Chapter 6

Fuzzy rule-based decision making model for classification of aquaculture farms

This chapter presents the fundamentals of fuzzy logic, and development, implementation and validation of a fuzzy rule-based model for classification of optimal location for aquaculture farming development. The last part of this chapter discusses the comparison of results of fuzzy rule-based model and decision making model discussed in chapter 5 for testing their accuracies.

6.1 FUNDAMENTALS OF FUZZY LOGIC

Fuzzy logic is an extension of the classical (Boolean) logic that can be used to handle mathematically the vagueness of human linguistics and thinking (Tanaka, 1996). In other words, it provides a logical system to formalize approximate reasoning (Zedeh, 1994; 1996). Actually, the foundation of fuzzy logic is the fuzzy set theory that was initially introduced by Zedeh (1965). However, currently there is a growing tendency to use fuzzy logic term as almost synonymous with fuzzy set theory (Zedeh, 1994).

6.1.1 FUZZY SETS AND LINGUISTIC VARIABLES

A fuzzy set is an extension of a crisp set. Crisp sets allow only full membership or no membership at all, whereas fuzzy sets allow partial membership. In a crisp set, membership or non membership of element \( x \) in set \( A \) is described by a characteristic function \( \mu_A(x) \), where \( \mu_A(x) = 1 \) if \( x \in A \) and \( \mu_A(x) = 0 \) if \( x \notin A \).

Fuzzy set theory extends this concept by defining partial membership, where \( \mu_A(x) \), where \( \mu_A(x) = 1 \) if \( x \in A \); \( \mu_A(x) = 0 \) if \( x \notin A \) and \( \mu_A(x) = p(0 < p < 1) \) if \( x \) partially belongs to \( A \). Mathematically, a fuzzy set \( A \) on a universe of discourse \( U \) is characterized by a membership function \( \mu_A(x) \) that takes values in the interval \([0,1]\) that can be defined as \( \mu_A : U \rightarrow [0,1] \). Fuzzy set represent commonsense linguistic labels viz., suitable, moderate, unsuitable, slow, very slow, fast etc. A given element can be a member of more than one fuzzy set at a time. A fuzzy set \( A \) in \( U \) may be represented as a set of ordered pairs. Each pair consists of a generic element \( x \) and its
grade of membership function; that is, \( A = \{ (x, \mu_A(x) / x \in U) \} \), \( x \) is called a support value if \( \mu_A(x) > 0 \) (Zadeh, 1965). The concept of a linguistic variable plays important role particularly in fuzzy logic. A linguistic variable is a variable whose values are expressed in words or sentences in natural language. 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 (Zimmermann, 1996).

### 6.1.2 MEMBERSHIP FUNCTIONS

Although both classical and fuzzy subsets are defined by membership functions, the degree to which an element belongs to a classical subset is limited to being either zero or one. This means that membership function may only be a step function (Figure 6.1a). On the other hand, in fuzzy logic, a membership function (MF) is essentially a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1 (Figure 6.1b).

![Figures 6.1. Membership function for (a) crisp set and (b) fuzzy set](image)

The membership functions are usually defined for inputs and outputs in terms of linguistic variables. Various types of membership functions are used, such as triangular, trapezoidal, bell, Gaussian, sigmoid functions. Triangular curves depend on three parameters \( a, b, \) and \( c \) and are given by (Zimmermann, 1996)
Trapezoidal curves depend on four parameters $a$, $b$, $c$, and $d$ and are given by

$$f(z; a; b; c; d) = \begin{cases} 
0 & z \leq a \\
\frac{z-a}{b-a} & a \leq z \leq b \\
\frac{c-z}{c-b} & b \leq z \leq c \\
0 & c \leq z
\end{cases}$$

(6.1)

Gaussian curves depend on two parameters $\sigma$ and $m$ and are defined by

$$f(z; \sigma; m) = e^{-\frac{1}{2} \left( \frac{z-m}{\sigma} \right)^2}$$

(6.3)

In designing a fuzzy inference system, membership functions are associated with term sets that appear in the antecedent or consequent of rules. Many researchers have used different techniques for determining membership functions. One of these approaches is fuzzy clustering (Sugeno and Yasukawa, 1993; Yoshinari et al., 1996; Hwang and Woo, 1995). Another technique for determining membership functions involves neural networks (Kosko, 1992). Genetic algorithms have also been used to determine the optimal shape for membership functions (Wiggins, 1992; Karr, 1991a,b; Karr and Gentry, 1993; Park et al., 1994). One of the most important techniques for determining the shape of membership functions is seeking knowledge of the system from experts, and then constructing membership functions that represent expert opinion (Kruse et al., 1994; Center and Verma, 1998; Pedrycz, 1994; 2001).
6.1.3 LOGICAL OPERATORS

Fuzzy set operations are analogous to crisp set operations. The most elementary crisp set operations are union, intersection, and complement, which essentially correspond to OR, AND, and NOT operators, respectively. Let \( A \) and \( B \) be two subsets of \( U \). The union of \( A \) and \( B \), denoted \( A \cup B \), contains all elements in either \( A \) or \( B \); that is, \( \mu_{A \cup B}(x) = 1 \) if \( x \in A \) or \( x \in B \). The intersection of \( A \) and \( B \), denoted \( A \cap B \), contains all the elements that are simultaneously in \( A \) and \( B \); that is, \( \mu_{A \cap B}(x) = 1 \) if \( x \in A \) and \( x \in B \). The complement of \( A \) is denoted by \( \complement_A \), and it contains all elements that are not in \( A \); that is \( \mu_{\complement_A}(x) = 1 \) if \( x \notin A \) and \( \mu_{\complement_A}(x) = 0 \) if \( x \in A \).

In fuzzy logic, OR, AND, and NOT operators are represented by max, min and complement respectively and these operators are defined as

\[
\mu_{A \cup B}(x) = \max[\mu_A(x), \mu_B(x)]
\]

\[
\mu_{A \cap B}(x) = \min[\mu_A(x), \mu_B(x)]
\]

\[
\mu_{\complement_A}(x) = 1 - \mu_A(x)
\]  

(6.4)

The union of two fuzzy sets \( A \) and \( B \) is specified by a binary mapping \( S \) that aggregates two membership functions as

\[
\mu_{A \cup B}(x) = S[\mu_A(x), \mu_B(x)]
\]  

(6.5)

These fuzzy union operators are known as T-conorm or S-norm operators, and they satisfy the following requirements:

- **boundary:** \( S(1,1) = 1, S(a,0) = S(0,a) = a \)
- **monotonicity:** \( S(a,b) \leq S(c,d) \) if \( a \leq c \) and \( b \leq d \)
- **commutativity:** \( S(a,b) = S(b,a) \)
- **associativity:** \( S(a,S(b,c)) = S(S(a,b),c) \)  

(6.6)

Similar to union operator, the fuzzy intersection operator is specified by the following binary mapping \( T \):

\[
\mu_{A \cap B}(x) = T[\mu_A(x), \mu_B(x)]
\]  

(6.7)
These fuzzy intersection operators are referred to as T-norm (triangular norm) operators, and they meet the following basic requirements:

- **boundary:** \( T(0,0) = 0, S(a,1) = S(1,a) = a \)
- **monotonicity:** \( T(a,b) \leq T(c,d) \) if \( a \leq c \) and \( b \leq d \)
- **commutativity:** \( T(a,b) = T(b,a) \)
- **associativity:** \( T(a,T(b,c)) = T(T(a,b),c) \) \hspace{1cm} (6.8)

### 6.1.4 IF-THEN RULES

A fuzzy system is a collection of if-then rules that link a string input of linguistic variables to an output value (Kosko, 1992; Goktepe et al., 2008). Expert knowledge is the most commonly used technique for determining rules (Mazloumzadeh et al., 2010). When no experts are available, other techniques such as fuzzy classifier (Yoshinari et al., 1996), neural network (Jang and Sun, 1995; Jang et al., 1997) and genetic algorithm (Park et al., 1994; Sugeno and Yasukawa, 1993) have also been used to discover rules. The number of rules would depend on the number of input variables and their linguistic variables. The total number of rules required for constructing a fuzzy system is defined by (Kim et al., 2001; Xu et al., 2002)

\[
N = \prod_{j=1}^{m} n_j , 1 < j \leq m
\]  

(6.9)

where \( m \) is the number of input variables and \( n_j \) is number of linguistic variables for each input variable.

A singleton fuzzy rule assumes the form “IF \( x \) is \( A \), THEN \( y \) is \( B \),” where \( x \in U \) and \( x \in V \), here \( U \) and \( V \) are universe of discourse, and has a membership function, \( \mu_{A\rightarrow B}(x,y) \), where \( \mu_{A\rightarrow B}(x,y) \in [0,1] \). In this, IF part of the rule, “\( x \) is \( A \),” is called the antecedent or premise, while the THEN part of the rule, “\( y \) is \( B \),” is called the consequent or conclusion.

### 6.1.5 FUZZY INFERENCE SYSTEM

Fuzzy Inference System (FIS) incorporate an expert’s experience into the system design and they are composed of four blocks (Figure 6.2) (Mazloumzadeh et al., 2010). A FIS comprises a fuzzifier that transforms the ‘crisp’ inputs into fuzzy inputs by membership functions that represent fuzzy sets of input vectors, a
knowledge base that includes the information given by the expert in the form of linguistic fuzzy rules, an inference engine that uses them together with the knowledge base for inference by a method of implication and aggregation, and a defuzzifier that transforms the fuzzy results of the inference into a crisp output using a defuzzification method (Herrera and Lozano, 2003; Roychowdhury and Pedrycz, 2001).

The knowledge base comprises two components: a database, which defines the membership functions of the fuzzy sets used in the fuzzy rules, and a rule base comprising a collection of linguistic rules that are joined by a specific operator. Based on the consequent type of fuzzy rules, there are two common types of FIS, which vary according to differences between the specifications of the consequent part (Equations 6.10 and 6.11). The first fuzzy system uses the inference method proposed by Mamdani in which the rule consequence is defined by fuzzy sets and has the following structure (Mamdani and Assilian, 1975)

\[
\text{IF } x \text{ is } A \text{ and } y \text{ is } B \text{ THEN } z \text{ is } C
\]  

(6.10)

The second fuzzy system proposed by Takagi, Sugeno and Kang (TSK) contains an inference engine in which the conclusion of a fuzzy rule comprises a constant (equation 6.11a) or a weighted linear combination of the crisp inputs (equation 6.11b) rather than a fuzzy set (Takagi and Sugeno, 1985). A fuzzy rule for the zero-order Sugeno method is of the form

\[
\text{IF } x \text{ is } A \text{ and } y \text{ is } B \text{ THEN } z = C
\]  

(6.11a)

where \( A \) and \( B \) are fuzzy sets in the antecedent and \( C \) is a constant. The first-order Sugeno model has rules of the form

\[
\text{IF } x \text{ is } A \text{ and } y \text{ is } B \text{ THEN } z = px+qy+r
\]  

(6.11b)

where \( A \) and \( B \) are fuzzy sets in the antecedent and \( p, q, \) and \( r \) are constants.

\[\text{Figure 6.2. Fuzzy Inference System (adopted from Mazloumzadeh et al., 2010)}\]
A general schematic of an FIS is shown in Figure 6.3. Consider a multi-input, single-output system. Let \( X = (x_1, x_2, \ldots, x_n)^T \) be the input vector and \( Y = (y_1)^T \) be the output vector. The linguistic variable \( x_i \) be the universe of discourse \( U \) is characterized by \( T(X) = (T_{x_1}, T_{x_2}, \ldots, T_{x_k})^T \) and \( \mu(X) = (\mu_{x_1}, \mu_{x_2}, \ldots, \mu_{x_k})^T \) where \( T(X) \) is a term set of \( x \); that is, it is the set of names of linguistic values of \( x \), with each \( T_{x_i} \) being a fuzzy member and the membership function \( \mu_{x_i} \) defined on \( U \). Similarly, linguistic variable \( y \) in the universe of discourse \( V \) is characterized by \( T(Y) = (T_{y_1}, T_{y_2}, \ldots, T_{y_l})^T \), where \( T(Y) \) is a term set of \( y \); that is, \( T \) is the set of names of linguistic values of \( y \), with each \( T_{y_i} \) being a fuzzy membership function \( \mu_{y_i} \) defined on \( V \).

**Production rules**

- If \( x_1 \) in \( T_{x_1} \) then \( y \) in \( T_{y_1} \)
- If \( x_2 \) in \( T_{x_2} \) then \( y \) in \( T_{y_2} \)
- If \( x_3 \) in \( T_{x_3} \) then \( y \) in \( T_{y_3} \)
- If \( x_n \) in \( T_{x_n} \) then \( y \) in \( T_{y_n} \)

**Figure 6.3. General schematic representation of a fuzzy inference system**

### 6.1.6 FUZZY INFERENCE PROCESS

The inference process for evaluating the system needs five steps (Figure 6.4)

**Figure 6.4. Fuzzy Inference Process**
6.1.6.1 FUZZIFICATION

The first step in evaluating the output of a FIS is to apply the inputs and determine the degree to which they belong to each of the fuzzy sets via membership function (Figure 6.5). This is required in order to activate rules that are in terms of linguistic variables. Once membership functions are defined, fuzzification takes a real time input value and compares it with the stored membership function to produce fuzzy input values. In order to perform this mapping, we can use fuzzy sets of any shape, such as triangular, Gaussian, \( \pi \)-shaped, etc.

![Figure 6.5. Fuzzification](image)

6.1.6.2 APPLYING FUZZY OPERATORS

A fuzzy rule base contains a set of fuzzy rule \( R \). For multi-input, single-output system is represented by

\[
R = (R_1, R_2, \ldots, R_n)
\]

where \( R_i \) can be represented as

\[
R_i = \text{if} \ (x_1 \ \text{is} \ T_{x_1}, \ \text{and} \ldots, \ x_m \ \text{is} \ T_{x_m} \ \text{then} \ (y_1 \ \text{is} \ T_{y_1})
\]
In this rule, m preconditions of \( R_i \) form a fuzzy set \( (T_{x_1} \times T_{x_2} \times \ldots \times T_{x_m}) \), and the consequent is single output. Generally, if-then-rule can be interpreted by the following three steps:

1. Resolve all fuzzy statements in the antecedent to a degree of membership between 0 and 1.

2. If the rule has more than one antecedent, the fuzzy operator is applied to obtain one number that represents the result of applying that rule. This is called firing strength or weight factor of that rule. For example, consider an \( i^{th} \) rule has two parts in the antecedent

\[
R_i = \text{if} \left( x_1 \text{ is } T_{x_1}^i \text{ and } x_2 \text{ is } T_{x_2}^i \right) \text{then } (y \text{ is } T_y^i) \quad (6.14)
\]

Then, the weight factor can be defined using either intersection operators (eq. 6.15) or product operators (eq. 6.16)

\[
\alpha_i = \min \left( \mu_{x_1}^i(x_1), \mu_{x_2}^i(x_2) \right) \quad (6.15)
\]

\[
\alpha_i = \mu_{x_1}^i(x_1) \mu_{x_2}^i(x_2) \quad (6.16)
\]

3. The weight factor is used to shape the output fuzzy set that represents the consequent part of the rule.

6.1.6.3 APPLYING IMPLICATION METHOD

The implication method is defined as the shaping of the consequent, which is the output fuzzy set, based on the antecedent. The input for the implication process is a single number given by the antecedent, and the output is a fuzzy set. Minimum or product (Kim et al., 2001; Xu et al., 2002; Mazloumzadeh et al., 2010) are two commonly used methods, which are represented by equations (6.17) and (6.18), respectively.

\[
\mu_y^i(o) = \min \left( \alpha_i, \mu_y^i(o) \right) \quad (6.17)
\]

\[
\mu_y^i(o) = \alpha_i \mu_y^i(o) \quad (6.18)
\]

where \( o \) is the variable that represents the support value of the membership function.
6.1.6.4 APPLYING AGGREGATION METHOD

Aggregation takes all truncated or modified output fuzzy sets obtained as the output of the implication process and combines them into a single fuzzy set (Zadeh 1965). The output of the aggregation process is a single fuzzy set that represents the output variable. The aggregated output is used as the input to the defuzzification process. Aggregation occurs only once for each output variable. Since the aggregation method is commutative, the order in which the rules are executed is not important. The commonly used aggregation method is the max method (Kim et al., 2001; Xu et al., 2002; Mazloumzadeh et al., 2010) which can be defined as follows:

\[ \mu_y(o) = \max \left( \mu_y^1(o), \mu_y^2(o) \right) \] (6.19)

To illustrate the process in Mamdani System, let us consider the following rules having two input variables \((X_1 \text{ and } X_2)\) in the premise part and one variable \((y)\) in the consequence part:

Rule 1: if \(X_1 \text{ is } T_{x_1}^1 \text{ and } X_2 \text{ is } T_{x_2}^1\) then \(y \text{ is } T_y^1\)

Rule 2: if \(X_1 \text{ is } T_{x_1}^2 \text{ and } X_2 \text{ is } T_{x_2}^2\) then \(y \text{ is } T_y^2\)

Suppose that \(x_1\) and \(x_2\) are inputs for the \(X_1 \text{ and } X_2\) variables respectively. The calculation of weight factor, implication and aggregation methods for these inputs using rules (1 & 2) are illustrated in Figure 6.6 and explained as follows:

1. The weight factor \(\alpha_i\) of each rule is calculated by using the MIN (AND) operation as follows:

   Weight factor of Rule 1: \(\alpha_1 = \min \left( \mu_{y_1}^1(x_1), \mu_{y_2}^1(x_2) \right)\) (6.20)

   Weight factor of Rule 2: \(\alpha_2 = \min \left( \mu_{y_1}^2(x_1), \mu_{y_2}^2(x_2) \right)\) (6.21)

2. The output fuzzy sets of each rule are obtained by applying weight factor of each rule to the fuzzy sets in the consequence part as follows:

   Implication of Rule 1: \(\mu_{y_1}^{1}(o) = \min \left( \alpha_1, \mu_{y_1}^{1}(o) \right)\) (6.22)

   Implication of Rule 2: \(\mu_{y_2}^{2}(o) = \min \left( \alpha_2, \mu_{y_2}^{2}(o) \right)\) (6.23)
3. An overall fuzzy set is obtained by aggregating the individual output fuzzy sets of each rule using max (OR) operation as follows:

$$\mu_y(o) = \max \left( \mu_y^1(o), \mu_y^2(o) \right)$$  (6.24)

**Rule 1**

![Diagram of Rule 1](image1)

**Rule 2**

![Diagram of Rule 2](image2)

**Figure 6.6. Weight factor, implication and aggregation methods in Mamdani System**
6.1.6.5 DEFUZZIFICATION

The defuzzifier maps output fuzzy sets into a crisp number. Defuzzification can be performed by several methods such as: center of gravity, center of sums, center of the largest area, first of the maxima, middle of the maxima, maximum criterion and height defuzzification. Of these, center of gravity (centroid method) and height defuzzification are the methods commonly used (Mazloumzadeh et al., 2010). The centroid defuzzification method finds the center point of the solution fuzzy region by calculating the weighted mean of the output fuzzy region. It is the most widely used technique because the defuzzified values tend to move smoothly around the output fuzzy region.

6.2 DEVELOPMENT OF FUZZY RULE-BASED MODEL

6.2.1 VARIABLES AND DATA SETS

As discussed in chapter 4, six main variables namely: water (W), soil (So), support (Su), infrastructure (Is), input (Ip) and risk factor (R) were used in the fuzzy rule-based model.

The water, soil, support, infrastructure, input and risk factor related data used in this study were obtained from 80 randomly selected aqua farms (or sites) in the study area such as Bhimavaram (A) (30 sites), Narsapuram (B) (10 sites), Mogalthur (C) (25 sites), and Kalla (D) (15 sites) (Figure 6.7), West Godavari district, Andhra Pradesh, India. Data gathered from A and B were used to train the fuzzy model, C for validating the model and D for comparing the results of two models for testing their accuracies. Combination of rank sum, pairwise comparison and TOPSIS methods, as discussed in the chapter 5, were used to process the aqua farm data and produce the required dataset in the form of main-variables. In this regard, data necessary to develop and validate the fuzzy model was obtained.
6.2.2 PROPOSED FUZZY RULE-BASED MODEL

In the proposed fuzzy model, both the antecedent and consequent part were expressed by the experts in fuzzy statements using linguistic variables such as suitable, moderate, or unsuitable. Therefore a Mamdani inference system was used to develop this model. Schematic representation of the proposed fuzzy model is shown in Figure 6.8.
Figure 6.8 Schematic representation of proposed fuzzy model (modified from Guney and Sarikaya, 2009, p.86)
6.2.3 FUZZY SETS AND MEMBERSHIP FUNCTIONS

For classification applications, fuzzy logic is a process of mapping an input space into an output space using membership functions and linguistically specified rules (Xu et al., 2002). In the proposed fuzzy model, six inputs and one output were used to classify the optimal location in aquaculture. The inputs were water (W), soil (So), support (Su), infrastructure (Is), input (Ip), and risk factor (R) represented by X and output was Aquaculture Farm Classification (AFC) represented by Z. Mathematically this can represented as

$$Z = F(X)$$ (6.25)

In this model, both input and output variables were split into three linguistic variables namely unsuitable (U), moderate (or acceptable) (M), and suitable (S). After splitting the variables, a membership function was defined for each linguistic variable. In this study, based on the training set (refer to Appendix D) and the experts’ experience and knowledge (Pedrycz, 1994; 2001), 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 (Guney and Sarikaya 2009) by

(i) $$\mu_{ij}(x) = \text{Gaussmf} \left( x; m_{ij}; \sigma_{ij} \right) = e^{-\frac{1}{2} \left( \frac{x-m_{ij}}{\sigma_{ij}} \right)^2}$$ (6.26)

for (i = 1 to 6; j = 1, 2, 3) \( x = (W, So, Su, Is, Ip, R) \)

where \( \mu_{ij} \) represent the \( j^{th} \) MF of the \( i^{th} \) input; \( m_{ij} \) is the mean of the \( j^{th} \) MF of the \( i^{th} \) input variable; \( \sigma_{ij} \) is the standard deviation of the \( j^{th} \) MF of the \( i^{th} \) input variable. The parameters \( m_{ij} \) and \( \sigma_{ij} \) for the input variables were defined by (Xu et al., 2002)

$$m_{ij} = \frac{x_{ij} + y_{ij}}{2} \quad i = 1,2,3,...,6; \quad j = 1,2,3$$ (6.27)

$$\sigma_{ij} = \frac{m_{ij} - x_{ij}}{3} \quad i = 1,2,3,...,6; \quad j = 1,2,3$$ (6.28)
where \([x_{ij}, y_{ij}]\) is the range of the \(j^{th}\) MF of the \(i^{th}\) input variable.

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

\[
\mu_{oj}(z) = \begin{cases} 
0 & z \leq a_{oj} \\
\frac{z - a_{oj}}{b_{oj} - a_{oj}} & a_{oj} \leq z \leq b_{oj} \\
\frac{c_{oj} - z}{c_{oj} - b_{oj}} & b_{oj} \leq z \leq c_{oj} \\
0 & c_{oj} \leq z 
\end{cases}
\]

for \((o = 1; j = 1, 2, 3)\) \quad \(z = \text{(AFC)}\)

where \(\mu_{oj}\) represent the \(j^{th}\) output MF; \(a_{oj}, b_{oj}, c_{oj}\) are the parameters that represent the shapes of the output MF. Table 6.1 presents the parameters for each of the input and output variables.

**Table 6.1. Parameters for the fuzzy sets of the input and output variables**

<table>
<thead>
<tr>
<th>Input and output variables</th>
<th>Linguistic variables (membership functions) and its parameters</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>Unsuitable</td>
</tr>
<tr>
<td>Input variables ([x_{ij}, y_{ij}]) (m_i, \sigma_i)</td>
<td>Water</td>
</tr>
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<td></td>
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<tr>
<td></td>
<td>Soil</td>
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<td>Input</td>
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<tr>
<td></td>
<td>Risk factor</td>
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<td></td>
<td></td>
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<tr>
<td>Output variable (AFC) (a_{oj}, b_{oj}, c_{oj})</td>
<td>0, 0.5, 1</td>
</tr>
</tbody>
</table>

\([x_{ij}, y_{ij}], m_i, \sigma_i\) - 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

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In this study, experts’ knowledge was used for the construction of fuzzy rule base. It would not be possible to derive directly all rules from the experts due to the combination of the input variables and their linguistic values. In this study, therefore, 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 experts. Hence, the reasoning and backbone arguments from the experts have been analyzed as foundations to derive the fuzzy rule base.

The proposed model has $3 \times 3 \times 3 \times 3 \times 3 \times 3 = 729$ rules based on the six input variables and their corresponding linguistic variables. These if-then rules were collated with AND operator because all the input variables must be captured simultaneously and applied in decision making by fuzzy logic for classification. The fuzzy rule base for the proposed model was defined as follows (for the whole set of rules refer to Appendix E):

1. if (W is $\mu_{11}$) and (So is $\mu_{21}$) and (Su is $\mu_{31}$) and (Is is $\mu_{41}$) and (Ip is $\mu_{51}$) and (R is $\mu_{61}$) then $R_1 = \mu_{a1}(z; a_{o1}, b_{o1}, c_{o1})$

2. if (W is $\mu_{11}$) and (So is $\mu_{22}$) and (Su is $\mu_{32}$) and (Is is $\mu_{41}$) and (Ip is $\mu_{51}$) and (R is $\mu_{62}$) then $R_2 = \mu_{a2}(z; a_{o2}, b_{o2}, c_{o2})$

3. if (W is $\mu_{11}$) and (So is $\mu_{23}$) and (Su is $\mu_{33}$) and (Is is $\mu_{41}$) and (Ip is $\mu_{51}$) and (R is $\mu_{63}$) then $R_3 = \mu_{a3}(z; a_{o3}, b_{o3}, c_{o3})$

... 728

728. if (W is $\mu_{13}$) and (So is $\mu_{23}$) and (Su is $\mu_{33}$) and (Is is $\mu_{43}$) and (Ip is $\mu_{53}$) and (R is $\mu_{62}$) then $R_{728} = \mu_{a728}(z; a_{o728}, b_{o728}, c_{o728})$

729. if (W is $\mu_{13}$) and (So is $\mu_{23}$) and (Su is $\mu_{33}$) and (Is is $\mu_{43}$) and (Ip is $\mu_{53}$) and (R is $\mu_{63}$) then $R_{729} = \mu_{a729}(z; a_{o729}, b_{o729}, c_{o729})$

In general, consequent of the rule was written as

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

(6.30)
where $\mu_{ij}$ is the $j^{th}$ MF of the $i^{th}$ input; $\mu_{ok}$ 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.

### 6.2.5 OPERATING MECHANISM OF THE PROPOSED MODEL

The proposed model consists of five operating mechanisms named as fuzzification, calculation of weight factor, implication, aggregation, and defuzzification (Figure 6.8).

**Step 1: 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 neighboring classes because decisions were distributed over more than one input class (Figures 6.9(a-f)). 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 (Figure 6.10).

![Figures 6.9a Membership function for ‘water’ input variables](image)

![Figures 6.9b Membership function for ‘soil’ input variables](image)
Figures 6.9c  Membership function for ‘support’ input variables

Figures 6.9d  Membership function for ‘infrastructure’ input variables

Figures 6.9e  Membership function for ‘input’ input variables

Figures 6.9f  Membership function for ‘risk factor’ input variables
Step 2: Calculation of weight factor

In this step, the weighting factor of each rule was calculated. 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

\[
\alpha_k = \min_k (\mu_y(W), \mu_y(So), \mu_y(Su), \mu_y(Is), \mu_y(Ip), \mu_y(R)) \quad k = 1, 2, \ldots, 729 \quad (6.31)
\]

Step 3: Implication

For classification applications, implication is carried out by either truncation or scaling (Xu et al., 2002; Lorestani et al., 2006). Truncation is done by chopping off the output MF, while scaling is done by compressing the function. In this model, truncation implication was used which is one of the most widely used implication in applications of fuzzy logic (Kim et al., 2001). This was computed by

\[
\mu_{imp,k} = \min_k (\alpha_k R_k) \quad k = 1, 2, \ldots, 729 \quad (6.32)
\]

Step 4: Aggregation

Since decisions are based on the testing of all of the rules in the model, rules must be combined in order to make decision. In this model, the aggregation was performed by using union (maximum) operator, which was represented by
\[
\mu_a(k) = \max_k \left( \mu_{imp,k} \right)
\]

\[
= \max_k \left( \min_k (\alpha_k R_k) \right)
\]

\[
= \max_k \left( \min_k (\alpha_k \mu_{ok}) \right) K = 1,2,\ldots,729
\quad (6.33)
\]

Step 5: Defuzzification

Among the different defuzzification mechanisms such as center of sums, center of largest area, first of maxima, and middle of maxima, center of gravity (COG) method is the most widely used one in classification 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 into a crisp number. The centroid of the aggregated area was defined by Xu et al (2002)

\[
AFC = \frac{\sum_{i=1}^{n} a_i c_i}{\sum_{i=1}^{n} a_i}
\quad (6.34)
\]

where \(a_1, a_2, \ldots, a_n\) be the areas of the truncated triangular areas under the aggregated function and \(c_1, c_2, \ldots, c_n\) be the coordinates of their center on the x-axis, \(n\) is the number of areas and AFC is the location of the centroid of the total areas. The location of COG determines the classification of optimal location for aquaculture farming development.

6.3 FUZZY MODEL IMPLEMENTATION AND ITS RESULTS

The proposed fuzzy model was implemented as a fuzzy rule-based tool using MATLAB (Version 7.0). In this study, fuzzy inference was performed based on the Mamdani’s inference method which uses minimum (MIN) operator in the implication process and maximum (MAX) operator in the aggregation process. The FIS editor of the developed program is shown in Figure 6.11. Summary of which is given below:
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)

![Figure 6.11 Schematic of proposed fuzzy model for classification of optimal location in aquaculture](image)

Then, the membership functions for each input variable and output variable were generated using the membership function editor in the Matlab fuzzy logic toolbox (Figures 6.12(a-g)). The rule editor was used for generating the 729 fuzzy if-then rules (Figure 6.13) in the Matlab.
Figures 6.12a  Membership function editor toolbox for ‘water’ input variables

Figures 6.12b  Membership function editor toolbox for ‘soil’ input variables
Figures 6.12c  Membership function editor toolbox for ‘support’ input variables

Figures 6.12d  Membership function editor toolbox for ‘infrastructure’ input variables
Figures 6.12e  Membership function editor toolbox for ‘input’ input variables

Figures 6.12f  Membership function editor toolbox for ‘risk factor’ input variables
Figures 6.12g Membership function editor toolbox for output variable

Figure 6.13 Generated fuzzy rules in Fuzzy rule editor toolbox
By using a numerical example illustration, the working procedure of the proposed model can be explained as follows:

Suppose that information concerning the input variables are expressed numerically as follows: water = 0.316 (Figure 6.14a), soil = 0.329 (Figure 6.14b), support = 0.027 (Figure 6.14c), infrastructure = 0.035 (Figure 6.14d), input = 0.018 (Figure 6.14e), and risk factor = 0.007 (Figure 6.14f).

Figures 6.14a Fuzzification of crisp input for water

Figures 6.14b Fuzzification of crisp input for soil

Figures 6.14c Fuzzification of crisp input for support
At the first step, fuzzification yields the following fuzzy inputs (Figures 6.14(a-f)) for the next step in the inference process:

- **Input 1:** Water is suitable with membership degree 0.99
- **Input 2:** Soil is suitable with membership degree 0.4
Input 3: Support is unsuitable with membership degree 0.95
Input 4: Infrastructure is moderate with membership degree 0.05 and unsuitable with membership degree 0.9
Input 5: Input is unsuitable with membership degree 0.4
Input 6: Risk Factor is unsuitable with membership degree 0.08

• Then, the fuzzified values were used by the proposed model to activate appropriate rules and 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 0.4) and (Risk Factor is unsuitable with membership degree 0.08) THEN Aqua Farm Classification is moderate with a membership degree of

\[ MIN\left(\{0.99,0.4,0.95,0.05,0.4,0.08\}\right) = 0.05 \]

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 Aqua Farm Classification is moderate with a membership degree of

\[ MIN\left(\{0.99,0.4,0.95,0.9,0.4,0.08\}\right) = 0.08 \]

• 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 farms (Figure 6.15).
The similar processes were carried out simultaneously by the model for the crisp values in the dataset. The result of this procedure for the test dataset is summarized in Table 6.2. From Table 6.2, it was seen that the sites (or aqua farms) 12 and 13 were classified as suitable. It also revealed that in site 12, water and soil variables were in the suitable range of linguistic value; support, infrastructure and input were in both moderate and unsuitable ranges; and risk factor was in unsuitable range of linguistic values. This activate the rules 42, 45, 51, 54, 69, 72, 78 and 81 and produces output fuzzy value as 2.32, which belongs to suitable classification. Similarly, in site 13, water and soil variables were in the suitable range of linguistic value; support was in moderate; infrastructure and input were in both moderate and unsuitable range; and risk factor was in unsuitable range of linguistic values. These combinations activate the rules 69, 72, 78 and 81 and produces fuzzy value 2.32. This fuzzy value classifies the site into suitable category. From Table 6.2, it could be observed that in site 8, water was in moderate range of linguistic value; soil and risk factor variables were in both moderate and unsuitable ranges; and support, infrastructure and input were in the unsuitable range of linguistic values. Based on the
combination of these linguistic values 296, 297, 620, and 621 rules were activated and it produces fuzzy value 0.503 which belongs to unsuitable classification.

Table 6.2. Outputs of the fuzzy rule-based model for test dataset

<table>
<thead>
<tr>
<th>Sites or aqua farms</th>
<th>Input (test dataset)</th>
<th>Active rules</th>
<th>Output crisp value</th>
<th>Classification</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Water</td>
<td>Soil</td>
<td>Support</td>
<td>Infrastructure</td>
</tr>
<tr>
<td>S1</td>
<td>0.316</td>
<td>0.329</td>
<td>0.027</td>
<td>0.035</td>
</tr>
<tr>
<td>S2</td>
<td>0.247</td>
<td>0.127</td>
<td>0.027</td>
<td>0.000</td>
</tr>
<tr>
<td>S3</td>
<td>0.191</td>
<td>0.102</td>
<td>0.000</td>
<td>0.023</td>
</tr>
<tr>
<td>S4</td>
<td>0.250</td>
<td>0.215</td>
<td>0.027</td>
<td>0.020</td>
</tr>
<tr>
<td>S5</td>
<td>0.196</td>
<td>0.022</td>
<td>0.035</td>
<td>0.000</td>
</tr>
<tr>
<td>S6</td>
<td>0.243</td>
<td>0.075</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>S7</td>
<td>0.152</td>
<td>0.076</td>
<td>0.027</td>
<td>0.000</td>
</tr>
<tr>
<td>S8</td>
<td>0.105</td>
<td>0.076</td>
<td>0.000</td>
<td>0.023</td>
</tr>
<tr>
<td>S9</td>
<td>0.117</td>
<td>0.112</td>
<td>0.044</td>
<td>0.024</td>
</tr>
<tr>
<td>S10</td>
<td>0.110</td>
<td>0.145</td>
<td>0.027</td>
<td>0.008</td>
</tr>
<tr>
<td>S11</td>
<td>0.316</td>
<td>0.148</td>
<td>0.044</td>
<td>0.034</td>
</tr>
<tr>
<td>S12</td>
<td>0.316</td>
<td>0.358</td>
<td>0.044</td>
<td>0.054</td>
</tr>
<tr>
<td>S13</td>
<td>0.316</td>
<td>0.358</td>
<td>0.066</td>
<td>0.054</td>
</tr>
<tr>
<td>S14</td>
<td>0.243</td>
<td>0.358</td>
<td>0.066</td>
<td>0.034</td>
</tr>
<tr>
<td>S15</td>
<td>0.288</td>
<td>0.358</td>
<td>0.066</td>
<td>0.034</td>
</tr>
</tbody>
</table>

6.4 VALIDATION OF FUZZY MODEL

6.4.1 VALIDATION METHOD

Without a proper validation it is not possible to compare the model with other ones (Begueria, 2006). Validation is a demonstration that a model within its domain
of applicability possesses a satisfactory range of accuracy consistent with the intended application of the model (Sargent, 1984; Edward and Rykiel, 1996). If the model output is in text form and there is no meaningful error describing values (such as the sum of squared error), the best way to validate the model is based on qualitative approaches (Heinonen et al., 2009). For validation of the developed fuzzy model, first the validation set (25 sites from Mogalthur mandal, West Godavari district) was classified by fuzzy model designed for this purpose and then the same set was classified by aquaculture expert, using field experience and knowledge. The model outputs and expert responses were expressed in terms of numbers and the accuracy of classification was calculated by (Lorestani et al., 2006)

\[
Accuracy = \frac{n}{N} \times 100
\]

where \( n \) is number of sites correctly classified by fuzzy model and \( N \) is total number of sites considered for validation.

### 6.4.2 VALIDATION RESULTS

The validity of the output of fuzzy model was evaluated by comparing the results of developed fuzzy model and aquaculture expert considering validation dataset. Table 6.3 depicted the results of the fuzzy model obtained for validation dataset. As shown in the Table 6.3, sites 2, 19, 24 and 25 were classified as suitable with output fuzzy values 2.32, 2.32, 2.32, and 2.24 respectively. Though risk factor was in unsuitable range of linguistic value in all the four sites, water and soil were in suitable range, and support, infrastructure and input were in moderate. It also revealed that, twelve sites 1, 5, 11, 12, 13, 14, 15, 16, 17, 18, 21, and 23 were classified as moderate and their output fuzzy values were in the range of 1 to 2. The remaining nine sites 3, 4, 6, 7, 8, 9, 10, 20, and 22 were classified as unsuitable. In these sites, either water or soil or both variables were in unsuitable range of linguistic value and other variables namely support, infrastructure, input, and risk factor were in either moderate or unsuitable or both range of linguistic values. 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. Comparison of results of developed fuzzy model and aquaculture expert for classification of sites in aquaculture are given in Table 6.4.
Table 6.3 Results obtained from the fuzzy model for the validation dataset

<table>
<thead>
<tr>
<th>Sites or aqua farms</th>
<th>Input (validation dataset)</th>
<th>Active rules</th>
<th>Output crisp value</th>
<th>Classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>0.316 0.215 0.027 0.035 0.018 0.007</td>
<td>45, 54</td>
<td>1.500</td>
<td>Moderate</td>
</tr>
<tr>
<td>S2</td>
<td>0.327 0.358 0.044 0.054 0.037 0.007</td>
<td>51, 54, 42, 45, 69, 72, 78, 81</td>
<td>2.320</td>
<td>Suitable</td>
</tr>
<tr>
<td>S3</td>
<td>0.117 0.145 0.027 0.008 0.018 0.030</td>
<td>296, 297</td>
<td>0.635</td>
<td>Unsuitable</td>
</tr>
<tr>
<td>S4</td>
<td>0.117 0.112 0.044 0.024 0.000 0.007</td>
<td>297, 324</td>
<td>0.894</td>
<td>Unsuitable</td>
</tr>
<tr>
<td>S5</td>
<td>0.316 0.148 0.044 0.034 0.037 0.007</td>
<td>123, 125, 132, 135, 150, 153, 159, 162</td>
<td>1.650</td>
<td>Moderate</td>
</tr>
<tr>
<td>S6</td>
<td>0.152 0.076 0.027 0.000 0.000 0.007</td>
<td>135, 297, 459, 621</td>
<td>0.509</td>
<td>Unsuitable</td>
</tr>
<tr>
<td>S7</td>
<td>0.105 0.076 0.000 0.023 0.009 0.030</td>
<td>296, 297, 620, 621</td>
<td>0.503</td>
<td>Unsuitable</td>
</tr>
<tr>
<td>S8</td>
<td>0.105 0.082 0.000 0.023 0.009 0.030</td>
<td>296, 297, 620, 621</td>
<td>0.573</td>
<td>Unsuitable</td>
</tr>
<tr>
<td>S9</td>
<td>0.243 0.075 0.000 0.000 0.000 0.030</td>
<td>134, 135, 296, 297, 458, 459, 647, 648</td>
<td>0.794</td>
<td>Unsuitable</td>
</tr>
<tr>
<td>S10</td>
<td>0.196 0.022 0.035 0.000 0.009 0.030</td>
<td>458, 459, 485, 486, 647, 648</td>
<td>0.501</td>
<td>Unsuitable</td>
</tr>
<tr>
<td>S11</td>
<td>0.316 0.329 0.027 0.035 0.018 0.007</td>
<td>45, 54</td>
<td>1.500</td>
<td>Moderate</td>
</tr>
<tr>
<td>S12</td>
<td>0.247 0.215 0.027 0.000 0.018 0.037</td>
<td>53, 54, 215, 216</td>
<td>1.010</td>
<td>Moderate</td>
</tr>
<tr>
<td>S13</td>
<td>0.247 0.127 0.027 0.000 0.018 0.037</td>
<td>134, 135, 296, 297</td>
<td>1.010</td>
<td>Moderate</td>
</tr>
<tr>
<td>S14</td>
<td>0.196 0.127 0.035 0.000 0.009 0.030</td>
<td>134, 135, 161, 162, 296, 297, 323, 324, 620, 621, 647, 648</td>
<td>1.010</td>
<td>Moderate</td>
</tr>
<tr>
<td>S15</td>
<td>0.191 0.102 0.000 0.023 0.018 0.037</td>
<td>116, 117, 296, 297, 458, 459, 620, 621</td>
<td>1.010</td>
<td>Moderate</td>
</tr>
<tr>
<td>S16</td>
<td>0.250 0.215 0.027 0.020 0.009 0.037</td>
<td>53, 54, 215, 216</td>
<td>1.410</td>
<td>Moderate</td>
</tr>
<tr>
<td>S17</td>
<td>0.191 0.102 0.000 0.035 0.018 0.037</td>
<td>125, 126, 134, 135, 287, 288, 296, 297</td>
<td>1.010</td>
<td>Moderate</td>
</tr>
<tr>
<td>S18</td>
<td>0.243 0.358 0.066 0.034 0.037 0.007</td>
<td>69, 72, 78, 81, 231, 234, 240, 243</td>
<td>1.790</td>
<td>Moderate</td>
</tr>
<tr>
<td>S19</td>
<td>0.316 0.358 0.066 0.054 0.037 0.007</td>
<td>69, 72, 78, 81</td>
<td>2.320</td>
<td>Suitable</td>
</tr>
<tr>
<td>S20</td>
<td>0.243 0.082 0.000 0.000 0.000 0.030</td>
<td>134, 135, 296, 297, 458, 459, 620, 621</td>
<td>0.911</td>
<td>Unsuitable</td>
</tr>
<tr>
<td>S21</td>
<td>0.288 0.358 0.066 0.034 0.037 0.007</td>
<td>69, 72, 78, 81</td>
<td>1.810</td>
<td>Moderate</td>
</tr>
<tr>
<td>S22</td>
<td>0.196 0.022 0.035 0.000 0.009 0.037</td>
<td>620, 621, 647, 648</td>
<td>0.517</td>
<td>Unsuitable</td>
</tr>
<tr>
<td>S23</td>
<td>0.252 0.215 0.027 0.020 0.009 0.037</td>
<td>53, 54</td>
<td>1.610</td>
<td>Moderate</td>
</tr>
<tr>
<td>S24</td>
<td>0.358 0.358 0.066 0.054 0.037 0.007</td>
<td>69, 72, 78, 81</td>
<td>2.320</td>
<td>Suitable</td>
</tr>
<tr>
<td>S25</td>
<td>0.371 0.358 0.044 0.054 0.037 0.007</td>
<td>51, 54, 42, 45, 69, 72, 78, 81</td>
<td>2.240</td>
<td>Suitable</td>
</tr>
<tr>
<td>Classification</td>
<td>Fuzzy model prediction</td>
<td>Total predicted</td>
<td>%</td>
<td></td>
</tr>
<tr>
<td>----------------</td>
<td>------------------------</td>
<td>-----------------</td>
<td>----</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Suitable</td>
<td>Moderate</td>
<td>Unsuitable</td>
<td></td>
</tr>
<tr>
<td>Aquaculture expert</td>
<td>4</td>
<td>1</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>Moderate</td>
<td>0</td>
<td>11</td>
<td>1</td>
<td>12</td>
</tr>
<tr>
<td>Unsuitable</td>
<td>0</td>
<td>0</td>
<td>8</td>
<td>8</td>
</tr>
<tr>
<td>Total observed</td>
<td>4</td>
<td>12</td>
<td>9</td>
<td>23</td>
</tr>
<tr>
<td>%</td>
<td>100</td>
<td>91.7</td>
<td>88.9</td>
<td>92.0</td>
</tr>
</tbody>
</table>

* Number of aqua farms correctly classified by fuzzy model

Based on the results in Table 6.4, out of 25 aqua farms 23 farms 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 Mamdani fuzzy system 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 optimal location for aquaculture farming development and also it involves less computation and has clear implementation and working schemes.

### 6.5 COMPARISON OF RESULTS OF BOTH THE MODELS

#### 6.5.1 COMPARISON METHOD

It is important to test the outputs from the decision making model discussed in chapter 5 and the outputs from the fuzzy model for their accuracies. Therefore, the comparisons between two models were made in terms of ranks and classification of aqua farms obtained from the models respectively. To facilitate the comparison, the test dataset (15 sites from Kalla mandal, West Godavari district) was ranked using decision making model (explained in chapter 5) and then the same dataset was classified into suitable, moderate, or unsuitable using fuzzy model.
6.5.2 COMPARISON RESULTS

Table 6.5 depicted the results obtained from the decision making model and fuzzy model for the test dataset.

**Table 6.5 Results of fuzzy model and decision making model for the test dataset**

<table>
<thead>
<tr>
<th>Aqua farms (or alternatives or sites)</th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
<th>S4</th>
<th>S5</th>
<th>S6</th>
<th>S7</th>
<th>S8</th>
<th>S9</th>
<th>S10</th>
<th>S11</th>
<th>S12</th>
<th>S13</th>
<th>S14</th>
<th>S15</th>
</tr>
</thead>
<tbody>
<tr>
<td>Decision making model (rank)</td>
<td>5</td>
<td>8</td>
<td>9</td>
<td>7</td>
<td>13</td>
<td>10</td>
<td>14</td>
<td>15</td>
<td>12</td>
<td>11</td>
<td>6</td>
<td>2</td>
<td>1</td>
<td>4</td>
<td>3</td>
</tr>
<tr>
<td>Fuzzy rule-based model (classification)</td>
<td>M</td>
<td>M</td>
<td>M</td>
<td>M</td>
<td>U</td>
<td>U</td>
<td>U</td>
<td>U</td>
<td>U</td>
<td>U</td>
<td>M</td>
<td>S</td>
<td>S</td>
<td>M</td>
<td>M</td>
</tr>
</tbody>
</table>

S- Suitable; M-Moderate; U-Unsuitable

The results revealed that, the most preferred sites S13 (rank 1) and S12 (rank 2) were classified as suitable by fuzzy model. The moderately classified sites S15, S14, S11, S4, S2 and S3 were identified as next higher ranks 3, 4, 5, 6, 7, 8 and 9 respectively. The fuzzy model classified worst six sites S6 (rank 10), S10 (rank 11), S9 (rank 12), S5 (rank 13), S7 (rank 14) and S8 (rank 15) as unsuitable. Comparison (Table 6.5) of results showed that both the models correctly identify and classify the optimal location for aquaculture farming development.