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Immediate water quality assessment in shrimp culture using fuzzy inference systems

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ABSTRACT

The continuous monitoring of physical, chemical and biological parameters in shrimp culture is an important activity for detecting potential crisis that can be harmful for the organisms. Water quality can be assessed through toxicological tests evaluated directly from water quality parameters involved in the ecosystem; these tests provide an indicator about the water quality. The aim of this study is to develop a fuzzy inference system based on a reasoning process, which involves aquaculture criteria established by official organizations and researchers for assessing water quality by analyzing the main factors that affect a shrimp ecosystem. We propose to organize the water quality parameters in groups according to their importance; these groups are defined as daily, weekly and by request monitoring. Additionally, we introduce an analytic hierarchy process to define priorities for more critical water quality parameters and groups. The proposed system analyzes the most important parameters in shrimp culture, detects potential negative situations and provides a new water quality index (WQI), which describes the general status of the water quality as *excellent*, *good*, *regular* and *poor*. The Canadian water quality and other well-known hydrological indices are used to compare the water quality parameters of the shrimp water farm. Results show that WQI index has a better performance than other indices giving a more accurate assessment because the proposed fuzzy inference system integrates all environmental behaviors giving as result a complete score. This fuzzy inference system emerges as an appropriated tool for assessing site performance, providing assistance to improve production through contingency actions in polluted ponds.

1. Introduction

Shrimp farming is a common activity in the coastal zone of many tropical countries around the world. The understanding of the ecological processes occurring in water bodies and in shrimp culture ponds can help to understand and solve some of the disease issues faced by shrimp farmers (Ferreira, Bonetti, & Seiffert, 2011). Water management in shrimp culture is crucial for a good growing of organisms, and it is a precedent for a good quality and quantity on the final product. On the contrary, adverse water quality conditions increase shrimp stress generating low reproduction and growing mortality rates, and favoring the emergence of diseases (Casillas, Nolasco, García, Carrillo, & Páez, 2007). The main objective in water management is to control environmental parameters that could have a negative effect over the ecosystem, avoiding potential crisis in shrimp ponds. Currently, knowledge based systems are important tools for treatment of water quality crisis and for disease/health management of aquaculture systems. These systems also provide different solutions to ecological problems in shrimp ponds (Duana, Fub, & Lib, 2003; Nan, Ruimei, Jian, Zetian, & Xiaoshuan, 2009; Xiaoshuan, Zetian, Wengui, Dong, & Jian, 2009).

Several methodologies for the assessment and monitoring of water pollutants have been implemented by organizations such as the US *National Sanitation Foundation* (NSF, 2010), the Canadian Council Ministry of Environment (CCME, 2004), the Catalan Water Agency (ACA, 2010) and the Mexican Ministry of Agriculture, Livestock, Rural Development, Fisheries and Food (SAGARPA, 2010). These organizations have developed indices for water quality. Additionally, in the literature some authors as Ferreira et al. (2011), Simões, Moreira, Bisinoti, Nobre, and Santos (2008) and Beltrame, Bonetti, and Bonetti (2004) have also proposed water quality indices, providing good alternatives for aquaculture assessment. However, all these and other similar indices have as drawback that some parameters in the index equation can dramatically influence the final score without a valid justification. However, the most critical deficiency of these indices is the absence of uncertainty or subjectivity management, which is present in this

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complex environmental problem when different parameter conditions induce to different water quality situations and they are not considered in the mathematical process.

Alternative models for assessing water quality using fuzzy logic theory have been proposed in the literature, these models introduce environmental levels in the respective parameters, which produces a more accurate water quality evaluation (Gutiérrez, 2004; Gutiérrez et al., 2006; Hernández & Villarreal, 1999; Ocampo, Ferré, Domingo, & Schuhmacher, 2006). However, those researches are based on fresh water bodies or these works do not perform a complete analysis of water quality parameters without integrating all parameters and harmful situations together in a complete quality index.

Other works analyze similar ecological problems for environmental pollution by applying artificial intelligence techniques such as artificial neural networks (Muttil & Chau, 2006; Salazar, 2007), associative memories (Yañez, López, & De la Luz, 2008), support vector machines (Li, Li, & Wang, 2006; Wang, Men, & Lu, 2008) and factor analysis (Bishoi, Prakash, & Jain, 2009) among others. All of them have the same lack of a reasoning process to handle uncertainty and subjectivity.

Recently in Carbajal, Sánchez, and Moreno (2010) a new fuzzy model for water quality assessment was proposed. This model can be used for assessing the most frequently and critical water quality parameters of shrimp culture (pH, salinity, dissolved oxygen and temperature; Chien, 1992). This model also has been applied to predict potential crisis in shrimp ponds, see for example Carbajal, Sánchez, Oropeza, and Felipe (2009), and Carbajal, Sánchez, and Progrebnyak (2011). In order to get a more accurate water assessment in shrimp culture, in this paper unlike in Carbajal et al. (2010) we use a more complete set of parameters, we assign priorities to critical parameters and we classify potentially harmful situations by handling uncertainty and subjectivity through a fuzzy inference system. Moreover, since monitoring a huge set of environmental parameters is a hard task in extensive farms the proposed fuzzy inference system allows an immediate water quality assessment using current parameters values unlike previous approaches, which assess water quality for time periods, requiring a set of measurements taken along the studied time period.

Finally, the proposed fuzzy inference system is used for analyzing the ecosystem of a shrimp farm in Sonora, Mexico area, where environmental parameters are assessed for establishing an indicator for good or bad water quality.

2. Aquaculture and water quality requirements

Aquaculture is defined as the high-density production of fish, shellfish and plant forms in a controlled environment. Water quality for aquaculturists, refers to the quality of water that enables successful reproduction of the desired organisms. The required water quality is determined by the specific organisms to be cultured and has many components that are interwoven. Aquaculture obeys a set of physical, chemical and biological principles. Since these principles compose the subject of water quality, in Section 2.1 we describe common water quality parameters related to these principles which have been used as indicators of water quality on shrimp marine culture, as well as the respective classification of these parameters by monitoring importance. In Section 2.2, we present a classification of the parameters based on their impact level in an ecosystem.

2.1. Physical, chemical and biological analysis

The monitoring of environmental parameters in shrimp aquaculture allows the control and good management of water quality in shrimp ponds, avoiding the occurrence of unfavorable conditions that can be harmful for organisms (Boyd, 2002; Ferreira et al., 2011).

Table 1
Water quality parameters classified by monitoring frequency.

Daily monitored	Weekly monitored	Monitored by request
Temperature (Temp)	Total ammonia (NH)	Alkalinity (Ak)
Dissolved oxygen (DO)	Nitrate (NO_3)	Phosphorus (P)
Salinity (Sal)	Nitrite (NO_2)	Hydrogen sulfide (H_2S)
pH	Non ionized ammonia (NH_3)	Non ionized hydrogen sulfide (HS^-)
	Turbidity (Tb)	Dioxide of carbon (CO_2)
		Suspended solids (Ss)
		Potential redox (Px)
		Silicate (Si)
		Chlorophyll A (ChA)
		Total inorganic nitrogen (N)
		Total marine bacteria (Tmb)
		Vibrio (Vb)
		Fecal coliforms (Fc)

Water quality is based on the results of toxicity tests. These tests measure the responses of aquatic organisms to defined quantities of specific pollutants (Chien, 1992; Páez, 2001). The aquatic species have different tolerances for a specific toxic compound; in this paper the characteristics of the *Litopenaeus vanammei* shrimp are analyzed to evaluate the performance of the model.

In extensive aquaculture systems on Central America, the water quality parameters are monitored in different frequencies. Dissolved oxygen, temperature, pH and salinity are monitored daily while ammonia, nitrates, turbidity and algae counts are analyzed weekly. Chemical analyses are not taken into consideration for water quality management on a routine bases, they are only monitored by request (Carbajal et al., 2011; Hirono, 1992). Table 1 lists common water quality parameters used as indicators of water quality on shrimp marine culture and their respective classification by monitoring frequency.

In order to understand the effects of these water quality parameters, Tables 2 and 3 show the optimal and harmful ranges (reported in the literature) for daily, weekly and by request parameters which will be considered for the assessment of water quality in our work.

2.2. Environmental classification

Water quality parameters can be classified in different impact levels, depending on the toxicity and harmful situations the parameters produced into the ecosystem. In order to classify the behavior of a water quality parameter, it is necessary to define levels and allowed deviations for optimal or harmful concentrations. These deviations are useful to determine the bounds of ranges where values are considered closer to or farther from specified levels. In this study, tolerance thresholds were chosen using minimal changes in water parameters (Boyd, 2000; SEMARNAP, 1996). The levels for classification of the water quality parameters were defined taken into account the levels and limits reported in the literature (see Table 2). In Tables 4–6 we show the classification, in different impact levels, for water quality parameters from Table 1. The deviation column in these tables represents the tolerance for each level.

3. Water quality index for immediate assessment (WQI)

The importance of water quality management, the correct interpretation of water parameters and the appropriated techniques for integrating these parameters are problems studied in the

Table 2
Daily and weekly measured water quality parameters and their importance to shrimp farming.

	Parameters	Importance on marine shrimp culture
Daily Monitored	Temperature	The demand of dissolved oxygen increases when temperature is high (Martínez, 1994). Changes in temperature rates can stress shrimp and consequently high mortality rates can be present in the population (Navarro et al., 1992). Temperature controls solubility of gases, chemical reactions and toxicity of the ammonia. Temperature can be considered as normal from 28 to 32 °C (Boyd, 1989; Carbajal et al., 2011; Hirono, 1992)
	Dissolved oxygen	Fluctuation of dissolved oxygen, hypoxia and anoxia crisis are events that can be normally presented in aquaculture systems. Dissolved oxygen is considered the most critical quality parameter, since shrimps in low dissolved oxygen concentrations are more susceptible to disease. The minimum levels recommended by authors oscillate between 4 and 5 ppm. It is recommended that dissolved oxygen level should be kept above 2 ppm (Boyd, 1992; Chien, 1992; Martínez, 1994)
	Salinity	High salinity concentrations reduce dissolve oxygen in water ponds. (Páez, 2001). The optimal concentrations of salinity are from 15 to 23 ppt (Boyd, 1992; Páez, 2001)
	pH	Extremely low or high pH stresses shrimp and causes soft shell and poor survival (Chien, 1992). Water bodies with 6.5 to 9.0 pH concentrations are appropriate for aquaculture production. Reproduction decrease out of this range. Acid death appears with values below than 4.0 and an alkaline death in values above 11 (Arredondo and Ponce, 1997; Carbajal et al., 2011; Martínez, 1994)
Weekly Monitored	Ammonia	Ammonia is the main end product of protein catabolism in crustaceans. Ammonia increases tissue oxygen consumption, damages gills and reduces the ability of blood to transport oxygen. Ammonia exists in water in both ionized (NH_4^+) and unionized (NH_3) forms. Unionized ammonia is the most toxic form of ammonia due to its ability to diffuse readily across cell membrane (Bower and Bidwell, 1978). The safe level for unionized ammonia, recommended by Chien (1992) and Wickins (1976), is less than 0.1 mg/l and for total ammonia is under 1.0 mg/l
	Water nitrogen	Inorganic nitrogen in water is chiefly present as ammonia, nitrate and nitrite. In shrimp, the respiratory pigment is hemocynanin, which can still bind oxygen in the presence of oxidizing agents as nitrite (Needham, 1961). The safe concentration of NO_2 is from 0.4 to 0.8 mg/l. Nitrates are nitrogenous compounds can be toxic when their levels rise. According to Clifford (1994), the optimal level for nitrates is from 400 to 800 μg/l. The expected total inorganic nitrogen recommended for crop is from 2.0 to 4.0 mg/l. (Chien, 1992; Páez, 2001)
	Turbidity	A high concentration of suspended solids can cause high turbidity in water, preventing the penetration of light and affecting photosynthesis. The amount of suspended solids can be determined indirectly by measuring the turbidity. The accepted range for suspended solids is from 50 to 150 mg/l; or turbidity from 35 to 45 cm depth (Martínez, 1994)

Table 3
Water quality parameters measured by request and their importance to shrimp farming.

	Parameters	Importance on marine shrimp culture
Monitored by request present	Alkalinity	Related to important factors in shrimp culture as buffer effect on daily variation of pH in the pond, setting the soluble iron precipitated, and in ecdysis (molting) and growth (Boyd, 2002; Ferreira et al., 2011)
	Phosphorus	Nutritive element, mainly appearing as orthophosphate, essential to aquatic life. For Esteves (1998), phosphorus acts particularly in metabolic processes of living beings, such as energy storage and structure of the cell membrane (Ferreira et al., 2011)
	Hydrogen sulfide	In water, hydrogen sulfide exists in unionized (H_2S) and ionized forms (HS^- and S_2). Only de unionized form is considered toxic to aquatic organisms. Unionized H_2S concentration is dependent on pH, temperature and salinity, and it is mainly affected by pH (Chien, 1992)
	Dioxide of carbon	When dissolved oxygen concentrations are low, carbon dioxide obstacles oxygen penetration. According to Boyd (2001), normal range of carbon dioxide is from 1 to 10 mg/l
	Potential redox	It is an indicator of substance oxidation or reduction levels. Low values are indicators of strong reduction of sediment, which is associated with toxic metabolites formation, hypoxic or anoxic conditions and low pH values. In a pond, optimal ranges of potential redox are from 500 to 700 mV for water and from 400 to 500 mV for sediment (Clifford, 1994)
	Silicate	Into water, it is a composite of high importance because diatoms to carapace composition use it. Optimal levels for silicate are established from 0.1 to 0.3 mg/l. (Esteves, 1998; Ferreira et al., 2011)
	Chlorophyll A	Phytoplankton biomass represents the primary consumer feed, and indirectly determines the feed availability of the next trophic system levels. The ideal concentrations for shrimp ponds are from 50 to 70 μg/l (Clifford, 1994)
	Total marine bacteria	Microorganisms, particularly bacteria, play a vital role in pond ecosystems. Both beneficial (nutrients recycling, organic matter degrading etc.) and harmful role (as parasites) are caused by bacteria in the pond ecosystem. Optimal range for total bacteria counts should be below 10,000 UFC/ml (Anand, Das, Chandrasekar, Arun, & Balamurugan, 2010; Ferreira et al., 2011)
	Vibrio	Vibriosis is a bacterial disease responsible for mortality of cultured shrimp worldwide (Chen, Liu, & Lee, 2000; Lightner and Lewis, 1975). Vibrio related infections frequently occur in hatcheries, but epizootics are also commonly in pond reared shrimp species. Optimal ranges are defined below 1000 UFC/ml
	Fecal Coliforms	Fecal Coliforms in water come from feces of warm-blooded animals and they are an indicator of water pollution. The optimal range of fecal coliforms is below 1000 MPN/ml and for crop it should not exceed 1400 MPN/ml (Boyd, 2000)

aquaculture field. This research deals with one of the most important objective of the aquaculture management: it proposes a new way to join dissimilar parameters for getting an accurate assessment of water quality, increasing the effectiveness of the proposed system over traditional methodologies. In this sense, we hypothesize that different effects and levels of parameter concentrations degenerate in different water quality, thus, an appropriated join of these parameters could determinate a better assessment of water quality. This assessment could be done using a fuzzy inference system, which involves different situations generated by water quality parameters.

3.1. Water quality assessment

A water quality index (WQI) expresses the overall water quality in a given place and time based on different physical, chemical and biological parameters (Ferreira et al., 2011). In our research, we propose to classify water quality in four levels; these levels were defined jointly with the experts in aquaculture taking into account the pollution effects of water parameters.

1. *Excellent*: Suitable for good crop.
2. *Good*: Suitable, but possible stress effects in shrimp organisms.

Table 4
Classification levels for daily monitored parameters.

Water quality parameters	Deviation	Levels				
		Hypoxia acid	Low	Normal	High	Alkaline
Temperature (°C)	1.0		0–20	20–30	<30	
Dissolved Oxygen (mg/l)	0.5	0–2	2–5	<5		
Salinity (ppt)	1.0		0–15	15–23	<23	
pH	0.5	0–4	4–6.5	6.5–9.5	9.5–11	11–14

Table 5
Classification levels for weekly monitored parameters.

Water quality parameters	Deviation	Levels		
		Low	Normal	High
Total ammonia (mg/l)	0.10	0–0.1	0.1–1.0	<1.0
Nitrites (μg/l)	100	0–400	400–800	<800
Nitrates (mg/l)	0.10		0–0.5	<0.5
Non ionized ammonia (mg/l)	0.01		0–0.1	<0.1
Turbidity (cm)	1.00	4–35	35–45	<45

3. *Regular*: Unsuitable for good crop; grater stress levels for shrimp.
4. *Poor*: Unsuitable for crop; potential crisis in pond and possible high mortality rates.

3.2. Fuzzy inference systems

Fuzzy inference is the process of formulating a mapping from a given input to an output using fuzzy logic. This mapping can help us to make decisions, or to discern patterns. The process of fuzzy inference involves three important concepts: membership functions, logical operations, and If-Then rules (Gutiérrez, 2004; Ocampo et al., 2006; Zadeh, 1965).

This section describes the proposed fuzzy inference process using water quality parameters as inputs to produce one water quality level (water quality index). The basic structure of the fuzzy inference system (FIS) is shown in Fig. 1.

3.2.1. Fuzzy inputs

Water quality parameters are defined by limits, which must not be exceeded. However, when a concentration is close to a boundary, the water quality condition could not be clearly established. In this sense, the uncertainty treatment determines the level of a concentration close to a limit and it is implemented in the inputs of the FIS as membership functions.

A membership function (μ) transforms a real value (measurement) into a $[0,1]$ value. The most common membership functions are triangular, rectangular and trapezoidal or Gaussian (Ocampo et al., 2006; Shen, Shun, & Pie, 2007). There is not a specific criterion to build custom membership functions; they can be implemented in different ways. However, for the purpose of the present study, linear fuzzy sets make easier the defuzzification process and provide good performance. Trapezoidal membership functions define the input transformation of the FIS (Carbajal et al., 2011; Ocampo et al., 2006), and they can be represented as in expression 1

$$\mu(x,a,b,c,d) = \min\left\{\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right\} \quad (1)$$

where x is a water quality variable; a, b, c and d are membership parameters. Fig. 2 shows the membership functions for WQI and daily measured parameters used in our study. Membership functions for weekly and by request monitoring were developed in a similar way using their respective levels and deviations, having similar shapes as those showed also in Fig. 2.

3.2.2. Fuzzy operators

After the inputs are fuzzified, the membership degree of each part of the rule antecedent is computed. If the antecedent of a rule has more than one input, a fuzzy operator is applied to obtain the result of the rule. In this case, three fuzzy operators (see expressions (2) to (4)) were used: union (OR), intersection (AND) and negation (NOT) operators (Zadeh, 1978).

$$\text{Union(OR)} \quad \mu_{A\cup B}(x) = \max\{\mu_A(x), \mu_B(x)\} \quad (2)$$

$$\text{Intersection(AND)} \quad \mu_{A\cap B}(x) = \min\{\mu_A(x), \mu_B(x)\} \quad (3)$$

$$\text{Negation(NOT)} \quad \mu_{\bar{A}}(x) = 1 - \mu_A(x) \quad (4)$$

3.2.3. Inference rules (reasoning process)

Subjectivity may refer to the specific discerning interpretations of any aspect of experiences. The proposed index uses subjectivity in order to determine different problems in the ecosystem generated by different parameter concentrations. This process is implemented using fuzzy rules, whose are included within the FIS.

Table 6
Classification levels for monitored by request parameters.

Water quality parameters	Deviation	Levels		
		Low	Medium	High
Alkalinity (mg/l)	10	0–100	100–140	<140
Phosphorus (mg/l)	0.01	0–0.1	0.1–0.3	<0.3
Hydrogen sulfide (mg/l)	0.01	0–0.05	0.05–0.1	<0.1
Non ionized hydrogen sulfide (mg/l)	0.001	0–0.002	0.002–0.005	<0.005
Carbón dioxide (mg/l)	2	0–10	10–20	<20
Suspension solids (mg/l)	5	0–50	50–150	<150
Potential redox (mV)	10	0–400	400–500	<500
Silicate (mg/l)	0.2	0–2.0	2.0–4.0	<4.0
Chlorophyll A (μg/l)	5	0–50	50–75	<75
Total inorganic nitrogen (mg/l)	0.2	0–2	2–4	<4
Total marine bacteria (UFC/ ml)	1000	0–5000	5000–10,000	<10,000
Vibrio (UFC/ ml)	100	0–500	500–1000	<1000
Fecal coliforms (MPN/ml)	100	0–500	500–1000	<1000

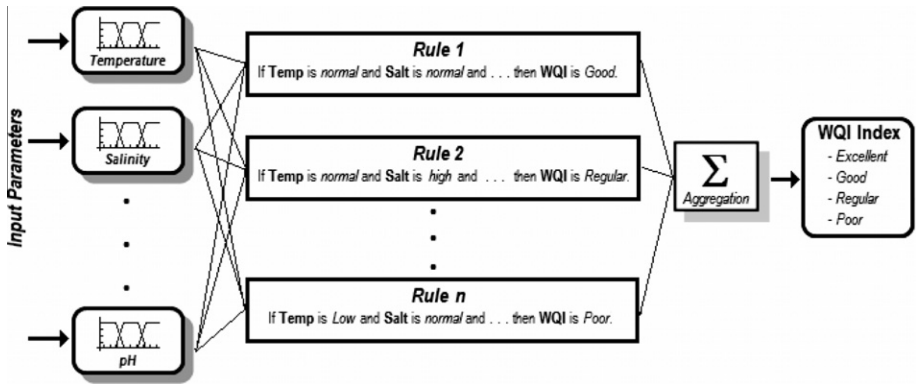

Fig. 1. Architecture of the fuzzy inference system using parameters and rules of shrimp aquaculture.

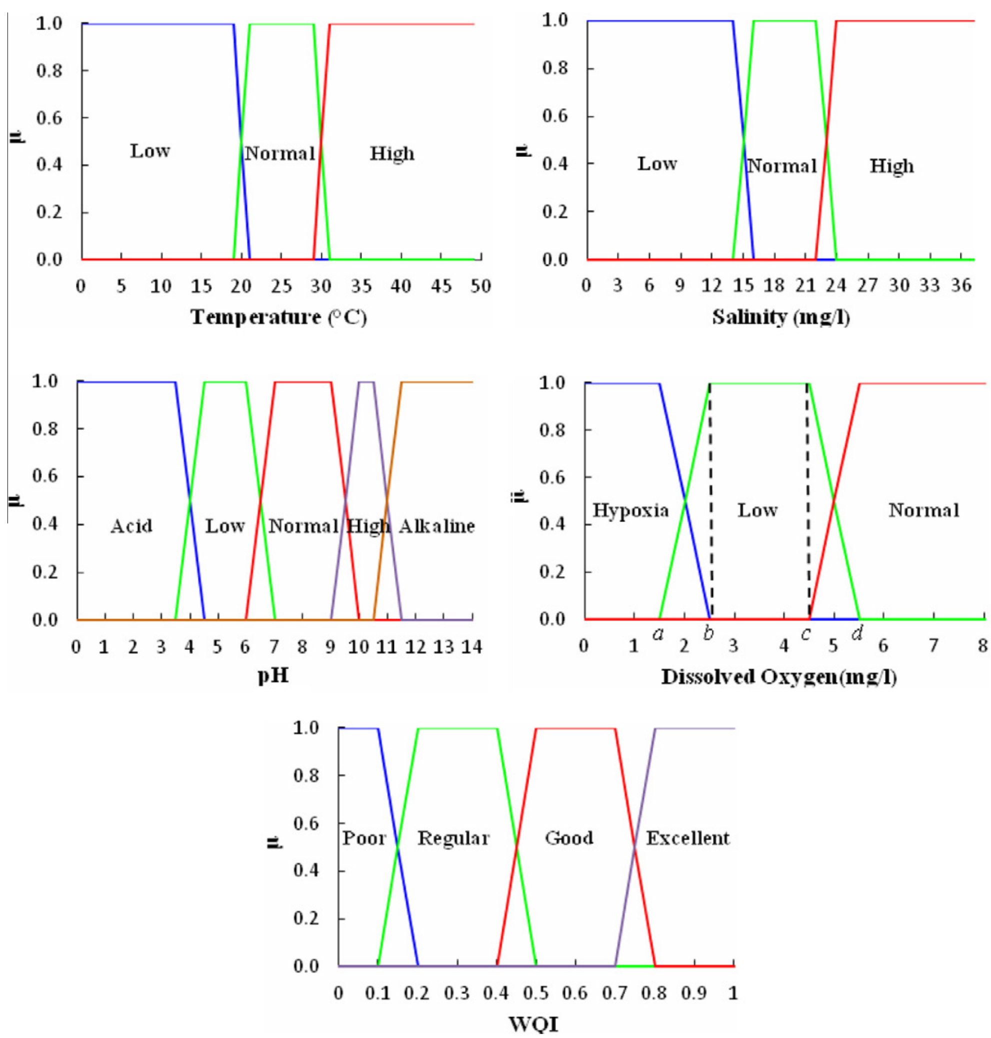

Fig. 2. Membership functions for WQI and daily measured parameters; temperature, salinity, dissolved oxygen, pH. These functions were built using the water quality parameters levels and deviations proposed in Tables 2–4.

When one critical water parameter takes a value (either low or high) out of the allowed limits, a mass-kill will ensue irrespective of the excellent conditions of other parameters. These conditions for the critical concentration range of dissolved oxygen (DO), salinity, pH, hydrogen sulfide, harmful nitrogenous compounds (unionized ammonia, nitrate, and nitrite) and pathogenic microbes must be taken into account in the rules of the FIS when assessing the environmental condition of a shrimp pond. In this way, the fuzzy inference system will be able to detect potential crisis only if the rules are built correctly.

In water quality assessment, experts frequently use expressions as the following: if the temperature is normal, the salinity level is

Table 7
Examples of rules used by the FIS, where E is *Excellent*, G is *Good*, R is *Regular* and P is *Poor*.

Daily parameters	Temp	Sal	DO	PH		WQI
	Normal	Normal	Normal	Normal		E
	Low	Normal	Normal	Normal		G
	Low	Normal	Normal	Low		R
	Normal	Normal	Hypoxia	Low		P
Weekly parameters	NH	NO3	NO2	NH3	Tb	WQI
	Normal	Normal	Normal	Normal	Normal	E
	Normal	High	Normal	Normal	High	R
	High	Normal	Normal	Normal	Normal	P
By request	Ak	WQI	CO2	WQI	Vb	WQI
	Low	E	Medium	R	High	P

normal, the pH concentration in a pond is normal, and the level of dissolved oxygen is normal, then the expected water quality is excellent. In fuzzy language, it could be enunciated as follows:

Rule 1: If **Temp** is *normal* AND **Salt** is *normal* AND **pH** is *normal* AND **DO** is *normal* then **WQI** is *Excellent*.

where *Temp*, *Salt*, *pH* and *DO* are the outputs of the corresponding membership functions. Rule 1 in our example is known as a fuzzy inference rule and it would be helpful for the construction of the FIS (Ocampo et al., 2006; Shen et al., 2007). The robustness of the system depends on the number and quality of the rules. More rules can be implemented in the same way; as example we enunciate three more rules showing the main water conditions:

Rule 2: If **Temp** is *normal* AND **Salt** is *normal* AND **pH** is *normal* AND **DO** is *low* then **WQI** is *Good*.
Rule 3: If **Temp** is *normal* AND **Salt** is *high* AND **pH** is *normal* AND **DO** is *low* then **WQI** is *Regular*.
Rule 4: If **Temp** is *normal* AND **Salt** is *high* AND **pH** is *normal* AND **DO** is *hypoxia* then **WQI** is *Poor*.

A set of 276 rules were built, 135 for the combination of daily parameters, 108 for the combination of weekly parameters, 33 for parameters by request and 3 for each partial score into groups. In the parameters by request, their combination generates a very huge set of rules. In order to make easy the rule building, they were developed using only one antecedent determined by their classification levels (see Table 6) as follows: if indicator x is "Low" then WQI is Excellent, if indicator x is "Medium" then WQI is Regular and if indicator x is "High" then WQI is Poor.

An output fuzzy rule can be computed, using the fuzzy operator AND, according the expression 5.

$$\mu_R = \min\left\{\mu^i_{Temp}, \mu^j_{Salt}, \mu^k_{pH}, \mu^l_{DO}\right\} \tag{5}$$

where *i*, *j*, *k* and *l* are the different levels of concentration (high, normal, low, alkaline, acid, and hypoxia respectively) for each parameter. All rules could be stored as a database, which contains the possible combinations and their respective classification as can be showed in Table 7.

3.2.4. Aggregation

WQI membership functions are used in a different way from the input functions. They are matched with fuzzy outputs (μ_R), depending of the consequent of the evaluated rule. Since decisions are based on testing all the rules in the system, these functions must be combined to produce a single fuzzy output. The input of the aggregation process is a list of truncated output functions returned by each rule. The output of the aggregation process is a fuzzy membership function, which has to be deffuzified. The aggregation procedure used in the FIS is the maximum method

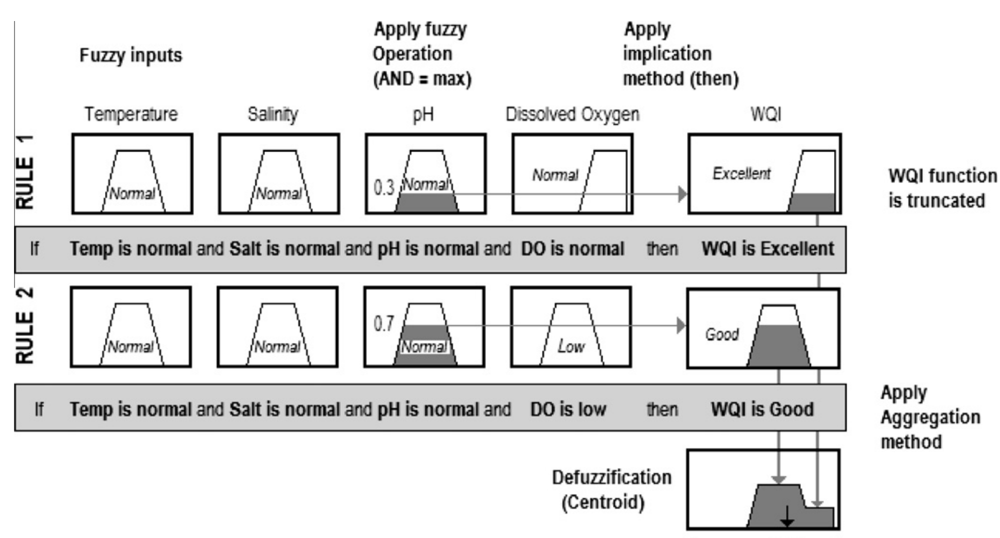

Fig. 3. Fuzzy inference diagram for the water quality scoring problem with four parameters and two rules. Rules 1 and 2 were used to exemplify the defuzzification process. The membership values (μ) of the four parameters are used to truncate the WQI membership function assessed in the respective rule. All truncated functions (μ_{WQI}) are combined creating a final membership function (μ_{out}), which is used to determine the WQI.

(Chow, 1997; Ocampo et al., 2006; Shen et al., 2007), which is the fuzzy union of all truncated outputs (Fig. 3).

3.2.5. Deffuzzification

The centroid function (*CF*) is the most prevalent and physically appealing of all available methods for a defuzzification process (Ocampo et al., 2006; Ross, 2004). The centroid method returns the center of area under the curve formed by the output fuzzy function according to expression 6:

$$CF = \frac{\int x\mu_{out}(x)dx}{\int \mu_{out}(x)dx} \tag{6}$$

Since the centroid function computes the center of area, the final score for the *CF* restricts the output result from the center of *poor* (0.078) to the center of *excellent* (0.87); this behavior can be observed in Fig. 4. Different water quality conditions fall inside this range: regular is 0.3 and good is 0.6. Therefore, the result must be normalized using expression 7; such that it takes values in [0,1].

$$WQI = \frac{CF - \min(CF)}{\max(CF) - \min(CF)} \tag{7}$$

where *WQI* (water quality index using fuzzy inference systems) is a new normalized water quality index.

3.3. Numerical example

If we want to evaluate the WQI in a shrimp pond using rules 1 and 2, having the parameters *temp*, *salinity*, *pH* and *dissolved oxygen* and their values 25.0, 20.0, 6.3, and 8.0 respectively. Using the membership functions proposed in Fig. 2. For "*R*1" and "*R*2" we can compute:

$$\begin{aligned}\boldsymbol{R}_1 : \mu_{R1}(x) &= \min\left\{\mu^n_{temp}(x), \mu^n_{salt}(x), \mu^n_{pH}(x), \mu^n_{DO}(x)\right\}\\ &= \min\{1, 1, 0.3, 1\} = 0.3\end{aligned}$$

$$\begin{aligned}\boldsymbol{R}_2 : \mu_{R2}(x) &= \min\left\{\mu^n_{temp}(x), \mu^n_{salt}(x), \mu^l_{pH}(x), \mu^n_{DO}(x)\right\}\\ &= \min\{1, 1, 0.7, 1\} = 0.7\end{aligned}$$

where n is normal, l is low and μ_{out} is the membership value calculated by R1 and R2. Calculating the aggregation functions, we obtain:

$$\mu_{out1}(x) = \min\left\{\mu_{R1}(x), \mu_{excellent}(x)\right\} = \min\{0.3, \mu_{excellent}(x)\} = 0.3$$

$$\mu_{out2}(x) = \min\left\{\mu_{R2}(x), \mu_{good}(x)\right\} = \min\left\{0.7, \mu_{good}(x)\right\} = 0.7$$

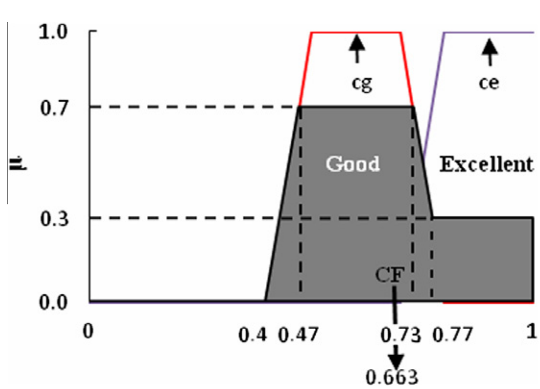

Fig. 4. Aggregated function of WQI index. In this example CF uses the aggregated function for computing the center of area having a restricted range from the center of *good* (cg) to the center of *excellent* (ce).

The μ values are used to truncate WQI functions (*excellent* and *good* showed in Fig. 4). By replacing the truncated functions in Eq. (7), the water quality index for R1 and R2 would be:

$$CF = \frac{\int_{0.4}^{0.47}(10x-4)xdx + \int_{0.47}^{0.73}(0.7)xdx + \int_{0.73}^{0.77}(-10x+8)xdx + \int_{0.77}^{1}(0.3)xdx}{\int_{0.4}^{0.47}(10x-4)dx + \int_{0.47}^{0.73}(0.7)dx + \int_{0.73}^{0.77}(-10x+8)dx + \int_{0.77}^{1}(0.3)dx} = 0.663$$

Fig. 4 shows the centroid function process. In this case, the interpretation of the water quality computed by *CF* is good with a tendency to excellent. This behavior is due to pH (6.3) present a value classified as *low* (see Fig. 2). However, this pH value is close to be classified as normal.

4. Analytic hierarchy process (AHP)

In aquaculture analysis, different water quality parameters generate different problems in the ecosystem. However, some parameters have higher impact or they are more susceptible to change than others. Derived of this behavior, environmental parameters must be prioritized in order to have an analysis more sensible. An analytic hierarchy process (AHP) is an effective tool that provides a priority order with different importance levels to parameters. In AHP, the decision task is made simpler by constructing a hierarchy and developing a mathematical model that generates the priority values for different criteria and subcriteria involved in the decision-making process (Chakraborty & Dey, 2006). The criteria or importance used in this paper was the proposed by Saaty (2004), which is shown in Table 8.

The application procedure of AHP can be divided in three steps. In the first step, the representation of the problem in a hierarchical structure, where the levels of the hierarchy represent the goal, criteria, sub-criteria, and alternatives of the given problem, must be proposed. Tables 9–12 show the scale values for the three proposed groups of parameters. The values used in our study were adjusted to the characteristics of north-pacific Mexican coastal waters and to tropical shrimp cultivation exigencies according to the SAGARPA and Mexican experts in coastal waters (Ávila et al., 2011).

The second step consists in making pairwise comparisons. The comparison values assigned to parameters are generally used to develop a consistent matrix. A consistent matrix is a positive reciprocal $n \times n$ matrix whose elements satisfy the relation $a_{ij} \ldots a_{jk} = a_{ik}$, for $i, j, k = 1, \ldots, n$. These pairwise comparisons can also be represented in the following matrix form:

Table 8
Scale values, Saaty (2004).

Scale value	Interpretation
1	Equal importance
2	Weak or slight
3	Moderate importance
4	Moderate plus
5	Strong importance
6	Strong plus
7	Very strong or demonstrated importance
8	Very, very strong
9	Extreme importance

Table 9
Scale values for parameters monitored daily.

Parameters	DO	Temp	Sal	pH
Hierarchy	9	8	7	9

Table 10
Scale values for parameters monitored weekly.

Parameters	NH	NO_3	NO_2	NH_3	Tb
Hierarchy	6	6	5	9	7

$$A = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{bmatrix} = \begin{bmatrix} \frac{w_1}{w_2} & \frac{w_1}{w_2} & \dots & \frac{w_1}{w_n} \\ \frac{w_2}{w_1} & \frac{w_2}{w_2} & \dots & \frac{w_2}{w_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{w_n}{w_1} & \frac{w_n}{w_2} & \dots & \frac{w_n}{w_n} \end{bmatrix} \tag{8}$$

where w_i is the weight scale for the ith criteria. The pairwise comparison matrix for the different water quality parameter groups are shown in Tables 13–16.

The third step consists in assigning priorities or preference values to the water quality parameters according to the next rules.

(a) First the square of A is calculated as follows:

$$B = A \cdot A = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{bmatrix} \cdot \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{bmatrix} \tag{9}$$

(b) The sum of the rows is computed according to the following equation:

$$C_i = \sum_{j=1}^{n} B_{ij} \tag{10}$$

(c) Finally the C_i vector is normalized as follows:

$$P_i = \frac{C_i}{\sum_{i=1}^{n} C_i}; \quad i = 1, \dots, n \tag{11}$$

The result is known as the first eigenvector (Saaty, 2004). This process must be iterated until the eigenvector solution does not change from the previous iteration. Finally the consistency ratio (CR) for the pairwise comparison matrix can be calculated according to the following expression:

$$CR = \frac{\lambda_{\max} - n}{(n-1)RI} \tag{12}$$

where $\lambda_{\max}$ is the maximum eigenvalue of the pairwise matrix, n is the matrix size and RI is the random consistency index that can be determined according to Table 17.

If the consistency radio is smaller than 10%, the pairwise matrix is acceptable (Saaty, 1994). Tables 13–15 show the priority weights for water quality indicators. The hierarchical tree for water quality assessment is shown in Fig. 5.

5. Experimental results

5.1. Water sampling

For our experiments we use a database of marine water quality parameters provided by the Center of Biological Research (CIB, 2008), located in the city of Hermosillo, Sonora, México. Four water quality parameters were chosen and analyzed: temperature, salinity, pH, and dissolved oxygen (daily monitored parameters).

Table 12
Scale values for groups.

Parameters	Daily	Weekly	By request
Hierarchy	9	6	4

Table 13
Pairwise comparison matrix for parameters monitored daily.

Criteria	DO	Temp	Sal	pH	Priority value
DO	1	9/8	9/7	1	0.28012
Temp	8/9	1	8/7	8/9	0.23958
Sal	7/9	7/8	1	7/9	0.21023
pH	1	9/8	9/7	1	0.27005

Table 14
Pairwise comparison matrix for parameters monitored weekly.

Criteria	NH	NO_3	NO_2	NH_3	Tb	Priority value
NH	1	1	6/5	6/9	6/7	0.18194
NO_3	1	1	6/5	6/9	6/7	0.18194
NO_2	5/6	5/6	1	5/9	5/7	0.15118
NH_3	9/6	9/6	9/5	1	9/7	0.27264
Tb	7/6	7/6	7/5	7/9	1	0.21227

These parameters were selected considering their correlation to hydrodynamic dominant characteristics of water masses; the spatial similarity of their distribution patterns in relation to other more difficult to collect parameters; and their importance to disestablish an ecosystem, generating crisis in high or low concentrations.

Water samples were collected in the "Gez Acuícola" marine shrimp farm, located in Huatabampo, Sonora, Mexico. The estuary "El Riito" provides a source of seawater to shrimp ponds. In order to have an accurate assessment, samples were taken monthly along 4 months, from May, 2008 to August, 2008, each 30 min during a day to obtain diary fluctuations and parameter behavior. This caution is especially important for parameters affected by photosynthesis, such as dissolved oxygen and pH.

5.2. Water quality assessment

There are several indices implemented by different international organizations that compute water quality in water bodies. In order to estimate how the WQI index performs in comparison to CCME and $(HI)_c$ indices. We performed a comparative analysis against these indices obtaining interesting conclusions. The Canadian Council Ministry of Environment (CCME, 2004) proposed a method that can be used in coastal water, and it is based on computing the number of failed tests of a set of environmental parameters, and the average of the deviations of them. CCME index is used for assessing water quality in any water body since it is based on statistical results of environmental tests. On the other hand, the $(HI)_c$ index was proposed by Ferreira et al. (2011) as a new effective water quality index for assessment of Litopenaeus vanammei shrimp. Appendix A describes briefly how to compute CCME and $(HI)_c$ indices.

WQI index is compared to the CCME and $(HI)_c$ indices using daily measured parameters. The treatment of the information within

Table 11
Scale values for parameters monitored by request.

Parameters	Ak	CO_2	Ss	P	H_2S	HS^-	Px	Si	ChA	N	Tmb	Vb	Fc
Hierarchy	9	6	6	3	3	3	3	3	3	3	8	8	8

Table 15
Pairwise comparison matrix for parameters monitored by request.

Criteria	Ak	CO_2	Ss	P	H_2S	HS^-	Px	Si	ChA	N	Tmb	Vb	Fc	Priority value
AK	1	9/6	9/6	9/3	9/3	9/3	9/3	9/3	9/3	9/3	9/8	9/8	9/8	0.13636
CO_2	6/9	1	1	6/3	6/3	6/3	6/3	6/3	6/3	6/3	6/8	6/8	6/8	0.09085
Ss	6/9	1	1	6/3	6/3	6/3	6/3	6/3	6/3	6/3	6/8	6/8	6/8	0.09085
P	3/9	3/6	3/6	1	1	1	1	1	1	1	3/8	3/8	3/8	0.04551
H_2S	3/9	3/6	3/6	1	1	1	1	1	1	1	3/8	3/8	3/8	0.04551
HS^-	3/9	3/6	3/6	1	1	1	1	1	1	1	3/8	3/8	3/8	0.04551
Px	3/9	3/6	3/6	1	1	1	1	1	1	1	3/8	3/8	3/8	0.04551
Si	3/9	3/6	3/6	1	1	1	1	1	1	1	3/8	3/8	3/8	0.04551
ChA	3/9	3/6	3/6	1	1	1	1	1	1	1	3/8	3/8	3/8	0.04551
N	3/9	3/6	3/6	1	1	1	1	1	1	1	3/8	3/8	3/8	0.04551
Tmb	8/9	8/6	8/6	8/3	8/3	8/3	8/3	8/3	8/3	8/3	1	1	1	0.12113
Vb	8/9	8/6	8/6	8/3	8/3	8/3	8/3	8/3	8/3	8/3	1	1	1	0.12113
Fc	8/9	8/6	8/6	8/3	8/3	8/3	8/3	8/3	8/3	8/3	1	1	1	0.12113

Table 16
Pairwise comparison matrix for parameters group.

Criteria	Groups			286
	Daily	Weekly	By request	Priority value
Daily	1	9/6	9/4	0.47368
Weekly	6/9	1	6/4	0.31578
By request	4/9	4/6	1	0.21052

Table 17
Random consistency index, Saaty (2004).

n	1	2	3	4	5	6	7	8	9	10
Random Index	0	0	0.52	0.89	1.11	1.25	1.35	1.4	1.45	1.49

the FIS directly influences the final score. The indices $(HI)_c$ and CCME take values always greater than 0.5, giving *good* or *excellent* water quality in a non-fuzzy environment; these scores are high because $(HI)_c$ and CCME indices do not consider particular situations as hypoxia, anoxia, alkalinity or acid concentrations, moreover the negative scores for critical parameters are compensated by other computed indicators. WQI matches better with real data since it considers the negative ecological impact of some parameters in the fuzzy inference process. For example, Fig. 6 shows very low concentrations of dissolved oxygen that are correctly penalized by the FIS. However, $(HI)_c$ and CCME take values greater than 0.5 (good conditions), it means these indices do not process correctly low concentrations of dissolved oxygen. A better analysis can be observed in Table 15, where numerical assessments of negative situations are processed by the three indices; they were scaled in a [0, 1] range in order to facilitate comparison. From this table, it can be observed that only the proposed WQI index correctly computes potentially harmful situations. $(HI)_c$ index is too sensitive to harmful concentrations, however, since it is built in a non-fuzzy environment, when concentrations are on the bound, it assesses with a zero score (poor water quality), giving a non-accurate assessment; for example, when dissolved oxygen concentrations are 1.9 or 2.1 mg/l respectively (see Table 18). This behavior can be also observed in Fig. 6.

Fluctuations of water quality parameters can be generated due to stocking rates, feeding rates, or routine water quality management protocols (i.e., water exchange rates, aeration intensity,

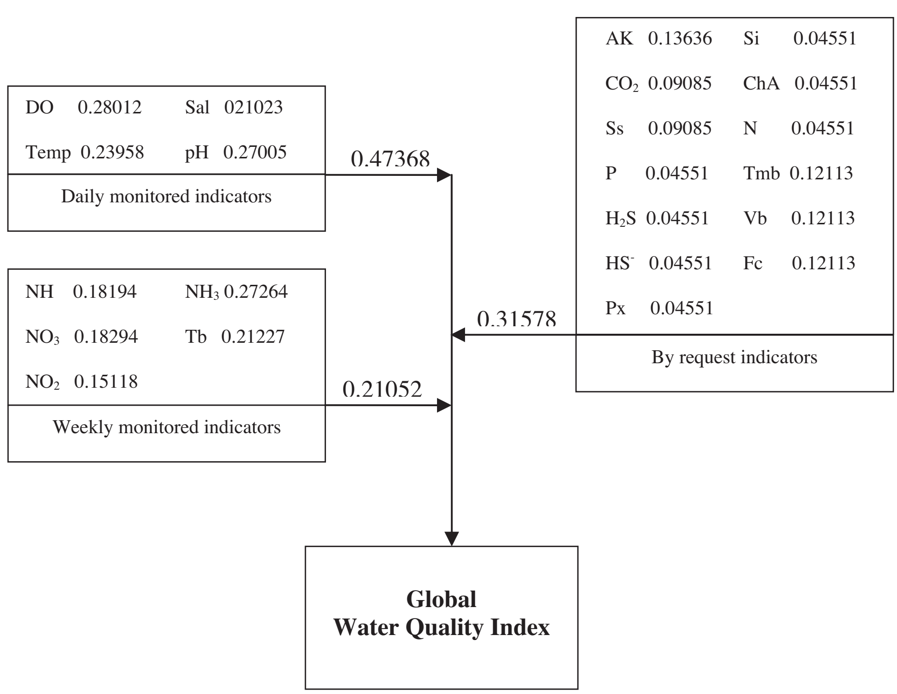

Fig. 5. Optimized weights for indicators included in the water quality index (WQI) estimated with the analytic hierarchy process methodology.

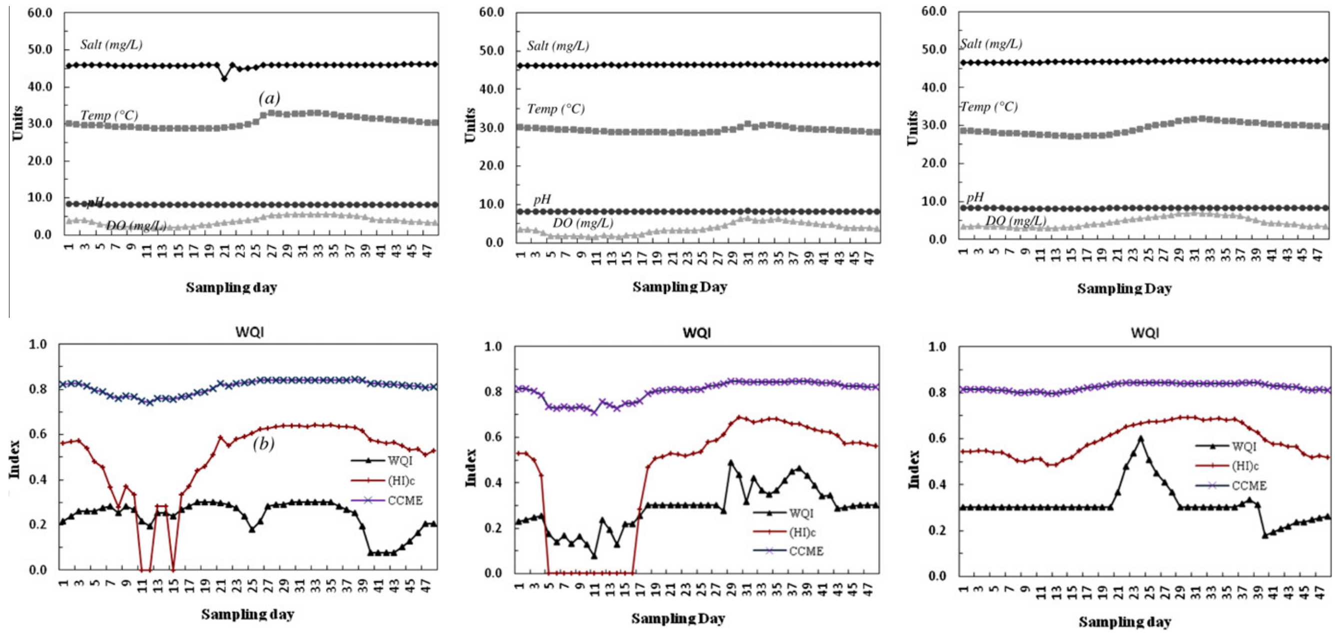

Fig. 6. Results of the assessment of the water quality of "Gez Acuícola" marine shrimp farm: (a) measurements, (b) results of water quality indices.

Table 18
Comparison between WQI, CCME and $(HI)_c$ indices using the daily measured data set.

Water quality parameters				Scores			Observations
Temp (°C)	Salt (mg/l)	DO (mg/l)	pH	WQI	$(HI)_c$	CCME	
28.0	45.8	1.9	8.2	0.18	0.00	0.75	Dissolved oxygen in hypoxia
28.0	45.8	2.1	8.2	0.15	2.83	0.74	Dissolved oxygen in hypoxia
25.0	47.0	6.8	8.2	0.66	6.92	0.84	Salt is high
22.0	47.0	5.8	8.2	0.66	6.18	0.84	Salt is high, pH low and temp high
28.0	19.0	5.6	3.1	0.00	0.00	0.88	pH is acid
16.0	21.0	6.3	11.7	0.00	0.00	0.97	pH is alkaline
28.0	35.0	3.0	6.0	0.01	4.23	0.79	DO low, Sal high and pH low
31.4	35.0	3.0	5.7	0.00	3.19	0.81	DO low, Sal high, pH low and temp high
33.3	11.0	3.0	9.8	0.00	2.80	0.87	DO low, Sal low, pH high and temp high
34.5	10.5	3.3	9.9	0.00	2.43	0.87	DO low, Sal low, pH high and temp high
25.0	12.0	7.0	10.5	0.00	0.00	0.88	Sal low, pH high
25.0	20.0	6.0	7.5	1.00	8.08	1.00	Optimal conditions

etc.) affecting directly water quality Hernández, Zirino, Marione, Canino, and Galindo (2003); Arredondo and Ponce (1998). Unlike $(HI)_c$ and CCME indices fluctuations can be efficiently detected by the proposed WQI index. Therefore, our index provides a powerful solution to detect anomalous conditions on shrimp ponds.

6. Conclusion and discussions

Some researchers have demonstrated that pollutant concentrations stress shrimp, and consequently organisms are more susceptible to disease (Li et al., 2006). Following this idea, aquaculture efforts are focused on tackling environmental problems in the ecosystem trying to control and prevent illness (for example Taura virus, White Spot Syndrome, Melanosis Syndrome, etc.). A fuzzy inference system as the proposed in this paper is an effective tool for supporting an accurate treatment of water, because it provides an immediate assessment. This characteristic of our system is very useful to reduce stress levels in organisms and to prevent illnesses. In early stages as well as for determining feeding and growth rates in extensive ponds.

In this paper, a fuzzy inference system based on a reasoning process, which implicates aquaculture criteria established by official organizations and researchers for assessing water quality, has been introduced. This fuzzy inference system allows an immediate assessment of concentrations and values of different water quality parameters that integrates a water ecosystem. The fuzzy inference system was built in three phases; the first, classifies the levels of the water quality parameters; the second phase evaluates the negative ecological impact of the parameters in the shrimp habitat using a fuzzy reasoning process; the third phase prioritizes the most critical parameters using an analytic hierarchy process, giving as result a new index of the ecological status of the water quality. Experimental results in a real shrimp farm in México demonstrate that the proposed fuzzy inference system works well.

Traditional reports on water quality tend to be too technical and detailed, presenting monitoring data on individual substances, without providing a complete and interpretable evaluation of water quality. To solve this gap, several water quality indices have been developed to integrate water quality parameters. Traditional models evaluate water quality in a rigorous sense, where certain levels of concentrations are classified in a strict level while the proposed fuzzy inference system classifies following a soft approach, thus measured concentrations for all the parameters are processed together giving as result a water pollution grade, which constitutes a water quality index (WQI). Although other water quality indexes ($(HI)_c$ and CCME) solve the problem of water pollution assessment, the reasoning process of harmful situations in WQI provides a more accurate evaluation. In addition, the proposed WQI integrates all parameter evaluations providing a complete water quality index.

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Appendix A

A.1. Water quality index of the Canadian Council of Ministers of the Environment

The CCME Index interprets the water quality status for any water body. It computes a statistical analysis of how many measurements are into a desired range and the deviation of measurements outside this range as follows:

$$CCME = 100 - \frac{\sqrt{\mathrm{F}_1^2 + \mathrm{F}_2^2 + \mathrm{F}_3^2}}{1.732}$$

where F_1 (scope) is the percentage of parameters whose current concentration is out of their allowed limits and it is calculated as follows:

$$F_1 = \frac{\text{Number of failed variables}}{\text{total of number of variables}} \times 100$$

F_2 (frequency) is the percentage of individual tests within each parameter that do not fulfill the limits and it is calculated as follows:

$$F_2 = \frac{\text{Number of failed variables}}{\text{total of number of variables}} \times 100$$

F_3 (amplitude) is the percentage of deviations in each individual test and it is calculated in three steps. First, the cases in which the test value must not be below or above the objective limit are computed (excursions):

$$excursion_i = \begin{cases} \frac{Objective_i}{Failed\ \ test\ \ Value_i} - 1 & \text{if value fall above } \textit{Failed test} \\ & Value_i Objective_i - 1 \quad \text{if value fall below} \end{cases}$$

Then the normalized sum of excursions (*nse*) is calculated as follows:

$$nse = \frac{\sum_{i=1}^{n} excursion_i}{number\ \ of\ \ tests} - 1$$

Finally, an asymptotic function that scales the normalized sum of the excursions from objectives (*nse*) to yield a value between 0 and 100 is calculated as follows:

$$F_3 = \frac{nse}{0.01nse + 0.01}$$

A.2. Hydrological water quality index (HI)$_c$

The $(\mathrm{HI})_c$ index was developed to allow allocation of a range of continuous weight from 0 to 5. A weight (VW) and a range (WR) are assigned to each water quality parameter. VW and WR are multiplied to obtain a score for each sampling station (SVS, Eq. (14)). The final score of the sampling station (FSS) is obtained by multiplying the score of each one of the four parameters (Eq. (15)).

$$\mathrm{SVS}_{var} = VW_{var} * WR_{var} \tag{13}$$

$$\mathrm{FSS} = \mathrm{SVS}_{salinity} * \mathrm{SVS}_{pH} * \mathrm{SVS}_{temp} * \mathrm{SVS}_{oxygen} \tag{14}$$

According to Ferreira et al. (2011) and Beltrame et al. (2004), applying the Eqs. (14) and (15) allows the FSS may vary between 0.0 and 18,750. In order to facilitate the understanding of the index, these values are mapped to the interval [0,10] according to the equation

$$(\mathrm{HI})_c = 0.8546(\mathrm{FSS})^{0.25} \tag{15}$$

where $(\mathrm{HI})_c$ corresponds to the shrimp culture hydrological index. Parameters weights, ranges and their respective assignments can be consulted in Beltrame et al. (2004) and Ferreira et al. (2011).

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