A Fisheries Swarm Intelligence Model Theoretically Directed Toward Small to Mid-Size Enterprise (SME) Sustainability

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As fish survival is dependent upon energy expended to avoid predation so are the strategies of small to mid-size enterprises (SMEs) directed toward avoiding the "big-fish" takeover. Transitioning natural science environmental decision-making to models for business organizational operations utilizing swarm intelligence may lead to improving sustainability of SMEs. This work proceeds from recognition of swarm intelligence theory to an application of fuzzy rough set theory in optimal spatial locations for artificial reefs, suggesting that similarly natural ecosystems can be applied to SME location decisions.

INTRODUCTION

Background literature is briefly presented on the fundamental concepts guiding the multi-criteria theory development.

Swarm Intelligence

Swarm Intelligence was introduced in 1989 (Beni & Wang) to refer to collective behavior of organized systems, which could be natural or artificial. Of importance to this study is that nature, predominately biological systems, has inspired researchers to translate intelligent behavior to human behavior and, more recently to organizational behavior. Examples include, ant colonies whereby better paths through graphs can be simulated based on the natural ants' inclination to produce pheromones to direct fellow ant paths (Dorigo & Stützle, 2004); bee colonies that simulate exploration and exploitation by employed bees, onlooker bees and scout bees (Karaboga , 2005) and then simulate communication of the scout bee back to the community (Pham et al., 2005; Pham & Castellani, 2009); bats' echolocation behavior (Yang, 2010), and glowworm optimization which, similar to the ant colony principle, uses the glowworm's production of its luminescent agent to search an area and identify another with brighter luminescence and move toward it (Krishnanand, 2005; Krishnannand & Ghose, 2006, 2008, 2009). Fish studies have recognized certain aspects of behavior similar to these other biological systems. Groups of threespine stickleback fish were presented with a robot fish that attempted to lead the group into potentially dangerous situations. It was discovered that while a single fish might follow the robot fish, larger groups ignored it, but when two or more robot fish were introduced the larger groups followed the robots into the dangerous waters (http:www.fishchannel.com/fish-news/2008/08/28/fish-behavior.aspx). This reef study and others at the Florida Keys National Marine Sanctuary and sites in the Caribbean are fundamental to the red snapper, reef-location model that forms the basis for aligning natural science with the social sciences in multi-criteria optimization.

Spatial & Temporal Models

The basis for the transitioning of natural science to social science applications relies heavily upon the research conducted by Shipley-Lozano (Shipley, 2008). Shipley's research sought to develop a temporally and spatially explicit model for bioenergetics of red snapper (*Lutjanus campechanus)* in an ecosystem representative of an artificial reef. For many years, it has been noted that spatially and temporally explicit models can contribute the functional link between biotic and abiotic aspects of aquatic ecosystems, and using these ecosystems can contribute to dialogue regarding fish behavior, growth, and consumption (Bevelhimer, 1990). Yet, while fundamental to an understanding of population dynamics processes (fish movements over time and space) and stock structure, (Quinn & Deriso, 1999) there have been limited applications in fisheries due to lack of data on fish movement and biological spatial variations. The model that Shipley (2008) contributed for red snapper on artificial reefs off the coast of Alabama, provided the data on fish movement, and differing spatial arrangements of artificial reef structures through simulations described below.

Fuzzy Logic Basics and Rough Set Theory

Fuzzy logic addresses the ambiguity of data and uncertainty in a decision making situation, where a fuzzy subset A of a set X is a function of X into [0,1]. For a brief foundation in the basics, see (Bellman & Zadeh, 1970; Dubois & Prade, 1980; Freeling, 1980; Zadeh, 2006). Letting A and B denote two fuzzy sets, the intersection, union, and complement are defined by:

$$A \cap B = \Sigma \gamma_i / x_i, \text{ where } \gamma_i = \text{Min } \{\alpha_i, ß_i\} \quad (1)$$
$$A \cup B = \Sigma \gamma_i / x_i, \text{where } \gamma_i = \text{Max } \{\alpha_i, ß_i\} \quad (2)$$
$$\neg A = \Sigma \gamma_i / x_i, \text{ where } \gamma_i = 1 - \alpha_i \quad (3)$$

and it is assumed that $B = \Sigma\, ß_i / x_i$ (Kaufmann & Gupta, 1985; Klir & Folger, 1988; Zadeh, 1965, 1975).

Extension principles (Dubois & Prade, 1980; 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:

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

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:

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

Considering a fuzzy subset A of U, as the Universe of Discourse, is defined by a characteristic function μ_A:U $\rightarrow$ [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. Following the previous discussion of fuzzy operators, 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 $\rightarrow$ B is defined by $\neg$A $\cup$ B. The corresponding characteristic function is Max {1 - A(x), B(x)}.

Two functions of pairs of fuzzy sets that will be used to determine rules are defined as:

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

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

Here 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. Indeed, if A and B are crisp sets it is easy to establish that $I(A \subset B) = 1$ if and only if $A \subset B$; otherwise it is zero (see for example: Pawlak, 1981; Grzymala-Busse, 1988; deKorvin et al., 1992; deKorvin et al., 1994; Shipley & deKorvin, 1995) .

The operators I and J will yield two possible sets of rules: the certain rules and the possible rules. The primary objective is to see to what degree a combination of attributes is a subset of the decision (certain rules) or intersects the decision (possible rules). The certain and possible rules for the red snapper artificial reef decision are detailed in the Results and Implications section that follows.

METHODOLOGY

Red snapper (*Lutjanus campechanus)* population dynamics on a single artificial reef were simulated for the reef ecosystem using a spatial model that considered foraging behavior and utilized parameters such as hydrographic variables. Ecospace was chosen as the simulation software because of its ability to quantify the ecosystem by considering populations while taking into account food web and environmental considerations (Marasco et al., 2007). Since adult red snapper feed primarily upon benthic fauna surrounding artificial reefs off the Alabama coast, rather than directly on the reefs themselves (McCawley,2003; McCawley & Cowan, 2007) foraging halos of depleted prey should be observable adjacent to the reef (Lindberg, et al., 1990). Thus with overlapping halos caused by reefs too closely spaced, the red snapper encounters a less than optimal feeding environment (Lindberg et al., 2006).

The simulation of habitats using Ecospace looks at the existence and movement of all species therein. It is also possible to define for a particular species a preferred pool of biomass that would be conducive to that species' growth and survival potential. The simulation looks at the static distribution of all species within a designated area but, more importantly, it allows visualization of predators and prey requirements. Species move throughout the grid areas to fulfill their need for sustenance while avoiding non-preferred areas where they can become victims of predators.

The bioenergetics modeling of red snapper consumption needs and foraging behavior suggests that red snapper must forage away from the reefs to fulfill their required prey demands to maintain observed growth rates. The overlapping of halos as areas of reduced prey abundance are visible when the snapper are competing for resources that may not sustain multiple reefs, or at the very least support optimal growth rates. Thus, the foraging behavior that shows when fish must leave the preferred safe haven of the reef environment to find prey when visible as overlapping halos can contribute to determination of optimal placement of artificial reefs where optimal locations provide for prey and predator relationships without being so close that prey and predator are unable to avoid one another.

RESULTS AND IMPLICATIONS

For Fisheries

When Ecospace was set for the first round of simulations, the preferred area was represented by a single reef. Since red snapper all had this preferred habitat, the single reef area yielded the highest biomass regardless of the age of the red snapper. Next, multiple reefs were placed throughout the area, some blocked and some clumped together representing from 6 to 10 reefs. Red snapper biomass was greater than that at the blocked and clumped patterns in both the 6 and 10 reef runs regardless of age when reefs were systematically placed. The ages of snapper contributed to differences being observed due to reef placement with less difference between the ages of 4 and 10+ being observed with the systematic versus the blocked arrangements than for the younger snapper. Indeed, different spatial arrangements had a greater effect overall on younger age classes.

While the systematical control of reef arrangements indicated some differences in biomass distributions, mostly observed for younger ages, increasing the number of reefs from 6 to 10 within the study area showed a decrease in red snapper biomass at the reef, regardless of age. The increase in number of reefs continued to have more impact on red snapper age 4 and under and less impact on those over age 10. This could be a reflection of the decline in foraging distances by older fish as energy and metabolism slow. Overall, mean biomass was not dramatically different by type of spatial arrangement although the addition of 4 reefs (from 6 to 10) in an area served to decrease biomass at the reefs. This fact becomes important to discussion of spacing reefs further apart and not arbitrarily building bigger reefs within an area given the significant differences for 10 reefs systematically placed versus blocked or clumped.

The decrease in prey species biomass noted with the addition of 4 reefs to the system, even if systematically placed was most significant for fish species considering mean biomass differences for 10 blocked and clumped reefs. Significant differences in mean biomass between 6 and 10 reefs for any reef placement strategy, but especially when systematically placed or clumped, supports the reef location and placement of artificial reefs as highly important to red snapper growth and survival at any age.

The halos from the simulations also contributed to this conclusion and its implications for fish sustainability through location aspects in fisheries management. Overlapping halos begin to appear as early as the third year of study and the prey species biomass appears notably lower on and immediately surrounding the reef structures within 2 more years when 6 or 10 artificial reef areas were systemically placed throughout the area. Using a single reef equivalent in size to that of the 6 to 10 reefs showed significant biomass levels around the clumped structure which expanded ever outward with prey species decreasing from the reef's edge. While one large reef may support the biomass, the red snapper must forage ever outward from this single reef and out of a safe haven habitat to potentially dangerous waters where they become susceptible to predation. As more energy is expended in foraging, then growth potential is also impacted.

An arrangement that places moderately large blocks of reefs into the corners of the 10 km^2 area as far apart as possible, shows less overlapping over time but the red snapper biomass does converge on the center between the two reefs and prey biomass becomes reduced within three years. Therefore, reefs built to enhance stocks rather than for fishing success should be small, widely scattered patch reefs with appropriately sized cavities for shelter, at least as applicable to a large mobile reef fish such as gag (Mycteroperca microlepis) (Lindberg et al., 2005) or red snapper (Shipley, 2008).

The spatial arrangement of the artificial reefs in the red snapper ecosystem does affect biomass observed through the simulations. Overall, the blocked reef arrangement showed biomass reductions immediately off of the reefs while clumped arrangements showed biomass decreasing more in open water. Adding the additional four reefs in either pattern served merely to divide the existing biomass between reefs. This is a continuing artificial reef issue as to whether reefs in general produce more biomass through productivity of the fish or serve merely to aggregate the biomass of fish already existing in the reef areas. Studying open water between reefs showed that biomass for systematical arranged reefs was higher in open water for age 4 red snapper and younger, while the older (10+) red snapper had noticeably lower biomass on the reefs and in the halos, but no differences in open water. The difference was only noticeable when the number of reefs increased to 10 so that biomass was spread between reefs, halos and open water. Overall, younger age classes exhibit a higher effect in biomass from the different spatial arrangements.

Fuzzy Logic Application to Results

Based upon the results from the bioenergetics modeling, fuzzy sets were introduced, in particular fuzzy rough set theory. The reef placement decisions were then reduced to the following:

- *High consumption at the reef (p-value) with Great or Small foraging consumption (g) does not overly influence reef placement.*
- *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.*
- *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).*

  (Shipley & Shipley, 2009)

The rough set theory rules are composed of those with certainty of belief and those with possibility. The certain rules with strong belief don't present a pattern of placement related consistently to either level of consumption at the reef or degree of foraging behavior as necessitated by reef locations. But, distance does seemingly play a part in reef placement to optimize all parameters.

While we generally look to certainty of belief in rules for stronger decision making indicators, we can learn from adding the information that has plausibility. Looking at possibility instead of certainty of belief, 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. Low consumption at the reef (p-value) and Small foraging consumption (g) were the most restrictive in placing artificial reefs no closer than 0.50 km, preferably 0.50-0.95 km (belief = .985).

Therefore, evidence through fuzzy set-based rough set theory leads to the overall conclusion that reef locations should be between 0.50 to 0.95 km so that no more than two fit within a 1 km^2 area (Shipley & Shipley, 2009; Shipley & Cowan, 2010).

Implications for SMEs

There are several implications for small and mid- sized organizations trying to survive in a diverse community with limited resources. The immediate transference of the fuzzy set-based rule is that: 1) If there are sufficient resources at the preferred location then there is no need to expend a lot of effort into new markets and 2) If there is not sufficient business/markets at the preferred location and there is limited business in other markets then these markets should be optimally spaced where competition for the customer base is not counterproductive to survival and growth of the enterprise. Thus, by the swarm intelligence inferences, just as the red snapper in the research must compete for resources necessary for survival, so must SMEs, both without entering into dangerous waters that may mean death for fish or business, and in direct consideration to optimizing their locations.

Resource dependence theory (RDT) is one of the most influential theories in organization theory and strategic management and it characterizes the corporation as an open system, dependent on contingencies in the external environment (Hillman, et al., 2009). As Pfeffer and Salancik (1978, p. 1) state, "to understand the behavior of an organization you must understand the context of that behavior—that is, the ecology of the organization." Swarm Intelligence coupled with RDT are the fundamental underpinnings of this relationship between natural and social sciences.

In this case, reefs and halos represent the organizational ecosystem. Based on the model, red snappers represent SMEs and predators- large organizations are likely to thrive and grow in their designated space within their respective ecosystem, if the latter are spread out within a certain radius in their macro environment. SMEs are able to find ample resources in the halos and large organizations thrive on the reefs themselves. In essence, both small and large organizations find their own resources and are likely to grow at a natural rate. However, uncertainty and disturbance in the macro environment may change resource dynamics. Based on the simulation, if ecosystems (reefs) overlap each other, for example, with the blurring and shifting of industry boundaries or with changing macro environmental conditions, survival for small players become difficult as resources become scarce. According to the simulation, with limited accumulated resource- biomass, SMEs, especially the younger companies, are faced with the danger of being acquired by large organizations, which may help reduce competition and resource depletion. The older SMEs may try to change their ecosystems by exploring new geographic and related product/service markets. However, in this process it is likely that they may not be able to survive. The chances of younger SMEs to survive through this ecosystem transition may be very low.

Optimal location analysis for SMEs is critical but this is even more so for introductory entrepreneurial ventures. Generally, just as the red snapper illustrates, by the age of 10 years or more in business, the SME is deemed established and generally not seeking the challenge of competitive markets. While impossible for location to be as specific as for the reef study, further simulations may result in rules for general location discussions throughout the life cycle of the enterprise with the fundamental purpose being when the SME should take chances and branch out versus when it might be optimal to stay in a safe, established environment.

Location decisions for red snapper can be aligned with levels of consumption and amount of foraging. Using the premise of swarm intelligence suggesting a rule for SMEs, competition for resources and outward sales potential from a location can become comparable. For example, utilizing the fuzzy set-based rule for red snapper, a parallel implication could be that if there is high competition at the SME's location but the SME has established sales potential through marketing in areas further from the location, then the location is not overly relevant. However, if a location shows low competition and the SME would not have to exert energy marketing at further distances, then the location decision is relevant and spacing of SMEs for growth and survival becomes important with optimal distances between SMEs preferred.

FUTURE RESEARCH

We posit to test the following propositions by simulating organizational data that will correlate to the bioenergetics modeling data for red snapper with subsequent reef location optimization to yield an ecosystem approach for SME survival and growth.

> *Proposition 1: Both SMEs and large organizations are likely to be profitable and grow in a 'preferred' ecosystem*
> *Proposition 2: Large organizations are likely to acquire younger SMEs more than older SMEs with changing ecosystem dynamics.*
> *Proposition 3: Older SMEs are more likely to succeed changing ecosystems than younger SMEs.*
> *Proposition 4: Fuzzy set-based rules can be determined for optimal SME location decisions*
> *(Shipley, et al., 2015)*

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