Groundwater contamination analysis using Fuzzy Water Quality index (FWQI): Yazd province, Iran

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Abstract

Fuzzy Water Quality Index (FWQI) was applied in order to assess the degree of drinking water resources in Yazd province, Iran. This study has also offered the creation of a new fuzzy water quality index (FWQI) to evaluate this tool's applicability. 12 chemical parameters including toxic and non-toxic heavy metals measured in 71 groundwater samples collected from drinking water resources in rural areas were used. In FWQI, input data are categorized into three linguistic terms ("Desirable" or "Low", "Acceptable" or "Medium" and "Not-acceptable" or "High") based on water quality standards for drinking water, Whereas the output data are categorized into five classes ("Poor", "Fair", "Medium", "Good" and "Excellent") based on water quality index (WQI). The results show that 8 groundwater samples were classified in the "Excellent" class with a certainty level of 5.33-76.67%, 41 samples in the "Good" group with a certainty level of 8.5-96.5%, 8 samples were in the "Medium" category with a certainty level of 14-93.5%, 1 sample in the "Fair" level with a certainty level of 36.5%, and 13 samples were classified in the "Poor" class with a certainty level of 54.8-81.5% for potable purposes. The proposed Index can be a useful tool to be used in decision-making and environmental.

Keywords: *Fuzzy, Water quality index, Yazd, Drinking water, Groundwater*

Introduction

The rate of increase in urban, agricultural, and industrial activities has raised scientists' concerns about environmental issues and in particular about water pollution (Gharibi *et al.,* 2012). Wastewater from these activities may contain various heavy metals including Zn, Cu, Pb, Cd, Ni, As, Al, depending upon the type of activities it is associated with (Singh *et al.,* 2010). These elements accumulating in groundwater induce a potential contamination of food chain and endanger the ecosystem safety and human health (Xin *et al.,* 2008). Thus, the investigation and management of water resources quality is important.

A comparative assessment of numerous physical and chemical parameters and soluble constituent, including toxic and non-toxic heavy metals, is necessary in determining the degree of pollution in environmental systems. However, interpretation of data sets and suggestion about final water quality comprising analyses of several metals is complicated. One approach of simplifying multivariate data is to generate and use a single value, which may subsequently be used for comparative purposes (Miyai *et al.,* 1985; Nimic & Moore, 1991). In national and international scenarios, approaches which make numerous water quality variables integrated, in a specific index, are increasingly desired. Consequently, several authors have developed a number of water quality indices (WQIs), employing various mathematical and statistical methods, over the past four decades, some of which have been implemented by water management and environmental agencies and are aiding decision-makers in water resource management, public health, and ecosystem protection. Comparing determined limits of different indicators of water quality, WQI assesses water quality by adding the multiplication of the respective weight factor by an appropriated quality-value for each parameter. However, WQI and other similar indices such as Subjective Water Quality Index (WQI_{sub}), WQI_{min}, and Canadian Water Quality Index (CWQI), have a series of weaknesses. For instance they assign the value of water quality using a limited number of parameters. Moreover, some pollutants such as toxic and nontoxic heavy metals, hydrocarbons and pesticides are not considered in most of these indices. On the other hand, despite the fact that their formulations are rather simple, and the number of variables involved are too limited, some parameters can influence the final water quality score noticeably without valid justification. But, the most critical deficiency of these indices is the lack of dealing with uncertainty and subjectivity present in this complex environmental problem (Ocampo *et al.,* 2006).

During the last two decades, fuzzy logic has undergone an explosive development in application in almost all the areas of research and has been easily accepted by both researchers and decision makers due to its ability to handle the uncertainties in Geosciences, water resources and particularly in water quality management. Consequently, great attention has been paid to develop the environmental indices using fuzzy logic (Gharibi *et al.,* 2012). Sadiq and Rodriguezz (2004), using fuzzy synthetic evaluation, have proposed a new indexing method of water quality. This method has been applied by Ocampo-Duque et al. (2006) and Lermontov *et al.,* (2009) to identify river water quality. Moreover, Liou *et al.,* (2003) applied two-stage fuzzy set theory to river quality evaluation. Gharibi et al. (2012) used it to assess water quality in Mamloo dam for drinking purposes. Dahiya *et al.,* (2007) and Venkat Kumar *et al.,* (2009) discussed the identification of groundwater quality using the fuzzy synthetic evaluation.

The current study aims to develop a Fuzzy Water Quality Index (FWQI) to groundwater quality assessment for drinking purposes including toxic and non-toxic heavy metals. A case study on the groundwater quality at Yazd province, Iran, was also conducted to check the performance of the proposed index.

Materials and methods

Fuzzy Inference

Zadeh (1965) founded fuzzy logic which is very useful in modeling complex and imprecise systems. Fuzzy inference is the result of the combination of fuzzy logic with expert systems (Lermontov *et al.,* 2009). Fuzzy logic provides basic for implementing expert supervised rules which is the main goal in the field of knowledge-based systems. By this way, the human expertise plays the most significant role in the engineering process.

Fuzzy inference is defined as the process of mapping a set of input data sets into a set of output data, using an approach based on fuzzy logic and falls under the category of black box models (Katambara & Ndiritu, 2009). A FIS tries to formalize the reasoning process of human language by means of fuzzy logic (that is, by building fuzzy IF-THEN rules). The fuzzy inference process usually involves four major parts:

Fuzzification and membership functions: This process comprises the definition of inputs, outputs, as well as their respective membership functions that transform the crisp value of a variable into a grade of membership for linguistic term of a fuzzy set.

Inference rules: In knowledge-based systems, the relation between input and output linguistic variables is expressed in terms of a set of fuzzy if–then rules (conditional propositional forms). In fuzzy inference system, a typical rule is represented as IF-(antecedent part)-THEN-(consequence part).

Inference engine: The inference system or the decision-making unit performs the inference operations on the rules. It handles the way in which the rules are combined (Mahapatra *et al.,* 2011). In other words, Using If-Then type, fuzzy rules convert the fuzzy input to the fuzzy output.

Defuzzification: this process consists in transforming the fuzzy output into a crisp value which can be used in no-fuzzy contexts (Silvert, 2000).

These concepts have been widely discussed in Ross (2004), Fuller (1995), Wang *et al.,* (2009) and Wang (1997).

Study area and data

Yazd province, with an area of 131575 Km^2 located in the center of Iran, was selected for this study (between 29º 52′_ to 33º 27′_ North latitude and 52º 55′_ to 56º 37′_ East longitude). The average annual rainfall of the study area has been reported as 108 mm. In this area, exploitation of aquifers is done through wells, springs and kanats. Excessive withdrawal of groundwater has decreased the water level and water quality so that some sources of potable water are out of the admissible limit of existing standards (i.e. WHO). So, handling water quality seems very imperative.

In this study, 71 groundwater samples were selected out of potable resources of 71 rural areas. The samples were collected from wells, springs and kanats. The study area and sample positions have been shown in Fig 1. Implementation and investigation of chemical and physical analysis on the samples showed that the proportion of some parameters influencing potability such as Coliform, Manganese (Mn^{2+}), ferrous ion (Fe^{2+}) was much less expected than the current standards. Therefore, 12 parameters, including: pH, Total hardness (TH), Total dissolved solid (TDS), Total alkalinity (TA), Arsenic (Cr), Lead (Pb), Cadmium (Cd), Nickel (Ni), Zinc (Zn), Copper (Cu), Aluminum (Al) and Nitrate (NO_3^-) were used to assess the groundwater quality for potable purposes using fuzzy water quality index.

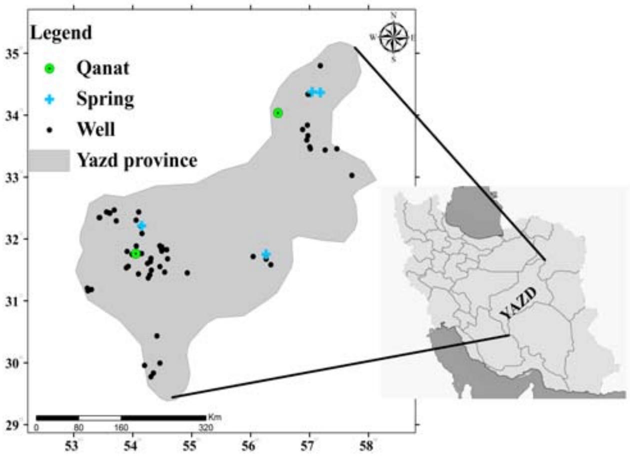

Figure1: Study area and sample positions

Development of the water quality index based on fuzzy method

To this end, 12 qualitative parameters were classified into three groups. TDS, TA, TH and pH Parameters were categorized in the first group, As, Pb, Cd and Ni in the second group and Zn, Cu, Al and NO_3^- in the third group.

Heavy metals are important factors for determining water quality with regard to potability. The contamination of these metals in water has received much concern due to their toxicity, abundance and persistence in the environment, and subsequent accumulation in aquatic habitats. These elements accumulating in microorganisms, vegetables and animals, and thus, enter into the human food chain and endanger ecosystem safety and human health (Varol & Sen, 2012). The importance of the selected parameters is presented in Table 1.

Table 1: Summary of main reason(s) for used parameters in the FWQI

Parameters	Reason	Reference(s)
As	Skin lesions, Blackfoot disease, Peripheral neuropathy, encephalopathy, Hepatomegaly, cirrhosis, altered heme metabolism, anaemia, skin cancer	Hughes, 2002; Choong *et al.*, 2007
Pb	causes a number of diseases ranging from anemia to nervous system degeneration, renal effects and hearing impairments	Lasheen *et al.*, 2008; Zietz *et al.*, 2001
Cd	Kidney damage, lung insufficiency, cancer, it changes the constitution of bone, liver and blood	Vasudevan and Lakshmi, 2011
Ni	genetic toxicity and carcinogenicity, the disturbance of respiratory system and asthma, birth defects, vomiting and damage to deoxyribonucleic acid (DNA) at high concentrations	Ryu *et al.*, 2012; Ntengwe and Maseka, 2006
Zn	fainting, nausea and stomach disorder	Ntengwe and Maseka, 2006
Cu	Idiopathic Copper Toxicosis (ICT), rare disorders of copper metabolism with established and putative genetic causes respectively. acute and chronic health effects including gastroin-testinal diseases and liver damage.	Sadhra *et al.*, 2007; Vargas *et al.*, 2010; Lagos *et al.*, 1999
Al	Neurotoxic agent in human with renal impairments,	Cech and Montera, 2000
No3	severe intoxication and methemoglobinemia (blue baby syndrome) or even death among infants	Zhaoa *et al.*, 2011, Erkekoglu and Baydar, 2010
Physical and Chemical Factors (such as TDS, TA, TH, pH)	Key parameters of water quality	-

Fuzzy membership functions constructed for all the selected parameters are either triangular or trapezoidal (are shown in Fig 2) on the basis of expert perception and prescribed limits by Word Health Organization (WHO, 2006) and Institute of Standards and Industrial Research of Iran (ISIRI, 1998) (Table 2), to developed fuzzy water quality index.

In this study, as Table 3 shows, the fuzzy sets for heavy metals are defined by linguistic terms “Low” (L), “Medium” (M) and “High” (H) and for others are defined by “Desirable” (D), “Acceptable” (A) and “Not-acceptable” (NA). The triangular and trapezoidal fuzzy membership functions are specified as the equations of (1) and (2).

Fig 3 shows the flow chart of the process, where the individual quality variables are processed by inference systems, yielding several groups normalized between 0 and 100. The groups are then processed for a second time, using a new inference, and the end result is the fuzzy water quality index (FWQI). The groups and FWQI classes were determined on the basis of expert view by the authors and prescribed limits for WQI and the CETEB WQI quality standards (Table 4). Fuzzy membership functions of the groups and FWQI as “Excellent” (E), “Good” (G), “Medium” (M), “Fair” (F) and “Poor” (P) are given in Fig 4. This figure is the consequent part of the current study.

For construction of the fuzzy model, a total number of 422 rules were developed on the basis of available datasets and experts’ perception. In this model, the number of rules depends on the number of input parameters and membership functions.

Table 2: The limits prescribed by Word Health Organization (WHO, 2006) and Institute of Standards and Industrial Research of Iran (ISIRI, 1998) for the studied parameters.

parameter	**WHO (2006)**		**IRISI**	
	Desirable	**Acceptable**	**Desirable**	**Acceptable**
PH	7-8.5	6.5-9.2	7-8.5	6.5-9.2
TA	200	600	-	-
TH	300	600	150	500
TDS	500	1500	500	1500
As	-	0.01		0.05
Pb	-	0.01		0.05
Cd	-	0.003		0.01
Ni	-	0.02		0.07
Zn	-	3	3	15
Cu	-	2	1	2
Al	-	0.2	0.1	0.2
NO_3^-	20	Not>100	20	45

Units are mg/L except pH.

$$triangular:\ f(x;a,b,c)=\begin{cases}0, & x<a\\ x-a/b-a, & a\le x\le b\\ c-x/c-b, & b\le x\le c\\ 0, & c<x\end{cases} \quad (1)$$

$$trapezoidal:\ f(x;a,b,c,d)=\begin{cases}0, & x\le a\\ x-a/b-a & a\le x\le b\\ 1, & b\le x\le c\\ d-x/d-c, & c\le x\le d\\ 0, & d\le x\end{cases} \quad (2)$$

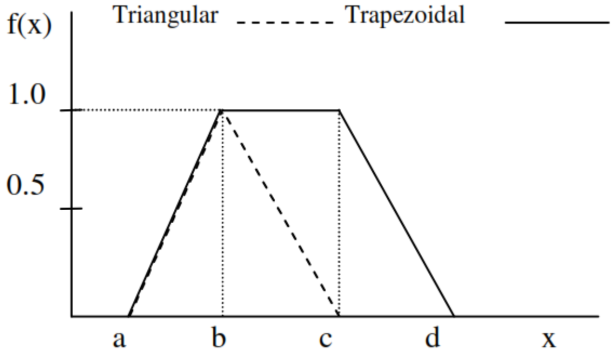

Figure 2: Triangular and trapezoidal membership functions

Table 3: parameter for membership function used in the fuzzy inference system

Group	**Indicator**	**Units**	**"Low"**			**"Medium"**				**"High"**			**Range**
			a	**b**	**c**	**a**	**b**	**c**	**d**	**a**	**b**	**c=d**	
Toxic chemicals	As	µg/L	0	0	3	0	3	9	11	9	11	55	0-55
	Pb	µg/L	0	0	3	0	3	9	11	9	11	40	0-40
	Cd	µg/L	0	0	0.6	0	0.6	3	4	3	4	6	0-6
	Ni	µg/L	0	0	10	0	10	20	25	20	25	30	0-10
Non- Toxic Chemicals	Zn	µg/L	0	500	600	500	600	2900	3100	2900	3100	3200	0-1559
	Cu	µg/L	0	850	1150	850	1150	1800	2100	1800	2100	2200	0-210
	Al	µg/L	0	80	120	80	120	190	220	190	220	450	0-450
	NO_3	µg/L	0	0	20	0	20	40	55	40	55	137	1.3-136.48

Group	**Indicator**	**Units**	**"Desirable"**				**"Acceptable"**				**"Not-acceptable"**			**Range**
			a	**b**	**c**	**d**	**a**	**b**	**c**	**d**	**a**	**b**	**c=d**	
Physical and Chemical Factors	TDS	mg/L	0	0	480	600	400	600	1450	1700	1300	1800	2989	184.96-2988.8
	TA	mg/L as $CaCO_3$	0	0	180	220	180	220	580	660	580	660	700	90-630
	TH	mg/L as $CaCO_3$	0	0	180	220	180	220	570	630	570	630	1720	100-1720
	pH	-	6.8	7.2	8.3	8.7	6.2 8.2	6.5 8.5	6.9 8.9	7.2 9.3	9 **a=b** 5	9.6 **c** 6.2	10 **d** 6.7	5.84-8.29

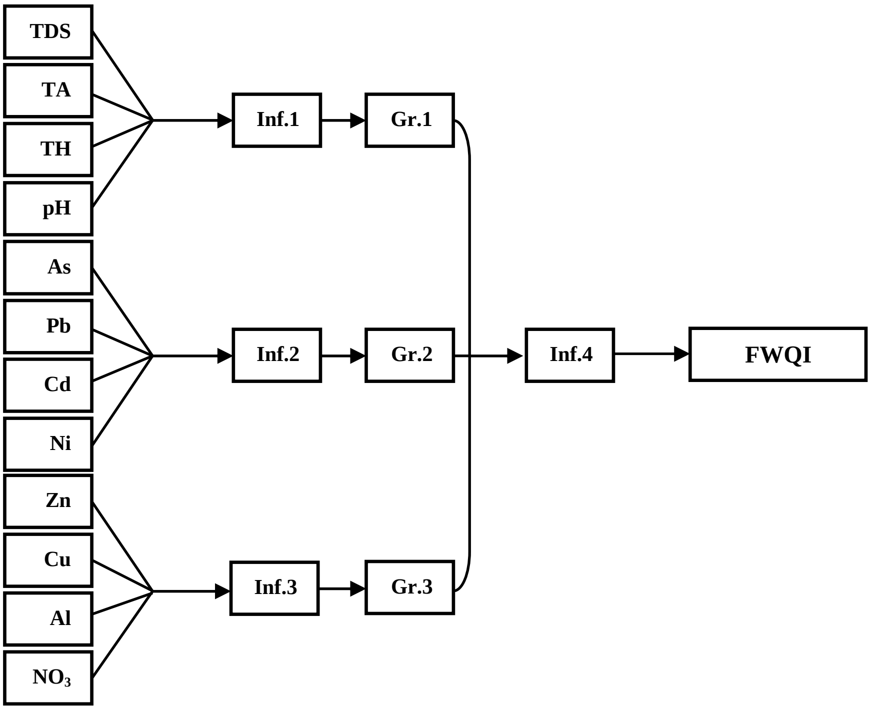

Figure 3: Schematic flow diagram of the FWQI

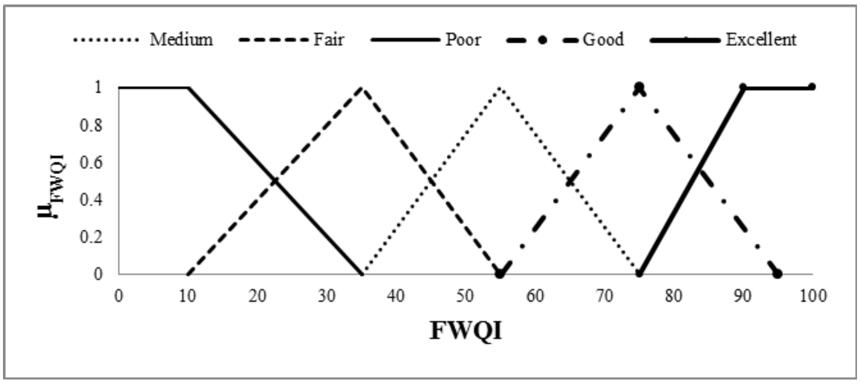

Figure 4: Graph of fuzzy set function

Table 4: Input and output fuzzy set for inference FWQI

Gr. 1, 2, 3 and FWQI 0-100								
	a	b	C	D	WQI Classes		CETESB WQI Classes	
Excellent	75	90	100	100	Excellent	90<WQI≤100	Excellent	79<WQI≤100
Good	55	75	90		Good	70<WQI≤90	Good	51<WQI≤79
Medium	35	55	75		Medium	50<WQI≤70	Fair	36<WQI≤51
Fair	10	35	55		Fair	25<WQI≤50	Bad	19<WQI≤36
Poor	0	0	10	35	Poor	0≤WQI≤25	Poor	0≤WQI≤19

If we take the number of each parameter membership function as μ(x) and the number of input parameters as n, then we can determine the number of rules R as (Firat *et al.,* 2009; Sen & Altunkaynak, 2009):

$$R(Rule) = \mu(x_1)\mu(x_2)\ldots\mu(x_n) \qquad (3)$$

Therefore, since the third group consists of 4 input parameters and each parameter consists of 3 membership functions, the implemented rules for this group equal 81 (3×3×3×3). In the same way, the implemented rules for each of the first and second groups equal 135 (5×3×3×3) and 81 (3×3×3×3), respectively. The relation between two of the selected parameters (e.g. TDS and TA) and their effect on the water quality score is shown in Fig 5. Some examples of the rules generated are given below:

If TDS is A and TA is D and TH is A and pH is A

then Gr1 is M
If As is L and Pb is L and Cd is L and Ni is L then Gr2 is E
If Zn is M and Cu is M and Al is M and NO_3 is L then Gr3 is F
If TDS is D and TA is A and TH is A and pH is D then Gr1 is G
If As is M and Pb is L and Cd is H and Ni is L then Gr2 is P
If Zn is L and Cu is H and Al is L and NO_3 is L then Gr3 is F
If Gr1 is E and Gr2 is P and Gr3 is E then FWQI is P
If Gr1 is M and Gr2 is E and Gr3 is E then FWQI is G

The proposed FWQI based on Mamdani implication of Max–Min operator was applied. In max-min operator, the minimum value from each rule is taken and stored in a group using fuzzy min operator and then by choosing the maximum value from that group gives the belongingness of that water sample quality to the specific category (Dahiya et al., 2007). The results of the rules were combined and defuzzified via center of gravity method as following:

$$Z_{COA} = \int_z \mu_A(z) z dz \Big/ \int_z \mu_A(z) dz \qquad (4)$$

Where Z_{COA} is the crisp value for the ''z'' output and $\mu_A(z)$ is the aggregated output membership function.

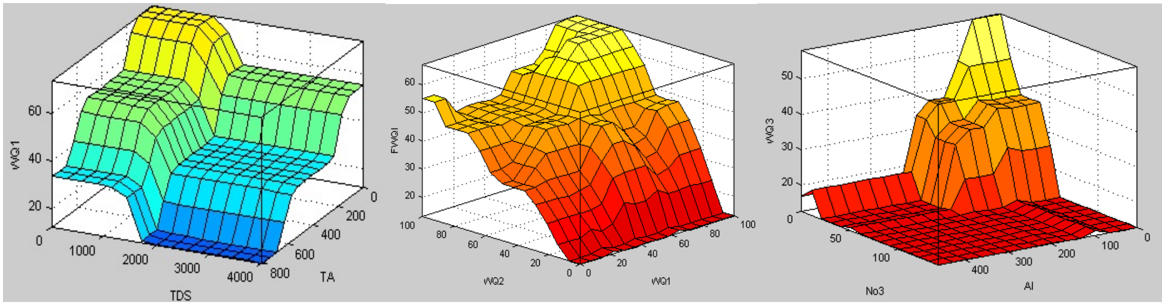

Figure 5: A surface graph representing the interaction between two of the parameters and water quality score.

Results and discussion

On the basis of FWQI, 71 groundwater samples were assessed. Table 5 presents the obtained data. The importance of this method is highlighted in the samples whose parameters values are placed in the definite limit borders. Taking into account the definite limit borders, uncertainties play a pivotal role in the decision making procedure and sometimes result into making wrong decisions. The comparison of FWQI and deterministic decision making is presented in table 5. On this basis, chemical quality of water samples No. 67, having a certainty level of 76.67%, is reported as Excellent; next in the ranking, water sample No. 70, having a certainty level of 75.33%, is reported as Excellent for potable usages. In deterministic method, some parameters may be at desirable level, while some of them may be in acceptable group and the others may be in not-acceptable group. This kind of decision making on the potable water quality is dubious for experts especially when human beings are taken into account.

The distinction in the decision level between the Fuzzy method (FWQI) and deterministic water quality method is clearly showed in samples No. 37 and 38 and samples No. 48 and 53 and also, samples No. 46 and 58. For example, In sample No. 37 with a deterministic method, seven parameters of TA, pH, Cd, Zn, Cu, Al and NO_3 were at a desirable level, four parameters of TH, As, Pb and Ni were in acceptable range and one parameter of TDS was in not-acceptable group and in water sample No. 38 with the same method, eight parameters of TA, pH, Cd, Ni, Zn, Cu, Al and NO_3 were at a desirable level, three parameters of TH, As and Pb Were in acceptable range and one parameter of TDS was in not-acceptable group (Table 5). As it is clear, the number of desirable, acceptable and not-acceptable parameters is almost similar in the two water samples. Even sample No. 38 in terms of quality parameters is better than sample No. 37. While, the decision taken with FWQI method for these two samples is entirely different. As the sample No. 37 with certainty level of 65% is at a "Good" category, the sample No. 38 with certainty level of 79% is at a "Medium" class.

Table 5: Detail on groundwater quality for drinking purposes by using FWQI method and deterministic method (as per WHO standards)

TW (no.)	Decision using FWQI	Decision using deterministic method

	method	Desirable	Acceptable	Not-Acceptable
1	Good (78)	TA,pH,TH,As,Cd,Zn,Cu,Al,NO3	TDS,Pb,Ni	-
2	Poor (65.6)	TA,pH,TH,As,Pb,Ni,Zn,Cu,Al	TDS	Cd
3	Medium (14)	TA,pH,TH,Ni,Zn,Cu,Al	TDS,As,Pb,Cd,NO3	-
4	Good (79.5)	pH,As,Pb,Cd,Ni,Zn,Cu,Al	TDS,TA,TH,NO3	-
5	Poor (73.2)	Pb,pH,Zn,Cu,Al	TA,As,Cd,Ni	TDS,TH,NO3
6	Good (49)	pH,Pb,Ni,Zn,Cu,Al,NO3	TDS,TA,TH,As,Cd	-
7	Medium (93.5)	pH,Cd,Zn,Cu,Al,NO3	TA,As,Pb,Ni	TDS,TH
8	Good (79.5)	TA,pH,As,Cd,Zn,Cu,Al	Pb,Ni,NO3	TDS,TH
9	Good (43)	TA,pH,Cd,Ni,Zn,Cu,Al	As,Pb,NO3	TDS,TH
10	Good (48)	TA,pH,Pb,Zn,Cu,Al,NO3	TH,As,Cd,Ni	TDS
11	Good (11.5)	pH,Pb,Cd,Ni,Zn,Cu,Al	TA,As,NO3	TDS,TH
12	Good (24)	pH,Pb,Ni,Zn,Cu,Al,NO3	TDS,TA,As,Cd	TH
13	Good (77.5)	TA,Pb,Ni,Zn,Cu,Al,NO3	TDS,pH,TH,As,Cd	-
14	Good (8.5)	TA,pH,Pb,Ni,Zn,Cu,Al,NO3	As,Cd	TDS,TH
15	Good (42)	pH,As,Pb,Ni,Zn,Cu,Al,NO3	Cd	TDS,TA,TH
16	Good (79.5)	pH,Pb,Cd,Ni,Zn,Cu,Al	TDS,TA,TH,As,NO3	-
17	Medium (64.5)	TA,Pb,Cd,Ni,Zn,Cu,Al	TDS,pH,As,NO3	TH
18	Poor (64.4)	TDS,TA,pH,TH,Pb,Cd,Ni,Zn,Cu,Al,NO3	-	As
19	Poor (61.6)	TDS,TA,pH,TH,Cd,Ni,Zn,Cu,Al	As,NO3	Pb
20	Poor (54.8)	TDS,TA,pH,TH,Pb,Cd,Zn,Cu,Al,NO3	Ni	As
21	Good (76)	TA,pH,TH,Pb,Cd,Zn,Cu,Al,NO3	TDS,As,Ni	-
22	Poor (57.2)	TDS,TH,Pb,Cd,Zn,Cu,Al,NO3	TA,Ni	pH,As
23	Poor (57.6)	pH,Pb,Cd,Zn,Cu,Al,NO3	TA,Ni	TDS,TH,As
24	Poor (66.4)	pH,Pb,Cd,Zn,Cu,Al	TDS,TA,TH,Ni,NO3	As
25	Good (78.5)	pH,Pb,Cd,Zn,Cu,Al	TDS,TA,TH,As,Ni,NO3	-
26	Good (77)	TA,pH,Pb,Cd,Ni,Cu,Al	TDS,TH,As,Zn,NO3	-
27	Good (78)	TA,pH,TH,Cd,Ni,Zn,Cu,Al	TDS,As,Pb,NO3	-
28	Poor (69.6)	TDS,TA,pH,TH,As,Pb,Ni,Zn,Cu,Al,NO3	-	Cd
29	Good (79.5)	pH,TH,As,Ni,Zn,Cu,Al	TDS,TA,Pb,Cd,NO3	-
30	Good (31)	TA,pH,Pb,Cd,Ni,Zn,Cu,Al	As,NO3	TDS,TH
31	Good (79.5)	pH,As,Pb,Cd,Ni,Zn,Cu,Al	TDS,TA,TH,NO3	-
32	Good (75.5)	pH,TH,As,Cd,Ni,Zn,Cu,Al,NO3	TDS,TA,Pb	-
33	Good (79.5)	pH,Cd,Ni,Zn,Cu,Al	TDS,TA,TH,As,Pb,NO3	-
34	Good (75.5)	TA,pH,Pb,Ni,Zn,Cu,Al	TDS,TH,As,Cd,NO3	-
35	Good (75)	TA,pH,TH,Pb,Cd,Ni,Zn,Cu,Al,NO3	TDS,As	-
36	Good (43)	TA,pH,Pb,Ni,Zn,Cu,Al	TDS,TH,As,Cd,NO3	-
37	Good (65)	TA,pH,Cd,Zn,Cu,Al,NO3	TH,As,Pb,Ni	TDS
38	Medium (79)	TA,pH,Cd,Ni,Zn,Cu,Al,NO3	TH,As,Pb	TDS
39	Good (83)	pH,TH,As,Cd,Zn,Cu,Al,NO3	TDS,TA,Pb,Ni	-
40	Poor (58.8)	TDS,TA,pH,TH,As,Ni,Zn,Cu,Al,NO3	Pb	Cd
41	Poor (63.6)	TDS,TA,pH,TH,Zn,Cu,Al,NO3	As,Pb,Ni	Cd
42	Good (60.5)	TA,pH,As,Cd,Ni,Zn,Cu,Al,NO3	Pb	TDS,TH
43	Good (96.5)	TDS,TA,pH,TH,Cd,Zn,Cu,Al,NO3	As,Pb,Ni	-
44	Good (78)	TA,pH,TH,As,Pb,Cd,Zn,Cu,Al	Ni,NO3	TDS
45	Medium (78)	TDS,pH,TH,Ni,Zn,Cu,NO3	TA,As,Pb,Cd,Al	-
46	Good (51)	TA,pH,TH,As,Pb,Ni,Zn,Cu,NO3	TDS,Cd	Al
47	Poor (58.4)	TDS,TA,pH,TH,As,Cd,Ni,Zn,Cu,NO3	Al	Pb
48	Excellent (20)	TDS,TA,pH,TH,Pb,Cd,Ni,Zn,Cu,Al,NO3	As	-
49	Fair (36.5)	TDS,TA,TH,Pb,Ni,Zn,Cu,NO3	As,Al	pH,Cd
50	Medium (78)	pH,Pb,Cd,Ni,Zn,Cu,NO3	TDS,TA,As	TH,Al
51	Good (41)	TA,pH,TH,Pb,Ni,Zn,Cu,NO3	TDS,As,Cd,Al	-
52	Good (76.5)	TA,pH,TH,Cd,Ni,Zn,Cu,Al,NO3	TDS,As,Pb	-
53	Good (91.5)	TDS,TA,pH,TH,As,Pb,Ni,Zn,Cu,Al,NO3	Cd	-
54	Good (75)	TA,pH,Cd,Ni,Zn,Cu,Al,NO3	TDS,TH,As,Pb	-
55	Poor (81.2)	TA,pH,TH,As,Cd,Ni,Zn,Cu,NO3	TDS	Pb,Al
56	Good (78)	TA,pH,Cd,Ni,Zn,Cu,NO3	TDS,TH,As,Pb,Al	-
57	Good (65)	TA,pH,TH,Pb,Cd,Ni,Zn,Cu,NO3	TDS,As,Al	-
58	Medium (84.5)	TDS,TA,pH,TH,As,Pb,Cd,Ni,Zn,Cu,NO3	-	Al
59	Medium (87.5)	TA,pH,As,Cd,Ni,Zn,Cu,NO3	TDS,TH,Pb	Al
60	Good (77.5)	TA,pH,TH,Pb,Cd,Ni,Zn,Cu,NO3	TDS,As,Al	-
61	Excellent (46.33)	pH,TH,As,Pb,Cd,Ni,Zn,Cu,Al,NO3	TDS,TA	-
62	Good (76.5)	pH,TH,As,Pb,Ni,Zn,Cu,Al,NO3	TA,Cd	TDS
63	Good (89.5)	TA,pH,As,Cd,Ni,Zn,Cu,Al,NO3	TH,Pb	TDS
64	Excellent (24.67)	TA,pH,TH,As,Pb,Cd,Ni,Zn,Cu,Al,NO3	TDS	-
65	Excellent (38)	pH,TH,Pb,Cd,Ni,Zn,Cu,Al,NO3	TDS,TA,As	-
66	Good (92.5)	pH,As,Pb,Cd,Ni,Zn,Cu,Al,NO3	TDS,TA,TH	-
67	Excellent (76.67)	TDS,TA,pH,TH,As,Pb,Cd,Ni,Zn,Cu,Al,NO3	-	-
68	Excellent (27.33)	pH,As,Pb,Cd,Ni,Zn,Cu,Al,NO3	TA,TH	TDS
69	Good (76)	TA,pH,TH,Pb,Cd,Ni,Zn,Cu,Al,NO3	TDS,As	-
70	Excellent (75.33)	TDS,TA,pH,As,Pb,Cd,Ni,Zn,Cu,Al,NO3	TH	-
71	Excellent (5.33)	TA,pH,As,Pb,Cd,Ni,Zn,Cu,Al,NO3	TDS,TH	-

This distinction is related to the parameters with concentrations greater than the desirable and admissible limits in each sample. In sample No. 37 the concentrations of acceptable and not-acceptable parameters are marginally higher than the desirable and admissible limits and stand in the domain of desirable and acceptable and acceptable and not-acceptable fuzzy membership functions, respectively. However in sample No. 38, the concentrations of acceptable and not-acceptable parameters are very high and lie in the range of acceptable and not-acceptable fuzzy membership function and not-acceptable fuzzy membership function respectively, which causes the water sample to be at "Medium" class. Therefore, the fuzzy method plays an important role in the decision making process for evaluating the potability of groundwater in which both prescribed limits of various organizations and expert opinion will be considered.

Conclusion

In this research, applicability of FWQI method for groundwater quality for potable purposes was investigated in comparison with deterministic methods. In deterministic methods, the quality of each parameter on the basis of prescribed limits, in drinking water standards (in this case WHO and ISIRI), was categorized in three forms of "Desirable or Low", "Acceptable or Medium" and "Not-acceptable or High". It is difficult and obscure to make a decision about of groundwater quality using deterministic methods. However in FWQI evaluation method, the potable water quality is classified in five forms of "Excellent, Good, Medium, Fair and Poor" and we can easily suggest about final groundwater quality, in addition we can specify the confidence level (or certainty level) to each form. In this study, among 71 groundwater samples, 8 samples (with certainty level of 5.33-76.67%) were classified in "Excellent" class for drinking, 41 samples (with certainty level of 8.5-96.5%) were in "Good" category, 8 samples (with certainty level of 14-93.5%) were in "Medium" group, 1 sample (with certainty level of 36.5%) was in "Fair" level and 13 samples (with certainty level of 54.8-81.5%) were in "Poor" class.

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