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A Prototype Agent Based Fishery Management Model of Hawaii's Longline Fishery

Run Yu[1], Minling Pan[2], Steven F. Railsback[3], and PingSun Leung[1]

[1] College of Tropical Agriculture and Human Resources, University of Hawaii at Manoa, Honolulu 96822
[2] Pacific Islands Fisheries Science Center, NOAA National Marine Fisheries Service, Honolulu 96822
[3] Lang, Railsback & Associates, Arcata, CA 95521
Email: run@hawaii.edu

Abstract: The recent advent of agent-based modeling (ABM) and the availability of software platforms for its implementation offer a powerful alternative to model the spatio-temporal behaviors of a fishery with the consideration of heterogeneity and interactivity. This paper describes a prototype agent-based fishery management model of Hawaii's longline fishery. The model simulates the daily fishing activities of 120 Hawaii longline vessels of diverse characteristics. Following the strategy of pattern oriented modeling (POM), we use the spatio-temporal distribution pattern of fishing efforts to calibrate the model. While POM has a record of success in ecology, the present application to socioeconomic systems such as fishing and fishery management is almost unprecedented.

We also use the calibrated model to evaluate three alternative fishery regulatory policies in Hawaii's longline fishery: 1) no regulation; 2) annual cap of 17 turtle interactions; and 3) close the north central area year round, with respect to their impacts on fishing productivity and by-catch of protected sea turtle. The prototype model, constructed using 1999 data, appears to be able to capture the responses of the fishery to these alternative regulations reasonably well, suggesting its potential as a management tool for policy evaluation in Hawaii's longline fishery.

Keywords: *Agent based modeling, fishery management, endangered marine species protection, policy evaluation*

1. INTRODUCTION

Incorporation of the spatio-temporal and behavioral aspects of a fishery into fishery models and fishery management is an on-going research endeavor (Shomura et al., 1995, Smith and Wilen 2003, Soulié and Thébaud 2006, Daw 2008). To incorporate the behavioral aspect of a fishery, existing empirical fishery models typically treat the behaviors of the entire fishery as a simple multiple of the behaviors of a representative fisher and neglect the interactive dynamics among the diverse fishers (Dreyfus-León 2006). In other words, these models neglect the behavioral heterogeneities and interactivities of the individual fishers, while both are deemed essential to fishery management (Moustakas et al., 2006, Gilman et al., 2006, Wilson et al., 2007). It is not surprising that these fishery models are oftentimes found having limited capacity in understanding the socioeconomic aspects of fisheries and evaluating comprehensively some of the contemporary fishery policies (Barton 2006, Marshall 2007), especially in predicting the responses of a fishery to change in regulations (Allen and Gough 2006). The shortcomings of these fishery models are primarily due to the inherent limitations of the mathematical programming and econometric techniques as their basic constructs, as these computational methodologies are very limited in their ability to derive the mathematical relations among interactive and diverse individuals (Tesfatsion 2001), not to mention the additional spatio-temporal aspect of the relations.

The recent advent of agent-based modeling (ABM) and the availability of software platforms for its implementation offer a powerful alternative to model the spatio-temporal behaviors of a fishery with the consideration of heterogeneity and interactivity. Typically, an agent-based fishery model will treat each individual fisher in the fishery as a unique entity, i.e., an agent; and the agents—fishers will be assumed to continuously perform fishing activities/decisions in a coordinate space according to certain behavioral rules and objectives. Most importantly, the results of individual fishers' behaviors/decisions generally will be assumed to be contingent on other fishers' behaviors/decisions. Due to this interactivity, the entire fishery as a whole might exhibit properties/phenomena that individual fisher does not possess, for example, the tragedy of common property. In this case, the fishery sector can be considered a complex system, i.e., a system whose aggregate activity cannot simply be derived from summation of the behaviors of individual components (Richards et al., 1998).

ABM is a powerful tool, but developing a good agent-based model is not trivial. Two problems have particularly contributed to the failure of many ABM-based studies (Grimm et al., 2005). First, agent-based models often fail by being too complex to understand and use, or by lacking processes essential for the problem they address. It is challenging for the modeler to set a limit to the model's complexity: how do we know what variables and processes must be in a model and which should be left out? Second, many agent-based models use the untested, ad hoc rules for individual decisions. They lack credibility and contribute nothing to theoretical science. The challenge in this regard relates to validating the most important part of ABM—the rules (and theories) used to represent individuals' behaviors. To avoid these problems in the current research, we will adopt the strategy of pattern-oriented modeling (POM) (Grimm et al., 2005). POM is a newly emerging strategy for systematically optimizing the desirable level of model complexity and validating the model structure (behavioral rules) of agent-based models.

POM starts by identifying a set of patterns that have been observed in the study system and seem to characterize its behavior with respect to the issues being addressed. The patterns, which are believed important for the issues addressed by the study, should emerge from the individual behaviors, environmental processes, etc. A variety of diverse, simple, often qualitative, patterns is most useful. One should be confident that a model is useful only if it can reproduce these patterns. The patterns are then used to design the agent-based model. The model includes only the variables and processes necessary to allow the patterns to emerge, and uses spatial and temporal scales at which the patterns were observed. The patterns are also used to test or develop theory for individual behavior: alternative rules for individual behavior are hypothesized, and the ones that cause the model to best reproduce the observed patterns are accepted as useful theory. After these POM steps establish the model's internal structure, model development can proceed in a more traditional way with calibration and testing of system-level results against data.

While POM has a record of success in ecology, the present application to socioeconomic systems such as fishing and fishery management is almost unprecedented (Grimm et al., 2005). Meanwhile, we use Hawaii's longline fishery (HLF) as a case study to illustrate the potential of ABM in realistically capturing the behaviors of diverse fishers and better predict the responses of fishery to changes in regulatory policies.

2. HAWAII'S LONGLINE FISHERY

Longline fishing uses hundreds of baited hooks hanging from a single line to catch fishes. Since its introduction to Hawaii in 1917, Hawaii's longline fishery has developed into a multimillion-dollar sector (approximately $50 million), harvesting mainly swordfish (*Xiphius gladius*) and tuna (*Thunnus albacares* and *Thunnus obesus*) for local, mainland U.S., and foreign markets. The continuing existence of Hawaii's longline fishery, however, has been questioned as it poses a potential danger to accidentally catching protected marine animals such as sea turtles, especially in the longline swordfish fishery.

A series of environmental lawsuits have been filed, seeking substantial restrictions on Hawaii's longline fishery (e.g. Center of Marine Conservation versus National Marine Fisheries Service (NMFS), Civ. No. 99-00152 DAE). As a result, Hawaii's longline swordfish fishery was completely closed on March 15, 2001. Based on newly designed fishing gear and techniques, National Marine Fisheries Service (NMFS) reopened the swordfish fishery in April 2004, but with a cap on fishing efforts (2120 sets per year) and sea turtle interactions (17 interactions for loggerhead turtle and 16 interactions for leatherback turtle). Under this new regulatory regime, if the hard cap of loggerhead turtle or leatherback turtle is reached, the entire swordfish fishery will be closed for the remaining of the calendar year. There is no doubt that this dramatic policy shift in Hawaii's longline fishery has caused profound socioeconomic impacts (Allen 2007). In 2005, the cap on sea turtle interactions was not reached while most of available fishing sets have been used. In 2006, the annual cap on sea turtle interactions was reached on March 17, and led to the closure of the entire swordfish fishery for the remaining of the year, incurring at least $1.6 million loss in revenue. In 2007, the fishery lasted for the entire year and interacted with 15 loggerhead turtles and 5 leatherback turtles.

Despite the successful reduction in sea turtle by-catch, Hawaii's longline fishery is expected to face further restriction for increasing concerns on the conservation of other marine animals (such as sharks) and overfishing of targeted species (bigeye and yellowfin) in the Pacific Ocean. Developing a fishery management regime that facilitates the formulation of an ecologically sustainable and responsible fishery therefore is of vital importance for Hawaii's longline fishery.

3. THE PROTOTYPE MODEL

Following Manson (2000, 2005), the conceptual framework of Hawaii's longline fishery (HLF) and fishery management can be illustrated as Figure 1.

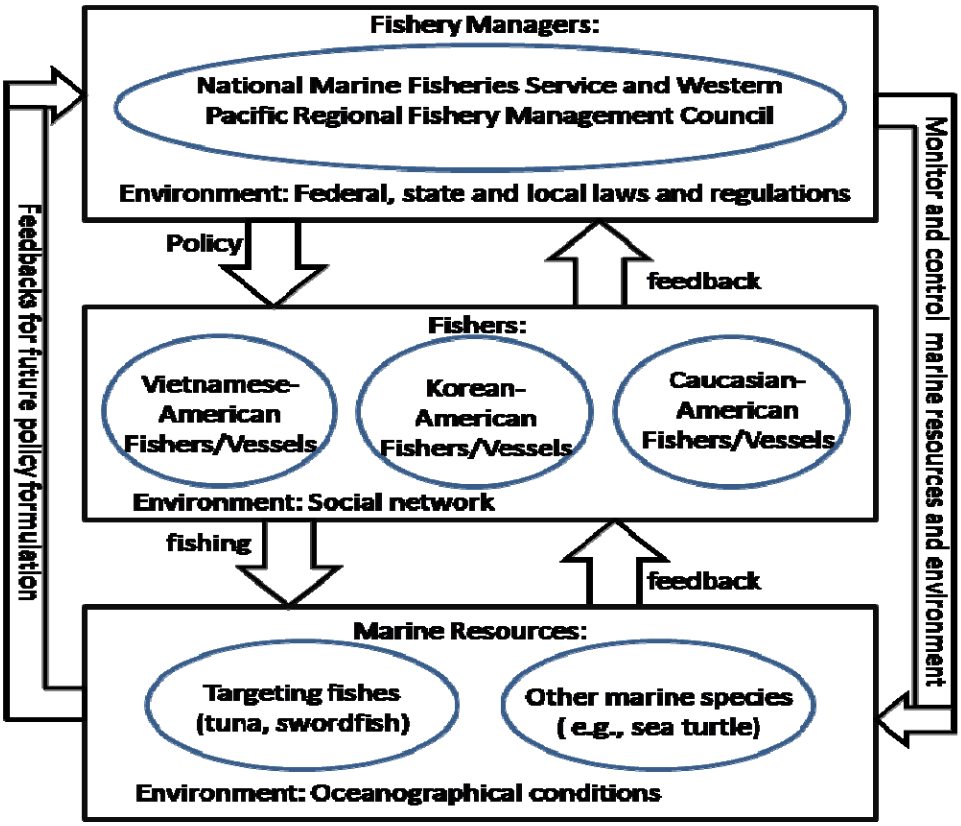


Figure 1. The conceptual framework of Hawaii's longline fishery

Following the strategy of POM, the prototype model must be capable of reproducing the key patterns and characteristics of HLF. In this exploratory study, we used the spatio-temporal distribution patterns of fishing efforts as the essential "pattern". The fishing grounds for the HLF can be divided into five areas (Figure 2) based on empirical observation of fleet operating patterns.

The spatio-temporal distribution of fishing efforts in HLF has been well documented in the literature (Pradhan and Leung 2004a, 2004b, Nemoto 2005). Most importantly, existing and intended fishery policies in HLF clearly affect, directly or indirectly, the spatio-temporal distribution of fishing efforts. For example, the closure of certain fishing grounds could directly change the spatial allocation of fishing efforts. The implementation of turtle cap in the swordfish fishery has driven more fishing efforts allocated to the first quarter.

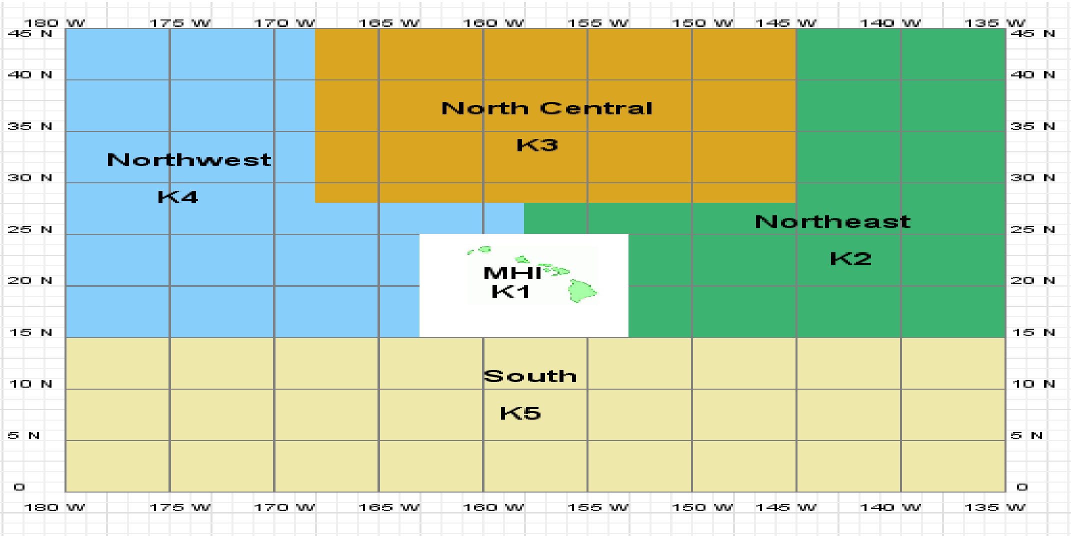
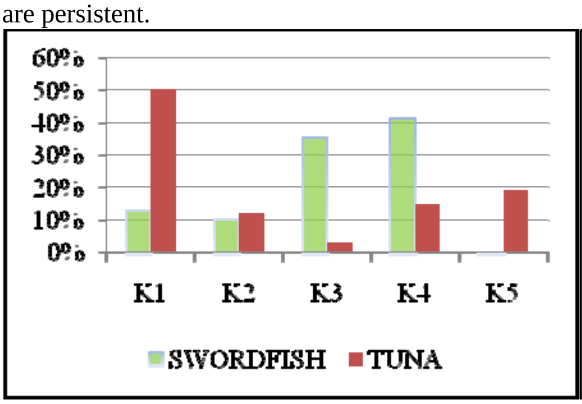


Figure 2. The fishing ground of Hawaii longline fishery

Figure 3 shows the annual fishing efforts distribution (% of total fishing sets) by area in 1999, indicating that one half of the total tuna sets were allocated to the main Hawaiian island (MHI) area (K1) and nearly 80% of the total swordfish sets were allocated to the North central and Northwest areas (K3 and K4). The spatial allocation of fishing efforts indeed varies slightly for each specific year. The general concentration patterns are persistent.



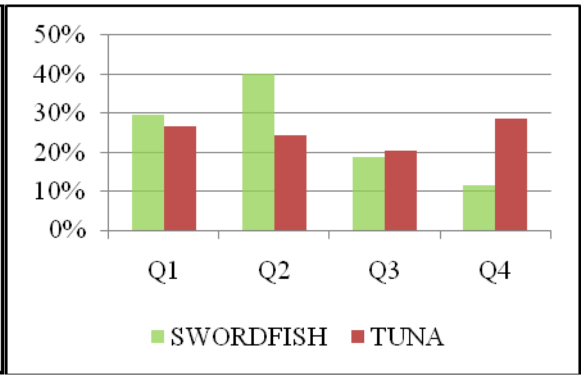


Figure 3. Fishing effort distribution by area, Y1999 **Figure 4**. Fishing effort distribution by quarter, Y1999

Previous studies (Chakravorty and Nemoto 2001, Pan et al., 2001) also suggested that the seasonal variation in fish price/weight and abundance (CPUE) affected effort allocation by the HLF. Figure 4 shows the annual fishing efforts distribution by season (quarterly) in 1999, indicating that nearly 70% of the total swordfish sets were executed in the first two quarters and the tuna fishing efforts declined gradually from the last quarter to the third quarter. It should be noted that such spatio-temporal patterns are much less prominent at individual vessel levels. The prototype model so far has successfully reproduced a fishing effort distribution patterns close to the actual situations.

The prototype model of Hawaii's longline fishery simulates 120 vessels and one fishery management entity. Each artificial vessel (i.e., agent) represents one actual vessel in Hawaii's longline fishery. Attributes that are deemed essential for fishing decision-making such as the size of the boat, the ethnicity of the vessel-owner and captain, the targeting fishes and gear types, fishing holding capacity and fuel holding capacity are assigned according to the previous research results and logbook data. The daily CPUEs of tuna (bigeye and yellowfin), swordfish, and other pelagic species, loggerhead turtles, leatherback turtles, and other turtle species at the 1 degree grid level are configured in accordance with the 1999 logbook data. The fish catchability and turtle interaction probability vary by area, season, and other oceanographic conditions such as sea surface temperature.

The fishing trip decision making procedure can be illustrated by Figure 5. Basically, the vessel captain/owner needs to decide which set type to take, deep set for catching tuna and shallow set for catching swordfish, and where to go. In the prototype model, it is assumed that the vessel captain/owner will choose the most profitable trip/area based on the expected fish catch and operating costs. Then, if the expected fishing trip is not profitable (e.g., revenue from fish catch is less than operating costs) or the fishery is closed, the vessel has to stay in the homeport. Once a trip is planned, the vessel will first travel to the target area and then start searching for fish roughly within a 200 miles distance. This searching pattern is well supported by the logbook data. The fishermen will cast the set in the location where the expected fish catch (CPUE) is the highest. Depending on the fishery management regimes, they might also take into account the possible turtle interactions. The vessel will keep fishing until one of the returning conditions is met. The first returning condition is fish quality control. Fish quality degrades as time goes by. Hence, swordfish trip usually only last for 20 days, and tuna trip usually only last for 12 days, after the first set with fish harvested. The second returning condition is fish holding capacity. The vessel usually has to return to the homeport when the boat is full. The third returning condition is the fuel holding capacity. The vessel has to return to the homeport before it runs out of fuel. Of course, fishing activities are restricted by fishery regulations. For example, if turtle cap is implemented, the vessel has to return to the homeport whenever the cap is reached.

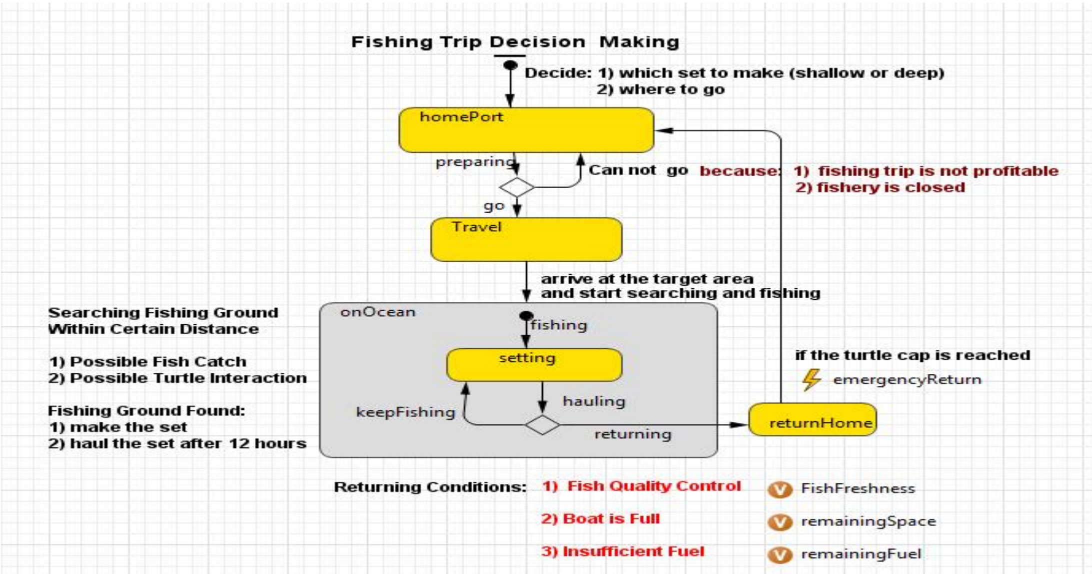


Figure 5. Fishing trip decision making

The main line of the longline fishing set typically ranges from 30 to 50 miles in length; and usually could float within 10-30 miles distance, according to our preliminary analysis of the logbook data. Thus, we specified that each grid (at 1 degree longitude and latitude resolution) could accommodate at most one vessel at one time. In this way, individual vessels actually interact, or more accurately, compete with each other. At this stage, we are only considering the competition aspect of the autonomous vessels. We plan to include other social interactions in the next phase of our work.

The prototype model is programmed in AnyLogic 6. We specified a 10 year "burn-in" period for the simulation to reach the steady state, and then collected 5 years of data for analysis. The simulated results actually converged rapidly, after a few years. A Flash video is available at http://www.soest.hawaii.edu/PFRP/nov08mtg/leung_yu.pdf, showing the main functionality of the prototype model.

4. POLICY EVALUATION

We evaluated three alternative fishery policies: 1) no regulation; 2) a cap of 17 interactions with loggerhead turtle; and 3) close the north central area year round, using the developed prototype model. The simulated spatio-temporal patterns of fishing efforts distribution are presented in Tables 1 and 2.

4.1. Policy Scenario 1-No Regulation

This scenario reflects the management regime where there is no fishing effort limit and turtle interaction limit. The model successfully reproduced the main characteristics of HLF in 1999. The simulated annual fish catch amounted to approximately 16 million pounds, and $44 million in value. The swordfish fishing efforts (shallow sets) would concentrate on the north central and northwestern areas; and in the first two quarters. The tuna fishing efforts (deep sets) would concentrate on the Main Hawaiian Island area and in the last and first quarters.

4.2. Policy Scenario 2-Turtle Cap

This scenario reflects the management regime where there is no fishing effort limit and turtle interaction limit. The model successfully reproduced the main characteristics of HLF in 1999. The simulated annual fish catch amounted to approximately 16 million pounds, and $44 million in value. The swordfish fishing efforts (shallow sets) would concentrate on the north central and northwestern areas; and in the first two quarters. The tuna fishing efforts (deep sets) would concentrate on the Main Hawaiian Island area and in the last and first quarters.

4.3. Policy Scenario3-Area Closure

This scenario assumes that the north central area (K3 in Figure 1) is closed for fishing year around. The simulation indicates that it would reduce the fish catch by approximately 6%. Meanwhile, it could also reduce the turtle interactions by approximately 40%. Reductions in total fishing efforts and turtle interactions from our ABM model are consistent with the results from the nonlinear programming model of Nemoto (2005). The predicted reallocation of fishing efforts caused by the closure is also consistent with the observed data in 2000 when the north central area was temporally closed for a few months, i.e., fishermen reallocated their fishing efforts to the northeast (K2 in Figure 1) area after the north central area (K3 in Figure 1) is closed.

Table 1. Simulated fishing effort distribution by area

	PS1: No Regulation		PS2: Turtle Cap		PS3: Area Closure	
Area	Swordfish Sets	Tuna Sets	Swordfish Sets	Tuna Sets	Swordfish Sets	Tuna Sets
K1	23%	49%	13%	49%	25%	52%
K2	5%	11%	25%	7%	5%	12%
K3	25%	4%	0%	3%	0%	0%
K4	48%	21%	63%	13%	70%	24%
K5	0%	15%	0%	28%	0%	12%

Table 2. Simulated fishing effort distribution by quarter

Quarter	PS1: No Regulation		PS2: Turtle Cap		PS3: Area Closure	
	Swordfish Sets	Tuna Sets	Swordfish Sets	Tuna Sets	Swordfish Sets	Tuna Sets
Q1	24%	15%	100%	17%	23%	14%
Q2	43%	22%	0%	23%	28%	27%
Q3	24%	19%	0%	27%	33%	25%
Q4	10%	44%	0%	33%	18%	33%

It should be noted that in the past few years there are significant changes in the fishing technology and equipments in HLF, along with the change in fishery regulatory policies. For example, the adoption of J hook has reduced the turtle interaction rate by more than 90% (Gilmore and Kobayashi 2007). The simulation of the above three policy scenarios, however, does not take into consideration the effects of the changes in the technology and equipments. Hence, it would be inappropriate to draw any conclusions or policy implications toward the management of the present HLF from the simulation results presented in this exploratory study.

The prototype model will be modified to reflect the current technological and operational situations of fishing vessels in HLF as soon as relevant data becomes available.

Table 3. Simulated results under alternative fishery management regimes*

Alternative Policies	PS1: No Regulation	PS2:Turtle Cap	PS3: Area Closure
Swordfish (1,000 lb)	5,010	2,561	4779
Bigeye Tuna (1,000 lb)	7,233	9,465	5,012
Yellowfin Tuna (1,000 lb)	4,015	5,799	4,709
Swordfish ($1,000)	$12,579	$5,892	$9,595
Bigeye Tuna ($1,000)	$23,799	$20,123	$21,930
Yellowfin Tuna ($1,000)	$9,012	$11,005	$9,677
Turtle Interactions	232	17	145

*The current model is constructed using information in 1999 and may not reflect the present fishing technology of HLF. Thus, the simulation results should be viewed in that light.

5. DISCUSSION AND CONCLUSION

This paper presents a prototype agent-based fishery management model for the purpose of simulating the fishing activities of Hawaii's longline vessels, using the strategy of pattern oriented modeling (POM). The model simulates the daily fishing activities of 120 Hawaii longline vessels of diverse characteristics. The prototype model successfully reproduced the spatio-temporal distribution patterns of fishing efforts in HLF, indicating the potential of ABM in realistically capture the performance of HLF through simulating the behaviors of individual fishermen/vessels. To further test the performance of the prototype model, we use it to evaluate three alternative fishery regulatory policies: 1) no regulation; 2) annual cap of 17 turtle interactions; and 3) close the north central area year round, with respect to their impacts on fishing productivity and by-catch of protected sea turtle. The simulated results are either close to the actual situation or consistent to the previous study results in the literature, indicating that the agent-based fishery management model could realistically capture the diverse behaviors of Hawaii's longline fishermen and predict the responses of the fishery to changes in management regimes.

The present study is an ongoing research effort; and the prototype model is currently under further calibration and testing.

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