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Determine of Surface Water Quality Index in Iran

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Abstract
In modeling complex of environmental problems, researchers often fail to define precise statements about input and outcomes of contaminants, but fuzzy logic could help to dominate this logical indecision. The goal of this work is to propose a new river water quality indicator using fuzzy logic. The proposed index combines six indicators, and not only does it exhibit a tool that accounts for the discrepancy between the two base indices, but also provides a quantifiable score for the determined water quality. These classifications with a membership grade can be of a sound support for decision-making, and can help assign each section of a river a gradual quality sub-objective to be reached. To show the applicability of the proposed approach, the new indicator was used to classify water quality in a number of stations along the basins of Qarah-chai and Siminehrood. The obtained classifications were then compared to the conventional physicochemical water quality indicator currently in use in Iran. The results revealed that the fuzzy indicator provided stringent classifications compared to the conventional index in 38% and 44% of the cases for the two basins respectively. These noted exceptions are mainly due to the big disagreement between the different quality thresholds in the two standards, especially for fecal coliform and total phosphorus. These large disparities put forward an argument for the Iranian water quality law to be upgraded.
Keywords: Fuzzy logic; Qarah-chai basin; Siminehrood; Water quality index

1. Introduction

Drinking water quality is currently certain only as the absence or presence of certain strictly limited undesirable substances. The availability and quality of groundwater as well as drinking water will be the main environmental and social issues in the future. Water quality monitoring and quality decision-making based on the obtained data is a complex and multidimensional task for decision makers. The basic reason of such heavy and challenging work is uncertainties that occur in all steps, from sampling to analysis. The sets of the monitored data and limits should not be as crisp set, but as fuzzy sets (Dahiya et al., 2007). In modeling complex of environmental problems, researchers often fail to define precise statements about input and outcomes of contaminants, but fuzzy logic could help to dominate this logical indecision. Fuzzy logic can be considered as a language that allows one to translate sophisticated statements from natural language into a mathematical formalism. Fuzzy logic can deal with highly variable, linguistic, vague and unknown data or knowledge and therefore has the ability to allow a logical, valid and transparent information stream from data collection to data usage in environmental application system. Fuzzy logic provides a framework to model indecision, the human way of thinking, reasoning and perception process (Bai, 2009). The results on water quality obtained using the index developed on the basis of fuzzy set theory were found to be more useful than those derived from the water quality indicator method that currently used (Roveda, 2010).

Fuzzy set theory (Zadeh, 1965) has been established to deal with uncertainty problems. It has been widely applied in decision-making and evaluation processes in incorrect situations (Mujumdar and Sashikumar, 2002; Dahiya et al., 2007). Many applications of Fuzzy set theory have been quoted in the last two decades, such as surface water and groundwater remediation (Cheng et al., 2002; Nasiri et al., 2007a; Tzionas et al., 2004) air pollution management (Fisher, 2003), soil modification (Busscher et al., 2007) and divers air, water and terrestrial ecosystem environmental studies (Astel, 2007). An evaluation approach has been developed based on Fuzzy logic and Fuzzy set theory, which has been demonstrated to be effective in solving problems of fuzzy boundaries and controlling the effect of monitoring errors on assessment results (Wang, 2002). The Fuzzy logic and Fuzzy set theory-based evaluation model can be used to describe fuzzy character of classified bounds for water quality and it could reflect the actual water quality on objective (Istrate and Grigoras, 2010; Pislaru et al., 2011). River water quality evaluation has been extensively studied in recent years (Benchea et al., 2011; Graca et al., 2002; Yilmaz, 2007; Liu et al., 2010). Nonetheless, disagreement frequently arises from: a) The lack of clear boundary distinctions between each water quality parameter; b) Short samples and incomplete information; c)

The uncertainty in the quality criteria employed; d) The imprecision, vagueness, or fuzziness in the decision-making output values (William et al., 2006). This caused some cases of unreliable river water quality evaluation in practice.

Furthermore, with fuzzy logic one can describing the water quality in a location as being 10% excellent and 90% just good, this is not might with classical near to water quality. Using fuzzy logic is very convenient in the assessment of environmental issues because it can solve properly the ambiguities and individuality inherent in these problems. It also supports conciliating conflicting observation due to human expertise, and last but not least, it can provide decision-makers with the ability to make well-informed decisions that are technically sound and legally defensible. Rules are derivative automatically based on the number of variables as well the number of membership functions, and the aggregation method used. In this work, an easy to use method is introduced; it simplify the generation of convenient membership functions based on a composition of already appointed standards by combining water quality thresholds in an automatic way. For any given indicator, the quality threshold values are resolute in both standards; triangular and trapezoidal membership functions are then derived automatically based on distance decussating and linear incorporation.

Recently, Gharibi et al. (2012) developed a FWQI, for which the water quality indicators were practical and easy to measure, including heavy metals, and used the index to recognize water quality in the Mamloo dam for drinking purposes. Also Lu et al. (1999); Chang et al. (2001) studied the possibility of applying Fuzzy Synthetic Evaluation to water quality. A new approach was carried out by Nasiri et al. (2007b); the authors proposed a fuzzy multi-attribute decision support system to compute the water quality index and to outline the prioritization of alternative plans based on the extent of improvements in water quality.

Ocampo-Duque et al. (2006) used fuzzy logic and a comprehensive multi-attribute decision-aiding method based on the Analytic Hierarchy Process to assessment the relative importance of water quality index. A 6-step procedure to develop a fuzzy water quality index was described in Icaga (2007), and was applied to lake water. Mahapatra et al. (2011) used a Cascaded Fuzzy Inference System to design a multi-input, multi-output water quality index. In a study, Shen et al. (2005) the Fuzzy Comprehensive Assessment method was used pollution and evaluate the soil environmental quality of the Taihu lake watershed. Liou et al. (2003) applied a two-stage fuzzy set theory to river quality evaluation in Taiwan. Lermontov et al. (2009); Roveda et al. (2010) developed fuzzy water quality indices for Brazilian rivers, and compared their performance with the conventional WQIs. A different approach based on hybrid fuzzy-probability models were adopted in Ocampo-Duque et al. (2013); Nikoo et al. (2011). Water quality indices target at turning several complex indicators into a single synthesized value that characterize the water quality of a particular source and which is intelligible by a wide audience including non-experts like the decision or public and policy makers(Tyagi, 2013). Fuzzy logic has shown a good behest in modeling new water quality index. In a recent work, Wang et al. (2014) used variable fuzzy set and the information entropy theory as an assessment model to evaluate water quality of the Meiliang Bay Taihu Lake Basin in China. In another study by Sadiq and Tesfamariam (2008), a Weighted Averaging Operator was used for aggregation in developing the water quality index.

River water quality evaluation is one of the safety problems of water resources in Iran. In Iran Rivers and streams, the water quality is becoming more and of relevance because of the substantial value of pollutants discharged into these ecosystems, in most cases without any treatment. Measurements and analyses are performed regularly by a number of public administrations. Nonetheless, these analyses remain insufficient given the variety of chemicals and the diversity of pollution sources. Considerable efforts have been deployed recently in Iran to improve water quality. A simplified set of indicators that are realistic and easy to measure are really used in the conventional index to estimate river water quality. In other indicators; the techniques used to evaluate these indicators are either complicated, costly, or time consuming, which results in discarding them from consideration in the final evaluation of water quality. At this is step to reclaim water quality assessment through enhancement of threshold values in order to account for real water pollution, the indicator still needs to reclaim to take into consideration contamination with heavy metals. For this object, the overall water quality indicator of Quebec (Hebert, 1997) was selected. There is a need to upgrade the Iranian legislation on water quality to include a new indicator. This an index must factor in the use of indicators with direct causes on human and animal health, as well as evaluation thresholds. The IQBP is analogous to the Iranian conventional water quality index. Both IRWQI and IQBP evaluation water quality based on a number of bacteriological and physicochemical indexes, and provide water quality classes for multiple applications. They are also similar in terms of the assessment method used which is based on the “minimum operator” that assigns the lowest index quality to the overall water quality in a given location. Nevertheless, the approach used to design the IQBP indicator relied on a group of thirty water quality experts and professionals from different horizons who have been conferred matching to the Delphi method (Linstone and Turoff, 1975).

A quick collation between the Iranian water quality indicator threshold values and the ones used in Quebec reveals a big disparity between the two standards. In this paper, fuzzy methodology is used to come up with a water quality indicator that we will be referring to as IFWQI (Iran Water Quality Index), by composed the

Iranian and Quebec standards. In the aforesaid studies about fuzzy index, the generation of membership functions is usually done based on expert opinions, and therefore remains hard to maintain or update because they require expert council every time. Membership functions for the different water quality indexes were developed thinking boundaries from both water regulatory bodies. A fuzzy conclusion system was used to distinguish water quality with a membership grade in number of station along the basin under study.

Method and Materials

In order to recognize the proposed fuzzy index, a case study of water quality was performed using measured environmental data on each sampling site of the monitoring network of the Qarah-chai basin collected during two primary campaigns in March and January and two more full campaigns that took place in December and May on its primary and secondary surface water networks. The total number of analyses performed over the study period for surface waters was up to 39 that location of the Qarah-chai sampling station shows in Fig. 1. All measurements were conducted according to standard methods. As can be seen in Table 1, both indices showed more or less correlated result with some sensibility to water pollution. The IRWQI and IFWQI had a correlation coefficient of 0.95, show the sound applicability of the indicator. In fact, the quality class obtained with the fuzzy index was lower for 56% of the sampled sited. In other cases, the assessment of water quality carried out by the two indices was analogous. However, the IFWQI resulted in a more severe evaluation compared to the conventional physicochemical index.

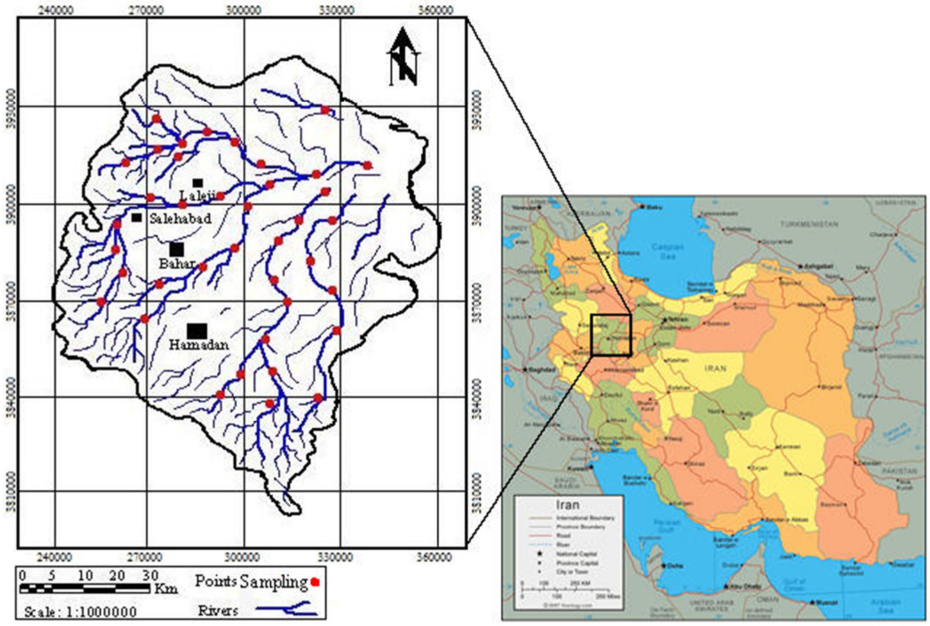

Figure 1. Location of the Qarah-chai sampling station, surface water station are shown in triangles

Table 1. Comparison of IRWQI and IFWQI indices for the different station of the Gharah-Chai basin

Location	December – 12		May – 13	
	IFWQI	**IRWQI**	**IFWQI**	**IRWQI**
St1	54	51	45	31
St2	69	65	33	42
St3	45	51	35	32
St4	58	69	45	56
St5	35	49	19	36
St6	26	36	29	39
St7	35	40	44	49
St8	37	15	50	41
St9	70	56	51	55
St10	54	68	25	36
St11	53	65	38	44
St12	55	46	40	37
St13	50	48	26	21

2. Results and Discussion

The results of comparison between the IFWQI and the conventional IRWQI for some sampling sites of the Siminehrood basin between 2012 and 2013 are illustrated in Table 1. By examining the respective distribution of these results by quality classes, it is obvious that difference between the two indices appear throughout all of the quality classes, particular in the lower ones. The water of has a good quality upstream and becomes gently polluted downstream near urban areas, due to urban evacuation. It can also be noticed in Table 1 and 2 that, when conventional and fuzzy indices do not produce a similar evaluation, the gap between the qualities classes is usually of a single class. These disagreements are observed at sites where a single index is always problematic. The water of Barfejin has good quality most of the time. Here again it can be seen that the quality class obtained with the fuzzy index was lower for 42% of the sampled sites. Not surprisingly, the proposed fuzzy index revealed some disagreement between the Iran water quality indicator and the other surface water quality standards. The fuzzy indicator is more efficient in the sense that it is more precise in detecting water pollution because it appeases between water quality ranges as prescribed by the two water regulative legislation, namely the Iran legislation and that of Quebec, which is considered to be stricter. Given the nature of the two indices and quality thresholds used for their computing, this is quite usual. Fecal coliforms and total phosphorus are appraised more harshly with the Quebec.

Table 2. Comparison of IRWQI and IFWQI index for the different stations of Ghareh-Chai basin

Location	**IFWQI**	**IRWQI**	Location	**IFWQI**	**IRWQI**
St1	48	22	St14	88	79
St2	60	24	St15	35	8
St3	68	40	St16	35	15
St4	15	22	St17	86	92
St5	78	61	St18	80	83
St6	79	52	St19	48	59
St7	80	70	St20	68	72
St8	84	42	St21	64	59
St9	86	32	St22	88	79
St10	69	63	St23	29	35
St11	81	55	St24	31	41
St12	72	43	St25	71	73
St13	81	55			

A weighted method was used to quantify the index and produced both a qualitative class and a score. This approach gives an excellent quantitative intuition, which can serve as a sound basis for further decision-making. Decision makers can assign several aims to several parts of a river depending on the membership grade. The conventional evaluation of water quality based on quality thresholds prescribed by the Iran legislation (IRWQI) gives the results in the form of qualitative classes, such as “good”, “average”, or “poor”, and so the information provided by the index is very limited. With the fuzzy index, not only does water quality move from a linguistic explanation to a quantifiable delegation without further computational overhead, but it produces a membership grade that shows to what strength a stream's water quality depend to a class. A contribution of a river qualified as being roughly halfway between “averages”, with a membership grade of 0.55, and “good” quality, with membership grade 0.48, can help professionals behave it differently from a portion qualified as having “average” quality with a membership grade of 1.

By allowing a situation to be partly true and partly false at the same time, fuzzy logic makes it appropriate to take into account any ambiguities or uncertainties. A key meaning in fuzzy logic is membership functions. Fuzzy logic is a deployment of Boolean logic made by (Zadeh, 1965) based on the theory of fuzzy sets, which a generalization of the classical is set theory. A degree of zero means that the value is not in the set, a degree of one means that the value is totally representative of the set, and a degree limited between zero and one means the value is partially in the set. The shape of the membership function is often selected based on the advice of an expert or by statistical studies. A Sigmoid shape, Trapezoidal, Triangular, Gaussian or any other type can be used. Let ***p*** be the universe of discourse and its elements denoted by ***x***. A fuzzy set ***a*** in universe ***p*** is characterized by a membership function μ_a: $p \rightarrow [0, 1]$. The fuzzy set A can be show by the set of pairs of an element $\boldsymbol{x} \in \boldsymbol{p}$ and its degree of membership specified by a membership function $\mu_a(x)$:

$$\mu_a : X \rightarrow [0,1] \quad (1)$$

$$A = \left[(\mu_A(x)),\ x \in X, \mu_A(X) \in [0,1]\right] \quad (2)$$

$$\mu_a : \begin{pmatrix} =1 & x\,is\ full\ memebr\ of\ \ A \\ \in (0,1) & x\,is\ partial\ memebr\ of\ \ A \\ =0 & x\,is\ not\ memebr\ of\ \ A \end{pmatrix} \quad (3)$$

$$a = \left[(x, a(x)) / x \in p \right] \quad (4)$$

The meaning of membership functions discussed above allows the description of fuzzy natural language systems that make use of linguistic variables, where the universe of discourse of variable is divided into a number of fuzzy sets with a linguistic description attributed to each one. Order to easily manipulate fuzzy sets; the operators of the classical set theory are adapted to the membership functions special to fuzzy logic, strictly allowing values between 0 and 1. Typically, the expanse of the union operator to fuzzy sets ***a*** and ***b*** defined over the same set ***p*** is defined as:

$$\mu_{a \cap b}(x) = \max \left[\mu_a(x),\ \mu_b(x) \right] \quad (5)$$

Where $\boldsymbol{\mu_a}$ and $\boldsymbol{\mu_b}$ are the membership functions for ***a*** and ***b*** respectively. Similarly, the fuzzy intersection is defined by:

$$\mu_{a \cap b}(x) = \min \left[\mu_a(x),\ \mu_b(x) \right] \quad (6)$$

Basic structure of a fuzzy inference system: A fuzzy inference system is an inference system based on fuzzy set theory, which maps input values to outputs. The fuzzy inference process involves four main steps (Ross, 1995): rule assessment: in this stage, the result of a fuzzy if-then rule is calculated. First, the rule stability is calculated by combining the *fuzzified* inputs. Composition of multiple conjunctive antecedents is performed using the fuzzy intersection operation. Multiple disjunctive antecedents are combined using the fuzzy union operation. Then, the rule consequent is correlated with the strength value of the rule antecedent; the most common method for rule implication is to cut the consequent membership function at the level of the antecedent truth. This method is called clipping. *Fuzzification*: in this stage, crisp input values are mapped into linguistic variable using membership functions. This is required in order to activate rules that are in terms of linguistic variables. The *fuzzifier* take input values and determines the degree to which they belong to each of the fuzzy sets via membership functions. *Defuzzification*: in this stage, the aggregated output fuzzy set is mapped into a crisp number. Several methods are used in practice for *defuzzification*, including the “centroid”, “maximum”, mean of maximum”, “height”, and “modified height”. Aggregation of rule outputs: outputs for all rules are then aggregated into a single fuzzy distribution. This is usually done using fuzzy union of all individual rule contributions. In fuzzy logic, *if-then* rules and fuzzy set operators are used to describe the relationships between input variables and output variables of a system. Fuzzy rules are a collection of linguistic statements that describe how a fuzzy conclusion system should make a decision regarding classifying an input or controlling an output. A fuzzy rule has one or more antecedents, usually connected by linguistic operators such as “and” or “or”. Rules are always written in the following from:

Ri: if m is Ai and / or n is Bi then ***s*** *is Ci.* (7)

Where ***m*** and ***n*** are the input variables and ***s*** is the output variable. ***Ai***, ***Bi*** and ***Ci*** are linguistic values for the variables ***m***, ***n*** and ***s*** respectively. Based on the IRWQI simplified quality grid shown in Table 3, the results of the monitoring performed during four campaigns showed that 91% of the sampled level water points had an average to good quality in December, as compared to 8% of average to poor quality. The results of comparison between the IFWQI and the conventional IRWQI each sampling site of the Gharah-Chai basin over the period under study are illustrated in Table 2. In May the quality improved to 23% points of average to poor quality as compared to 77% points of an average to good quality. Table 4 shows simplified rating table for the Iran water quality indicators (IRWQI). Nonetheless, in May the quality improved to 90% points of average to good quality as compared to 10% points of average to poor quality. Based on the IFWQI, the results showed that 89% of the sampled surface water points had an average to good quality December, as compared to only 11% of average to poor quality.

Table 3. Parameters weight and importance rate in NSF water quality index ranking (Wills and Irvine, 1996)

Sub-index	Weights	Status of water quality based on National Sanitation Foundation WQI	
		Quality	Range
DO (mg/l)	0.17	Excellent Water quality	90 – 100
BOD (mg/l)	0.11		
TS (mg/l)	0.07	Good Water quality	70 – 90
Nitrate (mg/l)	0.10		
Turbidity (NTU)	0.08	Average Water quality	50 – 70
Phosphate (mg/l)	0.10		
Temperature (ºC)	0.10	Poor Water quality	25 – 50
Fecal Coliform (CFU/100 ml)	0.16		
pH	0.11	Very poor Water quality	0 – 25

CFU: Colony forming units
NTU: Nephelometric turbidity unit

An application of the index was represent for surface waters in the basins of Qarah-chai and Siminehrood. Water quality was evaluated by means of six indexes (DO, BOD5, COD, FC, TP and NH^{+4}). In this work, the (Mamdani, 1974) approach was used to build the IFWQI fuzzy inference engine. The implication method used is the "Minimum" and the aggregation method is "Maximum". This approach is known for its simple structure and Maximum _ Minimum inference.

Table 4. Simplified rating table for the IRWQI water quality indicators (IFSWQM, 2010)

Sub-index	Weights	Status of water quality based on National Sanitation Foundation WQI	
		Quality	Range
DO (mg/l)	0.097	Excellent Water quality	> 85
BOD (mg/l)	0.117		
TS (mg/l)	0.059	Good Water quality	85 – 55
Nitrate (mg/l)	0.108		
Turbidity (NTU)	0.062	Average Water quality	55 – 30
Phosphate (mg/l)	0.087		
Temperature (ºC)	0.140	Poor Water quality	30 – 15
Fecal Coliform (CFU/100 ml)	0.051		
pH	0.097	Very poor Water quality	< 15

CFU: Colony forming units
NTU: Nephelometric turbidity unit

In the context of the ongoing efforts aimed at improving the environment in Iran, a new quality indicator for surface waters using fuzzy logic has been expanded (NSFWQI). A comparison between the conventional indicator and the new fuzzy indicator was carried out with the target of being able to point out the weaknesses of the contractual approach, and to propose an upgrade to Iran water legislation in a simple and significant way. Unlike the conventional indicator, the new fuzzy indicator allows the results to be interpreted quantitatively or qualitatively along with membership grades. The proposed indicator can decision problems of uncertainty and linguistic ambiguity inherent to this particular environmental problem. The proposed indicator has been shown to be more rigorous because it uses quality thresholds from the Quebec IQBP index (reputed to be very stringent), but yet it conserves the expert knowledge embodied in the Iran IRWQI index. It also allows a better analysis since experts can qualify a sampling station quality status as closer to its upper or lower limit. The conventional index does not fully agree with health expert knowledge about industrial and agricultural pollution known in the area. There is a clear need to review legislation about water quality that has been revealed by the proposed fuzzy indicator. The conventional indicator does not reflect the alarming condition of water quality; which minimizes the chances of triggering enough responses or the application of existing laws to handle the condition, and therefore the use of water for drinking or for agriculture from the rivers without treatment may expose the population to health risks. While it is not anticipated that the proposed approach will be used for water quality evaluation by local authorities, the purpose is to draw to the need for Iran to run an adjustment exercise align its water and environmental assessment methods with other countries in order to mitigate the risks of failing to arrive a good ecological status. Moreover, the conventional IRWQI is a state-oriented index, which someway fails to reflect the socio-economic pressures that result in water quality degradation related on different geographical zones. In Europe for example, a number of efforts have been deployed to account for the different pressures exerted by the socio-economic driving forces in addressing water problems (Borja et al. 2006). So, further efforts need to be taken to perform an integrated assessment that takes into attention socio-economic indexes besides ecological indicators.

3.1. Development of the Iranian fuzzy water quality index

The evaluation of surface water quality in Iran is performed using water quality indicator IRWQI defined by water legislation. The IRWQI propose recommended water quality using a number of bacteriological and physicochemical indexes, and aggregates them to produce a single quality class relevant on a given usage such as fish life, irrigation, industrial uses, cooling, or raw water supply intended for drinking. The IRWQI index consists of indicators: Dissolved Oxygen (DO), Biological Oxygen Demand during five days (BOD5), Chemical Oxygen Demand (COD), Ammonium (NH^{+4}), Fecal Coliforms (FC) and Total Phosphorus (TP). The simplified rating grid of surface waters shown in Table 4 establishes five dominant classes according to the utilization goals for which the water is intended. Each class is defined by a set of threshold values that the different bacteriological or physicochemical indexes, which are particularly significant, must not exceed. The IRWQI index applies the meaning of the lowest score, i.e., the "minimum operator" is used to produce the final index score. The approach dictates that the water quality in a sample corresponds to that of the indicator generating the lowest sub-index as calculate for every index using threshold values determined by Table 4.

IRWQI = minimum (BOD5 sub-index, DO sub-index, FC sub-index, NH^{4+} sub-index, COD sub-index, TP sub-index).

For example, if all the indexes have values corresponding to the "excellent" class, except one, which falls into the "average" class, the IRWQI will allocate the water body to the "average" class. Preliminary indications show that the "minimum operator" approach is a more useful aggregation method than additive and multiplicative techniques. Smith (1990) showed that most indicators based on additive or multiplicative approaches were insensitive; i.e., they were little influenced by the poor quality associated with one or two descriptors because of the aggregation method used. Other excellence of this approach is that the indicator ensures that a determined number of basic indexes are assessed clearly before an overall classification is assigned to a given water body. The rationale behind the method is that it is very significant to understand and determine the type of water pollution and the element that resulted in water quality change, in order to establish a clear diagnosis and identify the water quality problem. Since the IRWQI produces only qualitative classes such as excellent" or "poor" a quantification method is adopted in order to obtain a quantitative value that can be easily compared to the crisp concession produced by the fuzzy indicator.

To quantify the different classes, the values of the ranges set by the quality thresholds to evaluate water quality are converted into dimensionless numbers ranging from (for extremely poor water quality) to 100 (for absolutely excellent water quality). The sub-index of a given indicator is elaborated by weighting, which means the indicator is obtained by producing a value that is proportional to its real position in a class range. The formula for computing the weighted indicator (IF) is shown by Eq. (8).

$$IFpa = li + \{(ui - li) / (bs - lb)\} \times (ub - pa) \qquad (8)$$

Where, IF_{pa}: the weighted index for indicator pa; *li*: the lower index; *ui*: the upper index; *lb*: the lower bound; *ub*: the upper bound; *pa*: the analyzed indicator value.

3.2. The Quebec Water quality index (IQBP)

The IQBP indicator, water bodies are grouped into five classes according to all the possible used. To classify a water body, water quality is examined using ten indexes, namely: Nitrates (NO_3^-) / Nitrites (NHO_2), Ammonium (NH^{+4}), Total chlorophyll a (CHA), Dissolved oxygen percentage ($\%O_2$), Fecal coliforms (FC), Biological oxygen demand in five days (BODS), Suspended solids (SS), turbidity (TU), Total phosphorus (TP) and pH. Table 5 present the criteria used to assign one of the five classes to a water body. Like the Iran index, the IQBP is a downgrading type indicator; that is to say, for a given sample, the index value corresponds to the lowest sub-index associated with the most difficult substance. It can be noticed from the rating grids (Tables 4 and 5) that there are discrepancy in quality ranges between the Iran and Quebec standards. The IQBP requires, for each indicator analyzed, the change of measured concentration into a sub-index, with a rating curve for assessing the water quality. These differences exhibit tougher quality thresholds in the IQBP for all water indexes in common between the two standards, particularly for fecal coliform and total phosphorus. One problem with this type of highly subjective water quality evaluation rendered by both the IRWQI and IQBP is that the final indicator does not take into consideration the uncertainty about passable threshold values for each index. In the next section an alternative to the IRWQI index based on fuzzy logic is proposed with more relevance to the type of uncertainties involved in this special difficulty.

Table 5. Class boundaries of water quality for some indicators used in the IQBP (Hebert, 1997)

Parameters	Class				
	A	**B**	**C**	**D**	**E**
BOD5 (mg/l)	≤ 1.7	1.8-3.0	3.1-4.3	4.4-5.9	> 5.9
NO_X^- (mg/l)	≤ 0.50	0.51-1.00	1.01-2.00	2.01-5.00	> 5.00
SS (mg/l)	≤ 6	7-13	14-24	25-41	> 41
FC (cfu/100 ml)	≤ 200	201-1000	1001-2000	2001-3500	> 3500
NH^{4+} (mg/l)	≤ 0.23	0.24-0.50	0.51-0.90	0.91-1.50	> 1.50
O_2 (%)	88-124	0.03-0.05 125-130	70-79 131-140	55-69 141-150	< 55 > 150
TP (mg/l)	≤ 0.03	0.031-0.050	0.051-0.100	0.101-0.200	> 0.200

3.3. Building a fuzzy water quality index for Iran (IFWQI)

Membership functions for the different water quality indexes were developed considering boundaries from both water regulatory bodies. In order to combine the benefits from the two standards discussed above, fuzzy methodology is used to suggest a new water quality indicator by conciliating quality thresholds from the Iran and Quebec legislations. The method used to produce membership functions is very simple. A fuzzy inference system was designed and built to classify water quality with a membership grade. It can be concluded that the actual value belongs to the decussating of these intervals. If V and W respectively denote the quality ranges for a given class of water quality in the Iran standard and the Quebec one, then $V \cap W$ is considered as the distance where confidence is the highest, corresponding to a degree of membership equal to 1. Then, a linear concatenation is used for the remaining points not belonging to the decussating by liking the lower and upper bounds of both V and W to the decussating distance, which results in a trapezoidal shape. In cases where the decussating results in a single point, the shape is triangular.

Depending on the overlap between quality thresholds in the two standards, triangular and trapezoidal membership functions were derived from the parameters as shown in Table 6. Membership curves for input indexes and IFWQI are shown in Fig. 2. Overall, five fuzzy sets, which are “excellent”, “good”, “average”, “poor”, and “very poor” have been considered for this study for both input indexes and for the output water quality indicator. Using the several fuzzy sets of the considered indexes, *if-then* rules were then generated automatically. At first, since the inference methodology used relates the relevant subsets of each input global set to the subsets of the other system inputs through an intersection-rule configuration, a total number of 5 rules ware generated, representing the model of the water quality evaluation system from the set of 6 input indexes and their possible 5 classes. Nevertheless, as the conclusion is based on the minimum sub-index, an optimization could be made using a disjunction of inputs by means of the “OR” operator: the IFWQI is considered “very poor” if one of the indexes is “very poor”, and therefore the rule used for all possible compositions in that case Rule 3 as shown below. The examples below show three rules for “good”, “poor”, and “very poor” water quality respectively: *If*, *DO* is excellent and *BOD5* is excellent and *COD* is excellent and NH^{+4} is excellent and *TP* is excellent and *FC* is good then IFWQI is good (Rule 1). *If*, *DO* is excellent and *BOD5* is good and *COD* is average and NH^{+4} is poor and *TP* is good and *FC* is excellent then IFWQI is poor (Rule 2). *If*, *DO* is very poor or *BOD5* is very poor or *COD* is very poor or NH^{+4} is very poor or *TP* is very poor or *FC* is very poor then IFWQI is very poor (Rule 3).

Table 6. Importance rate for membership functions of the different indicators used in the IFWQI

		Excellent	Good	Average	Poor	Very poor
DO	a	9	6	2	1	0
	b	9	5	3	2	0
	c	15	9	5	4	1
	d	19	9	7	5	1
BOD5	a	0	2	3	4	8
	b	0	4	6	7	33
	c	2	6	7	14	180
	d	3.4	9	12	21	180
NH^{+4}	a	0	0.2	0.4	2	4
	b	0	0.4	2	4	6
	c	0.2	2	4	7	40
	d	0.4	4	4	10	200
FC	a	0	20	1000	2000	3500
	b	0	200	2000	3500	50000
	c	40	1000	20000	20000	1800000
	d	200	2000	20000	50000	1800000
COD	a	0	15	20	35	70
	b	0	20	30	35	65
	c	25	35	55	70	450
	d	35	40	55	80	450
TP	a	0	0.02	0.1	0.1	0.3
	b	0	0.1	0.1	0.2	2
	c	0.02	0.3	0.5	0.5	25
	d	0.1	0.3	1	5	25

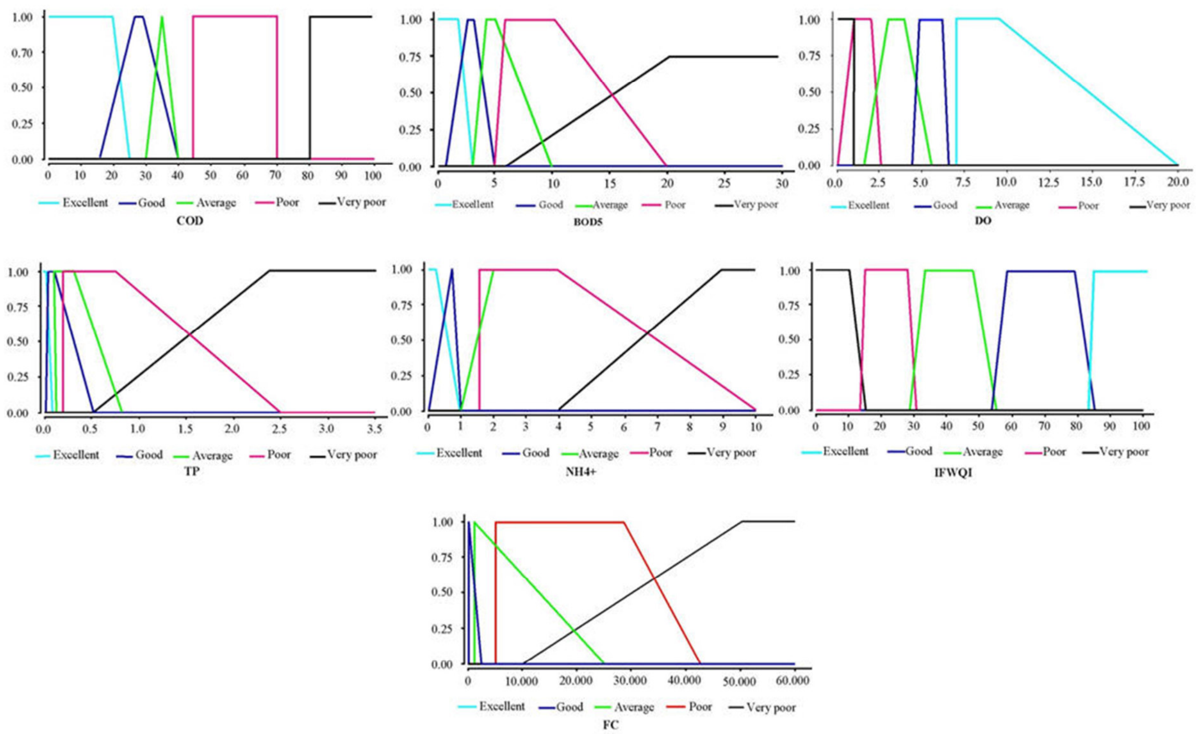

Figure 2. Membership function for DO, BOD5, COD, FC, NH^{+4}, TP and IFWQI

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