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Mamdani fuzzy rule based model to classify sites for aquaculture development

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ABSTRACT

Mamdani fuzzy inference system was applied as a decision making model to classify aqua sites based on water, soil, support, infrastructure, input, and risk factor related information. For input and output linguistic variables of the model, suitable Gaussian and triangular membership functions were selected. Totally, 729 rules with logical AND operator, truncation implication, and centriod method for defuzzification were employed to develop an efficient fuzzy model for decision making about classification of aqua sites. The model classifies each site in the datasets into one of the three classes such as suitable, moderate or unsuitable. In order to validate the performance of the proposed fuzzy model, the same sets were classified again by aquaculture expert. Classification results obtained from the developed fuzzy model showed 92% agreement with the results from the aquaculture expert. Thus the fuzzy rule based model is a feasible model for classification of aqua sites, it involves less computation and has clear implementation and working schemes.

Keywords: Aquaculture, Classification, Fuzzy set theory, Mamdani fuzzy inference system

Introduction

The success of aquaculture projects without adverse environmental effects largely depends upon the quality of the site selected for the projects (Boyd and Clay, 1998). There is a clear need for sustainability issues to be considered during the early planning stages for all types of aquaculture. Successful and sustainable aquaculture development depends on both the identification and classification of aquaculture sites based on the multiple variables (McKindsey *et al.,* 2006). Geographical Information System (GIS) and Remote Sensing (RS) technology have been applied successfully for identification of total potential areas in aquaculture under different categories. However, previous research showed that a number of environmental factors such as soil and water quality are difficult to handle by conventional Boolean (Crisp) logic, commonly used in GIS and RS (Tarunamulia, 2008). Recent development of fuzzy logic techniques has offered alternative ways of dealing with the disadvantages of crisp approaches associated with the complexity of real world (Tarunamulia, 2008). Fuzzy systems have been successfully applied to problems in classification, modeling control and in a considerable number of applications (Singh *et al.,* 2006). Further, fuzzy logic can improve such classifications and decision support models by using fuzzy sets to define overlapping class definitions. The application of fuzzy 'if-then's' rules also improves the interpretability of the results and provides more insight into the classifier structure and decision making process (Johannes *et al.,* 2003). In view of all the above aspects, in the present study a fuzzy rule based model was developed for classification of sites for aquaculture development.

Materials and methods

Identification of variables

A list of 24 variables was selected by reviewing the literature (Hajek and Boyd, 1994; Salam *et al.*, 2003; CIBA, 2009; Mahalakshmi and Ganesan, 2009) and after discussion with aquaculture experts, which were classified into six main variables *viz.,* water (W), soil (So), support (Su), infrastructure (Is), input (Ip) and risk factor (R). Each main variable has several sub-variables. Fig. 1 shows the main variable and their respective sub-variables used for the study.

Data sets

The water, soil, support, infrastructure, input and risk factor related data used in this study were obtained from 65 randomly selected aqua sites in the study areas *viz.*, Bhimavaram (A) (30 sites), Narsapuram (B) (10 sites), and Mogalthur (C) (25 sites), belonging to the West

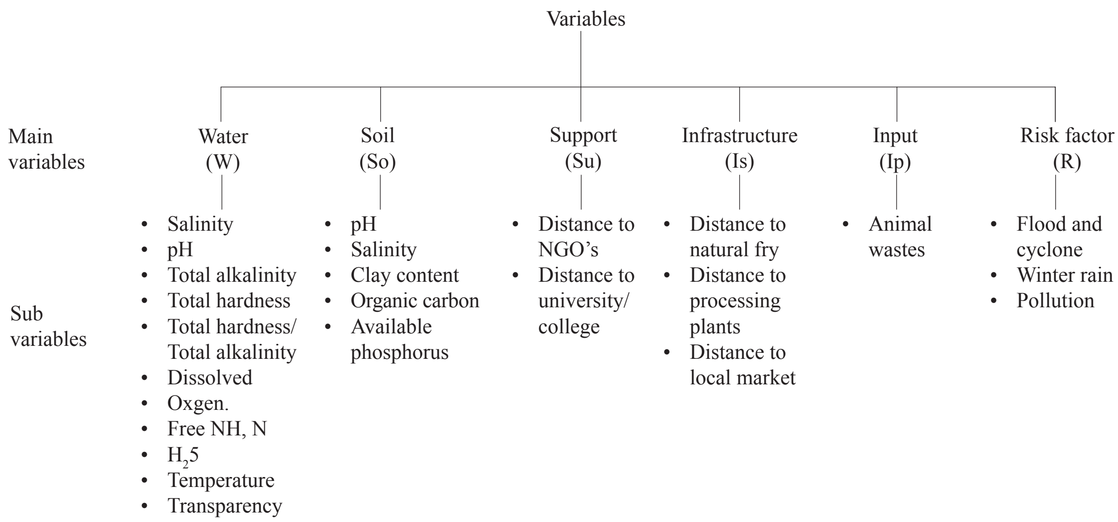

Fig. 1. Main variables and their corresponding sub-variables

Godavari District, Andhra Pradesh, India. This district lies between lat. $16^0 15$¢ to $17^0 30$¢ N and long. $80^0 55$¢ to 81^0 55 E. Data gathered from A and B were used to develop the fuzzy model, and that from C were used for validating the model. Combination of rank sum, TOPSIS and pair-wise comparison methods (Mahalakshmi *et al.*, 2012) were used to process the field data and produce the required dataset in the form of main variables.

Fuzzy sets and membership function

For each input and output variables, fuzzy sets are created by dividing its universe of discourse into a number of sub-regions and are named as linguistic variable (Xu *et al.,* 2002). A linguistic variable is a variable whose values are expressed in words or sentences in natural language and it is defined by suitable membership function (MF). 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, six inputs such as water (W), soil (So), support (Su), infrastructure (Is), input (Ip) and risk factor (R) and one output *viz*., aquaculture site classification (ASC), were used to classify the aqua sites. Both input and output variables were split into three linguistic variables named as unsuitable (U), moderate (M), and suitable (S). After splitting the variables, a MF was defined for each linguistic variable. There are many forms of MFs such as triangular, trapezoidal and Gaussian. In this study, based on the training set and the experts' experience and knowledge (Pedrycz, 1994; 2001), Gaussian (Fig. 2) and triangular (Fig. 3) 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 (Guney and Sarikaya, 2009) by:

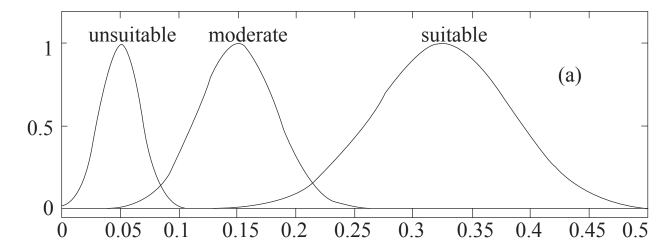

Fig. 2. Gaussian membership function of water input variable

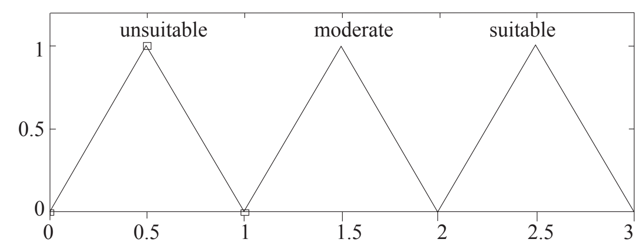

Fig. 3. Triangular membership function of output variable

(i) $\mu_{ij}(x) = Gaussmf\,(x;m_{ij};\sigma_{ij}) = e^{\frac{1}{2}\left(\frac{x-m_{ij}}{\sigma_{ij}}\right)^2}$
for (i = 1 to 6; j = 123) (1)

where, x is input variables; μ_{ij} represent the j^{th} MF of the i^{th} input; m_{ij} and σ_{ij} are the mean and standard deviation of the membership functions of input variables.

(ii) $\mu_{oj}(z) = Tri\,(z;a_{oj};b_{oj};c_{oj})$ for (o = 1; j = 1, 2, 3)
z = (ASC) (2)

$$= \left\{ \begin{array}{ll} 0 & z \le a_{oj} \\ \dfrac{z - a_{oj}}{b_{oj} - a_{oj}} & a_{oj} \le z \le b_{oj} \\ \dfrac{c_{oj} - z}{c_{oj} - b_{oj}} & b_{oj} \le z \le c_{oj} \\ 0 & c_{oj} \le z \end{array} \right\}$$

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. Table 1 shows the details of membership functions and its parameters for each of the input and output variables.

Table 1. Membership functions and its parameters for input and output variables

Variables	Membership functions and its parameters		
	Unsuitable	Moderate	Suitable
Input variables [*Xij, Yij*] *Mij σij*			
Water	[0,0.1] 0.05, 0.017	[0.05,0.25] 0.15, 0.033	[0.15,0.5] 0.325, 0.058
Soil	[0,0.1] 0.05, 0.017	[0.05,0.175] 0.113, 0.021	[0.15,0.4] 0.275, 0.042
Support	[0,0.06] 0.03, 0.01	[0.03,0.08] 0.055, 0.008	[0.07-0.1] 0.085, 0.005
Infrastructure	[0,0.06] 0.03, 0.01	[0.03,0.08] 0.055, 0.008	[0.07-0.1] 0.085, 0.005
Input	[0,0.06] 0.03, 0.01	[0.03,0.08] 0.055, 0.008	[0.07-0.1] 0.085, 0.005
Risk factor	[0,0.06] 0.03, 0.01	[0.03,0.08] 0.055, 0.008	[0.07-0.1] 0.085, 0.005
Output variable a_{oj} , b_{oj} ,c_{oj}			
ASC	0, 0.5, 1	1, 1.5 ,2	2, 2.5, 3

$[x_{ij},y_{ij}]$ m_{ij}; σ_{ij} - range; mean; and standard deviation of the membership functions of input variables

a_{oj}, b_{oj}, c_{oj} - parameters that represent the shapes of the output membership function

Fuzzy rule base

Many researchers have investigated techniques for determining rules such as fuzzy classifier, neural network, genetic algorithm and expert knowledge (Mazloumzadeh *et al.,* 2010). In this study, the expert was asked to summarise the knowledge about the system in the form of a cause and effect relationship. From these, the rules were formulated (Center and Verma, 1998). The fuzzy model has 3 x 3 x 3 x 3 x 3 x 3 = 729 rules based on the MF considered for inputs. These IF-THEN rules are collated with AND operator because all the input variables must be captured simultaneously and applied in decision making by fuzzy logic for classification. In general, the rule can be written as:

if (W is μ_{ij}) and (So is μ_{ij}) and (Su is μ_{ij}) and (Is is μ_{ij}) and (Ip is μ_{ij}) and (R is μ_{ij}) then,

$$R_k = \mu_{ok}(z; a_{ok}, b_{ok}, c_{ok}) \text{ for } k = 1, 2, 3, \ldots, 729 \quad (3)$$

where, μ_{ij} is the j[th] MF of the i[th] input; μ_{ij} is the k[th] output MF; R_k is the output of the k[th] rule; a_{ok} ,b_{ok} ,c_{ok} are the parameters that represent the shapes of the output MFs.

Fuzzy rule based model

Mamdani fuzzy inference system was used to develop the fuzzy rule based model. It consists of five operating mechanisms named as fuzzification, calculation of weight factor, implication, aggregation and defuizzification.

(*a*) *Fuzzification*

In this step, crisp inputs are transformed into the fuzzy inputs by the input MFs. In this model, fuzzy MF of each class in the input variables was overlapped with neighbouring 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 (Xu *et al.,* 2002) were used for the output variable.

(*b*) *Calculation of weight factor*

The weighting factor of each rule (α_k) was computed by first converting the input values to fuzzy membership values using the input MFs in the step1 and then applying the "and" (minimum) operator to these membership values. The weighting factor was represented as:

$$a_k = \min(\mu_{ij}(Wa), \mu_{ij}(So), \mu_{ij}(Su), \mu_{ij}(Is), \mu_{ij}(Ip)\ \mu_{ij}(R)) \quad k = 1, 2, \ldots, 729 \quad (4)$$

(*c*) *Implication*

In this model, truncation implication, which is one of the most widely used implication in applications of fuzzy logic, was used for shaping the output fuzzy set (Kim *et al.*, 2001). This was computed as:

$$\mu_{imp},k = \min_k (\alpha_k R_k) \quad k = 1, 2, \ldots, 729 \quad (5)$$

(*d*) *Aggregation*

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 model, the aggregation was performed by using union (maximum) operator, which was represented as:

$$\mu_o(k) = \max_k (\mu_{imp},k) \quad k=1,2,\ldots,729 \quad (6)$$

(*e*) *Defuzzification*

Among the different defuzzification such as center of sums, center of largest area, first of maxima, middle of maxima and center of gravity (COG), COG method is the most widely used in practical applications, because it is known to have a less mean square error and better steady-state performance (Kim *et al.*, 2001). In this model, COG method was used for defuzzification to convert the fuzzy output set to a crisp number. The centroid of the aggregated area was defined as (Xu *et al.,* 2002).

$$ASC = \sum_{i=1}^{n} aici \Big/ \sum_{i=1}^{n} ai \quad (7)$$

where a_1, a_2, ..., a_n be the areas of the truncated triangular areas under the aggregated function and c_1, c_2,

......., 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.

Validation of the proposed model

For validation of the fuzzy model, we classified the validation set by the model designed for this purpose and then the same set was classified by an aquaculture expert, having enough field experience and knowledge. The model outputs and expert responses were expressed in terms of numbers and the accuracy of classification was calculated following Lorestani *et al.* (2006).

$$Accuracy = \frac{n}{N} \text{ x } 100 \quad (8)$$

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

Results and discussion

Functioning and validation of fuzzy rule based model

The fuzzy system was implemented in MATLAB using 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’ Defuzzification: ‘CENTROID’ (centre of gravity). After implementing the system in MATLAB, validation dataset was entered into the model and each site was classified as: suitable, moderate or unsuitable (Table 2).

Using a numerical example illustration of site S11, the working procedure of the fuzzy model can be explained as follows: water = 0.316, soil = 0.329, support = 0.027, infrastructure = 0.035, input = 0.018 and risk factor = 0.007. At the first step, fuzzification yields the following fuzzy inputs for the next step in the inference process: water is suitable with membership degree 0.99; soil is suitable with membership degree 0.4; support is unsuitable with membership degree 0.95; infrastructure is moderate with membership degree 0.05 and unsuitable with membership degree 0.9; input is unsuitable with membership degree 0.4 and risk factor is unsuitable with membership degree 0.08. Then, the fuzzified values were used by the model to activate appropriate rules such as Rule 45 and 54 and to calculate weights factor as follows:

Rule 45: IF (water is suitable with membership degree 0.99) and (soil is suitable with membership degree 0.4) and (support is unsuitable with membership degree 0.95) and (infrastructure is moderate with membership degree 0.05) and (input is unsuitable with membership degree

Table 2. Results obtained from the fuzzy model for the validation data set

Sites or aqua farms	Input (validation dataset)						Active rules	Output crisp value	Classification
	Water	Soil	Support	Infrastructure	Input	Risk factor			
S1	0.316	0.215	0.027	0.035	0.018	0.007	45, 54	1.500	Moderate
S2	0.327	0.358	0.044	0.054	0.037	0.007	51, 54, 42, 45, 69, 72, 78, 81	2.320	Suitable
S3	0.117	0.145	0.027	0.008	0.018	0.030	296, 297	0.635	Unsuitable
S4	0.117	0.112	0.044	0.024	0.000	0.007	297, 324	0.894	Unsuitable
S5	0.316	0.148	0.044	0.034	0.037	0.007	123, 125, 132, 135, 150, 153, 159, 162	1.650	Moderate
S6	0.152	0.076	0.027	0.000	0.000	0.007	135, 297, 459, 621	0.509	Unsuitable
S7	0.105	0.076	0.000	0.023	0.009	0.030	296, 297, 620 621	0.503	Unsuitable
S8	0.105	0.082	0.000	0.023	0.009	0.030	296, 297, 620 621	0.573	Unsuitable
S9	0.243	0.075	0.000	0.000	0.000	0.030	134, 135, 296, 297,458, 459, 647, 648	0.794	Unsuitable
S10	0.196	0.022	0.035	0.000	0.009	0.030	458, 459, 485, 486, 647, 648	0.501	Unsuitable
S11	0.316	0.329	0.027	0.035	0.018	0.007	45, 54	1.500	Moderate
S12	0.247	0.215	0.027	0.000	0.018	0.037	53, 54, 215, 216	1.010	Moderate
S13	0.247	0.127	0.027	0.000	0.018	0.037	134, 135, 296, 297	1.010	Moderate
S14	0.196	0.127	0.035	0.000	0.009	0.030	134, 135, 161, 162, 296, 297, 323, 324,	1.010	Moderate
S15	0.191	0.102	0.000	0.023	0.018	0.037	116, 117, 296, 297, 458, 459, 620, 621	1.010	Moderate
S16	0.250	0.215	0.027	0.020	0.009	0.037	53, 54, 215, 216	1.410	Moderate
S17	0.191	0.102	0.000	0.035	0.018	0.037	125, 126, 134, 135, 287, 288, 296, 297	1.010	Moderate
S18	0.243	0.358	0.066	0.034	0.037	0.007	69, 72, 78, 81, 231, 234, 240, 243	1.790	Moderate
S19	0.316	0.358	0.066	0.054	0.037	0.007	69, 72, 78, 81	2.320	Suitable
S20	0.243	0.082	0.000	0.000	0.000	0.030	134, 135, 296, 297,458, 459, 620, 621	0.911	Unsuitable
S21	0.288	0.358	0.066	0.034	0.037	0.007	69, 72, 78, 81	1.810	Moderate
S22	0.196	0.022	0.035	0.000	0.009	0.037	620, 621, 647, 648	0.517	Unsuitable
S23	0.252	0.215	0.027	0.020	0.009	0.037	53, 54	1.610	Moderate
S24	0.358	0.358	0.066	0.054	0.037	0.007	69, 72, 78, 81	2.320	Suitable
S25	0.371	0.358	0.044	0.054	0.037	0.007	51, 54, 42, 45, 69, 72, 78, 81	2.240	Suitable

0.4) and (risk factor is unsuitable with membership degree 0.08) THEN Aquaculture Site Classification is moderate with a membership degree of *MIN* ({0.99, 0.4, 0.95, 0.05, 0.4,0.08})0.05

Rule 54: IF (water is suitable with membership degree 0.99) and (soil is suitable with membership degree 0.4) and (support is unsuitable with membership degree 0.95) and (infrastructure is unsuitable with membership degree 0.9) and (input is unsuitable with membership degree 0.4) and (risk factor is unsuitable with membership degree 0.08) THEN Aquaculture Site Classification is moderate with a membership degree of *MIN* ({0.99, 0.4, 0.95, 0.9, 0.4,0.08})0.08

Now, based on the weight factor, the fuzzy output of each rule was calculated using MIN operator and combined into one fuzzy output using MAX operator. Finally, the model performed defuzzification of the combined fuzzy output to generate crisp output value 1.5 and its corresponding linguistic value moderate as the output of the classification of aqua site S11.

After classification of validation set with fuzzy model, the same set was classified by the expert and both results were expressed in numbers for validation (Table 3). Based on the results given in Table 3, out of the 25 aqua sites 23 were classified correctly by the developed fuzzy model. This shows that classification results obtained from the developed fuzzy model showed 92% agreement with the results from the aquaculture expert. The level of agreement between the fuzzy model and human expert is not usually 100%, because fuzzy logic gives 'class' membership degrees to sites (Mazloumzadeh *et al.,* 2010). Thus the fuzzy-based model is a feasible model for classification of aqua sites and also it involves less computation and has clear implementation and working schemes.

The fuzzy rule based developed in the present study, for classification of aqua sites classifies each site into one of the three classes namely suitable, moderate or unsuitable based on the six input variables such as water, soil, support, infrastructure, input and risk factor. Classification results obtained from fuzzy model show a very good general agreement with the results from the aquaculture expert. Results of the present study suggest that this model has sufficient predictive power to help extension personnels and aquaculturists to classify the potential sites for aquaculture development and expansion.

Table 3. Comparison of the fuzzy model developed and results from the aquaculture expert

	Classification	Fuzzy model prediction			Total predicted	Percentage
		Suitable	Moderate	Unsuitable		
Aquaculture expert	Suitable	4	1	0	5	80.0
	Moderate	0	11	1	12	91.7
	Unsuitable	0	0	8	8	100
Total observed		4	12	9	23*/25	
Percentage		100	91.7	88.9		92.0

* Number of aqua sites correctly classified by fuzzy model

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