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Water quality assessment in shrimp culture using an analytical hierarchical process

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ABSTRACT

Water quality assessment is an important activity for controlling harmful crisis in aquaculture systems. The objective of our study was to develop a new Water Quality Index focused on monitoring of shrimp farms; detecting poor water quality and preventing negative effects in the ecosystem. Usually, several water quality parameters are monitored and measured in a shrimp farm during a farming period. Those parameters are classified according to their negative effects in the ecosystem and their respective allowed limits are also defined. The proposed Water Quality Index assigns a priority level to each water parameter through a new analytical hierarchical process (AHP), which allows an accurate assessment of the water quality. Our proposed index was applied to assess the water quality condition in extensive shrimp farms in Mexico. A comparison between our approach and those proposed in the literature shows its good performance when real environments are assessed.

1. Introduction

Aquatic organisms are susceptible to suffer stress when ecological conditions are not adequate. High stress levels generate low feeding and low growing rates; and promote the appearing of sickness in the organisms. A good water quality condition is essential for any aquaculture farming. Water quality affects reproduction, growth and survival of aquatic organisms. The criteria for good quality water assessment depend on the kind of organisms to be studied and are clearly established by safe levels. The ecosystem of a shrimp pond is composed by soil and water; the main factors affecting shrimp organisms are used as water quality parameters. However, the negative effects are reduced if ponds are monitored and controlled adequately, maintaining good water quality conditions (Boyd and Musin, 1992; Chien, 1992; Feliu et al., 2009).

A Water Quality Index (WQI) is a mathematical instrument used to transform large amounts of water quality data into a single number, which summarizes different water quality parameters to provide a whole interpretation of the behavior of the water quality parameters involved in shrimp culture (Simões et al., 2008; Ramesh et al., 2010). In the literature, several water quality indexes have been proposed; however, they only give a partial solution for this problem since the number of monitored water quality parameters is limited and they do not allow using them in a weighted way for water assessment (Ferreira et al., 2011; Cohen et al., 2005; Beltrame et al., 2004). Moreover, in the literature, we can also find techniques where several environmental quality indexes have been implemented based on artificial intelligence (Gharibi et al., 2012; Bishoi et al., 2009; Lermontov et al., 2009; Pedregal et al., 2009; Yañez et al., 2008; Wang et al., 2008; Salazar, 2007; Ocampo et al., 2006; Muttil and Chau, 2006; Li et al., 2006; Gutiérrez, 2004). These works have motivated the proposal presented in this paper for monitoring water quality parameters in shrimp culture, but assigning a priority level to each water parameter through a new analytical hierarchical process.

Additionally, international organizations have proposed some models for assessing water quality. Different criteria about good water quality practices, given by those international organizations, have been used as support of this type of work (ACA, 2010; NSF, 2010; CCME, 2010; SAGARPA, 2010). The Canadian Council Ministry of Environment (CCME, 2010) proposes a water quality model, which assesses water bodies based on statistical analyses, providing an index which has no limits about the number of parameters used. The National Sanitation Foundation (NSF, 2010) provides a Water Quality Index, which is used mainly for fresh water bodies. The Mexican Ministry of Environment, Natural Resources and Fisheries (SEMARNAP, 1996) provides a Water Quality Index based on statistical analysis. However, the CCME, NFS and other

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similar indexes have some weak points, for example some parameters involved in the index equations could dramatically influence the final score without any valid justification. However, the most critical drawback of this kind of indexes is that they cannot deal with water quality priorities in the sense that some parameters are more important than others for determining water quality condition.

Recently in Carbajal et al. (2011) and Carbajal-Hernández et al. (2012), new Water Quality Indexes were developed using fuzzy inference systems. In the first work, a water quality index (HWQI) was proposed using the most critical parameters (Beltrame et al., 2004; Hirono, 1992) in shrimp culture (temperature, dissolved oxygen, pH and salinity). This model also has been applied for water quality prediction using sample sets of different size. In the second work, a water quality model for immediate water quality assessment was developed. This model provides a whole interpretation of the water condition in an ecosystem giving a quick solution for water quality assessment. The use of subjectivity and uncertainty provided by a fuzzy inference system in water analysis, improves the assessment and crisis detection in shrimp ecosystems. However, the use of fuzzy inference is too complex. In this sense, the aim of this paper is to provide an accurate and easy to implement Water Quality Index, which can be adjusted depending on the requirements for a specific aquaculture system. Our hypothesis is that a correct and customizable assignment of priorities over a set of water quality parameters, penalizing those critical parameters that can disestablish an ecosystem, is enough for determining a potential crisis.

In our research, the proposed Water Quality Index is used for analyzing the ecosystem of Litopenaeus vannamei in shrimp farms of Sonora, México, where water quality parameters are assessed for evaluating the water quality condition.

The rest of this paper has been organized as follows: in Section 2, water quality parameters and their main characteristics in water assessment are explained. In Section 3, a new water quality index based on an analytical hierarchical process is proposed; we also give a numerical example for a better understanding of our proposal. Section 4 shows some experiments using real environments, where the proposed index is compared against other similar water quality indexes proposed in the literature and by international organizations; this section shows the performance and efficiency of our proposal. Finally, Section 5 provides our conclusions and future research directions.

2. Water quality parameters

A substance in the water that can cause harm to aquatic organisms is known as pollutant. Pollutants can be present in water as solid particles or gases. Pollutants are frequently monitored in order to avoid their negative effects in shrimp organisms (SEMARNAT, 2010; CCME, 2010). Water quality assessment is based on the results of toxicity tests. These tests measure the response of aquatic organisms to certain quantities of specific pollutants (Carbajal-Hernández et al., 2012; Páez, 2001; Chien, 1992). Different aquatic species have different tolerances for specific toxic compounds. When water quality parameters surpass those limits, the water quality condition is deteriorated; generating high stress levels in shrimp organisms.

Understanding ecological processes occurring in shrimp culture is useful to understand the disease issues faced by shrimp farmers. A bad water quality control increases shrimp stress level and compromises production, it also makes shrimp organisms more susceptible to diseases (Ferreira et al., 2011; Boyd, 2002).

The required water quality is determined by the type of organisms to be cultured. Since, physical, chemical and biological principles are usually taken as the basis of water quality assessment, in Section 2.1 we describe the water quality parameters used in this work for water quality assessment according to their monitoring frequency, as well as their importance in the shrimp ecosystem. In Section 2.2, optimal concentration levels of water quality parameters are given in order to understand the Water Quality Index proposed in this paper.

2.1. Water quality parameters importance

In most theoretical and experimental studies for assessing water quality, water quality parameters are monitored for detecting extreme negative situations focusing on critical values of these parameters (Ferreira et al., 2011; Simões et al., 2008; Beltrame et al., 2004; Hirono, 1992). Specifically, there are several difficulties in commercial shrimp farms for measuring water quality parameters like extremely hot weather; many and huge crop areas, high prices of new technologies, etc. Therefore, in practical situations, the analysis is commonly limited to measure a specific set of parameters, which are relevant for the ecosystem and relatively easy to measure (Carbajal et al., 2011; Páez, 2001; Chien, 1992). In order to determine the set of parameters, useful to assess water quality, in our work we reviewed what parameters have been used in the literature for different aquaculture systems in Mexico and Central America (Ferreira et al., 2011; Simões et al., 2008; Hirono, 1992). In Mexico, extensive and semi-extensive shrimp farms are placed in tropical or warm places. Central America countries have similar climate conditions as Mexico; therefore, shrimp practices are similar among countries, adopting those practices from extensive aquaculture systems in Mexico. Thus, we found that in most of the works (Ferreira et al., 2011; Carbajal et al., 2011; Simões et al., 2008; Páez, 2001; Chien, 1992; Hirono, 1992), dissolved oxygen, temperature and salinity are monitored daily; while, pH, ammonia, nitrates and turbidity and/or algae counts are analyzed weekly. Chemical analyses do not come into consideration for water quality management on a routine base and they are only monitored by requirement (Hirono, 1992; Carbajal et al., 2011). Non-ionized ammonia is characterized by its high toxicity for organisms and it is directly related to pH concentrations; due to this behavior and the relative simplicity for measuring pH through electronic sensors, pH is monitored daily instead of weekly. The four daily monitored variables require a special care; since a bad controlling of these parameters can disestablish the entire ecosystem, generating a potential crisis. Table 1 shows the water quality parameters organized by monitoring frequency.

In order to understand the importance and effects of these water quality parameters in a shrimp ecosystem, we provide a brief explanation of them. Tables 2–4 summarize the parameters analyzed in laboratory and their respective importance in shrimp culture. Water quality parameter descriptions are organized by monitoring frequency.

2.2. Water quality parameter levels

A good water quality condition can be determined when environmental tests of all water quality parameters fall inside their optimal range for shrimp organism. According to Tables 2–4, we can establish the optimal ranges as they have been defined in the literature. These ranges can be consulted in Table 5, grouped by monitoring frequency. In this case, the parameter deviation (d) helps to determine if a test value can be considered near or far from its desired range, this parameter is especially useful because a tight decision can directly influence the water quality assessment (see Section 3).

Table 1
Water quality parameters classified by monitoring frequency.

Monitoring frequency	Water quality parameters
Daily monitored	Temperature (Temp), dissolved oxygen (DO), salinity (Sal), pH.
Weekly monitored	Total ammonia (NH), nitrate (NO3), nitrite (NO2), non ionized ammonia (NH3), turbidity (Tb).
Monitored by request	Alkalinity (Ak), phosphorus (P), hydrogen sulfide (H_2S), non ionized hydrogen sulfide (HS^-), 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).

Table 2
Daily monitored parameters and their importance to shrimp farming.

Daily monitored parameters	Importance on marine shrimp culture
Water temperature	It is an important environmental factor for shrimp farming due to its influence on the metabolism of the crustacean (Ferreira et al., 2011). Temperature controls solubility of gases, chemical reactions and toxicity of the ammonia. The optimum range for growth juvenile Litopenaeus vannamei is from 28 to 32 °C (Carbajal et al., 2011; Martínez, 1994; Hirono, 1992; Boyd, 1989).
Dissolved oxygen	Dissolved oxygen is considered the most critical quality parameter. Low dissolved oxygen concentrations cause low growth rates. The minimum levels recommended in the literature oscillate between 4 and 5 ppm (Martínez, 1994; Boyd and Musin, 1992; Chien, 1992).
Salinity	High salinity concentrations reduce dissolved oxygen in water ponds (Páez, 2001). The optimal salinity concentrations are from 15 to 23 ppt (Páez, 2001; Boyd and Musin, 1992).
pH	Extremely low or high pH stresses shrimp and causes soft shell and poor survival (Chien, 1992). Water bodies with 6.5–9.0 pH concentrations are appropriate for shrimp aquaculture production (Carbajal et al., 2011; Hernández et al., 2003; Arredondo and Ponce, 1998; Martínez, 1994).

Table 3
Weekly monitored parameters and their importance to shrimp farming.

Weekly monitored parameters	Importance on marine shrimp culture
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 (Carbajal-Hernández et al., 2012; 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	Excessive amounts of nutrients, especially nitrogen and phosphorus, speed up the eutrophication process. Excessive nitrate (NO_3) in drinking water can cause human and animal health problems. Safe concentrations of NO_2 are from 0.4 to 0.8 mg/l. 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 (Páez, 2001; Chien, 1992; Needham, 1961).
Turbidity	Turbidity is a measure of the degree in which the water loses its transparency due to the presence of suspended particles. Optimal range for turbidity is from 35 to 45 cm depth (Martínez, 1994).

Table 4
Water quality parameters measured by request and their importance to shrimp farming.

Parameters monitored by request	Importance on marine shrimp culture
Alkalinity	Alkalinity is 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. Alkalinity concentrations should not exceed 140 mg/l (Boyd, 2002; Ferreira et al., 2011).
Phosphorus	It is a nutritive element, mainly appearing as orthophosphate, essential to aquatic life. According to Esteves (1998), phosphorus acts particularly in metabolic processes of living beings, such as energy storage and structure of the cell membrane. Phosphorous concentrations should not exceed 0.3 mg/l (Carbajal-Hernández et al., 2012; Ferreira et al., 2011).
Hydrogen sulfide	In water, hydrogen sulfide exists in unionized (H_2S) and ionized forms (HS^- and S_2). Only the 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. Optimal range for hydrogen sulfide is below 0.1 mg/l (Carbajal-Hernández et al., 2012; 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 (Carbajal-Hernández et al., 2012; Clifford, 1994).
Silicate	Into water, it is a composite of high importance because diatoms of carapace composition use it. Optimal levels for silicate are established from 0.1 to 0.3 mg/l (Carbajal-Hernández et al., 2012; Ferreira et al., 2011; Esteves, 1998).
Chlorophyll A	Phytoplankton biomass represents the primary consumer feed, and indirectly determines the feed availability of the next trophic system levels. The ideal concentrations of chlorophyll A for shrimp ponds are from 50 to 70 μg/l (Clifford, 1994).
Total marine bacteria	Marine bacteria can be beneficial (nutrients recycling, organic matter degrading, etc.) or harmful (as parasites) in ecosystems. Optimal range for total bacteria counts should be below 10,000 UFC/ml (Ferreira et al., 2011; Anand et al., 2010).
Vibrio	Vibriosis is a bacterial disease responsible for mortality of cultured shrimp worldwide (Chen et al., 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 (Carbajal-Hernández et al., 2012).
Fecal coliforms	Fecal coliforms are used as indicator of water pollution and they come from feces of warm-blooded animals. Fecal coliforms analyses should be below 1000 MPN/ml and for crop 1400 MPN/ml (Boyd, 2000).

Table 5
Optimal levels for water quality parameters.

Water quality parameters	Units	Deviation (d)	Range (l_b–l_a)
Daily monitored			
Temperature (Temp)	°C	1.0	20–30
Dissolved oxygen (DO)	ppm	0.5	<5
Salinity (Sal)	ppm	1.0	15–23
pH		0.5	6.5–9.5
Weekly monitored			
Total ammonia (NH)	mg/l	0.10	0.1–1.0
Nitrate (NO_3)	μg/l	100	400–800
Nitrite (NO_2)	mg/l	0.10	0–0.5
Non ionized ammonia (NH_3)	mg/l	0.01	0–0.1
Turbidity (Tb)	cm	1.00	35–45
Monitored by requirement			
Alkalinity (Ak)	mg/l	10	<140
Phosphorus (P)	mg/l	0.01	<0.3
Hydrogen sulfide (H_2S)	mg/l	0.01	<0.1
Non ionized hydrogen sulfide (HS^-)	mg/l	0.001	<0.005
Carbon dioxide (CO_2)	mg/l	2	<20
Suspended solids (Ss)	mg/l	5	<150
Potential redox (Px)	mV	10	<500
Silicate (Si)	mg/l	0.2	<4.0
Chlorophyll A (ChA)	μg/l	5	<75
Total inorganic nitrogen (N)	mg/l	0.2	<4
Total marine bacteria (Tmb)	UFC/ml	1000	<10,000
Vibrio (Vb)	UFC/ml	100	<1000
Fecal coliforms (Fc)	MPN/ml	100	<1000

Table 6
Scale priority proposed by Saaty (2004).

Scale value (groups)	Inverted scale (parameters)	Importance
1	9	Very weak
2	8	Weak or slight
3	7	Moderate
4	6	Moderate plus
5	5	Strong
6	4	Strong plus
7	3	Very strong
8	2	Very, very strong
9	1	Extreme

3. Water Quality Index

Environmental protection and sustainable economic development require building extensive databases derived from physical and chemical monitoring, as well as the application of effective methodologies for environmental assessment. Water quality parameters have non-linear relationships among them and trying to represent those underlying relationships using mathematical expressions and integrating them in a complete water quality index is a very hard task (Hernández et al., 1992). Recent studies for shrimp culture, as the one presented by Carbajal et al. (2011) or similar water quality index proposed by Ocampo et al. (2006), have provided a solution showing how non-linear relationships interacts among water quality parameters. In these works the authors expressed the ecological dynamic using artificial intelligence techniques. However, holistic approaches need to be based on realistic methods rather than complicated and time-consuming techniques, which are so complex to implement and to understand by end users. In this sense, our proposal is based on a procedure easy to understand and implement, which mainly assesses water quality parameters with higher importance levels, by monitoring especially those with a high potential for crisis generation. Also, parameter variations are quantified using a new special operator (the β operator), which is an indicator about how the behavior of the different parameter levels affects the ecosystem.

The proposed water quality index is built in three phases. First, a parameter assessment through average deviation of samples that fall outside their optimal ranges is computed using the proposed β operator. Then, a weight is assigned to each water quality parameter; this weight is computed based on its priority using a hierarchical analysis. Finally, the proposed Water Quality Index is built by integrating all water quality parameters; it takes into account both the weight of each parameter computed separately and the weight of each group of parameters (daily, weekly and by request).

3.1. Operator β for assessing parameter values

Water quality parameter measurements can be classified as optimal or not optimal for good farming. This behavior can be determined according to the ranges proposed in Section 2. Following this idea, we propose an *operator* denominated β for assessing whether a set of values fall inside or outside of their optimal ranges. In this sense, the first step is determining the allowed deviation (d) of those parameters which have values out of their optimal range. Then, we propose to compute the deviation (e) of the test values as follows:

$$e = \begin{cases} \dfrac{m - t_a}{2d} & \textit{if the value falls above the level} \\ \dfrac{t_b - m}{2d} & \textit{if the value falls below the level} \\ 0 & \textit{if the value falls inside } [t_b, t_a] \end{cases} \quad (1)$$

where m is the value of a test for a water quality parameter, d is the allowed deviation of the range, and t_a and t_b are the tolerances calculated as follows:

$$t_a = l_a - d \quad (2)$$

$$t_b = l_b + d \quad (3)$$

where l_a and l_b are the upper and lower limits of the evaluated range respectively (see Tables 5 and 6).

After, taking into account the individual deviations, the average deviation (Ad) is computed using Eq. (1):

$$Ad = \frac{\sum_i^n e_i}{n} \quad (4)$$

where i: 1, 2, ... n; n is the number of deviations and e_i is the ith deviation of the set of measurements.

Then, we propose a β operator that uses an asymptotic function in order to scale the average deviation score into [0, 1], as follows:

$$\beta = 1 - \frac{Ad}{\sqrt{1 + Ad}} \quad (5)$$

Values of β near to zero are interpreted as values outside the optimal range; while values of β near to one indicate the value of the water quality parameter is inside the optimal range. Fig. 1 exemplifies the index operation using salinity and temperature samples and their respective classification according to those optimal ranges defined in Tables 5 and 6. One day has 96 samples (one sample each 15 min), each day of the month is processed using the β operator (Fig. 1b). In this case, temperature values usually fall inside the optimal range (Fig. 1a); those values out of this range affect the final score resulting in a β index lower than one. Salinity values usually fall outside the optimal level, which are computed in a close to zero score; however, the proximity of those values and their respective deviation generates a non-zero result.

3.2. Priority assignment

In Section 2, water quality parameters were grouped by monitoring frequency. The monitoring frequency is related to their importance in shrimp culture; e.g. pH and dissolved oxygen are among the most critical parameters in a pond, because these

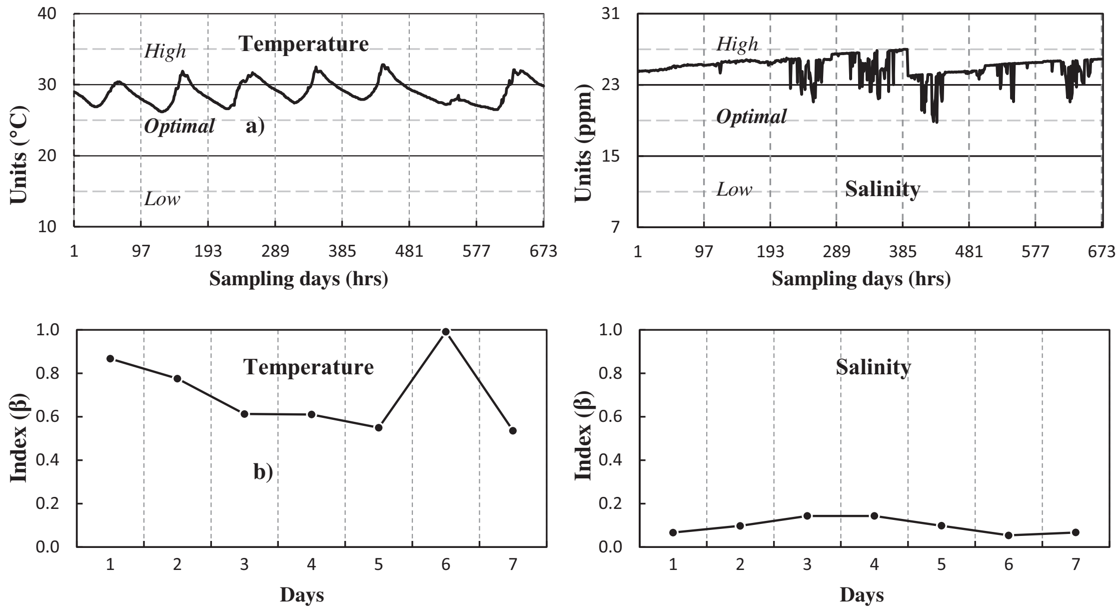

Fig. 1. A week of measurements was used to evaluate temperature values and salinity concentrations using the β operator. Values close to the limits deteriorate the status of the water quality parameters.

parameters can generate extremely harmful crisis if they are out of their optimal ranges. Therefore, they are daily monitoring; in this sense, there are parameters with higher priority than others.

The successful application of a Water Quality Index depends on an appropriate weight assignment to those variables involved in the ecosystem. These weights define the relative importance and influence of each water quality parameter in the final score. In this section, we introduce a comprehensive multi-variable method based on an analytical hierarchical process (AHP) to estimate the relative importance of each water quality parameter and groups of these parameters.

The aim of AHP is to construct a water quality parameter hierarchy which generates priority values from different criteria and sub-criteria involved in the decision-making process (Chakraborty and Dey, 2006; Saaty, 2004). First, an importance scale level is assigned to both, each parameter alone and each group of parameters (daily, weekly and by request). In this work, we use the scale proposed by Saaty (2004) for groups of parameters and the inverted scale level for water quality parameters (Table 6).

In our study, priority values were adjusted to the characteristics of north-pacific Mexican coastal waters and to tropical shrimp cultivation (Table 7) according to the SAGARPA (2010) and Mexican experts in coastal waters (Ávila et al., 2012; Carbajal-Hernández et al., 2012). However, priority assignment could be adjusted to the characteristics of any other specific farming process according to expert criteria and literature of a specific organism.

After, using the computed weights (w_n) a consistent matrix (A) is created. A consistent matrix is a positive reciprocal $n \times n$ matrix whose elements are quotients w_i/w_j that satisfy the relation $a_{ij} \cdot a_{jk} = a_{ik}$; for $i, j, k = 1, \ldots, n$ (Saaty, 2004). A consistent matrix can be represented as follows:

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \cdot \begin{bmatrix} \frac{w_1}{w_1} & \frac{w_1}{w_2} & \cdots & \frac{w_1}{w_n} \\ \frac{w_2}{w_1} & \frac{w_2}{w_2} & \cdots & \frac{w_2}{w_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{w_n}{w_1} & \frac{w_n}{w_2} & \cdots & \frac{w_n}{w_n} \end{bmatrix} \tag{6}$$

where w_i represents the assigned importance scale value to the ith water quality parameter of each group (daily, weekly or by request); for $i = 1, 2, \ldots, n$.

Finally, priorities are computed turning the pairwise matrix A into a ranking of priorities, using the principal eigenvector proposed by Perron (1907). The principal eigenvector represents dominance and therefore the priorities of the water quality parameters. Recently, Saaty (1990) demonstrated mathematically that the eigenvector solution is the best approach. The principal eigenvector is computed following the next steps:

(a) First, the pairwise matrix A is squared as follows:

$$B = A \times A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \cdot \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \tag{7}$$

(b) Then, the rows sums C_i, $i = 1, 2, \ldots, n$ are computed ($a_{i1} + a_{i2} + \cdots a_{in}$) using the following equation:

$$C_i = \sum_{j=1}^{n} B_{ij}, \quad \forall i = 1, 2, \ldots n. \tag{8}$$

(c) Finally, each C_i, $i = 1, 2, \ldots, n$ vector is normalized as follows:

$$P_i = \frac{C_i}{\sum_{i=1}^{n} C_i}, \quad \forall i = 1, 2, \ldots, n \tag{9}$$

where P_i contains the priorities of the water quality parameters (weights). This process must be iterated until the eigenvector solution does not change from the previous iteration. Each iteration, the input matrix A is replaced by the squared matrix $B = A \times A$ and the process is executed again, the calculation should stop when no significant difference between consecutive eigenvector solutions is computed. Tables 8–11 contain the pairwise matrices and priorities computed for the water quality parameters and groups of them using weights from Table 7. In this case, priority values converged in the first iteration. Fig. 2

Table 7
Scale values for parameter groups and monitored parameters using normal and inverted priorities respectively.

Parameters	Daily monitored				Weekly monitored					Groups		
	DO	Temp	Sal	pH	NH	NO_3	NO_2	NH_3	Tb	Daily	Weekly	By request
Scale value	1	2	3	1	4	4	5	1	3	9	6	4

Parameters	Monitored by requirement												
	Ak	CO_2	Ss	P	H_2S	HS^-	Px	Si	ChA	N	Tmb	Vb	Fc
Scale value	1	4	4	7	7	7	7	7	7	7	2	2	2

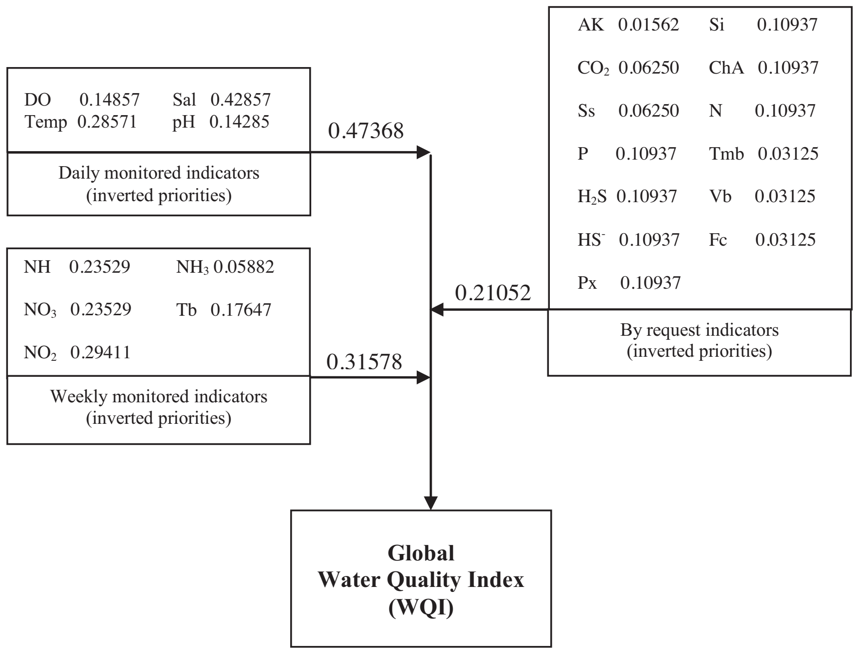

Fig. 2. Weights for the water quality parameters and groups, estimated with the analytic hierarchical process.

Table 8
Pairwise comparison matrix for parameters monitored daily using inverted priorities.

Parameters	DO	Temp	Sal	pH	Priority value
DO	1	1/2	1/3	1	0.142857
Temp	2	1	2/3	2	0.285714
Sal	3	3/2	1	3	0.428571
pH	1	1/2	1/3	1	0.142857

Table 9
Pairwise comparison matrix for parameters monitored weekly using inverted priorities.

Parameters	NH	NO_3	NO_2	NH_3	Tb	Priority value
NH	1	1	4/5	4	4/3	0.235294
NO3	1	1	4/5	4	4/3	0.235294
NO2	5/4	5/4	1	5	5/3	0.294118
NH3	1/4	1/4	1/5	1	1/3	0.058823
Tb	3/4	3/4	3/5	3	1	0.176471

Table 10
Pairwise comparison matrix for parameters monitored by request using inverted priorities.

Parameters	Ak	CO_2	Ss	P	H_2S	HS^-	Px	Si	ChA	N	Tmb	Vb	Fc	Priority value
AK	1	1/4	1/4	1/7	1/7	1/7	1/7	1/7	1/7	1/7	1/2	1/2	1/2	0.01562
CO_2	4	1	1	4/7	4/7	4/7	4/7	4/7	4/7	4/7	2	2	2	0.06250
Ss	4	1	1	4/7	4/7	4/7	4/7	4/7	4/7	4/7	2	2	2	0.06250
P	7	7/4	7/4	1	1	1	1	1	1	1	7/2	7/2	7/2	0.10937
H_2S	7	7/4	7/4	1	1	1	1	1	1	1	7/2	7/2	7/2	0.10937
HS^-	7	7/4	7/4	1	1	1	1	1	1	1	7/2	7/2	7/2	0.10937
Px	7	7/4	7/4	1	1	1	1	1	1	1	7/2	7/2	7/2	0.10937
Si	7	7/4	7/4	1	1	1	1	1	1	1	7/2	7/2	7/2	0.10937
ChA	7	7/4	7/4	1	1	1	1	1	1	1	7/2	7/2	7/2	0.10937
N	7	7/4	7/4	1	1	1	1	1	1	1	7/2	7/2	7/2	0.10937
Tmb	2	2/4	2/4	2/7	2/7	2/7	2/7	2/7	2/7	2/7	1	1	1	0.03125
Vb	2	2/4	2/4	2/7	2/7	2/7	2/7	2/7	2/7	2/7	1	1	1	0.03125
Fc	2	2/4	2/4	2/7	2/7	2/7	2/7	2/7	2/7	2/7	1	1	1	0.03125

shows the hierarchical tree for computing the Water Quality Index (WQI) using the corresponding priorities.

3.3. Water quality assessment

In this section, the Water Quality Index (WQI) is defined using the β operator and the analytical hierarchical process. When a water parameter reports values out of its optimal range, the good condition of the water quality should be decreased. However, parameters with more negative impact should be tightly supervised; in this sense, priorities are helpful to highly decrease water quality scores when parameters with a more critical behavior are out of range. Using these concepts, we define the WQI as the following process.

(a) First, the value of each parameter is multiplied by its priority factor as follows:

$$W_{par} = \beta_{par} P_{par} \quad (10)$$

where *par* refers to a water quality parameter and P_{par} refers to the assigned priority showed in Tables 12–14.

(b) The water quality condition of each group of parameters is determined according to:

$$Q_g = \frac{1}{P_{\min}} \cdot \min\{W_{par\_1}, W_{par\_2}, \ldots, W_{par\_n}\} \quad (11)$$

where g is the group of parameters to assess, and P_{min} is the lowest priority of this group.

(c) The water quality result of each group is multiplied by its respective priority weight:

$$WD_g = Q_g \cdot P_g \quad (12)$$

where P_g is the priority computed for each water quality group shown in Table 11.

(d) Finally, the Water Quality Index is defined as follows:

$$WQI = WD_{daily} + WD_{weekly} + WD_{requirement} \quad (13)$$

where the final score has a [0, 1] range.

The hierarchical tree for the environmental parameters and water quality assessment is shown in Fig. 2.

3.4. Numerical example

As an example, we can compute the WQI using the proposed equations and the priorities previously assigned as well as the measurement set showed in Table 12.

First, the β operator is computed for each water quality parameter. Table 13 shows the procedure for the β_{pH} calculation and the β scores computed for each parameter. In this case, the β_{pH} was computed using its respective range of [6.5, 9.5] and $d = \pm 0.5$.

After, the Q indexes are computed according to each group of parameters and the priorities assigned to each water quality parameter as follows:

(a)
$$Q_{daily} = \frac{1}{0.1428} \cdot \min\{(\beta_{temp} \cdot P_{temp}), (\beta_{DO} \cdot P_{DO}), (\beta_{salt} \cdot P_{salt}), (\beta_{pH} \cdot P_{pH})\}$$
$$Q_{daily} = \frac{1}{0.1428} \cdot \min\{(0.285 \cdot 0.667), (0.142 \cdot 0.182), (0.428 \cdot 0.143), (0.142 \cdot 0.714)\} = \frac{0.026}{0.14285} = 0.182$$

(b)
$$Q_{weekly} = \frac{1}{0.0588} \cdot \min\{(\beta_{NH} \cdot P_{NH}), (\beta_{NO3} \cdot P_{NO3}), (\beta_{NO2} \cdot P_{NO2}), (\beta_{NH3} \cdot P_{NH3}), (\beta_{Tb} \cdot P_{Tb})\}$$
$$Q_{weekly} = \frac{1}{0.0588} \cdot \min\{(0.235 \cdot 0.214), (0.235 \cdot 0.741), (0.294 \cdot 1), (0.058 \cdot 1), (0.176 \cdot 0.545)\} = \frac{0.0503}{0.0588} = 0.856$$

(c)
$$Q_{req} = \frac{1}{0.0156} \cdot \min\{(\beta_{Ak} \cdot P_{Ak}), (\beta_{CO2} \cdot P_{CO2}), \ldots, (\beta_{Px} \cdot P_{Px}), \ldots, (\beta_{Fc} \cdot P_{Fc})\}$$
$$Q_{req} = \frac{1}{0.0156} \cdot \min\{(0.0156 \cdot 1), (0.0625 \cdot 0.923), \ldots, (0.1093 \cdot 0.075), \ldots, (0.0312 \cdot 0.634)\} = \frac{0.0082}{0.0156} = 0.525$$

Table 11
Pairwise comparison matrix for parameter groups.

Criteria	Daily	Weekly	By request	Priority value
Daily	1	9/6	9/4	0.473684
Weekly	6/9	1	6/4	0.315789
By request	4/9	4/6	1	0.210526

Finally, the WQI is computed using the Q indexes and their respective priorities:

$$WQI = WD_{daily} + WD_{weekly} + WD_{requirement}$$
$$WQI = 0.47368 \cdot Q_{daily} + 0.3157 \cdot Q_{weekly} + 0.21052 \cdot Q_{requirement}$$
$$WQI = (0.47368 \cdot 0.182) + (0.3157 \cdot 0.856) + (0.21052 \cdot 0.525) = 0.467$$

The 0.467 score can be interpreted as a slightly poor water quality condition in a [0 (*poor*), 1 (*excellent*)] range. In this case, all the groups of parameters have values outside of their optimal ranges according to Table 5. However, the most negative impact was assessed in the *daily monitored group* where *dissolved oxygen* and *salinity* presented *very low* and *high* values respectively (Table 12).

4. Experimental results

In this section, we apply the proposed Water Quality Index (WQI) to assess the water quality in a real extensive shrimp farm. Additionally, we compare its performance compared against similar indexes reported in the literature.

4.1. Water sampling area

In extensive aquaculture systems of Mexico, measuring water quality parameters is a difficult task. Semi-extensive and extensive aquaculture systems have huge dimensions with so many ponds to control, additionally weather conditions are extreme (they are mainly located in hot places as a desert). On the other hand, assessing water quality with a complete set of parameters requires long time for collecting samples, too many chemical analyses, and the use of complex electronic sensors and informatics systems, which for this type of analysis are too expensive. These requirements are an obstacle for collecting samples for the complete set of parameters in this kind of aquaculture systems. A solution for assessing water quality is to take into account only critical parameters that should be frequently measured (Table 2) (Carbajal et al., 2011; Hirono, 1992). In the literature those critical parameters have been studied for providing an approximation of the ecological condition in the pond. In this sense, although those parameters represent a small part of the ecosystem, they provide a reliable interpretation of the water quality condition in shrimp ponds (Ferreira et al., 2011; Simões et al., 2008; Beltrame et al., 2004; Hirono, 1992).

Therefore, since in extensive shrimp farms is not feasible collecting samples for the complete set of parameters (Boyd and Musin, 1992; Hirono, 1992); in our experiments only critical

Table 12
Example of a measurement set of water quality parameters.

Daily				Weekly				
Temp	DO	Sal	pH	NH	NO_3	NO_2	NH_3	Tb
28.0	6.3	21.0	9.3	0.05	370	0.30	0.07	33
28.0	3.0	35.0	7.2	0.07	570	0.35	0.07	34
32.0	3.0	45.0	6.1	1.02	780	0.33	0.08	38

By requirement												
Ak	CO_2	Ss	P	H_2S	HS^-	Px	Si	ChA	N	Tmb	Vb	Fc
113	18	130	0.1	0.05	0.001	730	4.1	58	3.1	9572	856	1001
123	17	134	0.2	0.05	0.002	725	4.0	57	3.5	10,234	850	1013
130	19	141	0.3	0.06	0.001	754	4.2	58	4.2	10,394	876	1033

Table 13
Procedure for computing the β_{pH} index and the β scores for each water quality parameter.

pH	Criterion	$[t_b, t_a]$	Equation	*Ad*	β_{pH}
9.3	Above the level		$e=\frac{m-t_a}{2d}=\frac{m-(l_a-d)}{2d}=\frac{9.3-(9.5-0.5)}{2(0.5)}=0.3$		
7.2	Inside $[t_b, t_a]$	[6, 9]	$e=0$	0.4	0.714
6.1	Below the level		$e=\frac{t_b-m}{2d}=\frac{(lb+d)-m}{2d}=\frac{(6.5+0.5)-6.1}{2(0.5)}=0.9$		

β_{Temp}	β_{DO}	β_{Sal}	β_{NH}	β_{N03}	β_{N02}	β_{NH3}	β_{Tb}	β_{Ak}	β_{CO2}	β_{Ss}	β_{P}	β_{H2S}	β_{HS}	β_{Px}	β_{Si}
0.667	0.182	0.143	0.214	0.741	1.0	1.0	0.545	1.0	0.923	1.0	0.857	1.0	1.0	0.075	0.571

β_{ChA}	β_{N}	β_{Tmb}	β_{Vb}	β_{Fc}
1.0	0.75	0.652	1.0	0.634

parameters (temperature, dissolved oxygen, salinity and pH) were monitored and measured using electronic sensors, by the Northwest Biological Research Center (Centro de Investigaciones Biológicas del Noroeste, in Spanish with English acronym; NBRC, 2010), which is located in Hermosillo, Sonora, Mexico.

In our study the "Gez Acuícola" marine farm, located in Huatabampo, Sonora, Mexico was used for sampling the daily monitored parameters (critical parameters) during a shrimp farming period. In this case, three months were measured using a test pond (June, July and August, 2010). Due to extreme weather conditions during the farming period, some measures could not be acquired because failures in sensors. Those wrong measures were deleted for avoiding noise in the final score of water quality assessment (Fig. 3). Samples were collected each 15 min (i.e. 96 samples per day). There is not a rule about how many samples per day should be measured; however, the proposed frequency allows evaluating daily fluctuations and the behavior of this dynamical environment; such fluctuations are especially important since dissolved oxygen and pH variations can be extremely harmful when they fall to very low (or very high for pH) concentrations. Our proposed water quality index was tested using this database in order to show its effectiveness compared against other approaches.

4.2. Water quality analysis

Water quality assessment was performed using the proposed index and the sampling set provided by NBRC (2010). In this case, the proposed WQI was performed using the priority weights determined in Section 3.2. Those priority values were chosen by the experts according to the importance and interaction of the water parameters in the ecosystem, taking into account the characteristics of the ponds, the environment condition, geography, localization, feeding rates, etc. However, in our approach, priority interpretations can be adjusted according to the particular necesities of the specific aquaculture system.

In order to compare the performance of the proposed index (WQI), we compared it against similar indexes as CCME and HWQI. According to the Canadian Council Ministers of the Environment (CCME, 2010), its index can be used for marine or fresh water quality analyses; CCME index is based on calculating the average deviation of samples falling out of their desired ranges. The CCME index can be used with any set of variables, using statistical analysis. The HWQI was proposed by Carbajal et al. (2011) and it provides a complete interpretation of the water quality in marine shrimp systems. HWQI is based on a fuzzy inference system, which detects all

Table 14
Comparative between HWQI, CCME and WQI indexes.

Temp (°C)	DO (ppt)	Salt (ppt)	pH	HWQI	CCME	WQI	Observations
28.0	1.9	55.8	8.2	0.0	0.75	0.0	Hypoxia situation by dissolved oxygen; high salinity concentrations.
28.0	1.8	55.8	8.2				
28.0	2.8	57.0	8.2				
28.0	1.8	57.0	8.2				
28.0	5.6	19.0	3.1	0.21	0.85	0.04	pH is acid and alkaline.
28.0	6.3	21.0	11.7				
28.0	3.0	45.0	4.0				
31.4	3.0	45.0	5.0				
25.0	8.2	19.0	8.5	1.00	1.00	0.98	Optimal conditions.
24.0	8.3	18.5	8.6				
25.0	8.3	19.0	8.5				
25.0	8.4	17.0	8.5				

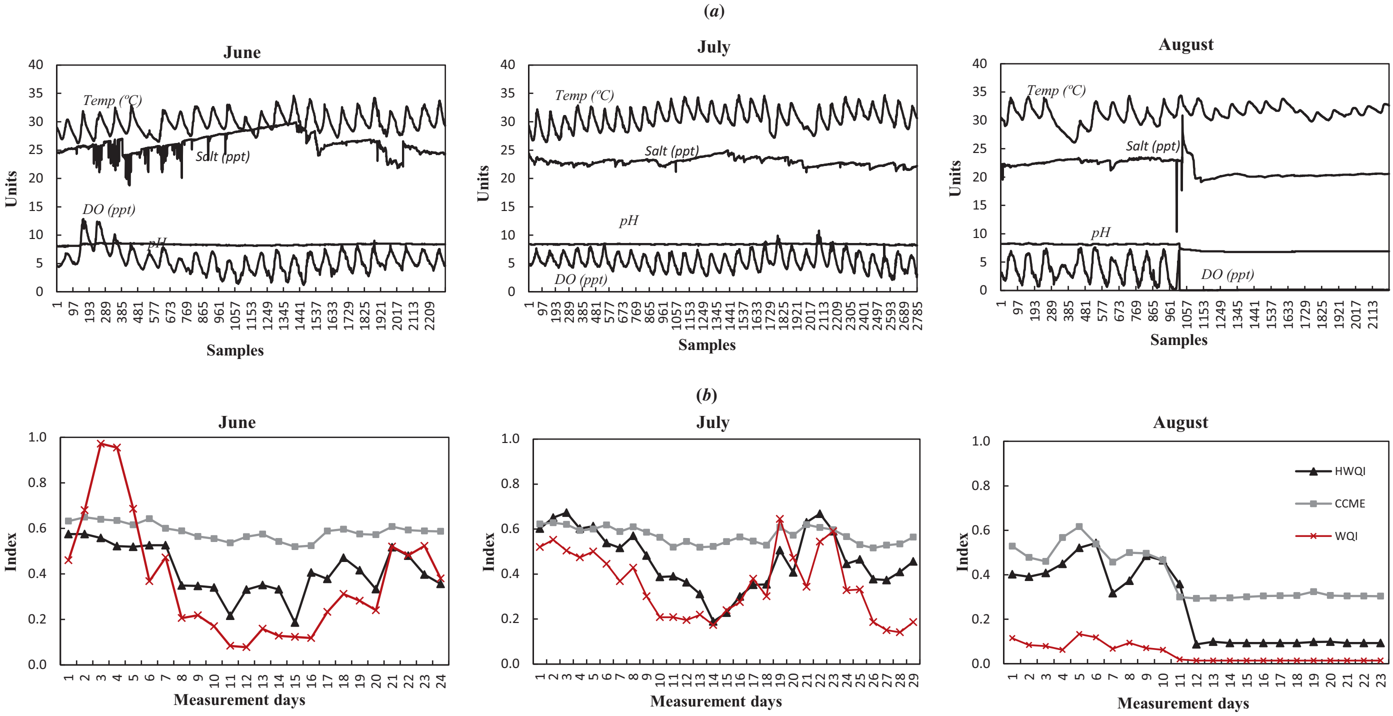

Fig. 3. Results of the assessment of the water quality of "Gez Acuícola" marine shrimp farm using three months of measurements (June, July and August, 2010): (a) water quality parameter samples and (b) scores of water quality assessments.

the ecological crisis and negative impacts by using fuzzy reasoning. Although both indexes have reported good results in marine shrimp environments, they have some drawbacks for their implementation. For example, in the CCME index equations, some water quality parameters can dramatically influence the final score without any valid justification, because different parameter conditions induce different water quality situations that are not considered in its mathematical model (see Appendix A). The HWQI index provides a very accurate approach for water quality assessment; however, its implementation is too complex and hard to understand. In this sense, the aim of the index proposed in this paper is to provide an easy to implement index, providing an accurate and easy interpretation of the ecosystem condition.

For showing the performance of the three indexes (WQI, CCME and HWQI) we apply them in the proposed database containing the daily monitored parameters during 3 months of farming (June, July and August, 2010). In June and July, the results provided by the three indexes were similar; water quality scores present values from 3 to 6 units which mean adequate conditions for the assessed ecosystem. In this case, the CCME index provides scores nearer to good conditions than HWQI and WQI indexes, whose results show a higher penalty in water quality analyses. In August, CCME and HWQI presented scores with regular to poor conditions in the first part of the month; however, at the second part of the month, only the HWQI scores were close to a real evaluation since the oxygen concentrations were below 2 ppt. In this case, the proposed index (WQI) showed an extremely bad water quality, since very low dissolved oxygen concentrations and high temperature values were the main factors of this water quality assessment. Measurements of the water quality parameters and the water quality assessments can be observed in Fig. 3. In Table 14, a numerical comparison of the three indexes is done. Three cases are assessed in order to show index performances: hypoxia, acid or alkaline crisis and optimal conditions. In those examples, as it is shown in Fig. 3, the CCME index does not efficiently detect harmful crisis, the CCME scores show good water quality conditions in all cases. While in the contrary, HWQI and WQI correctly detect potential crisis, where very low dissolved oxygen, alkaline or acid concentrations influenced the final score, indicating a bad water quality condition in both cases. An excellent water quality condition was detected in the third case, where parameter concentrations were in their optimal ranges.

5. Discussion

The success of an adequate water quality assessment mainly depends on the capacity of recognizing those water quality parameters that are more critical in the ecosystem, which can be harmful if they are not monitored and controlled efficiently. In our index, the priority assignment identifies those parameters having more importance than others; the parameters involved in the water assessment can be prioritized according to the particular organism, soil and water specifications, depending on the specific context of the aquaculture requirements. For example, in Section 4, the WQI index was customized taking into account the parameter priorities obtained through the proposed analytical hierarchical process in order to monitor and analyze the ecosystem of the Litopenaeus vannamei, farmed in shrimp ponds located in Sonora, Mexico. Other water quality indexes for shrimp culture assessment proposed in the literature do not provide an accurate assessment or they are too complex to implement. For this reason, the proposed index has been developed to be adaptable, easy to understand and implement in any aquaculture environment. Experimental results in real shrimp environments show that the proposed index has good performance and accuracy.

Traditional reports on water quality tend to be too technical and detailed, presenting monitoring data on individual substances, without providing a complete and interpretable water quality evaluation. To solve this gap, several Water Quality Indexes have been developed to integrate water quality parameters. Traditional indexes evaluate water quality in a rigorous sense, while the proposed index provides a more accurate analysis of the water quality parameters, integrating all available variables jointly with their weights for providing a complete evaluation of the water quality condition.

In the literature, different indexes have been implemented in order to evaluate specific water bodies. In shrimp culture, environmental models as Ferreira et al. (2011), Simões et al. (2008), Carbajal et al. (2011) and Carbajal-Hernández et al. (2012) the authors provide solutions for water quality assessments. In the first two works, Ferreira et al. (2011) and Simões et al. (2008) proposed water quality indexes, but the main drawback is that only one individual measurement for each parameter provides the pond water quality condition. In Carbajal et al. (2011) and Carbajal-Hernández et al. (2012) the authors proposed models based on fuzzy inference systems, where parameter relationships and the dynamic of the system can be established using fuzzy rules. However, these models are very complex and difficult to understand and implement. On the other hand, the CCME index can be used for analyzing parameter behavior since it evaluates the dynamic of a set of parameters by analyzing the variation and deviation of a sampling set. Nevertheless, this index gives the same level of importance to all water quality parameters, influencing the final score when non critical parameters are evaluated as critical ones. In contrast, in our proposed WQI, parameter variations are quantified using the β operator, which assesses the dynamic of each parameter using a set of samples; and the priority assignment provides higher importance to most critical water quality parameters. The experimental comparison presented in Section 4 among CCME, HWQI and the proposed WQI indexes shows the advantages of the WQI index.

It is important to remark that the database used in this work, for water quality assessment, only considers critical parameters (daily monitored parameters – Table 1), however, through an appropriate weight assignment of daily parameters, our model provides a good water quality assessment since, as it was shown, the proposed index (WQI) correctly assesses bad ecological conditions (i.e. very low dissolved oxygen concentrations), computing a poor water quality score: while in the contrary, the other indexes compute scores meaning good water quality conditions. Nevertheless, more accurate results could be obtained if a complete water quality analysis are computed using the entire set of water parameters. In this sense, the scores produced by the analysis of weekly monitored and monitored by request parameters will fit the final score. One of the most relevant aspects to highlight is that in the proposed index (WQI), water quality parameters are assessed by their relative importance in the ecosystem through the proposed analytical hierarchical process.

Water quality evaluation is an important problem in aquaculture systems worldwide. In this sense, this work provides the basis for future researches as the implementation of controlling and automation systems in shrimp farms. The improvement of current models to assess pollution by water discharges or for shrimp culture chemotherapy should also be developed in order to reach higher levels in aquaculture assessment that helps to increase the reproduction and good growing of the farmed organisms.

6. Conclusions

The success of a good water quality assessment resides in a good priority selection for each water quality parameter involved in the ecosystem. Although, the size of a complete set of parameters can be big, it is important to determine those parameters with a relative high importance and how they should be weighted for directly monitoring their effects over the water quality assessment. Therefore, in this work, a new Water Quality Index for monitoring and controlling shrimp culture systems using an analytical hierarchical process has been proposed. Based on our experimental results, we can conclude that priority parameter assignment provides a more effective water quality assessment than traditional approaches. In this sense, the proposed index fits more accurate final scores; as we have shown in our experiments, where we got a good performance of the proposed WQI index. Measuring water quality parameters in extensive aquaculture systems is a difficult task; however the WQI index is an accurate and easy to implement option which can be adjusted depending on the requirements of a specific aquaculture system, helping to face this problem. Finally, it is important to mention that introducing new concepts about how the relationships among parameters affect the ecosystem and building new indexes based on these concepts is a mandatory future work.

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Appendix A. Water Quality Index of the Canadian Council of Ministers of the Environment

The CCME can be determined in four steps. The first step consists in computing the percentage of parameters whose current concentration is out of their allowed limits. It is done as follows:

$$F_1 = \frac{number\ \ of\ \ failed\ \ parameters}{total\ \ number\ \ of\ \ parameters} \times 100$$

In the second step, the percentage of individual tests for each parameter that do not fulfill its allowed limits is determined as follows:

$$F_2 = \frac{number\ \ of\ \ failed\ \ tests}{total\ \ number\ \ of\ \ parameters} \times 100$$

The third step consists in computing the percentage of deviations in each individual test as follows:

(a) Those cases in which the test value must not be below or above the objective limit are computed (excursions):

$$excursion_i = \begin{cases} \dfrac{Objective_i}{Failed\ \ test\ \ value_i} - 1 & if\ \ value\ \ falls\ \ above \\ \dfrac{Failed\ \ test\ \ value_i}{Objective_i} - 1 & if\ \ value\ \ falls\ \ below \end{cases}$$

(b) The normalized sum of excursions (nse) is calculated as follows:

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

(c) An asymptotic function that scales the normalized sum of the excursions (nse) is calculated in order to yield a value between 0 and 100 as follows.

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

Finally, the CCME is computed as follows:

$$CCME = 100 - \frac{\sqrt{F_1^2 + F_2^2 + F_3^2}}{1.732}$$

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