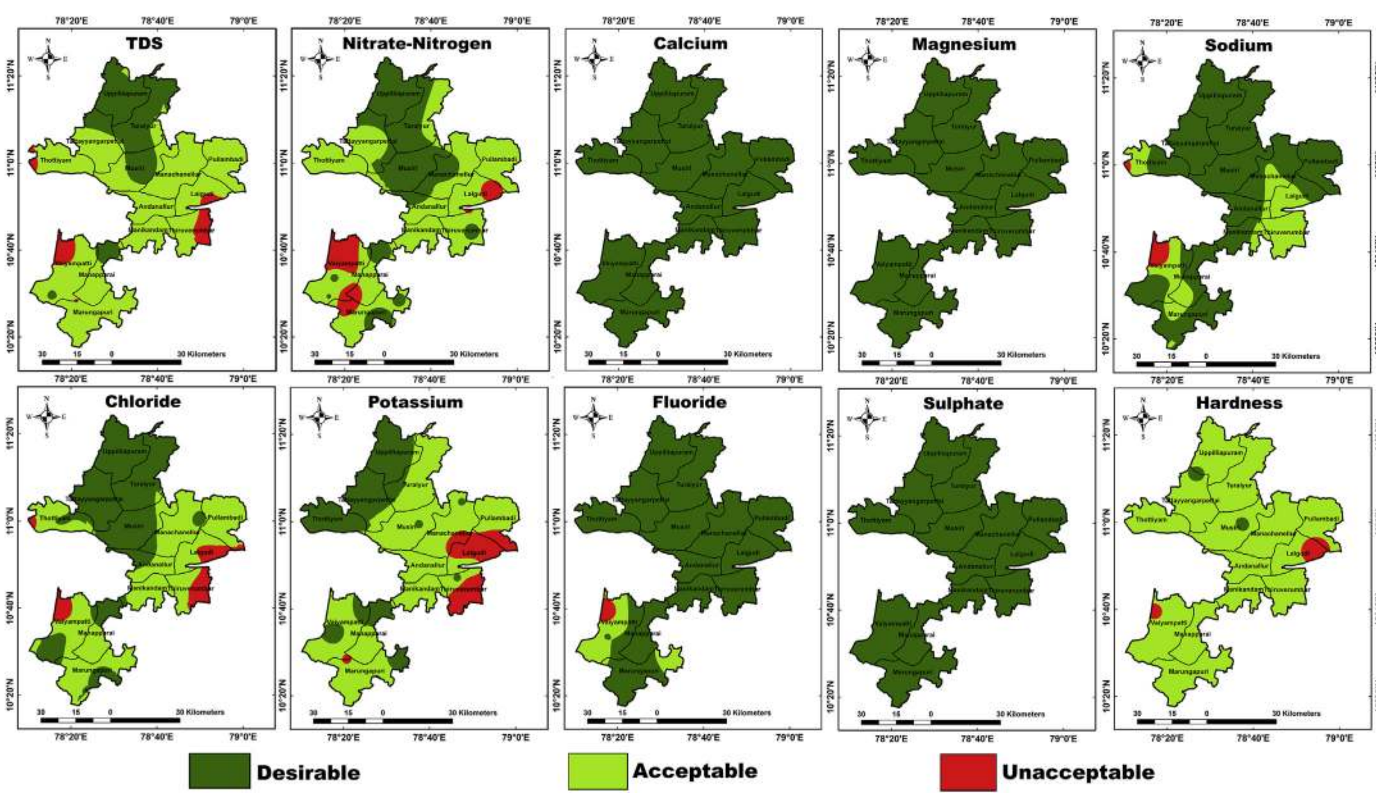

Fig. 6a. Concentration maps of the groundwater-quality parameters during ***pre-monsoon*** season.

of the study area and hence, they are considered as '*critical/concerned parameters*' for assessing the suitability of groundwater for drinking purpose. The spatial variability of groundwater quality during *pre-monsoon* and *post-monsoon* seasons is discussed in the subsequent sub-sections.

3.1.1. *Concentration maps of groundwater-quality parameters for the pre-monsoon season*

It is apparent from Fig. 6(a) that in the *pre-monsoon* season, groundwater in the unconfined aquifer underlying the south-western part of the study area (Vaiyampatti block) has unacceptable

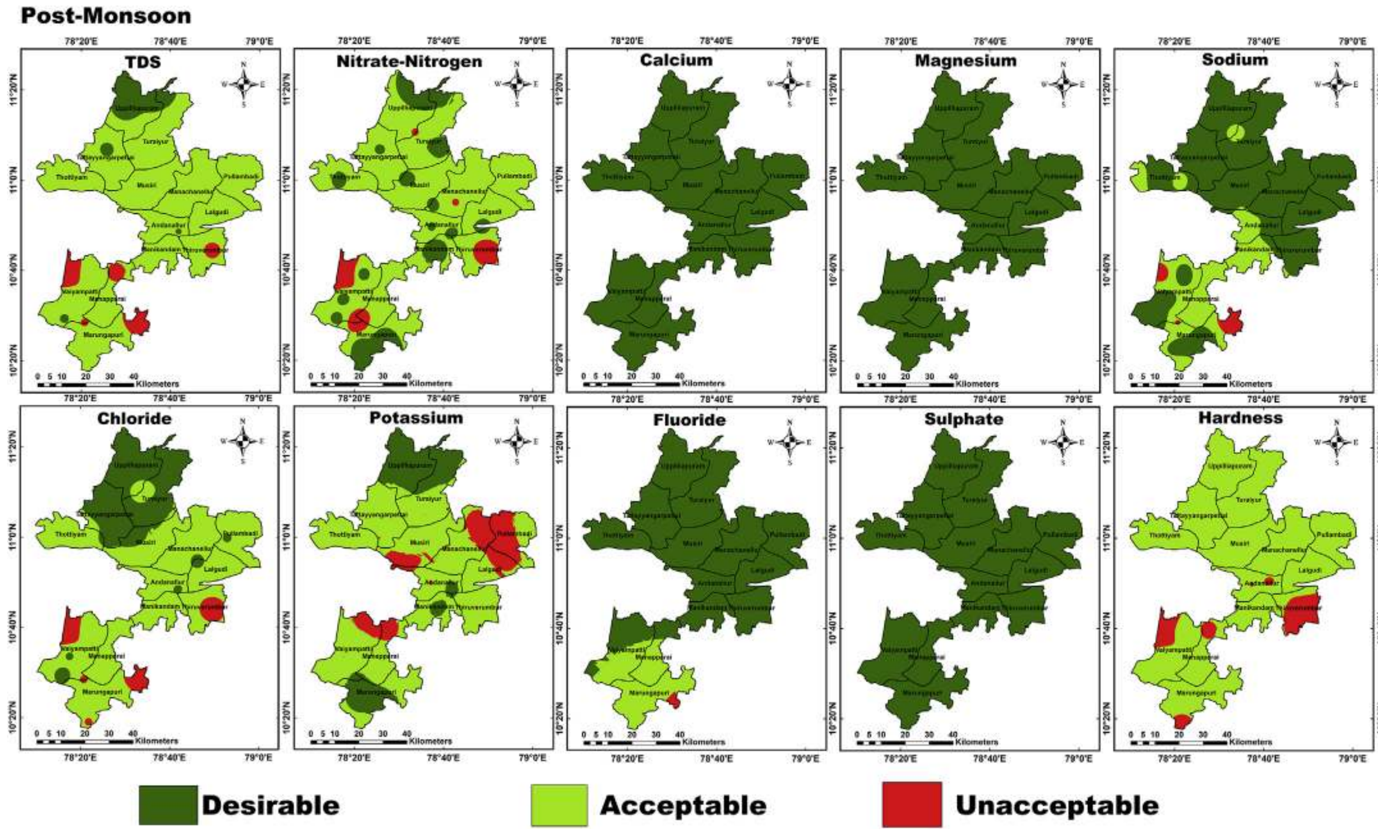

Fig. 6b. Concentration maps of the groundwater quality parameters during ***post-monsoon*** season.

concentrations of all the critical/concerned groundwater-quality parameters except Potassium. This is mainly due to the fact that Vaiyampatti block lies at the downstream end of the Cauvery River and a significant amount of surface pollutants from the upstream portion are deposited in this block, which gradually percolate into the unconfined aquifer. The concentration of TDS in groundwater ranges from 157 to 3202 mg/L (Table 1) and exceeds its permissible limit for drinking in 5% of the study area. Further, the NO_3^-−N concentration exceeds its permissible limit in 8% of the study area, which is mainly due to anthropogenic sources like chemical fertilizer application in the agricultural fields. Other non-agricultural sources of Nitrate include seepage from septic tanks and cesspools, heap of cattle dung, etc. Less than 2% of the area has unacceptable concentration of Sodium in groundwater in Vaiyampatti block. The Chloride concentration in groundwater is relatively higher in parts of Lalgudi, Thiruverumbur, Thottiyam, and Vaiyampatti blocks. The major source of Chloride is the effluent molasses from paper and pulp industries [Fig. 2(b)]. Potassium concentration in the groundwater exceeds the WHO prescribed limit of 12 mg/L in 10% of the study area. The increase in Fluoride concentration is mainly due to the geogenic source, i.e., dissolution of natural minerals like Apatite, Biotite, Cryolite, Fluorite, etc. From the igneous rocks. Fig. 6(a) shows that the total hardness of groundwater is relatively high in the study area which can be attributed to considerable limestone deposits in this region.

3.1.2. *Concentration maps of groundwater-quality parameters for the post-monsoon season*

Although some similar patterns of *pre-monsoon* can be observed in the *post-monsoon* season, the concentrations of groundwater-quality parameters significantly differ in the *post-monsoon* season [Fig. 6(b)]. The TDS concentration in groundwater during the post-monsoon season ranges from 190 to 3028 mg/L. The area under the 'desirable concentration' region has considerably decreased from 24.6% in the *pre-monsoon* season to 7.37% in the *post-monsoon* season. In case of NO_3^--N concentration in the area, unacceptable groundwater quality region has reduced to 5.7% in the *post-monsoon* season due to the dilution of pollutant in groundwater during monsoon season. Fig. 6(b) reveals that the concentrations of Calcium, Magnesium and Sulphate are within their prescribed limits in both the seasons. Unacceptable concentration of Sodium is found in some parts of Marungapuri block in the *post-monsoon* season in addition to Vaiyampatti block which suffers from high sodium concentration in the *pre-monsoon* season as well. Although only 5% of the study area shows unacceptable Chloride concentration in groundwater during the *post-monsoon* season, the area under desirable groundwater quality region has reduced from 44.41% in the *pre-monsoon* season to 27.6% in the *post-monsoon* season. The spatial distribution of Potassium concentration in groundwater shows that the unacceptable concentration occurs in many blocks viz., Manapparai, Manachanallur, Musiri, Vaiyampatti, Lalgudi and Pullambadi covering 13% of the study area. Furthermore, the concentration of Fluoride in groundwater exceeds its prescribed limit in less than 1% of the study area which is confined to the southernmost part of Marungapuri Block. The total hardness of groundwater ranging between 95 and 880 mg/L (Table 1) in the *pre-monsoon* has increased drastically to 150−1500 mg/L in the *postmonsoon* season. The area under the unacceptable level of hardness increased to 7.73% in the *post-monsoon* season compared to the *pre-monsoon* season.

Generally, the dilution of pollutants occurs during the rainy/monsoon season and hence, groundwater quality is expected to improve in the *post-monsoon* season as compared to the *pre-*

monsoon season. However, the spatial variability of the concentrations of different groundwater-quality parameters in the study area during *pre-monsoon* and *post-monsoon* seasons clearly reveals that the effect of pollutant dilution is very less in the study area. Consequently, unlike common observations in many past studies on groundwater-quality evaluation, the groundwater quality deteriorates in the *post-monsoon* season, thereby indicating that the concentration of groundwater-quality parameters in the study area is significantly increased by the recharge during the rainy/monsoon season.

Table 2
Basic statistics of the developed GQIs and FGQI.

Type of Index	GQI Values for *Pre-monsoon* Season			GQI Values for *Post-monsoon* Season		
	Minimum	Maximum	Mean	Minimum	Maximum	Mean
GQI-10	65.15	89.58	76.33	61.90	88.48	73.05
GQI-7	52.84	86.73	68.26	48.95	85.28	63.92
FGQI	12.18	86.42	59.80	13.81	86.42	55.22

Note: GQI-10 = Groundwater Quality Index using all 10 parameters; GQI-7 = Groundwater Quality Index using 7 'concerned' parameters; FGQI = Fuzzy Groundwater Quality Index using 7 'concerned' parameters.

3.2. Traditional GIS-based GWQI maps

The GQI-10 and GQI-7 maps for the *pre-monsoon* season are shown in [Fig. 7(a)] and [Fig. 7(b)], respectively. The values of GQI-10 vary from 65.15 to 89.58 with a mean value of 76.33 (Table 2). According to the values of indices obtained, the GQI-10 map of the study area was classified into two classes 'medium quality' (GQI-10 = 60–80) and 'high quality' (GQI-10 > 80) for drinking water (Babiker et al., 2007), with the northern portion of the study area belonging to the 'high quality' groundwater [Fig. 7(a)]. The GQI-7 map [Fig. 7(b)] significantly differs from the GQI-10 map, with GQI-7 values always lower than GQI-10 values. The GQI-7 values range from 52.84 to 86.73, with a mean value of 68.26 (Table 2). The southwest (Vaiyampatti block), eastern (Lalgudi block) and southeast (Thiruverumbur block) parts of the study area have 'lower quality' (GQI-7 <60) groundwater for drinking. However, the

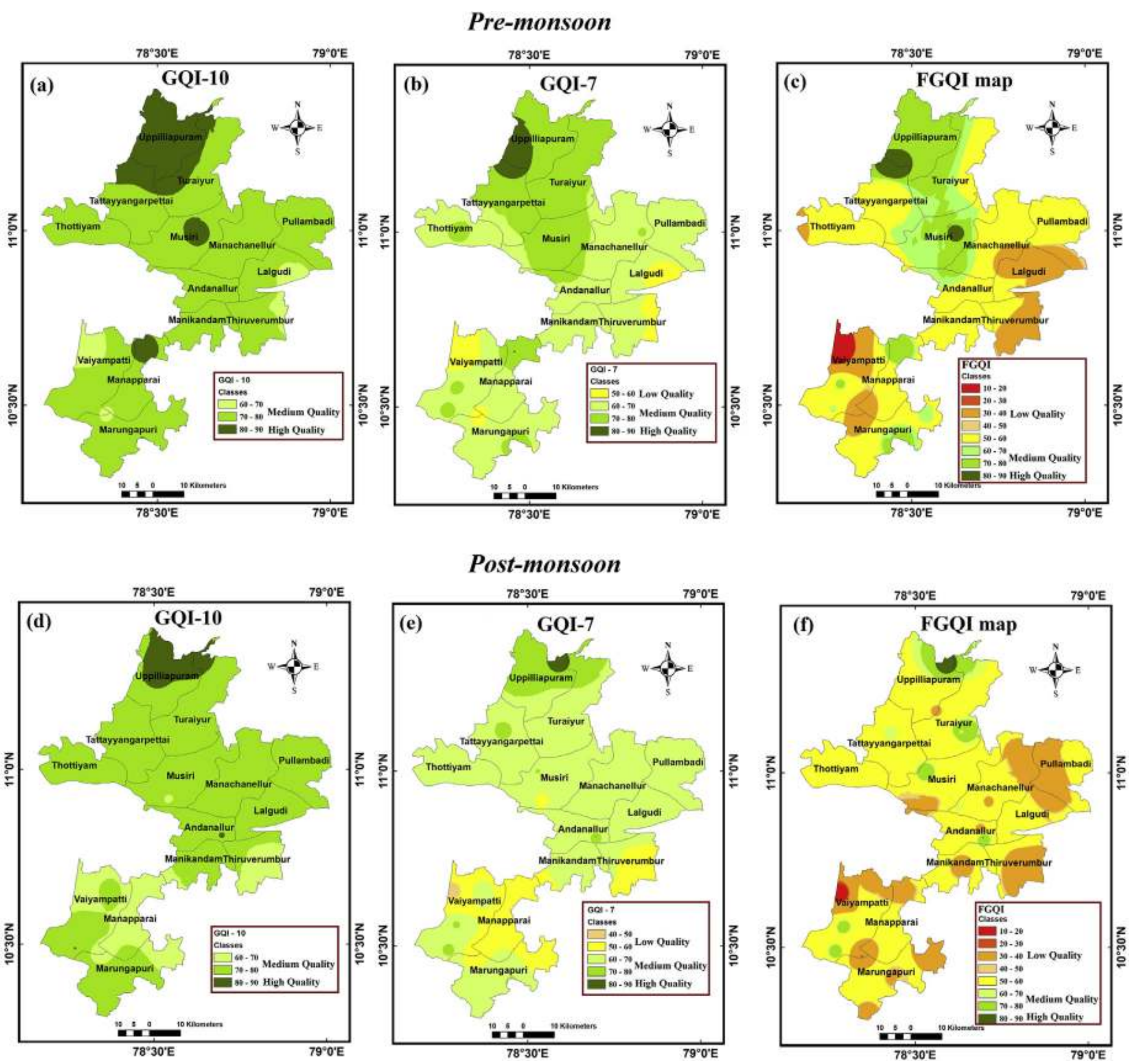

Fig. 7. (a–f). Groundwater-Quality Index (GQI) maps for the ***pre-monsoon*** season: (a) based on all 10 parameters (GQI-10); (b) based on 7 'concerned' parameters (GQI-7); (c) Fuzzy GIS-based Groundwater Quality Index (FGQI); and for the ***post-monsoon*** season: (d) based on all 10 parameters (GQI-10); (e) based on 7 'concerned' parameters (GQI-7); (f) Fuzzy GIS-based Groundwater Quality Index (FGQI).

northwest part of the study area (western portion of Uppliyapuram block) has 'high quality' groundwater, while the central portion of the study area has 'medium quality' groundwater for the drinking purpose [Fig. 7(b)].

Moreover, GQI-10 and GQI-7 maps of the study area for the *post-monsoon* season are shown in Fig. 7(d and e). The GQI-10 values range from 61.90 to 88.48 with a mean of 73.05 (Table 2). The classification of GQI-10 map for the *post-monsoon* season is similar to that of the *pre-monsoon* season and only the northern part of the study area has 'high quality' groundwater [Fig. 7(d)]. The GQI-7 map [Fig. 7(e)] for the *post-monsoon* season differs largely compared to the GQI-10 map, with the GQI-7 values varying from 48.95 to 85.28 (mean = 63.92) (Table 2). It evident that the southwest (Vaiyampatti block), southern (Manapparai block) and southern-east (Thiruverumbur block) parts of the study area have 'low quality' groundwater [Fig. 7(e)], but the northern part (Uppliyapuram block) has 'high quality' groundwater.

Based on the above discussion, it is emphasized that the GQI-7 values are always lower than GQI-10 values and the GQI-7 map is more practical and reliable than the GQI-10 map. The GQI-7 is able to successfully map the polluted blocks (Vaiyampatti, Lalgudi, Thiruverumbur, and Manapparai blocks) under the 'low quality' category, while the GQI-10 maps them under 'medium quality' category. Further, as GQI-10 uses more number of water-quality parameters compared to GQI-7, it introduces more uncertainty and high computation demand.

3.3. Fuzzy-GIS-based GQI (FGQI) maps

Fuzzy Logic was applied to the GIS-based concentration maps for the 'concerned parameters' to generate Fuzzy-GIS-based Groundwater Quality Index (FGQI) maps of the study area for *pre-monsoon* and *post-monsoon* seasons [Fig. 7(c and f)]. The FGQI was developed bearing in mind the inherent uncertainty associated with environmental systems.

The FGQI values for the *pre-monsoon* season range from 12.18 to 86.42 with a mean of 59.80 (Table 2) based on which FGQI map was prepared as shown in Fig. 7(c). It is apparent from this figure that except the northern (Uppliyapuram block) and central (Thuraiyur and Musiri blocks) parts of the study area, other parts of the area has 'low quality' (FGQI <60) groundwater for drinking. Extremely low values of FGQI (<20) can be seen in the southwest part of the study area [Fig. 7(c)]. On the other hand, the FGQI values for the *post-monsoon* season vary from 13.81 to 86.42 with a mean of 55.22 (Table 2). Based on the FGQI, most of the regions of the study area fall under the category of 'low quality' (FGQI<60) groundwater in the *post-monsoon* season, whereas the northern part of the study area falls under the category of 'high quality' (FGQI >80) groundwater [Fig. 7(f)]. A few locations (scattered patches) in the central and southern parts of the study area have 'medium quality' (60 < FGQI < 80) groundwater for drinking.

3.4. Comparison of traditional and fuzzy GIS-based GWQI models and validation

A comparative evaluation of the GQI-10, GQI-7 and FGQI models was performed to examine the relative performance of these models in predicting actual groundwater quality status during *pre-monsoon* and *post-monsoon* seasons in the study area as illustrated in Fig. 8(a and b). It is clear from these figures that the GQI-10 values are always higher than GQI-7 values. This is expected as the safe parameters increase the values of GQI. Further, for most of the observation wells, the FGQI values are much lower than GQI-10 and GQI-7 values. However, for the observation wells having concentrations of all the groundwater-quality parameters much lower than their permissible limits, the FGQI values are almost equal to or more than the values of GQI-10 and GQI-7 as evident in case of observation well numbers 6, 10, 15 and 20 in the *pre-monsoon* season [Fig. 8(a)] as well as observation well numbers 3, 5, 19, 31 and 33 in the *post-monsoon* season [Fig. 8(b)].

Moreover, the validation of traditional and Fuzzy GIS-based GWQI models for *pre-monsoon* and *post-monsoon* seasons is illustrated in Fig. 8(c and d). During the *pre-monsoon* season, it is obvious from Fig. 8(c) that the FGQI model predicts 'low quality' (GWQI<60) groundwater for drinking when the number of critical parameters is more than one, whereas the GQI-10 and GQI-7 models predict 'medium quality' (60<GWQI<80) groundwater for the same observation wells. Similar trend can be seen for the *post-monsoon* season as well [Fig. 8(d)]. These findings along with the findings of qualitative validation using land use/land cover and industry location maps clearly highlight the superiority of FGQI models and emphasize the need for using Fuzzy Logic in developing GIS-based groundwater-quality models for assessing groundwater quality at larger scales. The FGQI model evidently predicts groundwater drinking quality status as per the practical logic and correctly indicate the safe groundwater as 'high quality' (i.e., it can be directly consumed for drinking) and unsafe groundwater as 'low quality' (i.e., no direct consumption or domestic use).

One of the important findings while comparing the developed groundwater quality indices is that the *post-monsoon* groundwater quality is lower than the *pre-monsoon* groundwater quality, thereby indicating that the dilution effect in the monsoon season is not prevalent in the study area. The groundwater quality of the northern part of the study area which is occupied by mostly hilly forest is almost the same during *pre-monsoon* and *post-monsoon* seasons. In the remaining parts of the study area, the groundwater quality deteriorates in the monsoon/post-monsoon season, which is attributed to the improper management of effluents from industrial, mining and waste dumping areas as well as leaching of chemical fertilizers and pesticides in agricultural fields during monsoon seasons. There is a large decrease in FGQI and GQI values in the southwest part of the study area in the *post-monsoon* season [Fig. 7(d-f)]. This may be due to chemical, iron and steel industries located in this part of the study area [Fig. 2(b)]. Moreover, the central and southern parts of the study area seem to have lower FGQI and GQI values in the *post-monsoon* season because of nitrate and potassium pollution in the monsoon season due to agricultural activities. This calls for proper management of solid and liquid wastes, and efficient application of fertilizers and pesticides in the study area.

4. Conclusions

In this paper, a novel hybrid framework considering Fuzzy Logic and GIS-based Groundwater Quality Index (GQI) is proposed to evaluate and analyze groundwater quality at larger scales. The proposed hybrid approach is named "Fuzzy-GIS-based Groundwater Quality Index" (henceforth denoted as "FGQI"), and it is demonstrated through a case study in an unconfined aquifer system of Southern India using salient groundwater-quality parameters measured at multiple sites during *pre-monsoon* and *post-monsoon* seasons. Fuzzy Logic was applied to deal with nonlinearity and uncertainty inherent in natural/environmental systems. Traditional GIS-based Groundwater Quality Index (GQI) models and hybrid GIS-based GQI models using Fuzzy Logic were developed for both the seasons following the drinking water guidelines of World Health Organization (WHO, 2004) and Bureau of Indian Standards (BIS, 2012). For the first time, the developed GQI models were rigorously evaluated in this study through intercomparison and validation.

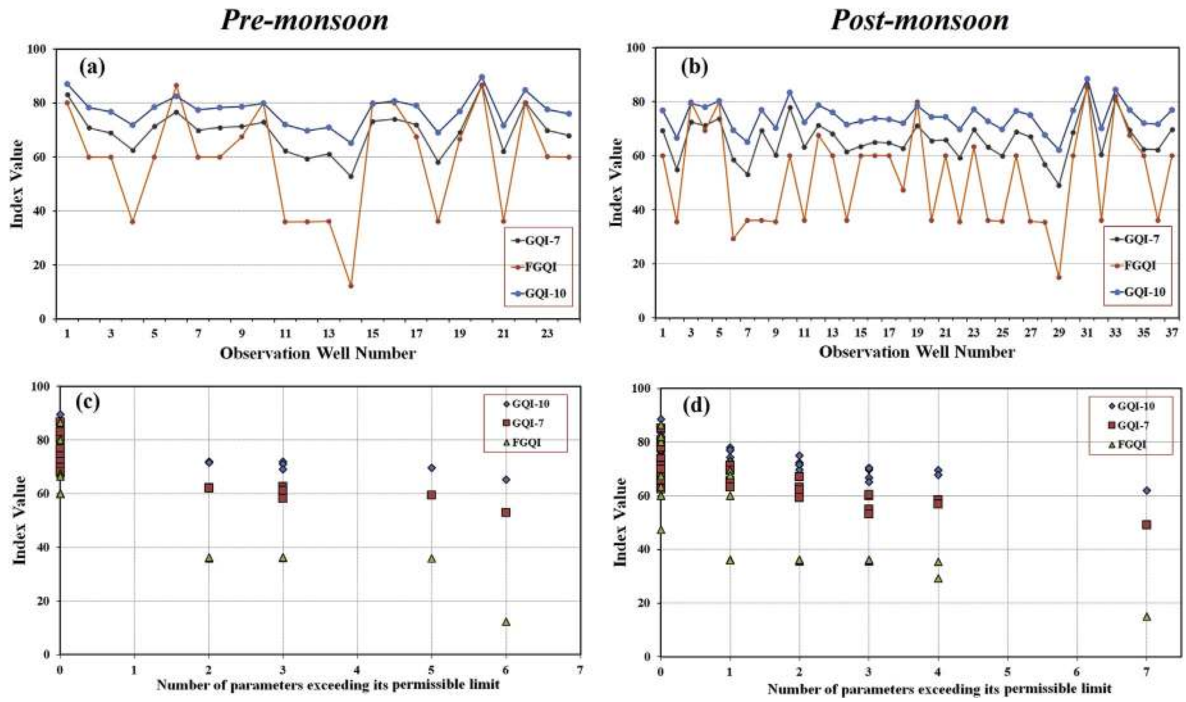

Fig. 8. (a–d). Comparison (**top**) and validation (**bottom**) of traditional GQIs and FGQI for the *pre-monsoon* season (**left**) and the *post-monsoon* season (**right**).

Initially, a geostatistical analysis was carried out to prepare concentration maps of different groundwater-quality parameters, and analyze their spatial and seasonal variability. Basic statistical analysis revealed that Ca^{2+}, Mg^{2+} and SO_4^{2-} are safe parameters (concentration values well within the WHO desirable limits for drinking water) during both *pre-monsoon* and *post-monsoon* seasons. However, the remaining seven parameters (TDS, NO_3^--N, Na^+, Cl^-, K^+, F^- and Hardness) are critical with concentration values greater than their permissible limits for drinking during both the seasons. Hence, traditional GIS-based GQI models were developed for *pre-monsoon* and *post-monsoon* seasons using all the ten groundwater-quality parameters (denoted as 'GQI-10') as well as using only seven 'concerned/critical parameters' (denoted as 'GQI-7'). In addition, FGQI models for both the seasons were developed using seven 'concerned/critical parameters' Experts' knowledge along with the WHO and BIS guidelines for drinking water were employed to design fuzzy inference rules. A comparative evaluation of the traditional GQI models and FGQI models indicated that the FGQI models predict groundwater-quality status more realistically than the traditional GQI models because the former incorporate human thinking and handle uncertainty involved in the natural system analysis efficiently. It also emphasizes that only critical/prominent water-quality parameters should be used for developing GIS-based GQI models in order to ensure reliable and useful results. Thus, the proposed fuzzy-based decision-making approach along with GIS-based GQI (FGQI) is more reliable for assessing groundwater quality at larger scales. GQI modeling results suggest that the groundwater of eastern and southern parts of the study area is unsuitable for drinking/domestic usage during both *pre-monsoon* and *post-monsoon* seasons. Moreover, the *post-monsoon* water quality status in the study area is lower than that of the *pre-monsoon* season, which indicates increased influx of pollutants from industrial, mining, agricultural and waste dumping areas during monsoon seasons.

The hybrid framework proposed in this study can easily be replicated in other regions of the world for evaluating the suitability of groundwater or surface water quality for domestic and/or agricultural purposes. Particularly, it is strongly recommended for the assessment and monitoring of groundwater quality at watershed/basin scales in other agro-climatic regions and hydrogeologic settings of India and the world. Based on the findings of this study, it is recommended that concerned water planners and decision-makers must formulate improved and comprehensive strategies for the efficient management of effluents from different industries, mining areas, waste disposal sites and agricultural fields so as to avoid groundwater contamination by anthropogenic sources in the region. Prevention of aquifer/surface water contamination is indispensable for protecting crucial groundwater and surface water resources so as to ensure sustainable utilization and management of available water resources. It is worth mentioning that the protection of groundwater resources and prevention or reduction of harmful hazards is more feasible and less expensive options than the remediation of polluted groundwater resources due to physical inaccessibility, complex processes and huge expenses. Therefore, future studies should focus on the efficient assessment of groundwater-contamination risk at basin/regional scales for the planning, decision-making, and policy perspectives of groundwater protection and recharge programs.

Authors contribution

Madan Kumar Jha: Conceptualization, Methodology, Resources, Manuscript Preparation – Review and Technical editing, Supervision, Research fund acquisition, Project administration. **Ankit Shekhar:** Conceptualization, Methodology, Software, Formal analysis, Resources, Manuscript Preparation – Original Draft, Writing - Review & Editing, Visualization. **M. Annie Jenifer:** Data collection, Data pre-processing, Investigation, Manuscript Preparation – Review of literature and preliminary editing.

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

Supplementary data to this article can be found online at https://doi.org/10.1016/j.watres.2020.115867.

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