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A Fuzzy Rule-Based Model for Artificial Reef Placement Related to Managing Red Snapper (*Lutjanus Campechanus*) Ecosystems in Alabama Waters

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Abstract. A rough set theory model utilising fuzzy sets was developed to investigate artificial reef placement based on fish ecosystem components. The model incorporates consumption estimates and presumed foraging behavior to provide a rule-based approach to determine how far apart artificial reefs must be placed to eliminate density-dependent competition for prey resources. Simulation of the ecosystem parameters and potential reef distances as triangularly defined fuzzy sets generates input into the rules. Then, based upon the strength of belief in a rule, the artificial reef placement location can be accepted or rejected as being conducive to consumption at the reef and foraging behaviour of the species. Ease of utilisation of the model is highlighted by spreadsheet application to a red snapper (*Lutjanus campechanus*) ecosystem in Gulf of Mexico waters off the coastal shelf of Alabama. Implications exist for similar applications to other ecosystems and different fish species. Further applications are relevant beyond fish management when viewed as a general managerial decision-making process involving fuzzy sets and simulation.

Keywords: Knowledge management; Rough set theory; fuzzy logic; fisheries management; ecosystem modeling; science-based management.

1. Introduction

Previously, knowledge-based systems and uncertainty problems in ecological research have been limited due to the difficulty in acquiring knowledge that can be suitably structured and formalised as well as the essential problem that uncertainty exists in expert knowledge and ecological data. Such uncertainty stems from inaccuracy of data, inaccuracy of interpolation methods and unreliability of measurement tools as well as the fact that some measurements are not possible. For example, the number of fish in a lake can be approximated, but is not quantifiable without allowances for error (Salski, 1992). Uncertainty may also be due to ambiguity in the linguistic terms (such as High, Medium, and Low) used to describe a specific situation, or by missing and/or erroneous data. (See for example, Zadeh, 1983; Yager, 1984; Arciszewski and Ziarko, 1986; Bobrow *et al.*, 1986; and Wiederhold *et al.*, 1986.) In an ecological investigation, perfect knowledge is rarely, if ever, available since natural systems do not conform to crisp definitions (Mackinson *et al.*, 1999).

The use of crisp (not fuzzy) sets requires the expert to establish sustainability thresholds for attributes, measure the attributes, and determine whether measured attributes attain or fall short of the thresholds. This approach assumes that the expert can make a sharp, unambiguous distinction which is incompatible with the numerous uncertainties in ecosystem assessments. According to Prato (2005), a fuzzy logic approach overcomes the conventional approach. Thus, when the components of an ecosystem are not exactly known, a fuzzy set model can be built based on expert knowledge even though that knowledge is generally, to some degree, imprecise. Compared to conventional knowledge-based systems, fuzzy set theory offers better representation and processing of imprecise data, and of vague knowledge in the form of linguistic rules (Salski, 1992).

Rules make associations by relating one event to another (Kosko, 1992). Heuristic rules expressed in natural language can be easily explained and understood. In contrast with an equation, comparison of rules can be made based on knowledge of specific biological and ecological characteristics providing a powerful tool to compare both scientific and nonscientific knowledge (Mackinson and Nøttestad, 1998). A fuzzy rule-based model is characterised by data richness and complexity, thrives in a data-poor environment, is adaptive such that better approximations are possible with more data, requires relatively few rules to describe the data, and can provide patches across traditional curve-based distributions (Mackinson *et al.*, 1999).

Typically, the utilisation of statistical processes requires probabilities to be estimated and a complete data set for a population in order to eliminate assumptions and uncertainty (Mamdani *et al.*, 1985). Fuzzy logic has a rigorous mathematical foundation shown not to contradict but to encompass probability theory (Kosko, 1990), while dealing with uncertainty where ambiguous terms are present (Articles in Zadeh, 1979, 1981 and 1983 illustrate the use of fuzzy sets). Rough set theory is another method that has been applied to uncertain and ambiguous situations. [Work with rough sets is illustrated in (Pawlak, 1981a, 1981b, 1982; Mrozek, 1985; Arciszewski and Ziarko, 1986; Fibak *et al.*, 1986; Mrozek, 1987; Grzymala-Busse, 1988; deKorvin and Shipley, 1993).] This study builds on these alternatives to statistics, allowing an inferred knowledge from the uncertainty associated with ambiguous (i.e., fuzzy) terms.

Thus, a rough set theory model utilising fuzzy sets was developed to investigate artificial reef placement as a function of fish consumption. Rules were developed according to:

1. consumption output generated by a bioenergetics model describing food requirements based upon empirically determined growth rates; and
2. artificial reef data predicted from simulating the effect of foraging, specifically related to food consumption by fishes on the reefs.

Since all food sources are not available at the reef, the fish must forage to find resources necessary to accommodate observed growth rates. If the reefs are too closely spaced, then the fish are most likely competing for resources. The fuzzy set model considers distances from maximum to minimum spacing and determines a strength of belief in the certainty or possibility of the hypothesised rules for reef placement. Based upon the strength of belief in a rule, the artificial reef placement location can be accepted or rejected as being conducive to consumption at the reef and foraging behaviour of the fish.

The rule structure considered is of the form:

$R =$ If Percentage of Maximum Consumption at the Reef is {High, Low} and Foraging Consumption is {Great, Small}, then Artificial Reef Distance Should be {Major, Minor}

where Major and Minor reef distances are set within a $1\,\text{km}^2$ area since it has been recommended that spacing artificial reefs 600–1000 m from natural reefs is best to minimise fish interaction (Grove and Sonu, 1983).

The paper proceeds as follows: Background information on fuzzy logic models in the natural sciences and fuzzy set fundamentals necessary to the reading of the paper are provided in Sec. 2. Application of the model is made to reef placement decisions based on red snapper bioenergetics in the Gulf of Mexico waters off the Alabama shelf in Sec. 3. Conclusions and implications of the fuzzy set-based modeling process to further science-based management decisions are in Sec. 4.

2. Background

2.1. *Fuzzy logic models for natural sciences & ecosystems*

Recognition of uncertainty in management of natural resources and ecological decision making has led to increasing fuzzy-set-based research in these areas. Bosserman and Ragade (1982) provided an ecological point of view to fuzzy set theory which was applied, a year later, to modeling competition in an ecological system (Giering and Kandel, 1983). Fuzzy graphs of such ecological systems have been generated with a computer program developed for forest succession (Roberts, 1989) representing the transition of environmental, fuzzy-logic based models to multispecies trawl fishery. Fuzzy mapping models have been used to assess the effects of creel limits and length-based regulations on walleye populations and angler behaviour in Minnesota (Radomski and Goeman, 1996) and the large-scale ecological system of the Lake Erie Lakewide Management Plan (Hobbs *et al.*, 2002).

Within fisheries science, it has been determined that there is a point at which recruitment drops due to overfishing (Cushing, 1971; Myers *et al.*, 1995). Recognised variations in recruitment present one of the most difficult management problems in the biological assessment of fisheries (Hilborn and Walters, 1987). To address this problem, a fuzzy-set based heuristic for analysis of stock-recruitment relationships and prediction of recruitment principles recognised the benefit of using a single fuzzy rule of the form If *this*, Then *that* (Mackinson *et al.*, 1999). Similarly, the uncertainties inherent in ecosystem assessments resulted in a model that developed fuzzy propositions about ecosystem attributes and strong sustainability, and then applied a rule to infer strong sustainability from fuzzy propositions (Prato, 2005).

Beyond sustainability of an ecosystem, the extinction vulnerabilities of marine fishes to fishing also found conventional methods to be inferior to fuzzy models because population data normally required by conventional methods are unavailable. A fuzzy rule model related biological characteristics to vulnerability based on published research, and concluded that the fuzzy system provided vulnerability estimates that correlated more closely to actual than models employing classical logic (Cheung *et al.*, 2005). Advantages to the fuzzy model were noted in flexibility of input data requirements, in the explicit representation of uncertainty, and in the ease of incorporating new knowledge from both quantitative studies and qualitative experts' knowledge (Mackinson and Nøttestad, 1998; Cheung *et al.*, 2005).

Further evidence of the benefit of fuzzy set based models to ecosystem management investigated the work of Liao *et al.* (1999) which utilised fuzzy classification to analyse hydroacoustic survey data and concluded that the fuzzy classification method was useful, particularly in categorising an upwelling area. How useful as compared to standard statistical methods was resolved by first utilising fuzzy methods to categorise data, and then using statistical processes for analysing the same biomass distribution and zooplankton composition. These tests concluded that, for some ecosystem situations, fuzzy methods may be better than the traditional methods (Lalli and Parsons, 1993; Lu *et al.*, 1994).

Of importance to this research study is the use of fuzzy set based rules with specific applicability to reef management studies. Meesters *et al.* (1998) utilised a fuzzy logic model to predict development of coral reefs under various levels of environmental stress, but was later criticised by O'Connor (2000) as being more an expert system for organising knowledge about reef development. More recently, Mackinson (2000) developed an adaptive fuzzy expert system for predicting structure, dynamics and mesoscale distribution of shoals of migratory adult herring during different stages of their annual life cycle. Fuzzy logic was utilised to capture and integrate scientific and local knowledge into heuristic rules. External factors such as food and predators, and abiotic attributes such as light, habitat and oceanographic features were considered with internal factors such as motivational state, maturation and swimming speed. Thus, heuristic fuzzy rules captured knowledge about the reef ecosystem contained in linguistic expressions given by interviewees (Mackinson, 2000).

Use of a fuzzy expert system is an admission that knowledge is incomplete and uncertain and a recognition that decisions based on qualitative and sometimes incomplete knowledge is better than making decisions without any understanding (Saila, 1996).

2.2. *Fuzzy logic fundamentals*

Fuzzy logic addresses the ambiguity of data and uncertainty in decision making, where a fuzzy subset A of a set X is a function of X into $[0,1]$. For a brief foundation in the generalised theory of uncertainty, the reader is referred to Zadeh (2007) and for fuzzy logic in decision making, the reader is referred to Bellman and Zadeh (1970), Dubois and Prade (1980), and Freeling (1980). Fuzzy logic is incompatible with Aristotelian logic since it allows partial membership in previously defined absolute sets such as true or false (Bashi, 2006).

2.2.1. *Fuzzy set theory*

Fuzzy logic notation begins with a definition of $A = \Sigma\alpha_i/x_i$ to mean that the value of the function A on x_i is α_i. The number $\alpha_i (0 \leq \alpha_i \leq 1)$ denotes the degree of membership of x_i in A. In fact, ordinary sets can also be viewed in this manner when $\alpha_i = 0$ or $\alpha_i = 1$. Another way to interpret this, is to view α_i as the degree of belief that a possible value of A is x_i.

While a new class of implication operators has been proposed (Yager, 2004), the more traditionally utilised fuzzy operations are used in this research. Thus, if A and B denote two fuzzy sets, then the intersection, union, and complement are defined by:

$$A \cap B = \Sigma\gamma_i/x_i \quad \text{where } \gamma_i = \text{Min}\{\alpha_i, \beta_i\} \qquad (1)$$

$$A \cup B = \Sigma\gamma_i/x_i \quad \text{where } \gamma_i = \text{Max}\{\alpha_i, \beta_i\} \qquad (2)$$

$$\neg A = \Sigma\gamma_i/x_i \quad \text{where } \gamma_i = 1 - \alpha_i \qquad (3)$$

and it is assumed that $B = \Sigma\beta_i/x_i$. For a general discussion of the fuzzy logic concepts above, see (Kaufmann and Gupta, 1985; Klir and Folger, 1988; Zadeh, 1965; Zadeh, 1975). Extension principles (see Dubois and Prade, 1980 and Zebda, 1984) often guide the computations when dealing with fuzzy sets. Letting f be a function from X into Y, with Y as any set and A as above, then f can be extended to fuzzy subsets of X by:

$$f(A) = \Sigma_y u_{f(A)}(y)/y \quad \text{where}$$
$$u_{f(A)}(y) = \underset{x \varepsilon f^{-1}(y)}{\text{Max}} A(x) \qquad (4)$$

Thus, $f(A)$ is a fuzzy subset of Y. In particular, if f is a mapping from a Cartesian product such as $X \times Y$ to any set, Z, then f can be extended to objects of the form (A, B) where A and B are fuzzy subsets of X and Y by:

$$f(A,B) = \Sigma u_{f(A,B)}(z)/z, \quad \text{where}$$
$$u_{f(A,B)}(z) = \underset{(x,y)\varepsilon f^{-1}(z)}{\text{Max}} \text{Min}\{A(x), B(x)\}. \qquad (5)$$

The above formula shows how binary operations may be extended to fuzzy sets.

2.2.2. *Fuzzy rough set theory*

Rough sets allow inference of knowledge by extraction of certain and possible rules and a measurement of how much the values of attributes determine an action (Pawlak, 1981a, 1981b, 1982, 1983, 1985; Grzymala-Busse, 1988). Fuzzy rough set notation transitions the basic rough set theory as follows (deKorvin *et al.*, 1992; deKorvin *et al.*, 1994; Shipley and deKorvin, 1995):

A fuzzy subset A of U is defined by a characteristic function $\mu A : U \to [0,1]$. The notation $\Sigma\alpha_i/x_i (0 \leq \alpha_i \leq 1)$ denotes a fuzzy subset whose characteristic function at x_i is α_i. If A and B are fuzzy subsets, $A \cap B$, $A \cup B$, and $\neg A$ are defined by Min $\{\mu_A(x), \mu_B(x)\}$, Max $\{\mu_A(x), \mu_B(x)\}$, and $1 - \mu_A(x)$, respectively. The implication $A \to B$ is defined by $\neg A \cup B$. The corresponding characteristic function is Max $\{1 - A(x), B(x)\}$. (See for example: Zadeh, 1965, 1968, 1973.)

Two functions are defined as pairs of fuzzy sets that will be the input into the rule based decision.

$$I(A \subset B) = \inf_x \text{Max}\{1 - A(x), B(x)\} \tag{6}$$

$$J(A\#B) = \underset{x}{\text{Max}}\text{Min}\{A(x), B(x)\} \tag{7}$$

where A and B denote fuzzy subsets of the same universe. The function $I(A \subset B)$ measures the degree to which A is included in B and $J(A\#B)$ measures the degree to which A intersects B. If A and B are crisp (non-fuzzy) sets, it is easy to establish that $I(A \subset B) = 1$ if and only if $A \subset B$; otherwise it is zero. Also, in the case of crisp sets $J(A\#B) = 1$ if and only if $A \cap B \neq \emptyset$; otherwise it is zero. The operators I and J yield two possible sets of rules: the certain rules and the possible rules. The highest level of belief in the certain rules and the highest plausible belief of the possible rules is based upon selection of the threshold of acceptance, α.

3. Application

The first step in setting up the model was defining the linguistic terms in the rule. First, the antecedent of the rule required defining the High and Low maximum Consumption (p-value), and Great and Small Consumption (g) from foraging behavior. The Consequent of the rule relied on Maximum and Minimum reef distances.

3.1. *Fuzzy rule parameter development*

Age-based data taken at reef sites were converted to measures of percent of maximum consumption (p-values) and the realised weight of food consumed [consumption (g)] for red snapper, *Lutjanus campechanus*. The average p-value determined from bioenergetics modeling was 0.7751 with standard deviation of 0.0698, and mean consumption was 16524.5 g with standard deviation of 10514.5 g (Table 1).

Four scenarios were conducted with a bioenergetics model to determine reasonable percent maximum consumption and foraging consumption estimates indicative of an acceptable range of values per age group. Start and end weights for each run varied depending upon combinations of four measures: the lowest recorded size within an age group, the average weight of the age group, the largest recorded weight of the age group, and the average weight of the subsequent age group. First, the lowest recorded size at age (cm) was converted to a weight (kg) (Patterson *et al.*, 2001, Fig. 6) for an age class and used as the start weight, with the average weight of that age for the end weight. The second run used lowest recorded weight as the start weight, but used the largest recorded weight for that age class (Patterson *et al.*, 2001, Fig. 6) for the end weight. A third run used the average weight of that age class as the start weight and the largest recorded weight for the end weight. Finally, a fourth run used the average weight for the age class as the start weight and the average weight for the subsequent age class as the end weight. From these runs, the maximum and minimum p-values and consumption values were determined for each red snapper age group from age 2 through age 10+. Any p-value, and its corresponding consumption value, greater than 1.1 was discarded as an outlier and not statistically usable (Table 1).

The maximum and minimum p-value and consumption (g) per age group from the four runs were used to define triangular distributions typical of fuzzy set-based logic. Crystal Ball[1] was utilised to simulate the triangularly defined distributions through 10,000 runs with input values of maximum, minimum and most likely as generated from the four scenarios. For each age category, the Maximum function was defined to be triangular with minimum p-value, but the likeliest was the maximum p-value which anchored the distribution around the maximum p-values observed. The Minimum function was generated from the minimum p-value and the maximum p-value where the likeliest was selected to be the minimum p-value. In a similar manner, consumption for each

[1]Crystal Ball is a product of Decisioneering Software. (www.decisioneering.com)

Table 1. Four scenario runs to determine minimum and maximum p-values and consumption (g).

Age	Start weight (g)	Final weight (g)	Run p-value	Consumption (g)
2	133.86	416.60	0.8329	2045.1
	133.86	829.42	0.8691	4253.9
	416.60	829.42	0.8130	3736.4
Avg (2:3)	416.60	916.20	0.8691	4253.9
3	333.21	916.20	0.7781	3503.1
	333.21	2999.06	1.3735	10954.4
	916.20	2999.06	1.0206	10340.2
Avg (3:4)	916.20	1738.80	0.7316	5934.4
4	675.97	1738.80	0.8513	6210.9
	675.97	4888.85	1.4833	17621.1
	1738.80	4888.85	1.0656	16034.9
Avg (4:5)	1738.80	2717.50	0.7306	8581.3
5	829.42	2717.50	1.0121	9534.7
	829.42	7465.20	1.8662	28679.0
	2717.50	7465.20	1.1557	23779.8
Avg (5:6)	2717.50	3854.20	0.7299	11403.1
6	1430.90	3854.20	1.0285	13153.2
	1430.90	9046.98	1.7761	33796.8
	3854.20	9046.98	1.1451	28301.7
Avg (6:7)	3854.20	5102.70	0.7499	14677.3
7	1682.60	5102.70	1.1209	17017.4
	1682.60	9046.98	1.6195	32089.1
	5102.70	9046.98	0.9605	25910.2
Avg (7:8)	5102.70	6420.10	0.7265	17111.5
8	4888.85	6420.10	0.7504	17415.4
	4888.85	9046.98	0.9862	26245.6
	6420.10	9046.98	0.8280	24072.5
Avg (8:9)	6420.10	7768.70	0.7236	19836.7
9	*6420.10	7768.70	0.7724	19804.8
	6420.10	10844.13	0.9613	30037.9
	7768.70	10844.13	0.8434	28057.1
Avg (9:10+)	7768.70	12121.20	0.9292	32296.4
10+	9046.98	12121.20	0.8074	29554.4
	9046.98	12871.52	0.8537	31989.9
	12121.20	12871.52	0.6592	27323.2
Avg (10+:15)	12121.20	15161.10	0.7856	34628.6

*: Weight calculation from Patterson *et al.* (2001) length at age figure yielded a minimum value for Age 9 red snapper equivalent to maximum value for Age 8 red snapper. Therefore, the average value for Age 8 red snapper was used as the minimum value for Age 9 red snapper.

age class was defined as a triangular function from minimum to maximum with the likeliest value selected based on which type of triangular function was being defined. The values simulated for the Maximum and Minimum fuzzy-set type triangular distributions provided expected p-values and consumption for each age group that defined the linguistic variables (Table 2).

Actual reef distances were not assumed to be constant for any age group but instead, values were randomly generated $[0.01, 1]$ km for each of the age categories through 10,000 simulation runs with Crystal Ball. Reef distances to represent Major (M) and Minor (N) were also generated through 10,000 runs using Crystal Ball simulation software setting up triangular functions

Table 2. *p*-value, consumption, and reef distance values with their corresponding fuzzy-set based simulated minimums and maximums.

Age	*p*-value (% of max consumption)	Max	Min	High (H)	Low (L)	Consumption (g)	Max	Min	Great (G)	Small (S)	Reef distance (km)	Max	Min	Major (M)	Minor (N)
2	0.8691	0.8504	0.8317	1.02	0.96	4253.9	3517.6	2781.4	1.21	0.65	0.95	0.503333333	0.503	1.89	0.53
3	0.7316	0.9243	0.8279	0.79	1.13	5934.4	8061.2	5782.1	0.74	0.97	0.34	0.503333333	0.503	0.68	1.48
4	0.7306	0.9539	0.8423	0.77	1.15	8581.3	12760.2	9485.6	0.67	1.11	0.66	0.503333333	0.503	1.30	0.77
5	0.7299	0.9180	0.8240	0.80	1.13	11403.1	19031.4	14283.1	0.60	1.25	0.80	0.503333333	0.503	1.59	0.63
6	0.7499	0.9356	0.8428	0.80	1.12	14677.3	23252.2	18202.7	0.63	1.24	0.89	0.503333333	0.503	1.77	0.57
7	0.7265	0.8825	0.8045	0.82	1.11	17111.5	22945.9	19981.7	0.75	1.17	0.25	0.503333333	0.503	0.49	2.02
8	0.7236	0.8987	0.8111	0.81	1.12	19836.7	23302.2	20358.8	0.85	1.03	0.46	0.503333333	0.503	0.91	1.10
9	0.9292	0.8983	0.8354	1.03	0.90	32296.4	28132.5	23968.7	1.15	0.74	0.81	0.503333333	0.503	1.60	0.62
10+	0.7856	0.7889	0.7240	1.00	0.92	34628.6	32193.5	29758.3	1.08	0.86	0.75	0.503333333	0.503	1.49	0.67

with a minimum of 0.01 km, maximum of 1.00 km, and the likeliest set at 0.50 km (Table 2).

3.2. *Belief functions for fuzzy set-based membership*

Belief in membership of the p-values and consumption generated from the bioenergetics modeling to the linguistic variables in the rule antecedent was accepted to be the ratio of the value to the simulated range of [Maximum, Minimum] for each age class. From Table 2, for example, Age 2 red snapper p-value of 0.8691 fits entirely (and surpasses) the simulated maximum of the range, so membership is 1.00 in High maximum percent consumption at the reef (Note: membership cannot be more than 100%). The ratio of the simulated minimum of 0.8317 to the Age 2 p-value determines its membership in Low as 0.96. Therefore, membership for Age 2 is:

$$P - \text{Value}_{\text{AGE2}} = 1.00/\text{High} + 0.96/\text{Low}$$

and based on 4253.9 g of consumption at Age 2, for the defined range of [3517.6, 2781.4]:

$$\text{Consumption}_{\text{AGE2}} = 1.00/\text{Great} + 0.65/\text{Small}.$$

In a similar manner, the membership functions were generated for all age groups (Table 3).

Next, belief in membership was accepted to be the ratio of the randomly generated distance for an age group in relation to the Maximum and Minimum reef distance based on the defined triangular distribution. Again, from Table 2 for Age 2 red snapper, the randomly generated reef distance of 0.95 exceeds (i.e., has membership of 1 in) the Maximum simulated reef distance value but the Minimum is only partially that of the reef distance designated for that age red snapper. Membership functions for Age 2 and all other ages of red snapper according to reef distances are given in Table 4.

Each linguistic variable was then defined from the membership functions in Table 4. Given the previous research on reef spacing (Grove and Suno, 1983), and concentrating within a 1 km^2 area, the focus was on defining the Major (M) distance, not Minor (N). Therefore, Major distances (0.50 km apart) between reefs as a function of Age of red snapper is:

$$\begin{aligned} M = {} & 1.00/\text{Age } 2 + 0.68/\text{Age } 3 + 1.00/\text{Age } 4 \\ & + 1.00/\text{Age } 5 + 1.00/\text{Age } 6 + 0.49/\text{Age } 7 \\ & + 0.91/\text{Age } 8 + 1.00/\text{Age } 9 + 1.00/\text{Age } 10+. \end{aligned}$$

Membership of High and Low p-value and Great and Small consumption (g) according to the age of red snapper is as follows:

$$\begin{aligned} H = {} & 1.00/\text{Age } 2 + 0.79/\text{Age } 3 + 0.77/\text{Age } 4 \\ & + 0.80/\text{Age } 5 + 0.80/\text{Age } 6 + 0.82/\text{Age } 7 \\ & + 0.81/\text{Age } 8 + 1.00/\text{Age } 9 + 1.00/\text{Age } 10+. \end{aligned}$$

$$\begin{aligned} L = {} & 0.96/\text{Age } 2 + 1.00/\text{Age } 3 + 1.00/\text{Age } 4 \\ & + 1.00/\text{Age } 5 + 1.00/\text{Age } 6 + 1.00/\text{Age } 7 \\ & + 1.00/\text{Age } 8 + 0.90/\text{Age } 9 + 0.92/\text{Age } 10+. \end{aligned}$$

$$\begin{aligned} G = {} & 1.00/\text{Age } 2 + 0.74/\text{Age } 3 + 0.67/\text{Age } 4 \\ & + 0.60/\text{Age } 5 + 0.63/\text{Age } 6 + 0.75/\text{Age } 7 \\ & + 0.85/\text{Age } 8 + 1.00/\text{Age } 9 + 1.00/\text{Age } 10+. \end{aligned}$$

$$\begin{aligned} S = {} & 0.65/\text{Age } 2 + 0.97/\text{Age } 3 + 1.00/\text{Age } 4 \\ & + 1.00/\text{Age } 5 + 1.00/\text{Age } 6 + 1.00/\text{Age } 7 \\ & + 1.00/\text{Age } 8 + 0.74/\text{Age } 9 + 0.86/\text{Age } 10+. \end{aligned}$$

3.3. *Possibility & certainty of beliefs in rules*

The triangular functions that were defined for each age for p-value, consumption (g), and reef distance (km) were set as assumptions with results generated as I and J functions (Eqs. (6) and (7)) based on a series of simulation runs as described previously. From (6)

$$I(A \subset B) = \inf_x \text{ Max}\{1 - A(x), B(x)\}$$

so the complements and the reef distance functions determine, for each age category, the maximum degree of belief in the subset relationship of {High, Low} p-value, {Great, Small} consumption (g) value and combinations of both parameters to reef distance.

Continuing the example, based on the simulated values in Table 2, for Age 2 red snapper with total (1.00) membership in "High" percent maximum consumption at the reef, the complement (1−H) would be 0, and the beliefs in the subset relationship to Major reef distance ($H \subset M$) would be $\{0, 1.00\}$ with maximum belief = 1.00. Then, the value of $I(H \subset M)$ is the minimum belief over all values for Ages 2 through 10+; 0.49 which occurs at the randomly generated reef distances of 0.25 km for Age 7. Then, the minimum set for which the function $I(H \subset M)$ measures the degree to which the p-value (percent maximum consumption) is included (i.e., a factor) in Major reef distance (0.503 km m) has belief of 0.49. All other I functions for Major (M) reef distance are calculated in this same manner such that:

$$\begin{aligned} I(H \subset M) &= 0.49 & I(H \cap G \subset M) &= 0.74 \\ I(L \subset M) &= 0.49 & I(H \cap S \subset M) &= 0.79 \\ I(G \subset M) &= 0.49 & I(L \cap G \subset M) &= 0.74 \\ I(S \subset M) &= 0.49 & I(L \cap S \subset M) &= 0.97 \end{aligned}$$

Table 3. Consumption membership functions for red snapper by age category.

Age	Membership for max % consumption at the reef	Membership for foraging consumption
2	1.00/High + 0.96/Low	1.00/Great + 0.65/Small
3	0.79/High + 1.00/Low	0.74/Great + 0.97/Small
4	0.77/High + 1.00/Low	0.67/Great + 1.00/Small
5	0.80/High + 1.00/Low	0.60/Great + 1.00/Small
6	0.80/High + 1.00/Low	0.63/Great + 1.00/ Small
7	0.82/High + 1.00/Low	0.75/Great + 1.00/Small
8	0.81/High + 1.00/Low	0.85/Great + 1.00/Small
9	1.00/High + 0.90/Low	1.00/Great + 0.74/Small
10+	1.00/High + 0.92/Low	1.00/Great + 0.86/Small

Table 4. Reef distance membership functions for each age class from Crystal Ball simulations.

Age	Membership of reef location to Major and Minor distances
2	1.00/Major + 0.53/Minor
3	0.68/Major + 1.00/Minor
4	1.00/Major + 0.77/Minor
5	1.00/Major + 0.63/Minor
6	1.00/Major + 0.57/Minor
7	0.49/Major + 1.00/Minor
8	0.91/Major + 1.00/Minor
9	1.00/Major + 0.62/Minor
10+	1.00/Major + 0.67/Minor

From Eq. (7), $J(A\#B)$ measures the degree to which A intersects B

$$J(A\#B) = \underset{x}{\text{Max}}\text{Min}\{A(x), B(x)\}$$

Again using the continuing example at Age 2, p-value belief is 1.00 in High, and belief is 0.96 in Major reef distance so that Min {1.00, 0.96} is 0.96 for $J(H\#M)$ or 0.96 belief that High maximum consumption at the reef for this category intersects with Major reef distance. The actual $J(H\#M)$ is calculated as the maximum belief from the minimum observed at each category. This value for $J(H\#M)$ is 1.00 which is observed for Ages 2, 9, and 10+. This represents 100 percent belief that if percent maximum consumption is High at the reef then the reef distances are Major (0.503 km). For the data in Table 2, again restricting maximum belief to 1, the degree to which the fuzzy sets for p-value and consumption (food consumed) intersect M are:

$$J(H\#M) = 1.00 \quad J(H \cap G\#M) = 1.00$$
$$J(L\#M) = 1.00 \quad J(H \cap S\#M) = 0.86$$
$$J(G\#M) = 1.00 \quad J(L \cap G\#M) = 0.96$$
$$J(S\#M) = 1.00 \quad J(L \cap S\#M) = 1.00$$

Therefore, for the above I and J functions determined from the 10,000 simulation runs in Table 2, the following certain and possible rules, respectively, can be written based upon a designated threshold of acceptance, α.

With a threshold of $\alpha = 0.95$, a certain rule for major reef distance is:

1. If realised consumption at the reef (p-value) is Low and food consumed (g) is Small then reef distance should be Major (0.5033). (Certain with Belief = 0.97)

at $\alpha = 0.75$, a certain rule for major reef distance is:

2. If realised consumption at the reef (p-value) is High and food consumed (g) is Small then reef distance should be Major (0.5033). (Certain with Belief = 0.79)

Two other rules of lesser certainty are:

3. If realised consumption at the reef (p-value) is High and food consumed (g) is Great then reef distance should be Major (0.5033). (Certain with Belief = 0.74)
4. If realised consumption at the reef (p-value) is Low and food consumed (g) is Great then reef distance should be Major (0.5033). (Certain with Belief = 0.74)

With $\alpha = 0.95$, seven of the eight rules show strong belief in the possibility that reef distance should be 0.503 km.

The above results relate only to one series of simulated data given in Table 2. As a complete fisheries management decision making problem, the study was expanded and artificial reef placement distances were allowed to vary to test the optimal location; i.e., those represented by highest certainty and/or possibility of the rules. Nine scenarios were tested for reef distances from 0.01–0.50 km, to 0.50–0.95 km under the assumptions for Maximum and Minimum consumption at the reef (p-values) simulated as described previously using the bioenergetics modeling results for each age group.

Belief functions for membership of red snapper realised consumption at the reef (p-value) as High or Low, and food consumed (g) as Great or Small were determined. Certainty of the rules was calculated, again based on the 10,000 simulation runs for each designated reef distance. As certainty of any rule approached 100 percent, the minimum of the range was set (0.50 km) and the maximum was allowed to increase incrementally to 0.95 km. The means with standard deviations, ranges, and certainty based on triangular function assumptions as noted, are given in Table 5 for each distance scenario. In a similar manner, all possibility functions were determined as given in Table 6.

Table 5. Certain belief functions based on Crystal Ball runs of reef distance from 0.10 km to 0.95 km.

Reef distance (km)	High % max consump; then major distance	Low % max consump; then major distance	Great consump; then major distance	Small consump; then major distance	If high % max consump and great consump; then major distance	If high % max consump and small consump; then major distance	If low % max consump and great consump; then major distance	If low % max consump and small consump; then major distance
0.01–0.50	0.73±0.20 [0.50,1.98] 90.6%	0.73±0.20 [0.50,1.98] 90.6%	0.73±0.20 [0.50,1.98] 90.6%	0.73±0.20 [0.50,1.98] 90.6%	0.81±0.15 [0.66,1.98] 90.6%	0.86±0.13 [0.68,1.98] 90.6	0.82±0.15 [0.66,1.98] 88.9%	1.00±0.13 [0.68,1.98] 38.7%
0.25–0.50	0.60±0.09 [0.50,0.99] 100%	0.60±0.09 [0.50,0.99] 100%	0.60±0.09 [0.50,0.99] 100%	0.60±0.09 [0.50,0.99] 100%	0.74±0.05 [0.66,0.99] 100%	0.79±0.05 [0.68,0.99] 100%	0.75±0.06 [0.66,1.00] 100%	0.94±0.11 [0.68,1.25] 59.2%
0.35–0.50	0.56±0.05 [0.50,0.71] 100%	0.56±0.05 [0.50,0.71] 100%	0.56±0.05 [0.50,0.71] 100%	0.56±0.05 [0.50,0.71] 100%	0.72±0.04 [0.66,0.91] 100%	0.78±0.04 [0.68,0.96] 100%	0.73±0.06 [0.66,0.99] 100%	0.91±0.12 [0.68,1.26] 69.2%
0.45–0.50	0.51±0.01 [0.50,0.55] 100%	0.51±0.01 [0.50,0.55] 100%	0.51±0.01 [0.50,0.55] 100%	0.51±0.01 [0.50,0.55] 100%	0.71±0.03 [0.66,0.89] 100%	0.76±0.04 [0.68,0.96] 100%	0.72±0.05 [0.66,0.97] 100%	0.88±0.12 [0.68,1.18] 78.8%
0.50–0.55	0.47±0.01 [0.45,0.50] 100%	0.47±0.01 [0.45,0.50] 100%	0.47±0.01 [0.45,0.50] 100%	0.47±0.01 [0.45,0.50] 100%	0.69±0.05 [0.62,0.88] 100%	0.75±0.06 [0.62,0.91] 100%	0.70±0.06 [0.62,0.98] 100%	0.87±0.14 [0.62,1.19] 78.4%
0.50–0.65	0.42±0.03 [0.38,0.50] 100%	0.42±0.03 [0.38,0.50] 100%	0.42±0.03 [0.38,0.50] 100%	0.42±0.03 [0.38,0.50] 100%	0.68±0.06 [0.57,0.86] 100%	0.74±0.05 [0.59,0.92] 100%	0.68±0.07 [0.57,1.00] 100%	0.86±0.14 [0.59,1.15] 79.3%
0.50–0.75	0.38±0.04 [0.33,0.50] 100%	0.38±0.04 [0.33,0.50] 100%	0.38±0.04 [0.33,0.50] 100%	0.38±0.04 [0.33,0.50] 100%	0.68±0.06 [0.57,0.88] 100%	0.74±0.05 [0.59,0.90] 100%	0.68±0.07 [0.57,0.98] 100%	0.86±0.13 [0.59,1.14] 84.5%
0.50–0.85	0.34±0.04 [0.29,0.50] 100%	0.34±0.04 [0.29,0.50] 100%	0.35±0.04 [0.29,0.50] 100%	0.34±0.04 [0.29,0.50] 100%	0.68±0.06 [0.57,0.85] 100%	0.74±0.05 [0.59,0.92] 100%	0.68±0.07 [0.57,0.95] 100%	0.84±0.12 [0.59,1.11] 94.7%
0.50–0.95	0.31±0.04 [0.26,0.49] 100%	0.31±0.04 [0.26,0.49] 100%	0.31±0.04 [0.26,0.49] 100%	0.31±0.04 [0.26,0.49] 100%	0.67±0.06 [0.57,0.84] 100%	0.73±0.05 [0.59,0.92] 100%	0.68±0.06 [0.57,0.97] 100%	0.81±0.10 [0.59, 1.09] 98.5%

Table 6. Possible belief functions based on Crystal Ball runs of reef distance from 0.10 km to 0.95 km.

Reef distance (km)	High % max consump; then major distance	Low % max consump; then major distance	Great consump; then major distance	Small consump; then major distance	If high % max consump and great consump; then major distance	If high % max consump and small consump; then major distance	If low % max consump and great consump; then major distance	If low % max consump and small consump; then major distance
0.01–0.50	0.65±0.08 [0.50,0.84] 100%	0.69±0.13 [0.50,0.98] 100%	0.54±0.04 [0.48,0.77] 100%	0.59±0.07 [0.48,0.87] 100%	0.54±0.04 [0.48,0.76] 100%	0.58±0.07 [0.48,0.79] 100%	0.54±0.04 [0.48,0.77] 100%	0.59±0.07 [0.48,0.87] 100%
0.25–0.50	0.60±0.08 [0.50,0.81] 100%	0.60±0.09 [0.50,0.93] 100%	0.54±0.04 [0.48,0.74] 100%	0.56±0.06 [0.48,0.83] 100%	0.54±0.04 [0.48,0.74] 100%	0.56±0.06 [0.48,0.78] 100%	0.54±0.04 [0.48,0.74] 100%	0.56±0.06 [0.48,0.83] 100%
0.35–0.50	0.56±0.05 [0.50,0.71] 100%	0.56±0.05 [0.50,0.71] 100%	0.53±0.03 [0.48,0.69] 100%	0.54±0.04 [0.48,0.71] 100%	0.53±0.03 [0.48,0.69] 100%	0.54±0.04 [0.48,0.71] 100%	0.53±0.03 [0.48,0.69] 100%	0.54±0.04 [0.48,0.71] 100%
0.45–0.50	0.51±0.01 [0.50,0.55] 100%	0.51±0.01 [0.50,0.55] 100%	0.51±0.01 [0.48,0.55] 100%	0.51±0.01 [0.48,0.55] 100%	0.51±0.01 [0.48,0.55] 100%	0.51±0.01 [0.48,0.55] 100%	0.51±0.01 [0.48,0.55] 100%	0.51±0.01 [0.48,0.55] 100%
0.50–0.55	0.47±0.01 [0.45,0.50] 100%	0.47±0.01 [0.45,0.50] 100%	0.47±0.01 [0.45,0.50] 100%	0.47±0.01 [0.45,0.50] 100%	0.47±0.01 [0.45,0.50] 100%	0.47±0.01 [0.45,0.50] 100%	0.47±0.01 [0.45,0.50] 100%	0.47±0.01 [0.45,0.50] 100%
0.50–0.65	0.42±0.03 [0.38,0.50] 100%	0.42±0.03 [0.38,0.50] 100%	0.42±0.03 [0.38,0.50] 100%	0.42±0.03 [0.38,0.50] 100%	0.42±0.03 [0.38,0.50] 100%	0.42±0.03 [0.38,0.50] 100%	0.42±0.03 [0.38,0.50] 100%	0.42±0.03 [0.38,0.50] 100%
0.50–0.75	0.38±0.04 [0.33,0.50] 100%	0.38±0.04 [0.33,0.50] 100%	0.38±0.04 [0.33,0.50] 100%	0.38±0.04 [0.33,0.50] 100%	0.38±0.04 [0.33,0.50] 100%	0.38±0.04 [0.33,0.50] 100%	0.38±0.04 [0.33,0.50] 100%	0.38±0.04 [0.33,0.50] 100%
0.50–0.85	0.34±0.04 [0.29,0.50] 100%	0.34±0.04 [0.29,0.50] 100%	0.34±0.04 [0.29,0.50] 100%	0.34±0.04 [0.29,0.49] 100%	0.34±0.04 [0.29,0.50] 100%	0.34±0.04 [0.29,0.49] 100%	0.34±0.04 [0.29,0.50] 100%	0.34±0.04 [0.29,0.49] 100%
0.50–0.95	0.31±0.04 [0.26,0.49] 100%	0.31±0.04 [0.26,0.49] 100%	0.31±0.04 [0.26,0.49] 100%	0.31±0.04 [0.26,0.49] 100%	0.31±0.04 [0.26,0.49] 100%	0.31±0.04 [0.26,0.49] 100%	0.31±0.04 [0.26,0.49] 100%	0.31±0.04 [0.26,0.49] 100%

The certain and possible rules from the simulation results in Tables 5 and 6 would be:

Certain rules: ($\alpha \geq 0.94$)

1. If realised consumption at the reef (p-value) is High, then reef distances should be 0.25 km to 0.95 km. (Belief = 1.00)
2. If realised consumption at the reef (p-value) is Low, then reef distances should be 0.25 km to 0.95 km. (Belief = 1.00)
3. If food consumed is Great, then reef distances should be 0.25 km to 0.95 km. (Belief = 1.00)
4. If food consumed is Small, then reef distances should be 0.25 km to 0.95 km. (Belief = 1.00)
5. If realised consumption at the reef (p-value) is High and food consumed (g) is Great, then reef distances should be 0.25 km to 0.95 km. (Belief = 1.00)
6. If realised consumption at the reef (p-value) is High and food consumed (g) is Small, then reef distances should be 0.25 km to 0.95 km. (Belief = 1.00)
7. If realised consumption at the reef (p-value) is Low and food consumed (g) is Great, then reef distances should be 0.25 km to 0.95 km. (Belief = 1.00)

All of the above rules had strongest belief in reef distances greater than 0.25 km apart. However, more refinement of distances but with lower belief was observed by the following:

8. If realised consumption at the reef (p-value) is Low and food consumed (g) is Small, then reef distances should be 0.50 km to 0.95 km. (Belief = 0.985)
9. If realised consumption at the reef (p-value) is Low and food consumed (g) is Small, then reef distances should be 0.50 km to 0.85 km. (Belief = 0.947)

Possible rules: ($\alpha \geq 0.95$)

All rules are possible for reef distances 0.01–0.50 km; 0.25–0.50 km; 0.35–0.50 km; and 0.45–0.50 km and 0.50–0.95 km.

3.4. *Rule-based outcomes for reef placement decisions*

High consumption at the reef (p-value) with Great or Small foraging consumption (g) does not overly influence reef placement. Similarly, Low p-value and Great consumption (g) does not overly influence reef placement. The minimum distance that received perfect (100% belief) strength for any parameter or combination of parameters was reef placement of no closer than 0.25 km. However, with slightly lesser strength, Low consumption at the reef (p-value) and Small foraging consumption (g) placed reef distances at a minimum of 0.50 km with sufficient belief in the certainty of this relationship (belief of 0.985).

The high belief in the possibility of all parameters tested for each of nine distance scenarios supports that consumption at the reef {High, Low} and foraging consumption {Great, Small} do appear to relate equally as possible influences upon reef distances from 0.01 to 0.95 km. However, the overriding factors in reef placement are Low consumption at the reef (p-value) and Small foraging consumption (g) which suggest that reef placement should be no closer than 0.50 km, preferably 0.50–0.95 km (belief = 98.5). The possibility results with perfect belief (1.00) for each range show that the two factors have a strong degree of relationship to reef locations. Therefore, the results of the fuzzy set-based rough set modeling provides evidence that reef locations should be between 0.50 to 0.95 km such that no more than two fit within a 1 km^2 area.

4. Conclusions: Implications for Science-Based Management

This research builds on the concept that predicting how management actions can influence an ecosystem requires simulation modeling; a classic use of ecosystems models (Minns, 1992) whether from the perspective of a crisp or fuzzy research focus. The developed model utilises an extensive simulation process to generate the distributions upon which the fuzzy rules can be evaluated. Previous research on reef placement formed the basis for the rule specifics, and the definition of the 1 km^2 area considered. Ultimately, however, the simulation runs provided the trial-and-error evaluations of the rule antecedent and consequents. Using a readily available simulation package that works with Excel, the simulations were easily conducted on a laptop computer. The model can be readily updated as necessary to react to Sakuramoto's (1995) suggestion that refinement of the rules is always a consideration, and accumulation of sufficient data upon which to base the simulation of distributions of ecological variables should be ongoing.

While Prato (2005) questions whether the use of fuzzy set based research in ecological settings is practical at this time, he does ultimately concur with the value of simulation to science-based management research. A negative he presents is that fuzzy logic in ecosystem management requires a higher level of technical expertise than the conventional method (Prato, 2005). A benefit of the fuzzy rule-based model presented herein is that while the technical data must be derived by bioenergetics modeling or obtained through field research, once available, simulation and subsequent analysis of the belief functions do not require extensive technical knowledge of the decision maker. Indeed, as a spreadsheet applicable modeling process, management decisions can be made in the field.

Prato (2005) further proposes that the worth of fuzzy logic in ecosystem modeling can only be judged in terms of whether the benefits exceed the costs. He recommends that application of fuzzy logic to ecosystem management can be enhanced by incorporating results generated by stochastic simulation models of environmental processes (Prato, 2005). The fuzzy set-based modeling process described and applied in this research illustrates that simulation can be an enhancement to data generation of parameters in previously unknown ecosystems such as that for red snapper. In addition, fuzzy membership functions are important since they allow a procedure to be fit to observational data rather than a costly or impractical reliance on gathering all data. An advantage is, therefore, that historical databases that might have to be discarded if accepting only rigorously quantitative measurements can be used in fuzzy-set based modeling (Silvert, 2000).

Mathematical models have a place in offering a quantitative expression of the differing values and needs, which can help clarify the underlying issues but cannot alone be used to solve complex social and political issues (Silvert, 2000). The fuzzy logic model presented in this paper is a viable means by which ecosystem knowledge and data can be combined and simulated to provide rule-based outcomes for fish and other science-based management decisions.

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