Journal of Environmental Management 112 (2012) 87–95

Contents lists available at SciVerse ScienceDirect

Journal of Environmental Management

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

A novel approach in water quality assessment based on fuzzy logic

Hamed Gharibi[a,b], Amir Hossein Mahvi[a,c,g,*], Ramin Nabizadeh[a], Hossein Arabalibeik[d], Masud Yunesian[a,e], Mohammad Hossein Sowlat[f]

[a] Department of Environmental Health Engineering, School of Public Health, Tehran University of Medical Sciences, Enghelab St., Tehran, Iran
[b] Students' Scientific Research Center, Tehran University of Medical Sciences, Tehran, Iran
[c] National Institute of Health Research, Tehran University of Medical Sciences, Tehran, Iran
[d] Research Center for Science and Technology in Medicine (RCSTIM), Tehran University of Medical Sciences, Keshavarz Boulevard, Tehran, Iran
[e] Institute for Environmental Research (IER), Tehran University of Medical Sciences, Kargar St., Enghelab Sq., Tehran, Iran
[f] Young Researchers Club, Medical Branch, Islamic Azad University, Tehran, Iran
[g] Center for Solid Waste Research, Institute for Environmental Research, Tehran University of Medical Sciences, Tehran, Iran

ARTICLE INFO

Article history:
Received 21 July 2011
Received in revised form
20 June 2012
Accepted 5 July 2012
Available online

Keywords:
Fuzzy logic
Water quality index
Water quality assessment
Mamloo dam

ABSTRACT

The present work aimed at developing a novel water quality index based on fuzzy logic, that is, a comprehensive artificial intelligence (AI) approach to the development of environmental indices for routine assessment of surface water quality, particularly for human drinking purposes. Twenty parameters were included based on their critical importance for the overall water quality and their potential impact on human health. To assess the performance of the proposed index under actual conditions, a case study was conducted at Mamloo dam, Iran, employing water quality data of four sampling stations in the water basin of the dam from 2006 to 2009. Results of this study indicated that the general quality of water in all the sampling stations over all the years of the study period is fairly low (yearly averages are usually in the range of 45–55). According to the results of ANOVA test, water quality did not significantly change over time in any of the sampling stations ($P > 0.05$). In addition, comparison of the outputs of the fuzzy-based proposed index proposed with those of the NSF water quality index (the WQI) and Canadian Water Quality Index (CWQI) showed similar results and were sensitive to changes in the level of water quality parameters. However, the index proposed by the present study produced a more stringent outputs compared to the WQI and CWQI. Results of the sensitivity analysis suggested that the index is robust against the changes in the rules. In conclusion, the proposed index seems to produce accurate and reliable results and can therefore be used as a comprehensive tool for water quality assessment, especially for the analysis of human drinking water.

1. Introduction

The rate of increase in urban, agricultural, and industrial activities has raised scientists' concerns about environmental issues and in particular about water pollution. Therefore, much effort has been made in the development of a comprehensive index that is representative of the overall water quality. The most common index, called the Water Quality Index (WQI), was developed by the National Sanitation Foundation (NSF) (Ott, 1978). Since then, several modified water quality indices have been developed based on the WQI (Liou et al., 2004; Nasiri et al., 2007; Said et al., 2004); however, use of these traditional indices raises many problems. One of the most important problems is that values with different distances from a limit have the same effect on the final index score (Icaga, 2007). This leads to an unclear distinction between each mode of the index and causes inaccuracies and ambiguity when making decisions about boundary values (Chang et al., 2001). Another important problem is the fact that the traditional indices are not capable of dealing with the uncertainty and subjectivity of the environmental issues (Silvert, 2000).

In recent years, artificial intelligence (AI) computational methods, such as knowledge-based systems, neural networks, genetic algorithms, and fuzzy logic, have been increasingly applied to environmental issues (Chau, 2006), because they are believed to be effective in resolving the aforementioned problems. Fuzzy logic was introduced by Zadeh (1965) and has become one of the most common approaches in the field of AI. It is believed to be appropriate for

* Corresponding author. Department of Environmental Health Engineering, School of Public Health, Tehran University of Medical Sciences, Enghelab St., Tehran, Iran. Tel.: +98 21 889 549 14; fax: +98 21 88950188.

E-mail addresses: hgharibi65@gmail.com (H. Gharibi), ahmahvi@yahoo.com (A.H. Mahvi), rnabizadeh@tums.ac.ir (R. Nabizadeh), arabalibeik@yahoo.com (H. Arabalibeik), yunesianm@yahoo.com (M. Yunesian), hsowlat@gmail.com (M.H. Sowlat).

0301-4797/$ – see front matter © 2012 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.jenvman.2012.07.007

developing environmental indices, because it has the ability to reflect human thoughts and expertise in the indices, enabling them to deal with non-linear, uncertain, ambiguous and subjective information. It also enables us to include parameters with different values and meaning in the index, including both qualitative and quantitative variables. Furthermore, it is a reliable method for reporting the results of an assessment in linguistic terms, which are understandable for the public, managers, decision-makers, and non-experts in general (McKone and Deshpande, 2005; Silvert, 2000).

Therefore, great attention has been paid to the development of environmental indices based on fuzzy logic (Gharibi et al., 2012; Lu et al., 1999; Mirabbasi et al., 2008; Sasikumar and Mujumdar, 1998; Sowlat et al., 2011), especially when applied to the analysis of water quality (Chang et al., 2001; Icaga, 2007; Lermontov et al., 2009; Liou et al., 2003; Ocampo-Duque et al., 2006, 2007). However, since the number of parameters included in the WQI and the above mentioned fuzzy indices is limited, these indices do not seem to be representative of the overall water quality and an individual parameter may have a considerable impact on the final index value (Ocampo-Duque et al., 2006). On the other hand, the fuzzy water quality index (FWQ) developed by Ocampo-Duque et al. (2006) included twenty seven parameters, some of which (such as atrazine, BTEX, trichlorobenzenes, hexachlorbutadine) are either not of critical importance when dealing with water importance or the methods used to measure these variables are difficult, time-consuming, and practically impossible for routine measurements, making them undesirable for consideration.

Therefore, the present study aimed to develop a fuzzy index for water quality assessment that is representative of overall water quality for which the parameters are practical and easy to measure. For this purpose, the parameters included in the WQI were taken as a basis and other critical quality parameters (such as heavy metals content) were added to develop an improved water quality index. A case study on the water quality at Mamloo dam, Iran, was also conducted to check the performance of the proposed index.

2. Materials and methods

2.1. Fuzzy logic

Zadeh (1965) introduced fuzzy logic to create systems closer to the spirit of human thinking. This method is proven to be capable of dealing with complex systems under uncertain and imprecise conditions. Even an expert cannot predict water quality using only his mind, since the complexity of environmental conditions affects the final result; this problem is related to the "principle of incompatibility" (Zadeh, 1973). Fuzzy logic uses the expert's knowledge to develop a system; the experts' knowledge is used together with the other parameters through the rules defined in a fuzzy inference system to create a system based on the knowledge captured.

Developing an index based on the fuzzy logic necessitates comprehension of three important parts of the fuzzy inference system, including membership functions, fuzzy set operations and inference rules, which are briefly described below. Each selected input or input set has a domain called the *universe of discourse* that is divided into subsets which are expressed by linguistic terms. The relationships between the subsets of inputs and outputs, as well as those among the subsets of inputs, are defined by if-then rules and fuzzy set operators.

2.2. Membership functions

A fuzzy subset of an input is defined by a membership function and this can be expressed in various forms such as trapezoidal, triangular, Gaussian, etc. The membership function links each point in a fuzzy set to a membership grade between 0 and 1.

Fuzzy set A is a subset of the *universe of discourse* X which is denoted by the following nomenclature:

$$A = \{(x_1, \mu_A(x)) | x \in X\} \quad 0 \leq \mu_A(x) = 1 \tag{1}$$

where, x_1 belongs to X and is an element of fuzzy set A, and the value of $\mu A(x)$ shows the membership grade of x_1 in fuzzy set A.

Different methods such as fuzzy clustering (Jang and Sun, 1995), neural networks (Jang and Sun, 1995), expert knowledge (Turksen, 1991) and genetic algorithms (Karr and Gentry, 1993) can be used to determine membership functions.

2.3. Fuzzy set operations

The relationships among the fuzzy subsets are defined by using the fuzzy set operators. Different fuzzy set operators can be used in developing different systems based on fuzzy logic, of which three basic operators are briefly described below.

Table 1
A summary of the reason(s) for selection of the parameters included in the LWQI.

Category	Parameters	Reason	Reference(s)
Heavy metals	- As - Pb - Hg - Ba - Cd - Cr	- Adverse impacts on the gastrointestinal tract, kidneys, nervous and immune system, and the liver. - Clastogenic, carcinogenic, and mutagenic effects. - Impaired development of the nervous system, nephrotic damage and pulmonary damage. - Toxic effects on the gastrointestinal, cardiovascular, musculoskeletal, and nervous system. - Carcinogenic effects. - Carcinogenic effects.	- Duker et al. (2005) - García-Lestón et al. (2010) - Counter and Buchanan (2004) - Stokinger (1981) - Järup and Åkesson (2009) - De Flora et al. (1990)
Microbial quality	- TC - Cryp.	- Indicator of possible fecal pollution - Human pathogen	- (Nemerow et al., 2009) - (Smith and Nichols, 2010)
Psychochemical properties	- DO, BOD, pH, & Temp. - TS & Turbidity	- Key parameters of water quality; impact on water DO and in turn algal growth - Provision of a medium for the growth of pathogenic microorganisms; indicators of disease-causing organisms	- Clark (2008) - Clark (2008)
Minerals	- NO_2 & NO_3 - PO_4 - SO_4 - Cl^- - F^-	- Methemoglobinemia. - The major cause of eutrophication in water resources - Diarrhea and laxative effects. - Stomach discomfort - Fluorosis, hip fracture, impacts on immune system, reproductive flaws, and possible impacts on the kidneys and gastrointestinal tract	- Gangolli et al. (1994) - Rittmann and McCarty (2001) - USEPA (2011) - USEPA (2011) - Harrison (2005)

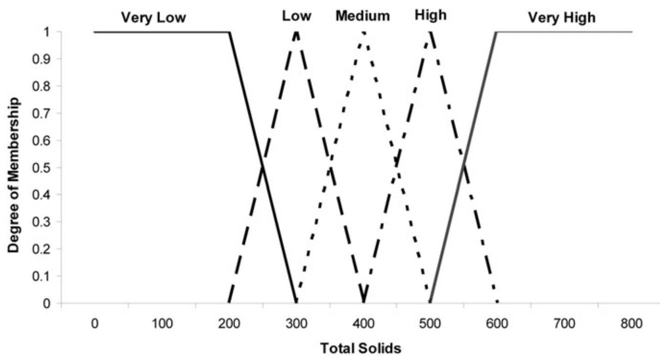

Fig. 1. Example of membership functions for total solids.

2.3.1. *Intersection (AND)*

This type of operator denotes the intersection of two or more fuzzy sets. It is defined by the following equation (Ross, 2004):

$$\text{AND}: \mu_{A\cap B}(x) = \mu_A(x) \cap \mu_B(x) = \min(\mu_A(x), \mu_B(x)) \tag{2}$$

2.3.2. *Union (OR)*

The union operation makes a new subset from the input subsets by uniting them. It should be mentioned that each fuzzy set operator creates a new subset from two or more subsets. The union operator is defined by the following equation (Ross, 2004):

$$\text{OR}: \mu_{A\cup B}(x) = \mu_A(x) \cup \mu_B(x) = \max(\mu_A(x), \mu_B(x)) \tag{3}$$

2.3.3. *Negation (NOT)*

The negation operator makes a complement set to the input sets on which it operates. The negation operator is defined by the following equation (Ross, 2004):

$$\text{NOT}: \mu_{\overline{A}}(x) = 1 - \mu_A(x) \tag{4}$$

The three aggregation operators mentioned above are the basic operators and are sufficient most of the time. A more complete definition of the aggregation operators can be found in Ross (2004) and Yager and Filev (1994).

2.4. *Inference rules*

Inference rules define the relationships among the subsets of the inputs and outputs. This process is carried out by if–then rules which generate a new output subset. Each rule consists of two parts including an “if-” part, which is called the antecedent, and a “then-” part, which is called the consequent. The if–then rules are written in the following way:

IF A is a THEN C is c.

IF B is b THEN C is c.

where *a*, *b*, and *c* are the linguistic terms for the subsets defined for sets *A*, *B*, and *C*, respectively. These rules are more comprehensively described in Ross (2004).

2.5. *Justifying inclusion of extra quality parameters*

A comprehensive description of the rationale behind the selection of the parameters included in the index is presented in this section. The parameters included in the fuzzy-based index can be classified into physicochemical properties, microbial quality, minerals, and finally toxic compounds in the water. According to Table 1, all of the selected parameters either have significant health implications for human or considered as key indicators of drinking water quality. It should be noted that the parameters were weighted according to their importance for and health implications on human health. In the fuzzy-based indices, this can be done by two methods. In the first method, direct weighting factors are assigned to each parameter and the final score is calculated based on these weighting factors. In the second approach used in the present study, expert’s knowledge is captured in the body of the index and the priority of one parameter over another one is assigned in the rules (the rule set) written for developing the index. In our index, for example, parameters such as temperature or pH, which do not have direct influence on human health, were given lower priorities compared to heavy metals.

2.6. *Development of a water quality index based on the fuzzy logic*

Twenty quality parameters were included in the index based on their importance, including dissolved oxygen (DO), biochemical

Table 2
Fuzzy sets and linguistic terms for the fuzzy-based index developed.

Group	Parameters	Units	Very low			Low			Medium			High			Very high			Range
			a = *b*	*c*	*d*	*a*	*b*	*c*	*a*	*b*	*c*	*a*	*b*	*c*	*a*	*b*	*c* = *d*	
1	DO	mg/l	0	2	4	2	4	6	4	6	8	6	8	10	8	10	12	0–12
	BOD	mg/l	0	1	2	1	2	3	2	3	4	3	4	5	4	5	6	0–6
2	pH	–	0	3	5	3	5	7	5	7	9	7	9	11	9	11	14	0–14
	Temp.	°C	0	5	10	5	10	15	10	15	20	15	20	25	20	25	30	0–30
3	TS	mg/l	0	200	300	200	300	400	300	400	500	400	500	600	500	600	800	0–800
	Turb.	NTU	0	1	2	1	2	3	2	3	4	3	4	5	4	5	6	0–6
4	Crypt.	–	0	1	2	1	2	4	2	4	8	4	8	16	8	16	30	0–30
	TC	CFU/100 ml	0	1	2	1	2	6	2	6	10	6	10	14	10	14	100	0–100
5	As	μg/L	0	5	10	5	10	15	10	15	20	15	20	25	20	25	30	0–30
	Pb	μg/L	0	10	15	10	15	20	15	20	25	20	25	30	25	30	40	0–40
6	Hg	μg/L	0	1	2	1	2	3	2	3	4	3	4	5	4	5	6	0–6
	Ba	μg/L	0	1	2	1	2	3	2	3	4	3	4	5	4	5	6	0–6
7	Cd	μg/L	0	3	5	3	5	7	5	7	9	7	9	11	9	11	14	0–14
	Cr	μg/L	0	40	70	40	70	100	70	100	130	100	130	160	130	160	200	0–200
8	NO_2	mg/l	0	1	2	1	2	3	2	3	4	3	4	5	4	5	6	0–6
	NO_3	mg/l	0	10	15	10	15	20	15	20	25	20	25	30	25	30	35	0–35
9	PO_4	mg/l	0	1	2	1	2	3	2	3	4	3	4	5	4	5	6	0–6
	SO_4	mg/l	0	200	400	200	400	550	400	550	700	550	700	850	700	850	1000	0–1000
10	Cl	mg/l	0	100	200	100	200	300	200	300	400	300	400	500	400	500	600	0–600
	F	mg/l	0	2	3	2	3	4	3	4	5	4	5	6	5	6	7	0–7
Fuzzy-based index		–	0	10	30	10	30	50	30	50	70	50	70	90	70	90	100	0–100

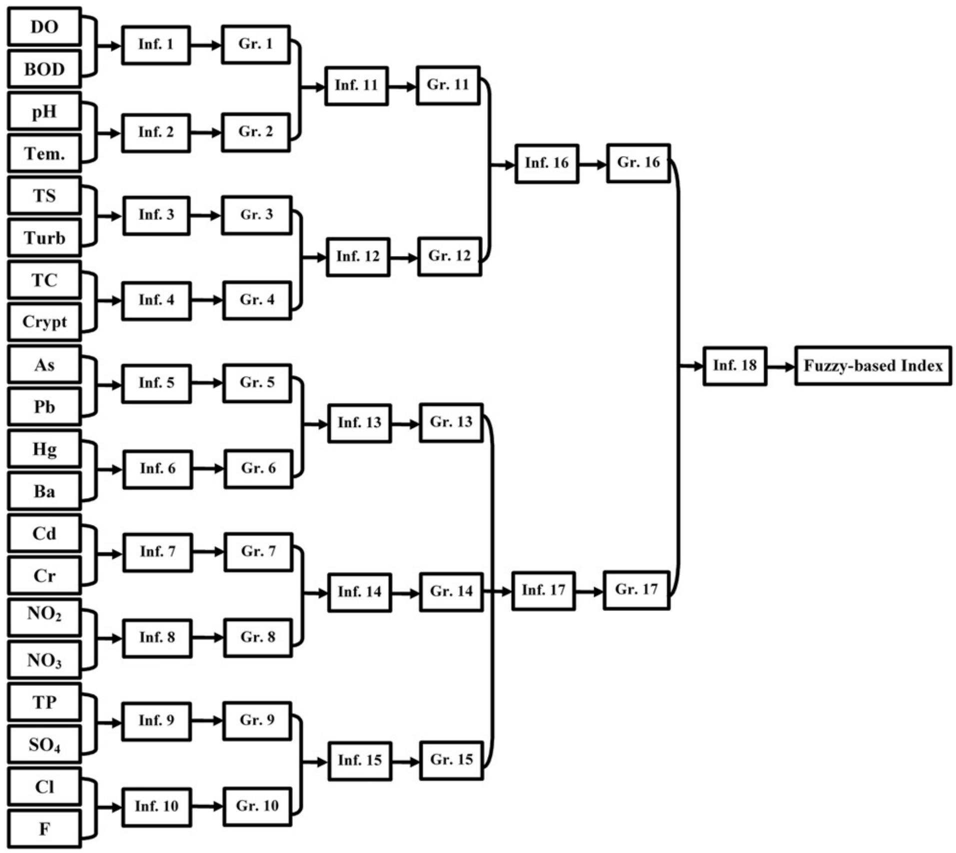

Fig. 2. Schematic flow-diagram of the fuzzy-based index developed.

oxygen demand (BOD), pH, temperature (Tem.), total solids (TS), turbidity (Tur.), cryptosporidium (Crypt.), total coliforms (TC), arsenic (As), lead (Pb), mercury (Hg), barium (Ba), cadmium (Cd), chromium VI (Cr VI), nitrite (NO_2), nitrate (NO_3), total phosphate (TP), sulfate (SO_4), chloride (Cl), and fluoride (F). Further discussion on the importance of the selected parameters is presented in Section 2.5. Two kinds of membership functions, based on the expert's knowledge, were defined for each parameter. Fig. 1 shows as example of the membership functions used for the input "total solids" (TS). The fuzzy sets, in the present study, were defined by the linguistic terms very low (VL), low (L), moderate (M), high (H), and very high (VH). Each parameter as an input was assigned to one of the five fuzzy sets in terms of membership functions. Based on the data presented in Table 2, the fuzzy sets were developed according to the following equations:

$$\text{Triangular}: f(x;a,b,c) = \left\{ \begin{matrix} 0 & x < a \text{ or } c < x \\ \dfrac{(a-x)}{(a-b)} & a \le x \le b \\ \dfrac{(c-x)}{(c-b)} & b \le x \le c \end{matrix} \right\} \tag{5}$$

$$\text{Trapezoidal}: f(x;a,b,c,d) = \left\{ \begin{matrix} 0 & x < a \text{ or } d < x \\ \dfrac{(a-x)}{(a-b)} & a \le x \le b \\ 1 & b \le x \le c \\ \dfrac{(d-x)}{(d-c)} & c \le x \le d \end{matrix} \right\} \tag{6}$$

Regarding the ranges selected for each variable, it should be mentioned that the standard value was set as a cut-point, meaning that the values below the standard value for each parameter were classified into two categories (very low and low), and the values above the standard value were classified into three categories (moderate, high, and very high). Regarding the ranges of the output variable, the most common scoring system for water quality assessment is values between 0 and 100, in which values near 100 represent higher quality of water. According to Table 1, the cut-point value for acceptable drinking water is 70.

The rules were created based on expert's knowledge and it was supposed that the human mind cannot handle this kind of high amount of data (Chau, 2006; Zadeh, 1973). Hence, to reduce possible imprecision, the 20 parameters were divided into 10 groups, so only 2 parameters were left for decision making at each step. The algorithm developed for the water quality index based on fuzzy logic is shown in Fig. 2. In the first step, the 20 parameters were normalized to a value between 0 and 100 and put into 10 groups. These groups were then normalized to values between 0 and 100 at each step to generate the final 2 groups. Finally, the last 2 groups were processed through the new inference system to give the final water quality index. In the traditional method, normalization of the parameters is performed using tables, curves and/or weighting factors. However, in the present study, the normalization was performed using the fuzzy inference system. We tried to capture the experts' knowledge and utilize it in developing a water quality index based on fuzzy logic; therefore, the Mamdani inference system was used as it is known for its ability to mimic an expert's knowledge in a way that is close to human thoughts and manners (Ross, 2004). We tried to cover the maximum possible number of modes of water quality through creating the inference rules. The algorithm and normalization of the 2 parameters developed at each step reduced the number of the rules to 550. Some examples of the rules generated are given below:

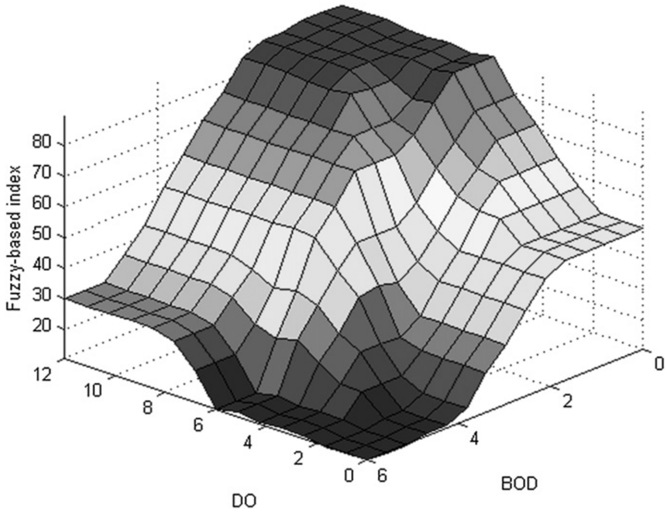

Fig. 3. A surface graph representing the interactions between DO, BOD and the final index value.

If DO is VL and BOD is H then Gr1 is VL.

If Crypt is VL and TC is M then Gr4 is VL.

If Hg is VL and Ba is VL then Gr6 is VH.

If Gr1 is VL and Gr2 is L Gr11 is VL.

If Gr3 is L and Gr4 is L then Gr12 is L.

If Gr16 is VH and Gr17 is VH then WQI is VH.

Defuzzification of the outputs was carried out by using the center of gravity (COG) method. The COG method, among the other methods of defuzzification, is the most conventionally and physically applicable method. Its derivation is based on the following equation (Ross, 2004):

$$Z = \frac{\int \mu(z) z \mathrm{d}z}{\int \mu(z) \mathrm{d}z} \tag{7}$$

Finally, Fig. 3 illustrates the relationships between two of the parameters included in the index (e.g. DO and BOD) and their effect on the final index score. All computations were carried out using the "fuzzy logic toolbox" in MATLAB version 7.9.0.

2.7. NSF Water Quality Index (WQI) and Canadian Water Quality Index (CWQI)

U. S. National Sanitation Foundation has developed a water quality index which consists of 9 parameters, including DO (0.17), fecal coliforms (0.16), BOD (0.11), pH (0.11), temperature

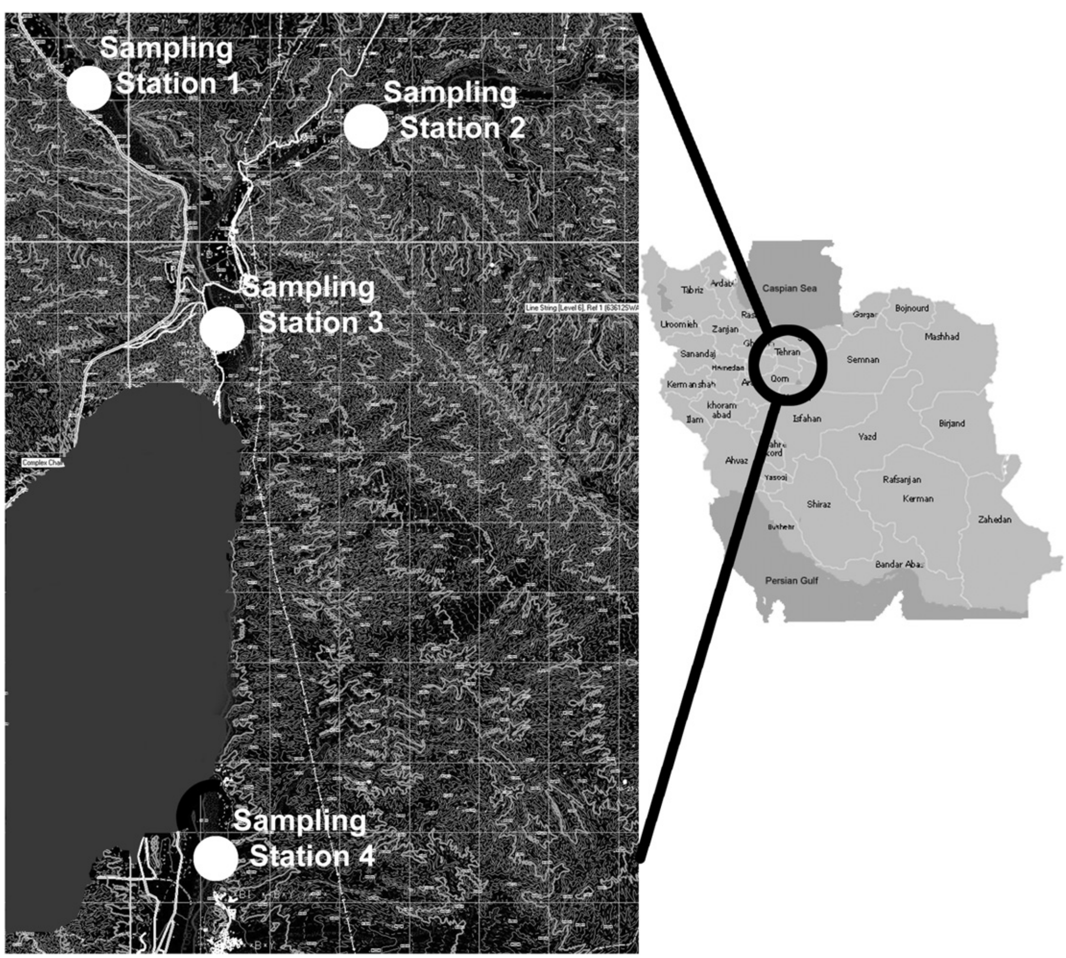

Fig. 4. Location of the sampling stations.

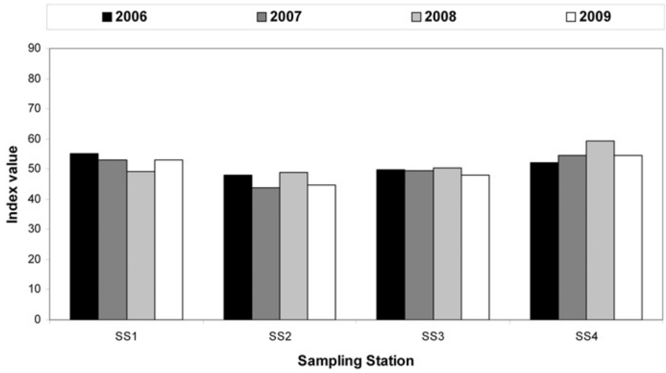

Fig. 5. Annual averages of the fuzzy-based index values in all sampling stations over the study period.

change (0.1), total phosphate (0.1), nitrate (0.1), turbidity (0.08), and total solids (0.07). The importance of each parameter is defined by a specific weighting factor, which is shown in the parenthesis. In order to calculate the final water quality index, the appropriated quality value should be multiplied by the respecting weighting factor and added to those of other parameters, making the final index value between 0 and 100 (Lermontov et al., 2009).

Another index which has been used in the present study to be compared with the proposed index is the Canadian Water Quality Index (CWQI). The index reflects the quality of water using three factors according to the following equation:

$$CWQI = 100 - \left[\frac{\sqrt{F_1^2 + F_2^2 + F_3^2}}{1.732}\right] \tag{8}$$

where, F_1 (scope) is the exceeded percentage of parameters from guideline; F_2 (frequency) is the exceeded percentage of individual tests within each parameter from guideline; and F_3 (amplitude) is the excursion of the exceeded failed tests from guideline. The final water quality index value is reported with a number between 1 and 100; the quality ranges from the poorest value (1) to the best value of the water quality (100) (UNEP, 2007).

3. Case study

To assess the performance of the proposed index under actual conditions, a case study of water quality was carried out at Mamloo dam, Iran, employing monthly measured water quality data of four sampling stations in the water basin of the dam over the period 2006–2009. The first sampling station is located at Jajrood River, covering a length of 40 km and a surface area of 710 km^2. The river is located at north-east of Tehran, Iran's capital, and originates from Mt. Damavand. The second sampling station was located on the River Damavand, which also originates from Mt. Damavand and flows into the River Jajrood. These two rivers are of critical importance in the area because they provide drinking water for the mega city of Tehran, which has a population of 9 million. The third sampling station was located on the River Jajrood, after its intersection with the River Damavand. Finally, the last sampling station was located on the Mamloo dam reservoir, which has a water quality that is a combination of those found in the two rivers. Locations of the sampling stations are illustrated in Fig. 4. Water quality data was collected by the Ghatrab Zolal Corporation.

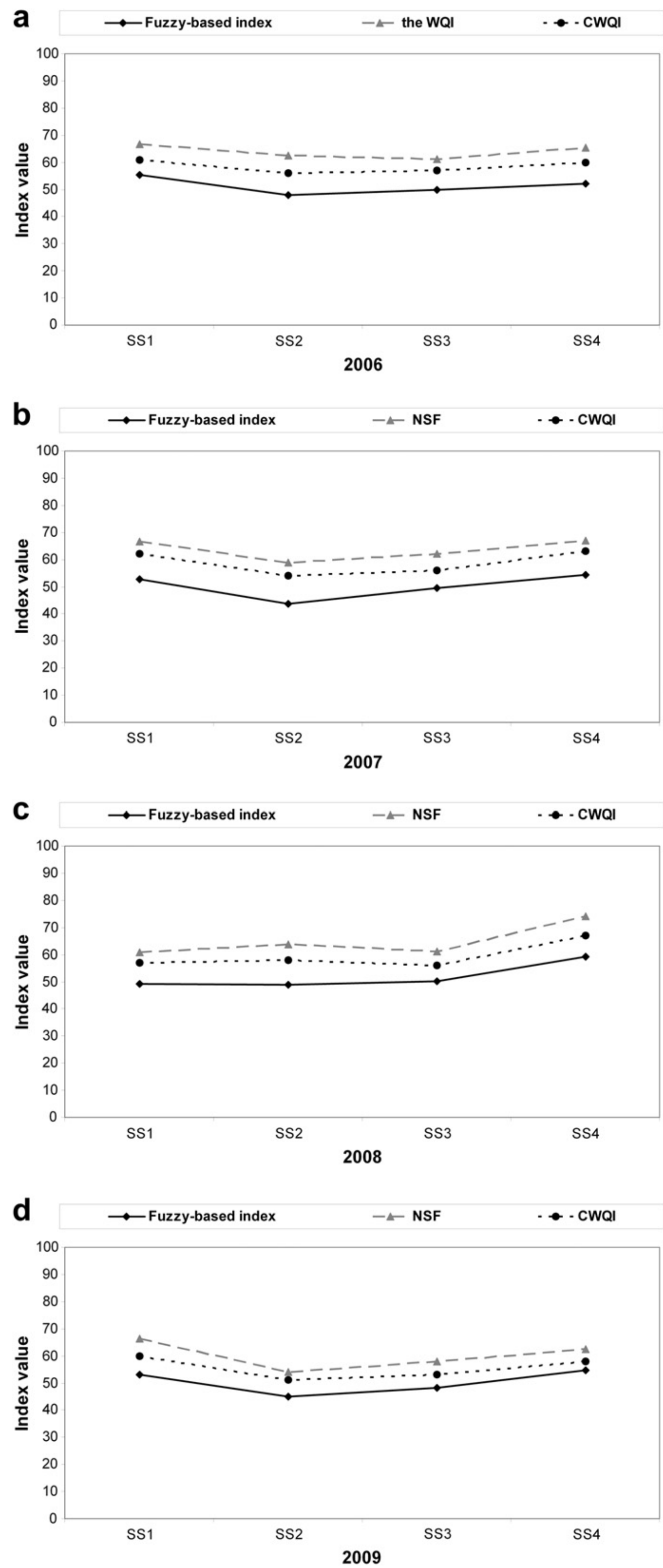

Fig. 6. Annual averages of the fuzzy-based index values in all sampling stations compared with those of the WQI and the CWQI for the years 2006 (a), 2007 (b), 2008 (c), and 2009 (d).

4. Results and discussions

4.1. Evaluation of the proposed index using water quality data from the Mamloo dam

Fig. 5 illustrates the annual averages of the final scores of the fuzzy-based index for the four sampling stations over the study period (2006–2009). As can be seen from the figure, the general quality of water in all the sampling stations over all the years of the study period is fairly low (yearly averages are usually in the range of 45–55), which implies that this water was inappropriate for human drinking purposes.

In all sampling stations, according to the results of an analysis of variance (ANOVA), water quality did not significantly change over time ($P > 0.05$); even the small differences observed between the yearly averages of the year 2009 and those of the other years were not significant. Additionally, for each specific year the water quality did not vary significantly at different sampling stations ($P > 0.05$). This may be because no appropriate pollution control was being taken toward improving the water quality in the area.

Fig. 6(a–d) shows a comparison of the outputs of the fuzzy-based proposed index with those of the NSF Water Quality Index (the WQI) and the Canadian Water Quality Index (CWQI) at the four sampling stations over the period 2006–2009. As shown in the figure, all indices showed similar results and were sensitive to changes in the level of water quality parameters. However, the index proposed by the present study produced a more stringent output than the WQI and CWQI. This is probably due to the fact that environmentally critical pollutants like heavy metals are not included in the WQI, which meant that higher water quality scores were produced by the WQI index due to its lower sensitivity to changes in the levels of water quality parameters. Regarding the CWQI, although any parameter can be included (here we applied all of the twenty parameters), the index values were still higher than those of the fuzzy-based proposed index since only the percentage of the samples exceeding the standard value for each parameter is considered in the calculation (rather than how high the value is compared with the standard level). Additionally, since the quality of water from different stations at Mamloo dam generally lay in the moderate range, we also calculated the above three index values for two different river waters having poor and high quality to test and compare the performance of the fuzzy index with those of the WQI and the CWQI indices under extreme conditions, the results of which are illustrated in Fig. 7. As with normal conditions, the high

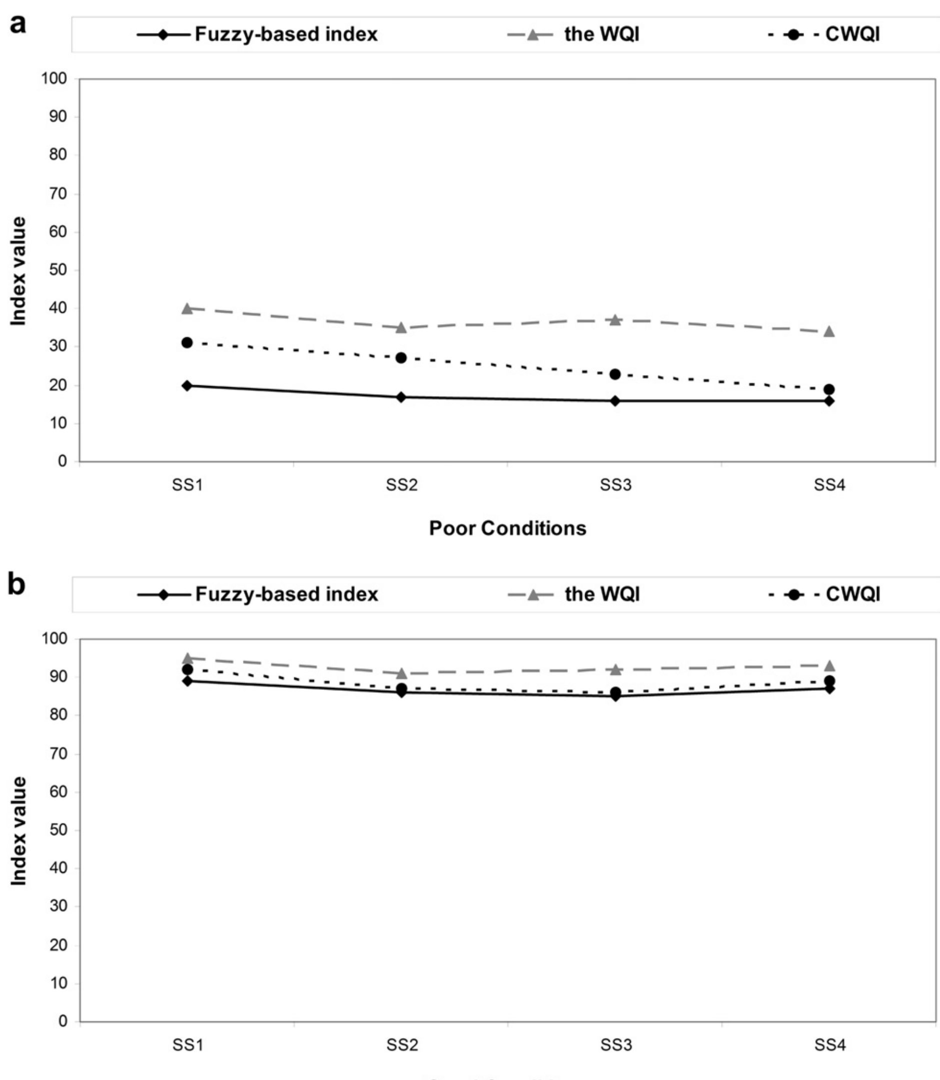

Fig. 7. Comparison of the outputs of the fuzzy-based index with those of the WQI and the CWQI under extreme water quality conditions: a) poor conditions; and b) good conditions.

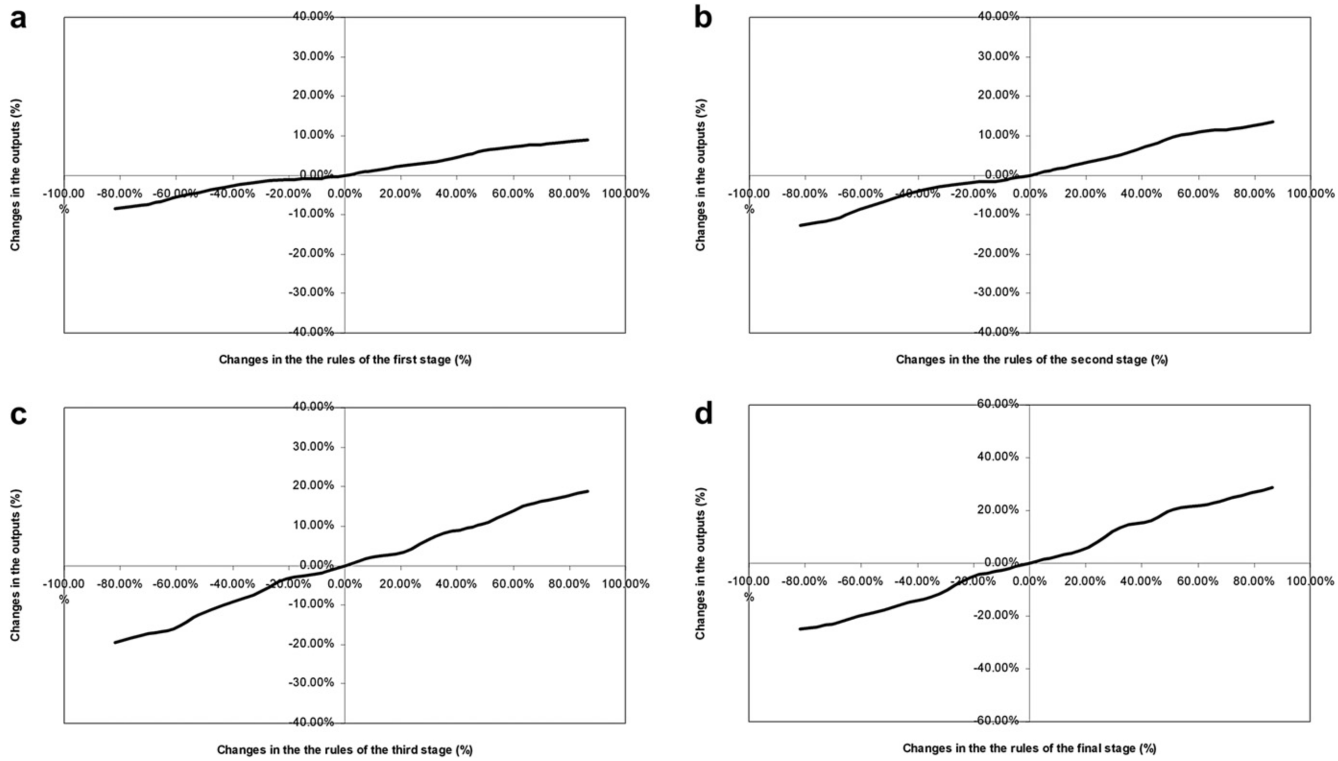

Fig. 8. Results of the sensitivity analysis conducted to evaluate the effect of changes in the rules on the final index value (a–d).

correlation between the values from different indices was maintained, implying the robustness of the proposed fuzzy index even under extreme conditions. Similar results have been reported by other studies that have described the development of water quality indices based on fuzzy logic (Icaga, 2007; Lermontov et al., 2009; Liou et al., 2003; Ocampo-Duque et al., 2006).

In another study conducted by our research group, a dairy cattle water quality index (DCWQI) was developed to indicate the appropriateness of drinking water quality for dairy cattle (Gharibi et al., 2012). In the above index, we sought to explore the indirect impacts of environmental pollution on human health through the food chain since the contaminants, such as heavy metals, accumulated in the body of dairy cattle via drinking polluted water can finally transport to human body and pose their adverse effects. However, the present index was developed with the aim of assessing the direct influence of environmental pollution on human health via drinking contaminated water. In addition, the previous work can be considered as the first drinking water quality index for dairy cattle, while the current index could be thought of as an improvement over the so far existing fuzzy-based indices mentioned earlier. Furthermore, since the aims of the two indices differed significantly, we included different quality parameters in each index based on the specified objectives. Therefore, not only the inference rules we applied to each index, but also their importance varied significantly based on the objectives. Finally, another advantage of the current index, compared to the previous indices, is that not only does it deal with numerical data, but it can also apply expert's knowledge and experience through the inference rules.

4.2. Index validation

Although it is very difficult to validate the proposed index, validation can be attempted through three distinct approaches. One of the most critical approaches is the methodology used in developing the index, that is, fuzzy logic. This methodology has been proven to be appropriate for development of environmental indices, because it has the ability to reflect human thoughts and expertise, which enables it to deal with non-linear, uncertain, ambiguous, and subjective information. In addition, since the index is based on linguistic terms, the process as well as the results are more understandable for the public, managers, and non-experts in general (McKone and Deshpande, 2005; Silvert, 2000).

The second approach addresses the inclusion of the parameters in the index. As described in Section 2.5, all of the parameters that were included in the index were of considerable importance for the overall quality of water and can greatly affect human health if the water is used for drinking purposes. Therefore, it seems that all of these parameters should be included in the index if it is to be representative of the overall water quality.

Finally, we assessed the robustness of the index by a sensitivity analysis. For this purpose, we considered the final rule set of the index as the baseline, and then measured the changes/deviations, which were intentionally made, from the baseline as the percentage of change/variation in the rule sets of different stages. In fact, the percent of change in the rules of each stage was obtained by calculating the number of rules that differed from that of the baseline rule set. For instance, considering a total of 25 rules in the rule set of the final stage, if 5 rules had been manipulated in the rule set of this stage, the percent of change/variation would have been 25%. The results of the sensitivity analysis are illustrated in Fig. 8(a–d). This figure suggests that the changes in the rules of different stages of the fuzzy-based index did not significantly change the index outputs. This can be illustrated by a nearly 80% change in the fuzzy rules of the first stage which changed the index outputs by only 8%, implying that the index is quite robust against the changes.

5. Conclusions

According to the results of the present study, the following conclusions can be drawn:

- The fuzzy-based water quality index we developed produces more stringent results than those of the WQI due to the distinct computational method applied, as well as inclusion of a higher number of parameters, all of which are critical for assessment of water quality, particularly for human drinking purposes.
- The index proposed by the present study seems to produce accurate and reliable results. Therefore, it is suggested that it be used as a comprehensive tool for assessment of water quality, especially when assessing water for human consumption.

Acknowledgments

We wish to thank the Ghatrab Zolal Corporation because of their great help in provision of the water quality data. In addition, we are grateful to the experts who participated in developing and revising the rules applied to the index.

References

Chang, N.B., Chen, H.W., Ning, S.K., 2001. Identification of river water quality using the fuzzy synthetic evaluation approach. J. Environ. Manage. 63, 293–305.
Chau, K.W., 2006. A review on integration of artificial intelligence into water quality modelling. Mar. Poll. Bull. 52, 726–733.
Clark, K., 2008. Cow Creek Water Quality Monitoring Report 2006–2008. Idaho Association of Soil Conversation Districts, Moscow.
Counter, S.A., Buchanan, L.H., 2004. Mercury exposure in children: a review. Toxicol. Appl. Pharmacol. 198, 209–230.
De Flora, S., Bagnasco, M., Serra, D., Zanacchi, P., 1990. Genotoxicity of chromium compounds. A review. Mutat. Res. 238, 99–172.
Duker, A.A., Carranza, E.J.M., Hale, M., 2005. Arsenic geochemistry and health. Environ. Int. 31, 631–641.
Gangolli, S.D., van den Brandt, P.A., Feron, V.J., Janzowsky, C., Koeman, J.H., Speijers, G.J.A., Spiegelhalder, B., Walker, R., Wishnok, J.S., 1994. Nitrate, nitrite and N-nitroso compounds. Eur. J. Pharmacol. Environ. Toxicol. Pharmacol. 292, 1–38.
García-Lestón, J., Méndez, J., Pásaro, E., Laffon, B., 2010. Genotoxic effects of lead: an updated review. Environ. Int. 36, 623–636.
Gharibi, H., Sowlat, M.H., Mahvi, A.H., Mahmoudzadeh, H., Arabalibeik, H., Keshavarz, M., Karimzadeh, N., Hassani, G., 2012. Development of a dairy cattle drinking water quality index (DCWQI) based on fuzzy inference systems. Ecol. Indic. 20, 228–237.
Harrison, P.T.C., 2005. Fluoride in water: a UK perspective. J. Fluorine. Chem. 126, 1448–1456.
Icaga, Y., 2007. Fuzzy evaluation of water quality classification. Ecol. Indic. 7, 710–718.
Jang, J., Sun, C., 1995. Neurofuzzy modeling and control. Proc. IEEE 83, 378–406.
Järup, L., Åkesson, A., 2009. Current status of cadmium as an environmental health problem. Toxicol. Appl. Pharmacol. 238, 201–208.
Karr, C., Gentry, E., 1993. Fuzzy control of pH using genetic algorithms. IEEE Trans. Fuzzy Syst. 1, 46–53.
Lermontov, A., Yokoyama, L., Lermontov, M., Augusta, M., Machado, S., 2009. River quality analysis using fuzzy water quality index: Ribeira do Iguape river watershed, Brazil. Ecol. Indic. 9, 1188–1197.
Liou, S., Lo, S., Wang, S., 2004. A generalized water quality index for Taiwan. Environ. Monitor. Assess. 96, 35–52.
Liou, S.M., Lo, S.L., Hu, C.Y., 2003. Application of two-stage fuzzy set theory to river quality evaluation in Taiwan. Water Res. 37, 1406–1416.
Lu, R.S., Lo, S.L., Hu, J.Y., 1999. Analysis of reservoir water quality using fuzzy synthetic evaluation. Stoch. Environ. Res. Risk Assess. 13, 327–336.
McKone, T.E., Deshpande, A.W., 2005. Can fuzzy logic bring complex environmental problems into focus? Environ. Sci. Tech. 15, 42–47.
Mirabbasi, R., Mazloumzadeh, S.M., Rahnama, M.B., 2008. Evaluation of irrigation water using fuzzy logic. Res. J. Environ. Sci. 2, 340–352.
Nasiri, F., Maqsood, I., Huang, G., Fuller, N., 2007. Water quality index: a fuzzy river pollution decision support expert system. J. Water Resour. Plan. Manage. 133, 95–105.
Nemerow, N.L., Agardy, F.J., Sullivan, P., Salvato, J.A., 2009. Environmental Engineering: Water, Wastewater, Soil and Groundwater Treatment and Remediation, sixth ed. John Wiley & Sons Inc, New York.
Ocampo-Duque, W., Ferre-Huguet, N., Domingo, J.L., Schuhmacher, M., 2006. Assessing water quality in rivers with fuzzy inference systems: a case study. Environ. Int. 32, 733–742.
Ocampo-Duque, W., Schumacher, M., Domingo, J.L., 2007. A neural-fuzzy approach to classify the ecological status in surface waters. Environ. Pollut. 148, 634–641.
Ott, W.R., 1978. Water Quality Indices: a Survey of Indices Used in the United States. US Environmental Protection Agency, Washington, DC.
Rittmann, B.E., McCarty, P.L., 2001. Environmental Biotechnology: Principles and Applications. McGraw-Hill, Singapore.
Ross, T.J., 2004. Fuzzy Logic with Engineering Applications. John Wiley & Sons, New York.
Said, A., Stevens, D., Selke, G., 2004. An innovative index for evaluating water quality in streams. Environ. Manage. 34, 406–414.
Sasikumar, K., Mujumdar, P.P., 1998. Fuzzy optimization model for water quality management of a river system. J. Water Resour. Plan. Manage. 124, 79–88.
Silvert, W., 2000. Fuzzy indices of environmental conditions. Ecol. Modell. 130, 111–119.
Smith, H.V., Nichols, R.A.B., 2010. Cryptosporidium: detection in water and food. Exp. Parasitol. 124, 61–79.
Sowlat, M.H., Gharibi, H., Yunesian, M., Mahmoudi, M.T., Lotfi, S., 2011. A novel, fuzzy-based air quality index (FAQI) for air quality assessment. Atmos. Environ. 45 (12), 2050–2059.
Stokinger, H.E., 1981. The metals. In: Putty's Industrial Hygiene and Toxicology. Wiley, New York.
Turksen, I., 1991. Measurement of membership functions and their acquisition. Fuzzy Sets Syst. 40, 5–38.
UNEP, 2007. Global Drinking Water Quality Index Development and Sensitivity Analysis Report. United Nations Environment Programme Global Environment Monitoring System/Water Programme. From: http://www.gemswater.org (accessed 20.12.11.).
USEPA, 2011. Drinking Water Contaminants. National Primary Drinking Water Regulations. From: <http://water.epa.gov/drink/contaminants/> (accessed 20.12.11.).
Yager, R., Filev, D., 1994. Essentials of Fuzzy Modeling and Control. John Wiley & Sons, Inc, New York.
Zadeh, L.A., 1965. Fuzzy sets. Inf. Control 8, 338–353.
Zadeh, L., 1973. Outline of a new approach to the analysis of complex systems and decision processes. IEEE Trans. Syst. Man. Cybern. 3, 28–44.