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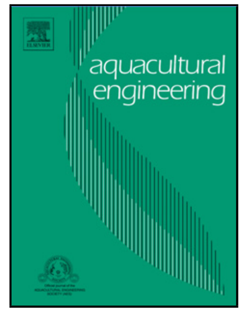

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Evaluating the Rearing condition of Rainbow Trout (*Oncorhynchus Mykiss)* Using Fuzzy Inference System

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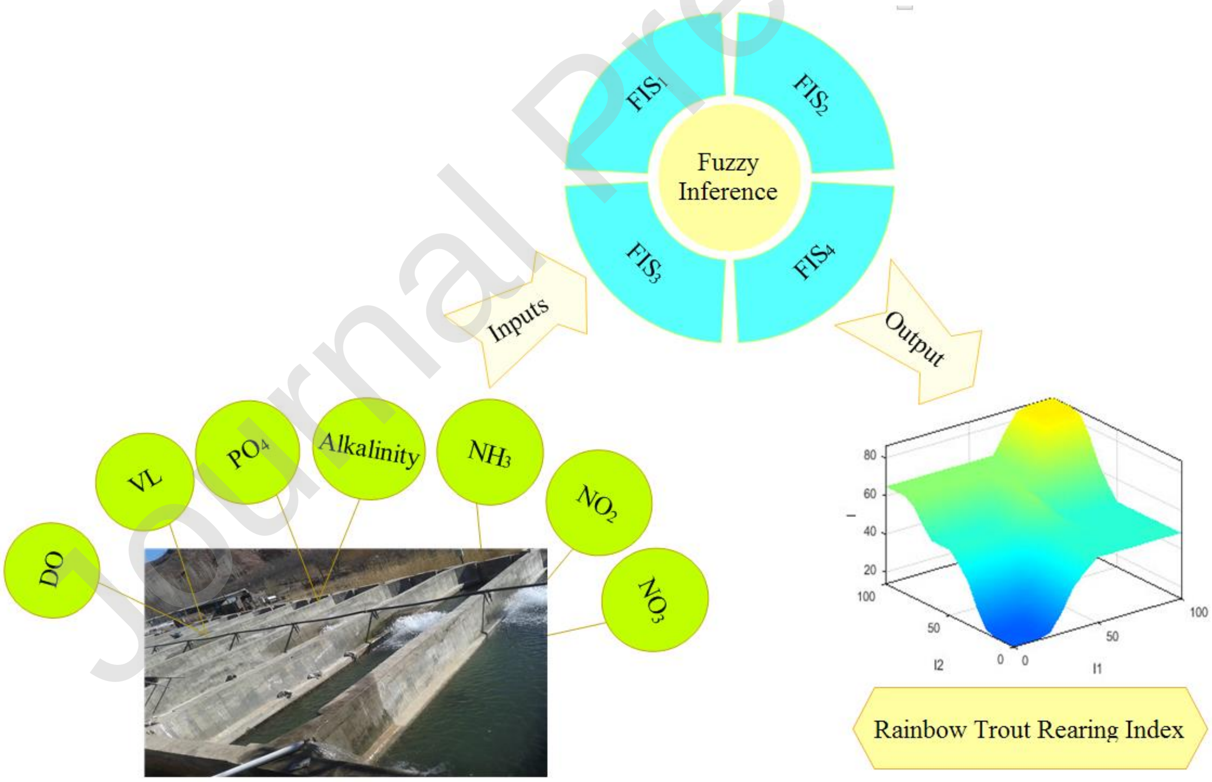
Graphical Abstract



Highlights

- The fuzzy inference system was used to develop a rainbow trout rearing index.
- The study farm with a rearing index value of 65 was in a very good range.
- Water quality parameters directly affected rainbow trout rearing condition.

Abstract

Rainbow trout (*Oncorhynchus mykiss*) is one of the most popular aquacultured species in the world. Sustainable production of this fish at commercial scale is very important but requires maintaining good water quality throughout the total rearing period. The present study aimed to develop a rainbow trout production index in order to raise awareness about the conditions of the rearing environment, enhance production, and reduce losses. For this purpose, an intensive rainbow trout production system was selected as the study system. In this system, there were seven stations including (a) 3000 5-g fish, (b) 3000 25-g fish, (c) 3000 50-g fish, (d) 3000 100-g fish, (e) 3000 220-g fish, (f) 2000 350-g fish, and (g) 2000 830-g fish. The fuzzy inference system was used to develop the target rearing index. Water quality parameters involved in the variation in the rainbow trout rearing conditions were classified into three groups including un-ionized ammonia, nitrite, and nitrate, Alkalinity and phosphate, along with dissolved oxygen and linear velocity. For each group and condition of rearing, a separate fuzzy inference system was defined and the output of each fuzzy system was named I_1, I_2, I_3. Finally, I_1, I_2, and I_3 were considered as the inputs to a fuzzy system in order to evaluate their effects on the index of general rearing conditions (I). The results indicated that un-ionized ammonia, nitrite, nitrate, and phosphate had negative effects while dissolved oxygen, linear velocity, and alkalinity positively affected water quality and rearing index. Most of the decline in the rainbow trout rearing index was related to the effect of un-ionized ammonia, nitrite, and nitrate due to food decomposition. Therefore, intelligence feeding based on fish appetite through reducing food conversion rate and water pollution can improve rainbow trout production in this system. The index of rainbow trout production conditions reflects the type, amount, and effect of water quality pollutants on rearing conditions. Producers can use this information to reduce the negative environmental effects and improve the product quality.

Keywords: Fuzzy Inference, Rearing Index, Rainbow Trout

1.Introduction

Water quality parameters are closely related to both fish health and environmental quality. Organic aquaculture can help maintain natural environment, biodiversity, and animal welfare, which include the ecologically integrated systems enhancing the quality and health of the products. Water quality and effluent are considered as serious concerns in the ecosystems (Lembo and Mente, 2019), and good water quality is one of the vital requirements of successful aquaculture. Food input leads to the reduction of water quality in the pools and increase of stress. As the food input increases, the metabolic waste entering the pools increases as well. Due to the food input, the concentration of phytoplanktons, total ammonia, and carbon dioxide increases while the concentration of dissolved oxygen decreases (Anyadike et al., 2016).

Water quality is usually determined through toxicity tests, which assess the tolerance power of various aquatic organisms against different toxic ingredients. Each aquatic species can have a different response to a specific toxic compound (Carbajal-Hernández et al., 2012). Although water quality may be simultaneously reduced by different environmental factors, focusing on major ones can make water conservation and renewal more economic and facilitate determining management priorities (Li et al., 2015). In this regard, dependable monitoring and assessment programs are required for the numerous and complicated changes in water quality in order to achieve a comprehensive understanding of pollution and its effects. Long-term monitoring generates a large set of intricate data. Accordingly, more suitable techniques to manage water quality variables, acceptable range interpretation of each parameter, and methods to integrate different parameters in the evaluation process are clearly required (Ferreira et al., 2011).

Artificial intelligence methods are regarded as a suitable substitute technique for modeling a complex and non-linear system in many fields (Liu et al., 2013). Fuzzy models are the most widely used artificial intelligence technique water quality modeling with the benefits of flexibility, clarity, and user friendliness (Akerkar and Sajja, 2010). Such models discover the nonlinear relationships between ecological variables with regards to the inherent uncertainty of the variables (Kampichler et al., 2000). In addition, the indicators, as a representative of the constituted elements, integrate scientific knowledge in order to facilitate decision-making (Valenti et al., 2018).

Carbajal-Hernández et al. (2012) developed an indicator to evaluate the water quality for shrimp culture based on a fuzzy inference system. To this end, the water quality parameters were classified and the negative environmental effects of the parameters in the shrimp habitat were evaluated by the fuzzy inference system. Then, the most important parameters were prioritized using hierarchical analysis and finally, a new indicator was developed to assess the ecological condition of water quality. In another study, Forio et al. (2017) used a fuzzy inference system to identify the key factors in the water quality of the aquatic ecosystems in the America Guayas River Basin. The variables of the system included land use, chlorophyll, and flow velocity. The results of the study indicated that land use played the most determining role in the water quality of aquatic ecosystems in that area. In addition, Bórquez-Lopez et al. (2018) evaluated two methods of fuzzy logic and mathematic functions as two dynamic feeding strategies in the intensive shrimp culture system. They used dissolved oxygen and temperature variation in both methods. The results demonstrated that the dissolved oxygen significantly affected food conversion rate while the effect of temperature on the rate was not much significant. Further, the results demonstrated that food conversion rate considerably improved in the fuzzy logic strategy. About 35% of food was saved compared to the control group, i.e. the conventional feeding table. In a study conducted by Zhou et al. (2018), a feeding control method was proposed based on machine vision, near-infrared, and adaptive network-based fuzzy inference system in order to achieve auto decision-making feeding based on fish appetite. The quantitative index of fish feeding behavior was extracted by Delaunay triangulation and image texture. Network-based fuzzy inference system was established based on fuzzy rules and was employed to obtain auto on-demand feeding. The performance of the method was evaluated using specific growth rate, weight gain rate, food conversion rate, and water quality parameters. Based on the results, the accuracy of the feeding decision of the adaptive neural-based fuzzy inference system (ANFIS) was 98%. Although, this method did not show a significant difference in the growth promotion of fish compared to the feeding table, food conversion rate could be reduced by 10.77% and water pollution could be also lowered. Furthermore, Wu et al. (2015) employed fuzzy logic controller and adaptive network-based fuzzy inference system to support decision-making about the feeding process of silver perch based on fish appetite. Fish appetite was detected by measuring the concentration of dissolved oxygen through evaluating two flocking indexes and struggle strength characteristics. The results indicated that a decision threshold of 0.17 was inferred from the fuzzy logic method, and the rate of judgment accuracy of 97.9% was obtained from ANFIS.

The results of the previous studies revealed that how fuzzy inference system can quickly and accurately predict the relationship between water quality parameters, evaluate the importance of each parameter, and report the condition of water quality as one integrated score. The producers in organic aquaculture aim to avoid the negative environmental effects on production procedures with the lowest price (Luna et al., 2019). Therefore, since water quality in any aquaculture system represents the condition of aquatics rearing, awareness of water quality can provide a framework to eliminate possible risks, such as diseases, incidence, and mortality, and control the production condition without any cost. The present study aimed to develop a rearing index for rainbow trout based on the effect of the essential parameters, including dissolved oxygen and linear velocity, as well as the contaminant parameters, including un-ionized ammonia, nitrite, nitrate, phosphate, and alkalinity, of water quality by using a fuzzy inference system. Developing such an urgent and comprehensive rearing index for raising awareness about water quality is considered as an innovation in organic aquaculture, which undoubtedly helps farmers control and manage aquatic systems effectively. Accordingly, they can prevent great losses and treatment costs through timely actions.

2. Materials and methods

2.1. Study area and system

The study area was a fish production farm in the Ortkand area, Kalat County, Razavi Khorasan province in Iran (36° 59′ N, 59° 46′ E). The farm was located in the mountainous area of the Sarrud village and the water was supplied from Ortkand River with a minimum and maximum discharge of 600 and 2300 l /s, respectively. The farm produced 80 t fish and 10 million fingerlings every year (Fig. 1). The study system was an intensive aquaculture system with seven stations including (a) 3000 5-g fish, (b) 3000 25-g fish, (c) 3000 50-g fish, (d) 3000 100-g fish, (e)

3000 220-g fish, (f) 2000 350-g fish, and (g) 2000 830-g fish. The system had concrete pools with the dimensions of 30 × 3 × 2 m^3. The pools were filled with the river water and the depth of water in them was 2 m. The schools of fish evaluated in this study were from a native trout species in Iran, which were different in terms of evolutionary stages. In the schools, the fish weighing up to 1 gr were classified as frys, fish weighing 25-30 gr as fingerlings, fish up to 100 gr as pre-fattened, and fish over 150 and under 1000 gr were classified as fish fattened (Nafisi Behbaadi, 2006).

2.2. Data collection

The present study employed the physical parameters, such as linear velocity, and chemical parameters, such as un-ionized ammonia, nitrite, nitrate, alkalinity, phosphate, and dissolved oxygen, of water quality in fuzzy inference systems in order to develop a model for assessing the rearing conditions of rainbow trout. Dissolved oxygen (mg/L) was measured using the Portable multimeter model AZ-8603 with 0.01 precision. The linear velocity was obtained by dividing the flow rate of the input water in each pool into the surface of the pool (Eq.1):

$$V = \frac{Q}{S} \tag{1}$$

Where *V* denotes linear velocity (cm/s), *Q* denotes the flow rate of input water in each pool (m^3/s), and *S* denotes the surface of each pool (m^2).

The parameters such as un-ionized ammonia (mg/L), nitrite (mg/L), nitrate (mg/L), phosphate (mg/L), and alkalinity (mg/L) were measured by the ultraviolet visible spectrophotometer apparatus DR 5000 ™ model.

2.3. Fuzzy inference system

Fuzzy inference is a process which maps the input data to output data based on fuzzy logic. Decision-making can be done based on mapping or pattern recognition (Ocampo-Duque et al., 2006). In general, the process of evaluating the fuzzy inference system in comprised of three stages including fuzzification, inference, and defuzzification. In the first stage, the inputs are read and the degree of their membership to each of the fuzzy sets are determined through membership functions. The output of this step is a fuzzy degree between zero and one, determining the amount of input membership in the fuzzy set. Fuzzy rules are actually the heart of the fuzzy system, which describe the relationship between the fuzzy sets defined in the fuzzy inference system with each other and how they affect the output. The duty of the fuzzy inference engine is to calculate the fuzzy output by considering and combining fuzzy rules. In other words, the fuzzy inference engine learns how to convert a collection of inputs into outputs by calculating any of the fuzzy rules in the fuzzy rules base. Defuzzification is the last principal stage of any fuzzy system, which specifies each point in a fuzzy set in the form of a precise number as an output (Hosseini, 2018).

2.4. Developing a rainbow trout rearing index

After collecting the required data and in order to facilitate investigating the effect of the interaction between water quality parameters on the changes in rainbow trout rearing conditions, the data were classified into three groups including un-ionized ammonia, nitrite, and nitrate as the first group, Alkalinity and phosphate as the second group, and dissolved oxygen and linear velocity as the third group according to the degree of adaptation and coordination. Then, a separate fuzzy inference system was defined for each group and rearing condition, and the outputs of each fuzzy system, which was in fact the same rainbow trout rearing index, were named as I_1, I_2, I_3. Finally, I_1, I_2, and I_3 were considered as the inputs to a fuzzy system in order to evaluate their effects on the index of general rearing conditions (I) and study the overall effect of all water quality parameters on the rearing index (Fig. 2).

2.5. Extended fuzzy systems

The fuzzy system (1) consisted of three input parameters, including un-ionized ammonia, nitrite, and nitrate, 125 laws, and an output parameter (I_1). The fuzzy systems (2) and (3) each one consisted of two input parameters, the first were alkalinity and phosphate and the second were dissolved oxygen and linear velocity, 25 laws, and one output parameter (I_2 in the second system and I_3 in the third system). Finally, the fuzzy system (4) included three input parameters, i.e. I_1, I_2, and I_3, 125 laws, and one output parameter (I). Fig. 3 illustrates an overview of the four fuzzy systems. Triangular and trapezoidal membership functions were used for input and output parameters. For each membership function related to the input parameters, five linguistic expressions were defined including very low (VL), low (L), moderate (M), high (H), and very high (VH). Regarding the membership functions associated with the output parameters, five linguistic expressions including very bad (VB), bad (B), good (G), very good (VG), and excellent (E) were considered. The membership functions used for the parameters of un-ionized ammonia, nitrite, nitrate, and I_1 are shown in Fig. 4, which are similar to the membership functions associated with other parameters. For each parameter, five fuzzy sets were determined corresponding to the related linguistic expressions. For instance, the output parameter rearing index varied from very bad (0-35), bad (20-50), good (35-65), very good (50-80) to excellent (65-100). In addition, the units, domain, and fuzzy sets were defined for the input and output parameters of the fuzzy systems and are presented in Table 1.

The rules defined for fuzzy systems in the present study are based on the science of the specialists' knowledge in the aquaculture sector and available resources (Nafisi Behbaadi, 2006; Parsley Barry, 2001). For example, the first rule of the fuzzy system (1) is "If the concentration of un-ionized ammonia is very low and the concentration of nitrite is very low and the concentration of nitrate is very low, then the rainbow trout rearing index is at an excellent level". Further, the first rule of the fuzzy system (2) states that "If the amount of alkalinity is very low and the concentration of phosphate is very low, then the rainbow trout rearing index is at a bad level". Furthermore, the first rule of the fuzzy system (3) expresses that "If the concentration of dissolved oxygen is very low and the linear velocity is very low, then the rainbow trout rearing index is very bad". Finally, in the fuzzy system (4), the first rule is "If I_1 is very bad and I_2 is very bad and I_3 is very bad then, the rainbow trout rearing index is at a very bad level". Other rules were similarly defined. The subscription operator and Mamdani fuzzy inference system was used to construct the rules and aggregation, and the gravity center method was employed for defuzzification. These methods were implemented in the MATLAB software (version 2016b).

3. Results and discussion

3.1. Analysis of fuzzy models

The rainbow trout rearing index was 65, which was in the range of very good. The results of the four fuzzy inference systems are presented in the form of surface response diagrams in Fig. 5. As can be seen, increasing the un-ionized ammonia, nitrite and nitrate concentration leads to the decrease in value of the rainbow trout rearing index. Although ammonia and nitrite are toxic and dangerous substances in rainbow trout rearing environment, rainbow trout is sensitive to low ammonia concentrations, i.e. less than 0.02 mg/L. Nitrite is produced by Nitrosomonas bacteria as a result of ammonia oxidation. Another toxic substance is nitrate, which is produced by Nitrobacter bacteria due to the oxidation of nitrite in water sources. In general, nitrate in low concentrations, i.e. less than 300 mg/L, is not considered as hazardous for rearing rainbow trout. However, in some conditions such as recirculating aquaculture systems, its concentration increases to a very high amount, i.e. over 1000 mg/L, which is dangerous. Under such conditions, nitrate must be removed from the environment by fresh water (Nafisi Behbaadi, 2006). Therefore, increasing the concentration of these substances can decrease the rainbow trout rearing index as indicated in Fig. 5(a-b). Dissolved oxygen in water is one of the major factors in cold water fish rearing since this fish needs more oxygen than warm water fish. In general, the dissolved oxygen in the input water to the rainbow trout farms should be at the saturation level (Nafisi Behbaadi, 2006). Since the variations of the flow velocity change the concentration of dissolved oxygen (Wu et al., 2015), there is a direct relationship between these two. Accordingly, increasing these parameters can increase the rainbow trout rearing index as shown in Fig. 5(c). Tallar and Suen (2016) developed an indicator for assessing the quality of aquaculture based on the parameters of dissolved oxygen, fecal coliform, ammonia, and pH. The results of multiple regression analysis in their study indicated that the aquaculture water quality index had a positive and significant correlation with dissolved oxygen and fecal coliform. Thus, increasing the dissolved oxygen results in increasing the aquaculture water quality while increasing the ammonia and pH decreases the quality. The results of Tallar and Suen's (2016) study are consistent with those of the present study. Phosphate is considered as one of the main sources of water pollution and is dangerous to aquatic organisms, leading to a decrease in the rainbow trout rearing index. However, Fig. 5(d) displays that increasing alkalinity is beneficial due to the reduced sensitivity of fish to carbon dioxide, and it increases the rainbow trout rearing index (Nafisi Behbaadi, 2006). In general, any changes in the concentration of water quality parameters have a direct effect on the variation of total rainbow trout rearing index as illustrated in Fig. 5(e-f). In a study by Yalcuk and Postalcioglu (2015), the pool water quality was evaluated in a four-trout farm with different sources, including the input of water from the mountain for three farms and from the artesian for one farm, and at different times, i.e. once a week in hard conditions and twice a week during normal times, in the form of chemical oxygen demand, nitrogen ammonium, pH, and electrical conductivity through a fuzzy inference system. The results demonstrated the effectiveness of the fuzzy inference system method in predicting water quality parameters in trout production pools. It is difficult to compare the results of their study to those of the present study since the parameters, water supply sources of the pools, and sampling climate conditions of the studies are different. Nevertheless, the results are similar to each other. In the present study, the essential and contaminated parameters of rainbow trout rearing and their interactions were evaluated. One integrated score was allocated to the rainbow trout rearing conditions in the system understudy. Since fish had different weights and sizes in the system of the present study, the results can cover all the growth stages of rainbow trout. Further, the linear velocity was considered, which indicated the dissolved oxygen variation as the most essential element in culturing the rainbow trout. However, the numerous number of rules, types of membership functions, selection of parameters, and determination of fuzzy sets could be sources of error in the present study.

3.2. Intelligence methods and controlling water quality

Water quality in intensive aquaculture can be drastically reduced by food input and food is regarded as one of the main sources of costs (Zhou et al., 2018). The present study identified un-ionize ammonia, nitrite, and nitrate as the main pollutants of water quality, produced as a result of food decomposition. Inappropriate and unreasonable feeding led to considerable waste of food as leftover, an increase in fish faces, and consequently significant water contamination and economic losses. In addition, traditional feeding approach is arduous and susceptible to error since it depends on the operator's observation and experience. Therefore, it is necessary to investigate and apply more precise tools and methods for managing production and nutrition in aquaculture (Wu et al., 2015). Nowadays, intelligent methods, such as fuzzy inference system and adaptive network-based fuzzy inference system, are developed in order to control the feeding process. Such expert methods can significantly reduce food waste and water pollution, save a lot of money, and create sustainable aquaculture production by precisely estimating fish appetite, food searching behavior, and main variations in water quality parameters, such as dissolved oxygen, temperature, and nitrogenous compounds (Hosseini et al., 2018; Lopez et al., 2018; Wu et al., 2015; Zhou et al., 2018).

3.3. Benefits of present study for rainbow trout farmers

The present study and similar research help to increase the production and improve the performance of rainbow trout by informing producers about the condition of the production system. Being aware about the general rearing conditions in the form of one integrated score is a simple and understandable approach which helps the aquaculturists to better manage different decisions, including the necessary arrangements to control the rearing system and increase profits. The results of the present study can be a starting point for further research and developing an application, which can establish a mutually beneficial contact between experts and farmers for a sustainable production system.

4. Conclusion

In the present study, the fuzzy inference system was used to develop a rainbow trout rearing index in an intensive production system in Iran. The farm understudy was in a very good range with the rainbow trout rearing index of 65. The results indicated that there is a close relationship between the parameters of water quality and rainbow trout rearing conditions. Increasing ammonia, nitrogenous compounds such as nitrite and nitrate, and phosphate decreases the rainbow trout rearing index whereas increasing the dissolved oxygen, linear velocity, and alkalinity increases the index and improves the growth performance of the fishes.

Conflict of Interest

All authors have participated in (a) conception and design, or analysis and interpretation of the data; (b) drafting the article or revising it critically for important intellectual content; and (c) approval of the final version.

* This manuscript has not been submitted to, nor is under review at, another journal or other publishing venue.

* The authors have no affiliation with any organization with a direct or indirect financial interest in the subject matter discussed in the manuscript

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Table 1
Fuzzy sets and thresholds related to input and output parameters in rainbow trout rearing condition model.

Variable	Units	Range	Fuzzy set parameters
NH_3	(mg/L)	(0.0-1.2)	(-∞ 0.1 0.13 0.14) (0.13 0.14 0.15) (0.14 0.15 0.16) (0.15 0.16 0.17) (0.16 0.17 0.2 ∞)
NO_2	(mg/L)	(0-0.4)	(-∞ 0 0.1 0.15) (0.1 0.15 0.2) (0.15 0.2 0.25) (0.2 0.25 0.3) (0.25 0.3 0.4 ∞)
NO_3	(mg/L)	(0-1000)	(-∞ 0 300 400) (300 400 500) (400 500 600) (500 600 700) (600 700 1000 ∞)
PO_4	(mg/L)	(0.7-1.6)	(-∞ 0.1 3.1 3.6) (3.1 3.6 4.1) (3.6 4.1 4.6) (4.1 4.6 5.1) (4.6 5.1 7.6 ∞)
Alkalinity	(mg/L)	(30-150)	(-∞ 30 70 80) (70 80 90) (80 90 100) (90 100 110) (100 110 150 ∞)
DO	(mg/L)	(1-13)	(-∞ 1 5 6) (5 6 7) (6 7 8) (7 8 9) (8 9 13 ∞)
V_L	(cm/S)	(0-8)	(-∞ 0 2 3) (2 3 4) (3 4 5) (4 5 6) (5 6 8 ∞)
I	VB B G VG E	(0-100)	(-∞ 0 20 35) (20 35 50) (35 50 65) (50 65 80) (65 80 100 ∞)

Fig. 1. Study farm in Orktand region, Kalat County, Razavi Khorasan Province, Iran.

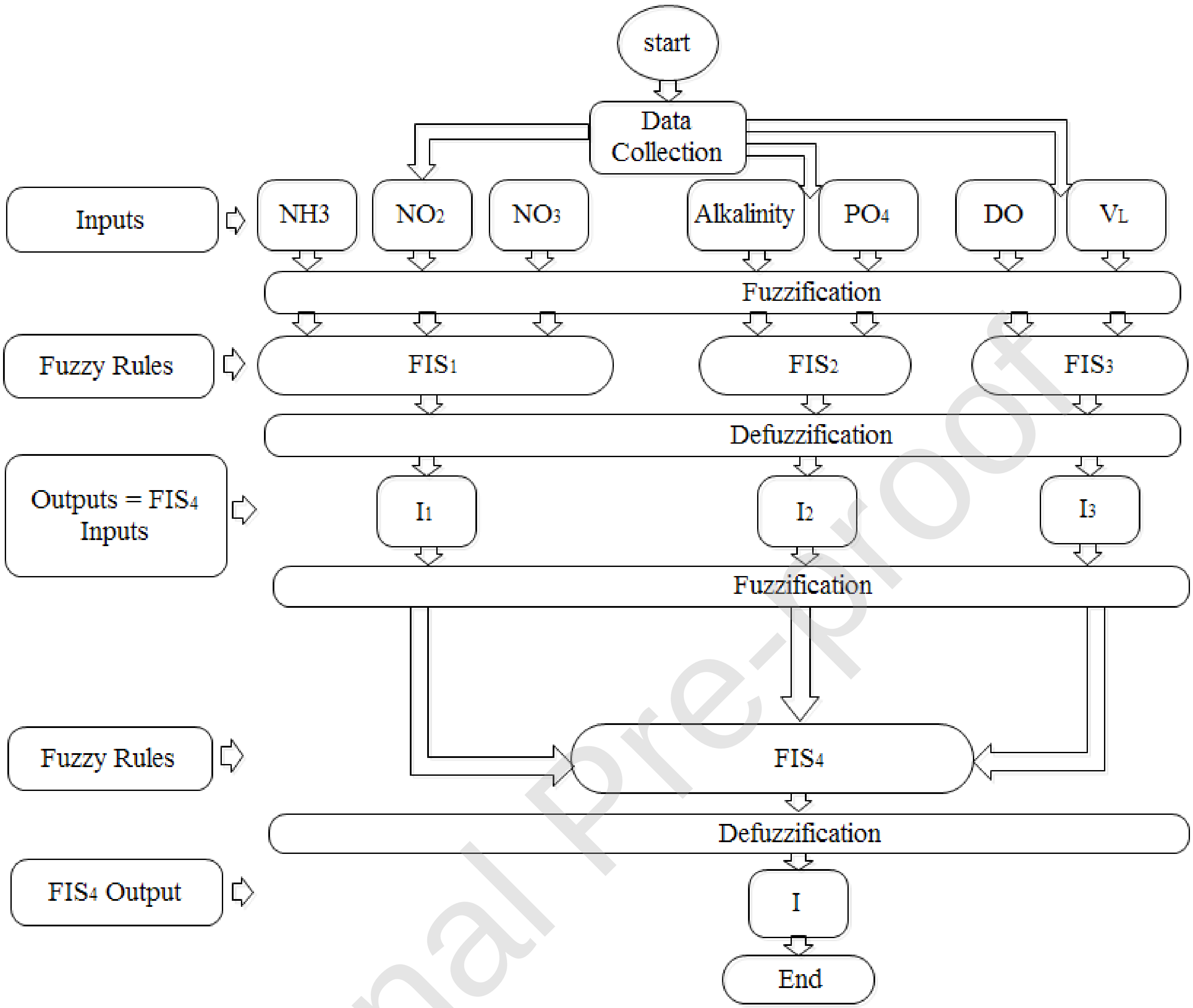

Fig. 2. The general structure of the fuzzy inference systems developed in this study (Fuzzy system(1): Investigate the relationship between un-ionized ammonia, nitrite, nitrate and indicator of rainbow trout rearing conditions; Fuzzy system(2): Assess the relationship between phosphate and alkalinity with the index of rainbow trout rearing conditions; fuzzy system(3): Evaluate the relationship between dissolved oxygen and linear velocity with index of rainbow trout rearing conditions; fuzzy system(4): It combines the results of the relationship between un-ionized ammonia, nitrite, nitrate, phosphate, alkalinity, dissolved oxygen and linear velocity with index of rearing conditions, and provides a general index for rainbow trout rearing conditions.

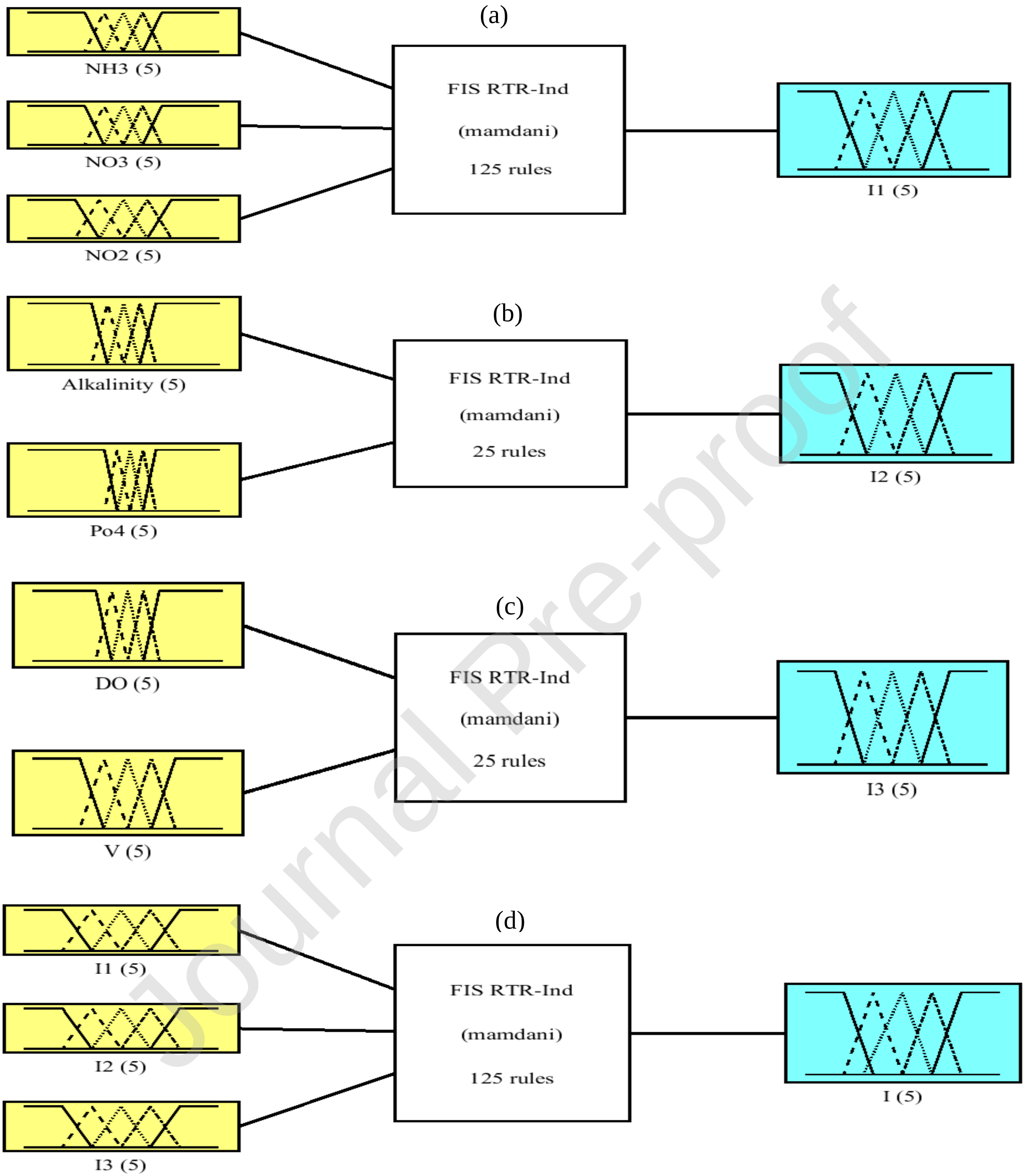

Fig. 3. Overview of the fuzzy systems constructed in this study (a) The general structure of the fuzzy system(1); (b) The general structure of the fuzzy system(2); (c) The general structure of the fuzzy system(3); (d) The general structure of the fuzzy system(4).

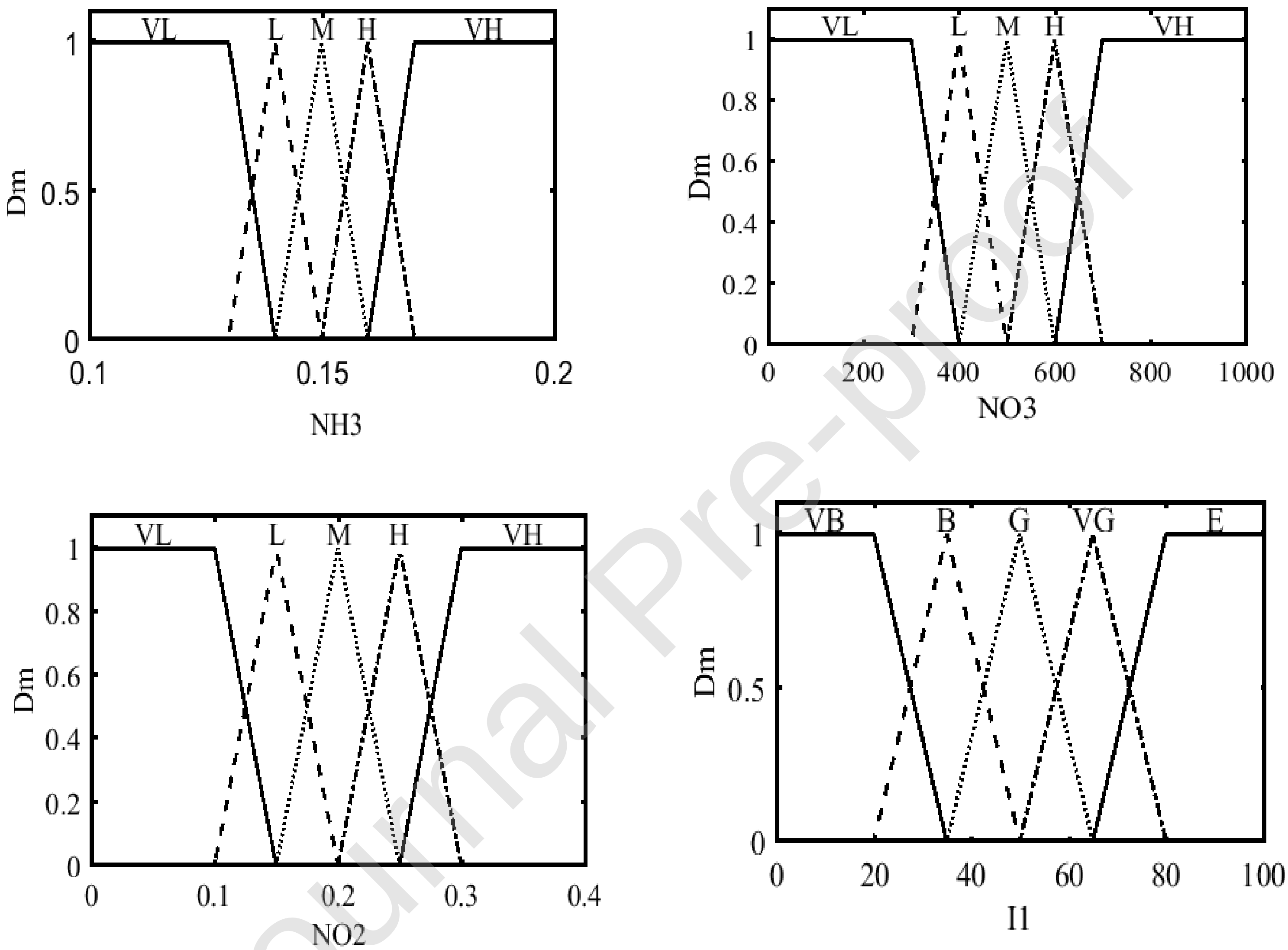

Fig. 4. Membership functions used for un-ionized ammonia, nitrite, nitrate and I_1 parameters (Dm: Degree of memberships)

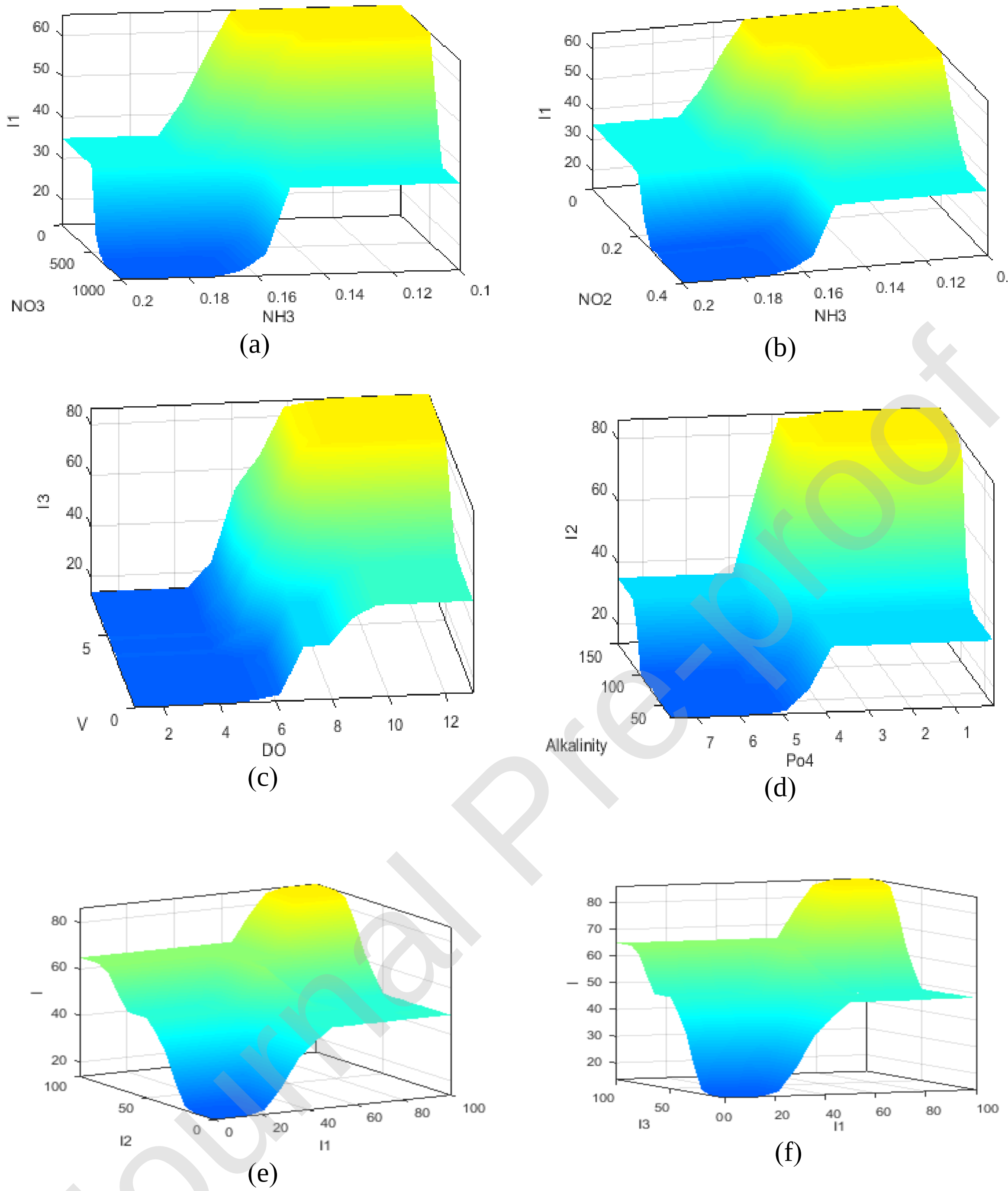

Fig. 5. Response surface diagrams derived from fuzzy inference systems (a: represents variation of the rearing index in relation to changes in un-ionized ammonia and nitrate concentrations; b: indicates variation of the rearing index in relation to changes in ammonia and nitrite concentrations; c: shows the variation of the rearing index relative to changes in dissolved oxygen concentrations and linear velocity; d: shows variation of the rearing index relative to changes in phosphate and alkalinity concentrations; e: illustrates variation of rearing index relative to I_1 and I_2 changes; f: shows the rearing index changes relative to the I_1 and I_3 changes.)