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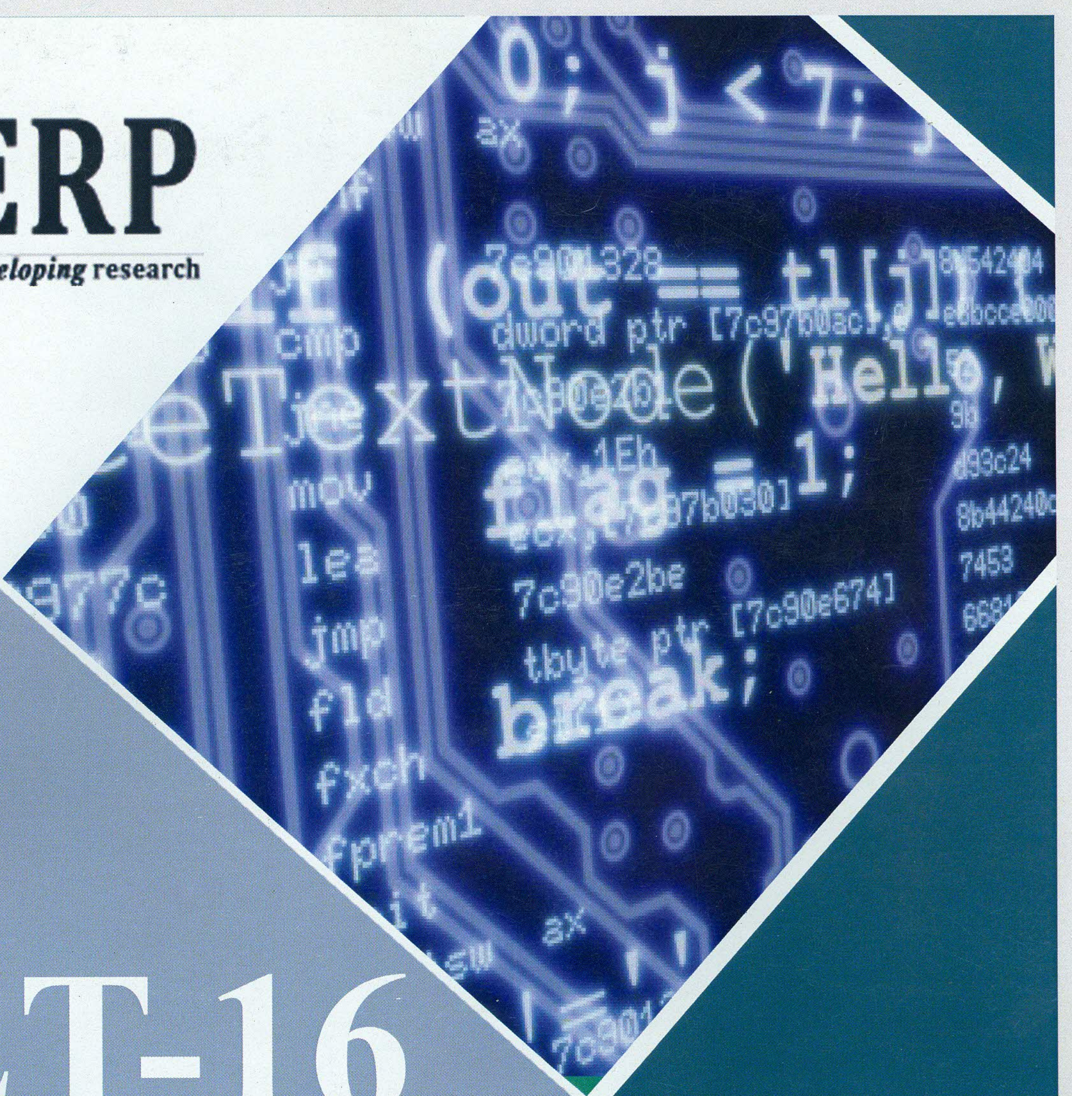

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Fuzzy Decision Support System For Evaluating Suitability Of Sites For Aquaculture Development

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Abstract: **Fuzzy decision support system was developed using MATLAB software for classification of aqua sites for evaluating suitability for aquaculture development. Twenty seven input variables identified to the system were categorized into five broad heads of key variables namely: water (9 sub variables), soil (7 sub variables), support (4 sub variables), infrastructure (5 sub variables) and risk factor (2 sub variables). Gaussian and triangular membership functions were used for defining the unsuitable (U), moderate (M), and suitable (S) linguistic variables for both input variables and output variable such as Aquaculture Site Classification. Totally 243 fuzzy rules with logical AND operator, truncation implication and centriod method for defuzzfication were employed to develop the fuzzy system for decision making about classification of aqua sites. The system classifies site into one of the three classes such as suitable, moderate or unsuitable. Case study was conducted to validate the performance of the developed fuzzy decision support system for evaluating the land suitability for aquaculture development in Krishna district, Andhra Pradesh, India. After collecting the required information from the study area, first aqua sites were classified by the fuzzy system developed for this purpose and then the same sites were classified by the existing fuzzy logic based classification model developed by Mahalakshmi and Ganesan using the same variables under the six broad heads of main variables and 729 fuzzy rules. Classification results obtained from the developed fuzzy system showed 86% agreement with the results from the fuzzy logic based classification model. Developed system appeared to be confident and robust in proof-of-concept application for aquaculture farming development in Krishna district, Andhra Pradesh, India.**

Key words: Fuzzy logic; decision support system; aquaculture; suitability of sites.

I. INTRODUCTION

Modern computer technologies such as database management system, decision support system, Geographical Information System (GIS), Remote Sensing (RS), and fuzzy logic etc. have promoted their application in a multitude of disciplines. In aquaculture the need for computer applications is immense. Nowadays, aquaculture development is considered as a vital source for augmenting protein supply in the developing countries where shortage of protein supply exists. However, the success of aquaculture projects without adverse environmental effects largely depends upon the quality of the site selected for the projects [1]. In addition, successful and sustainable aquaculture development depends on both the identification and classification of aquaculture sites based on the multiple variables [2]. GIS and RS technology have been applied successfully for identification of potential areas for aquaculture under different categories. However, earlier research showed that a number of environmental factors soil and water quality are difficult to handle by conventional Boolean (Crisp) logic as commonly used in the GIS and RS technology [3].

Among the new technologies, fuzzy logic can be a powerful technique capable for handling conventional crisp approaches related to environmental factors [3]. Fuzzy logic, first introduced by Zadeh [4], is a self-learning technique that provides a mathematical tool to convert linguistic evaluation variables based on expert knowledge into an automatic evaluation strategy. Following the introduction of the fuzzy set, Zadeh [5-8] contributed in developing the necessary inferencing mechanisms and modeling techniques to bring this concept to fruition.

Recent development of fuzzy logic techniques offer alternative ways of dealing with the disadvantages of crisp approaches associated with the complexity of real world [3]. Fuzzy systems have been successfully applied to problems in classification, modeling control and in a considerable number of applications [9]. Further, fuzzy logic can improve such classifications and decision support models by using fuzzy sets to define over-lapping class. The application of fuzzy if-then rules also improves the interpretability of the results and provides more insight into the classifier structure and decision making process [10]. In view of all the above aspects, Fuzzy Decision Support System (FDSS) was developed for classification of sites for evaluating suitability of sites for aquaculture farming development.

II. MATERIAL AND METHODS

The developed fuzzy decision support system consists of input variables, base information in the form of data sets, fuzzy membership functions and fuzzy rule base, and fuzzy operational mechanisms (Fig. 1).

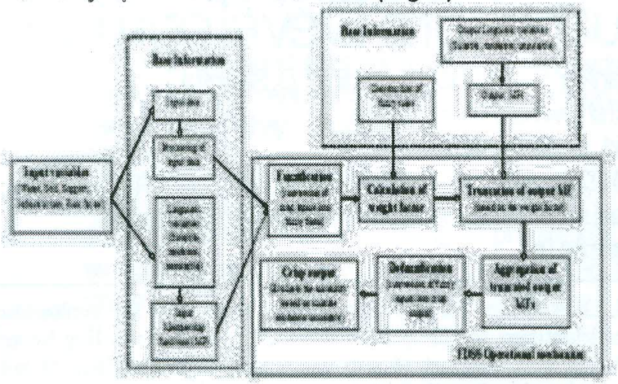

Fig. 1. Block diagram of fuzzy system

A. Input variables, study areas and data sets

Twenty seven variables were selected by reviewing the literature [11, 12, 13, 14] and then classified into five categories of main variables namely: water (9 sub-variables), soil (7 sub-variables), support (4 sub-variables), infrastructure (5 sub-variables) and risk factor (2 sub-variables) were used for the development of fuzzy system (Table 1).

Table 1. Main variable and their corresponding sub variables

Main variables	Sub variables
Water	Salinity, pH, Dissolved Oxygen, TSS, Free Ammonia, Nitrate - N, H_2S, Temperature and Transparency
Soil	pH, Calcium carbonate, Organic carbon, Available phosphorous, Available nitrogen, Textural class and Electrical conductivity
Support	Distance to NGO, Distance to fisheries department, Distance to Research station and Distance to university/college
Infrastructure	Distance to hatchery/natural fry, Distance to processing plant, Distance to river, Distance to road and Distance to local market
Risk factor	Flood and cyclone and Nearby pollution area

The study areas were Bhimavaram and Narsapuram from West Godavari district and Peddapalem, Peddakammavaripalem, Edurumondi, Chinnakammavaripalem and Nagayalanka from Krishna district in the state of Andhra Pradesh, India. These areas were chosen purposefully in view of the concentration of aquaculture, and also as coastal aquaculture is a major economic activity in these areas [15]. The West Godavari district lies between the northern latitudes of 16^0 15′ to 17^0 30′ and the eastern longitudes of 80^0 55′ to 81^0 55′. The global location of Krishna district is between 15^0 43′ northern latitudes and 17^0 10′ eastern longitudes.

The water, soil, support, infrastructure and risk factor related data used in this study were obtained from 54 randomly selected aquasites in the study areas such as Bhimavaram (A-30 aqua sites) and Narsapuram (B-10 aqua sites) from West Godavari district, Andhra Pradesh, and 14 aqua sites from Krishna district (C), Andhra Pradesh. Data gathered from A and B was used to develop the fuzzy system, C for validating the system. Combination of rank sum, TOPSIS and pair-wise comparison methods [16] were used to process the field data and produce the required dataset in the form of main variables, which are necessary to develop and validate the fuzzy system.

B. Membership function and fuzzy rule base

Fuzzy logic is a process of mapping an input space into an output space using membership functions (MF) and linguistically specified rules [17]. In this study, five inputs such as water (W), soil (So), support (Su), infrastructure (I) and risk factor (R) and one output, Aquaculture Site Classification (ASC), were split into three linguistic variables named as unsuitable (U), moderate (M) and suitable (S). After splitting the variables, a membership function (MF) was defined for each linguistic variable. A MF is a curve that defines how each point in the input space is mapped to a membership value between 0 and 1. In this study, based on the training set and the experts' experience and knowledge [18,19], Gaussian and triangular MFs and their ranges were selected for input and output variables respectively as they could represent the linguistic variables more effectively. Gaussian and triangular MFs were defined by Guney and Sarikaya [20]

$$\mu_{ij}(x) = Gaussmf(x; m_{ij}; \sigma_{ij}) = e^{-\frac{1}{2}\left(\frac{x-m_{ij}}{\sigma_{ij}}\right)^2}$$

for (i = 1 to 5; j = 1, 2, 3) ; x = (W, So, Su, I, R)

Where μ_{ij} represent the jth MF of the ith input; m_{ij} is the mean of the jth MF of the ith input variable; σ_{ij} is the standard deviation of the jth MF of the ith input variable. The parameters m_{ij} and σ_{ij} for the input variables were defined by Xu *et al.* [17]

$$m_{ij} = \frac{x_{ij} + y_{ij}}{2} i = 1,2,3....,5; j = 1,2,3$$

$$\sigma_{ij} = \frac{m_{ij} - x_{ij}}{3} i = 1,2,3....,5; j = 1,2,3$$

Where $[x_{ij}, y_{ij}]$ is the range of linguistic value of jth MF of the ith input variable.

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$$\mu_{oj}(z) = Tri(z; a_{oj}; b_{oj}; c_{oj})$$

For (o = 1; j = 1, 2, 3); z = (ASC)

Where μ_{oj} represent the j[th] output MF; a_{oj}, b_{oj}, c_{oj} are the parameters that represent the shapes of the output MF.

Many researchers have investigated techniques for determining rules such as fuzzy classifier [21], neural network [22] and genetic algorithm [23]. Expert knowledge is mostly used technique for determining rules [24]. In this study, the rules have been derived using indirect approach in which the order of importance of the variables, and its cause and effect relationship has been discussed intensively with the expert [25]. From these 3 X 3 X 3 X 3 X 3 = 243 rules based on the MF considered for inputs are formulated with logical AND operator.

C. *Fuzzy system operations*

Fuzzy system consists of five operating mechanisms named as fuzzification, calculation of weight factor, implication, aggregation and defuzzification (Fig. 1).

Step 1: Fuzzification

In this step, crisp inputs are transformed into the fuzzy inputs by the input MFs. Table 2 shows the details of membership functions and its parameters for each of the input and output variables. In this system, fuzzy MF of each class in the input variables was overlapped with neighboring classes because decisions are distributed over more than one input class. Furthermore, to make the output clear and unbiased, the symmetrical, non-overlapping equal-size membership functions [17] were used for the output variable.

Table 2. Membership functions and its parameters for input and output variables

Linguistic variables	Input variables $[x_{ij}, y_{ij}]$ m_{ij}, σ_{ij}					Output Variable (ASC) a_{oj}, b_{oj}, c_{oj}
	Water	Soil	Support	Infrastructure	Risk factor	
Unsuitable	[0,0.15] 0.075, 0.025	[0,0.2] 0.1, 0.033	[0,0.6] 0.3, 0.1	[0,0.6] 0.3, 0.1	[0,0.6] 0.3, 0.1	[0 0.5 1]
Moderate	[0.05,0.35] 0.2, 0.05	[0.1,0.5] 0.3, 0.067	[0.3,0.8] 0.55, 0.083	[0.3,0.8] 0.55, 0.083	[0.3,0.8] 0.55, 0.083	[1 1.5 2]
Suitable	[0.2,0.8] 0.5, 0.1	[0.3,0.8] 0.55, 0.083	[0.7, 1.0] 0.85, 0.05	[0.7, 1.0] 0.85, 0.05	[0.7, 1.0] 0.85, 0.05	[2 2.5 3]

$[x_{ij}, y_{ij}]$; m_{ij}; σ_{ij} - range, mean, and standard deviation of the membership functions of input variables and a_{oj}, b_{oj}, c_{oj} - parameters that represent the shapes of the output membership function

Step 2: Calculation of weight factor

In this step, weighting factor of each rule (w_k) was determined by evaluating the membership expressions in the antecedent of the rule. This was computed by first converting the input values to fuzzy membership values by using the input MFs in the step1 and then applying the "and" operator to these membership values. The "and" operator corresponds to the minimum of input membership values. The weighting factor was represented as

$$w_k = \min_k(\mu_{ij}(W), \mu_{ij}(So), \mu_{ij}(Su), \mu_{ij}(I), \mu_{ij}(R)) \quad k = 1, 2, \ldots, 243$$

Step 3: Implication

Implication is defined as the shaping of the output fuzzy set, based on the antecedent in a way of either truncation or scaling [17, 26]. Truncation is done by chopping off the output MF, while scaling is done by compressing the function. In this system, truncation implication was used which is one of the most widely used implication in applications of fuzzy logic [27]. This was computed by

$$\mu_{imp,k} = \min_k(w_k(rules)_k) \quad k=1,2,\ldots\ldots, 243$$

Step 4: Aggregation

Since decisions are based on the testing of all of the rules in the system, rules must be combined in some manner in order to make decision. Aggregation is the process by which the truncated output functions that represent the outputs of each rule are combined into a single fuzzy set that represents the output variable. In this system, the aggregation was performed by using union (maximum) operator, which was represented by

$$\mu_o(k) = \max_k(\mu_{imp,k}) \quad k=1,2,\ldots\ldots,243$$

Step 5: Defuzzification

Among the different defuzzification methods, center of gravity (COG) method was used for defuzzification to convert the fuzzy output set to a crisp number because it is known to have a less mean square error and better steady-state performance [27]. The centroid of the aggregated area was defined by

$$ASC = \sum_{i=1}^{n}(ta)_i c_i \Big/ \sum_{i=1}^{n}(ta)_i$$

where $ta_1, ta_2, \ldots\ldots, ta_n$ be the areas of the truncated triangular areas under the aggregated function and $c_1, c_2, \ldots\ldots, c_n$ be the coordinates of their center on the x-axis, n is the number of areas and ASC is the location of the centriod of the total areas. The location of COG determines the classification of aqua sites.

D. Implementation

MATLAB software was used to develop the fuzzy decision support system. The software has many in-built functions, such as construction of membership functions and fuzzy rule base, and formation of mathematical equations, which will be useful for the study.

E. Validation of the fuzzy decision support system

Case study was conducted to validate the performance of the developed fuzzy decision support system for evaluating the land suitability for aquaculture development in Krishna district, Andhra Pradesh, India. After collecting the required information from the study area (c), first aqua sites were classified by the fuzzy decision support system developed for this purpose and then the same sites were classified by the fuzzy logic based classification model developed by mahalakshmi and ganesan [28] using the same variables under the six broad heads of main variables and 729 fuzzy rules. The fdss output and existing fuzzy logic based classification model output were expressed in terms of numbers and the accuracy of classification was calculated by (lorestani et al., 2006) [26]

$$Accuracy = \frac{n}{N} \times 100$$

where n is number of sites correctly classified by FDSS and N is total number of sites considered for validation.

III. RESULTS AND DISCUSSION

The fuzzy membership functions of water, soil, support, infrastructure and risk factor and construction of fuzzy rule base were implemented in MATLAB with the following properties: Type = 'mamdani'; Decision method for fuzzy logic operators AND: MIN; Decision method for fuzzy logic operators OR: MAX; Implication method: MIN; Aggregation method: MAX; and Defuzzification: CENTROID (centre of gravity).

Based on the operating mechanisms (discussed in the section fuzzy system operations), the fuzzy system classified the validation dataset (C) collected from the Krishna district, Andhra Pradesh. Table 3 depicted the results of the fuzzy system obtained for validation dataset. From table 3, it was seen that the aqua sites 1, 2, 5, 9 and 13 were classified as suitable. It also revealed that in site 1, water variable was in suitable range of linguistic value; soil variable was in both suitable and moderate range of linguistic value; support, infrastructure and risk factor were in moderate range of linguistic values. The combination of these linguistic variables activates the fuzzy rules and produces the output fuzzy value for site 1 as 2.26, which belongs to suitable classification. Similarly, in site 2, water, soil, support, infrastructure variables were in the suitable range of linguistic value and risk factor was in moderate range of linguistic value. This combination produces fuzzy value 2.48 and classifies the site into suitable category. In site 5 and 9, water and soil variables were in both suitable and moderate range of linguistic value combinations; support was in suitable range of linguistic value; and infrastructure and risk factor were in moderate range. This combination classifies both the sites as suitable with fuzzy value as 2.03 and 2.11 respectively. Similarity site 13 was also classified as suitable with fuzzy value as 2.12. From table 3, it could be observed that in sites 7 and 8, water, soil and support were in both moderate and unsuitable range of linguistic value; and infrastructure and risk factor variable was in unsuitable and moderate range of linguistic values respectively. Based on the combination of these linguistic values fuzzy rules were activated and produces fuzzy value 0.689 (site 7) and 0.682 (site 12) which belongs to unsuitable classification. As shown in the table 3 the sites 3, 4, 8, 10, 11, and 14 were classified as moderate with the output fuzzy values 1.09, 1.47, 1.64, 1.62, 1.46 and 1.63 respectively. For example, in site 8, water and soil variables were in both suitable and moderate range of linguistic value; and support, infrastructure and risk factor were in moderate range of linguistic value. This combination produces fuzzy value as 1.64.

The validity of the output of fuzzy system was evaluated by comparing the results of the existing fuzzy logic based classification model considering validation set (Table 4). Based on the results in table 4, out of 14 aqua sites 12 sites were classified correctly by the developed fuzzy decision support system. This shows that classification results obtained from the developed fuzzy system showed 86% agreement with the results from the existing fuzzy logic based classification model. The level of agreement between the fuzzy decision support system and fuzzy logic based classification model is not usually 100% because fuzzy logic gives 'class' membership degrees to sites [24].

IV. CONCLUSIONS

A simple-to-use fuzzy decision support system has been developed for classification of aqua sites for evaluating their suitability for aquaculture development. The system has developed based on 27 input variables under five broad heads of main variable such as water (9 sub-criteria), soil (7 sub-criteria), support (5 sub-criteria), infrastructure (3 sub-criteria), and risk factor (3 sub-criteria). Other environmental/socio and economic criteria, e.g. extension media contact and awareness of culture practices in aquaculture etc, have not been considered. The presence and absence of these environmental/socio and economic criteria, may also impact on the success or otherwise of the aquaculture facility. Identification of suitable aqua sites in aquaculture could also be further improved with incorporation of criteria currently not considered.

The case study results suggest that developed fuzzy system has sufficient predictive power to help all the stakeholders who may be unfamiliar with the specific requirements of aquaculture to classify the aqua sites for farming development. This system will enhance the decision making capacity of anyone engaged in the design and construction of new / existing aquaculture farming system. The flexible and modular fashion of fuzzy module in MATLAB can be easily adapted to other closely related industries such as agriculture and other activities located on the same source water in the study area. FDSS is also useful in educational and research institutions for demonstration and training purposes.

Table 3. Outputs of the fuzzy decision support system for validation dataset

Sites	Input (validation dataset)					Fuzzy value (Classification)
	Water	Soil	Support	Infrastructure	Risk factor	
1	0.426	0.489	0.350	0.490	0.5	2.26 (S)
2	0.417	0.784	0.764	0.880	0.5	2.48 (S)
3	0.121	0.191	0.681	0.490	0.5	1.09 (M)
4	0.241	0.191	0.350	0.670	0.5	1.47 (M)
5	0.297	0.382	0.764	0.670	0.5	2.03 (S)
6	0.241	0.341	0.350	0.149	0.5	0.666 (U)
7	0.178	0.191	0.350	0.149	0.5	0.689 (U)
8	0.241	0.365	0.691	0.485	0.5	1.64 (M)
9	0.328	0.257	0.764	0.670	0.5	2.11 (S)
10	0.241	0.341	0.681	0.490	0.5	1.62 (M)
11	0.296	0.193	0.350	0.670	0.5	1.46 (M)
12	0.121	0.193	0.350	0.149	0.5	0.682 (U)
13	0.241	0.268	0.691	0.880	0.5	2.12 (S)
14	0.444	0.341	0.350	0.670	0.5	1.63 (M)

TABLE 4. COMPARISON OF DEVELOPED FDSS AND EXISTING FUZZY LOGIC BASED CLASSIFICATION MODEL

		Developed FDSS			Total predicted	%
Existing fuzzy model	Classification	S	M	U		
	S	4	0	0	4	100
	M	1	6	1	8	75
	U	0	0	2	2	100
Total observed		6	5	6	3	12/14
%		100	80	100	67	86

S-Suitable; M-Moderate; U-Unsuitable; * Number of aqua sites correctly classified by fuzzy system

REFERENCES

[1]. CE. Boyd, and JW. Clay, "Shrimp aquaculture and the environment", Sic Am Vol.278, pp.58-65, 1998.

[2]. CW, McKindsey, H. Thetmeyer, T. Landry, and W. Silvert, "Review of recent carrying capacity models for bivalve culture and recommendations for research and management", Aquaculture Vol.26, pp.451-462, 2006.

[3]. Tarunamulia, "Application of Fuzzy Logic, GIS and Remote Sensing to the Assessment of Environmental Factors for Extensive Brackishwater Aquaculture in Indonesia", Unpublished Ph.D thesis, School of Biological, Earth & Environmental Sciences, The University of New South Wales Sydney, NSW 2052, Australia, pp.206, 2008.

[4]. L. Zadeh, "Fuzzy sets" Inform Control, 8:338-353, 1965.

[5]. L. Zadeh, "outline of a new approach to the analysis of complex systems and decision processes", ieee t syst man cy , vol. Smc3, pp.28-44, 1973.

[6]. L. Zadeh, "the concept of a linguistic variable and its application to approximate reasoning: part 1", inform sciences, vol.8, pp.199-249, 1975a.

[7]. Zadeh I (1975b) the concept of a linguistic variable and its application to approximate reasoning: part 2. Inform sciences 8:301-357.

[8]. L. Zadeh, "the concept of a linguistic variable and its

application to approximate reasoning: part 3", inform sciences, vol. 9, pp.43-80, 1976.

[9]. J. Singh, n. Singh, and jk. Sharma, "fuzzy modeling and identification of intelligent control for refrigeration compressor", j sci ind res, vol. 65, pp.22-30, 2006.

[10]. r. Johannes, m. Setnes, and j. Abonyi, "learning fuzzy classification rules from labeled data", inform sciences, vol. 150, pp.77-93, 2003.

[11]. F. Hajek and ce. Boyd, "rating soil and water information for aquaculture", , vol. 13, pp.115-128, 1994.

[12]. Ma. Salam, lg. Ross, and mcm. Beveridge, "a comparison of development opportunities for crab and shrimp aquaculture in southwestern bangladesh using gis modelling", aquaculture vol. 220, pp.477-494, 2003.

[13]. Ciba, "advanced technologies for the management of soil and water environment in brackishwater aquaculture", ciba special publication no. 43, central institute of brackishwater aquaculture, pp.136, 2009.

[14]. P. Mahalakshmi and k. Ganesan, "mahalanobis taguchi system based variables selection for shrimp aquaculture development, comput electron agric, vol. 65, pp.192-197, 2009.

[15]. P. Mahalakshmi and k. Ganesan, v. Venkatasubramanian, "dmtiola: decision making tool for identification of optimal location for aquaculture farming development", aquacult int, vol. 20, pp. 911-925, doi: 10.1007/s10499-012-9516-6, 2012.

[16]. P. Mahalakshmi and k. Ganesan, "decision making models for aquaculture farming development", today & tomorrow's printers and publishers, new delhi, pp. 257, 2012.

[17]. Xu, ds. Dale, and h. Huang, "cotton color classification by fuzzy logic" text res j, vol. 72, pp.504-509, 2002.

[18]. W. Pedrycz, "why triangular membership function?", fuzzy set syst, vol. 64, pp.21-30, 1994.

[19]. W. Pedrycz, " fuzzy equalization in the construction of fuzzy sets", fuzzy set syst, vol. 119, pp. 329-33, 2001.

[20]. K. Guney and n. Sarikaya, "comparison of mamdani and sugeno fuzzy inference system models for resonant frequency calculation of rectangular microstrip antennas", pier b, vol. 12, pp.81-104, 2009.

[21]. Y, yoshinari, w. Pedrycz and k. Hirota, "construction of fuzzy models through clustering techniques", fuzzy set syst. Vol. 78, pp. 1-4, 1996.

[22]. J. Jang and c. Sun, "neurofuzzy modeling and control", proceedings of the ieee, vol. 83, no.3, pp. 378 - 406, 1995.

[23]. H. Hwang and k. Woo, "linguistic fuzzy model identification", ieee proceedings control theory and applications, vol. 142, pp.7-544, 1995.

[24]. Sm. Mazloumzadeh, m. Shamsi, and h. Nezamabadi-pour, "fuzzy logic to classify date palm trees based on some physical properties related to precision agriculture", precision agriculture, vol. 11, pp. 258–273, 2010.

[25]. Center and b. Verma, "fuzzy logic for biological and agricultural systems", artif intell rev, vol. 12, pp.213-225, 1998.

[26]. N. Lorestani, m. Omid, s. Bagheri shooraki, am. Borghei, and a. Tabatabaeefar, "design and evaluation of a fuzzy logic based decision support system for grading of golden delicious apples", int j agr biol , vol. 8, pp.440-444, 2006.

[27]. S. Kim, k. Kim, j. Lee, and d. Cho, "application of fuzzy logic to vehicle classification algorithm in loop/piezo-sensor fusion systems", asian journal of control, vol. 3, no.1, pp. 64-68, 2001.

[28]. P.mahalakshmi and k. Ganesan, "fuzzy logic based classification model for aquaculture development", advanced applied research, vol. 4, no. 2, pp. 90-95, 2012.