Developing a Spatially Explicit Agent-based Model of Queen Conch Distribution in a Marine Protected Area in the Turks and Caicos Islands

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ABSTRACT

Queen conch, *Strombus gigas*, is an important commercial resource in the Turks and Caicos Islands (TCI). The TCI government is funding the development of an agent-based model (ABM) to help better understand queen conch distribution and manage the artisanal fishery. ABMs are built from the 'bottom up' and simulate each individual agent – conch, fishers and the fishery manager – within the pertinent system. Agents follow relatively simple rules of behavior at the individual level but

in a computer generated artificial fisheries management laboratory, potentially increasing our ability to implement the principle of adaptive management while reducing the risk and/or time lags of real-world experiments. The purpose of this paper is to outline the development of the spatial components of a pilot model in which simple foragers (conch) live, grow, and disperse. The model of the South Caicos East Harbor Lobster and Conch Reserve (EHLCR) uses habitat data derived from Landsat 7 satellite imagery as an environmental base and is implemented using the *Swarm* modeling platform. In the model, conch survival is dependent on (1) food intake and (2) mortality risk within each habitat type. The challenges of expanding the model from this pilot phase to incorporate more sophisticated fisher and fishery management agents in an expanded commercial fishery model are outlined.

KEY WORDS: Queen conch, Marine Protected Areas, Agent-based models, swarm

INTRODUCTION

An important commercial fishery for queen conch (*Strombus gigas*) exists in the Turks & Caicos Islands. As an Appendix 2 species under CITES, the government of the TCI is mandated to manage the fishery sustainably in order for TCI exporters to maintain access to international markets for conch. Sustainable management of the conch fishery requires an understanding of the distribution and population dynamics of queen conch on the Caicos Bank. In addition, it requires that fishery managers understand how fishers react to alternative policies that might be used to manage the conch fishery. Without such insights, the TCI conch fishery may well be over-fished and follow the decline of other fisheries in the Caribbean region (see Appeldorn 1994).

Traditional fisheries science models can be used to set aggregate total allowable catch (TAC) for the conch fishery in the TCI (Medley and Ninnes 1999), but provide little insight about the effects of alternative policy approaches for fishery management when species distribution is patchy and/or fishers are heterogeneous in skills or preferences. Increasing computer power and the recent development of powerful object-oriented programming languages and geographic information systems (GIS) have opened up opportunities for alternative approaches to fishery modeling. Agent-based models (ABMs) (or individual-based models, as they are known by ecologists) are one such new modeling tool (e.g., Railsback et al. 1999, Janssen et al. 2000, Kohler and Gumerman 2000).

ABMs, as the name suggests, incorporate individual agents into a model that is spatially and temporally explicit. The environment itself can display heterogeneity in resource endowment (e.g., food, energy, space, habitat quality), distribution, and rate of renewal. Populations of agents are represented by real numbers rather than population densities. Autonomous agents are situated in the environment, can sense it, and can both act on, and be affected by, the environment while pursuing individual or collective goals. Agents interact locally with other agents in a spatially-explicit model and, therefore, interact with an effectively low population (Uchmanski and Grimm 1996).

In order to improve understanding of conch distribution and the effects of various policy options on ecological and economic outcomes, a pilot agent-based model of the South Caicos East Harbor Lobster & Conch Reserve (EHLCR) region is being developed. The model will simulate key processes driving abundance, location, and production of conch. We use Landsat satellite imagery to develop an environmental base for use within the Swarm modeling platform. Modeling experiments will comparatively assess fishery policies, including design of this important conch MPA. The purpose of this paper is to outline the development of the spatial components of a pilot model of a fishery in which simple foragers (conch) live, grow, and disperse.

METHODOLOGY AND RESULTS

Image Preparation and Processing

A radiometrically-calibrated Enhanced Thematic Mapper plus (ETM+) image acquired by Landsat 7 on 20 Sep 1999 was purchased from the US Geological Survey by the School for Field Studies, Center for Marine Resource Studies (CMRS). The procedures for various image preparation and analyses throughout this project are largely based on protocol developed at the Center for the Study of Institutions, Population and Environmental Change (CIPEC), Indiana University (Green 1999).

The ETM+ sensor records data for three bands of visible (Bands 1, 2, 3 – wavelengths of 0.450 – 0.515, 0.525 – 0.605, 0.630 – 0.690 microns, respectively) and three bands of near infrared (NIR) (Band 4 – 0.75-0.90 microns) and infrared (IR) (Bands 5 and 7 – 1.55-1.75 and 2.09-2.35 microns, respectively) electromagnetic radiation at a resolution of 30 meters. It also records a thermal band (Band 6, 60-m resolution), and a high-resolution (15 - m) visible band (Band 8), which were not used in this project. Each band at 30 - m resolution consists of 7,801 columns and 6,941 rows of data. Thus, there are almost 325 million data points for the six relevant visible and infrared bands. Figure 1 shows the footprint of the Landsat 7 image.

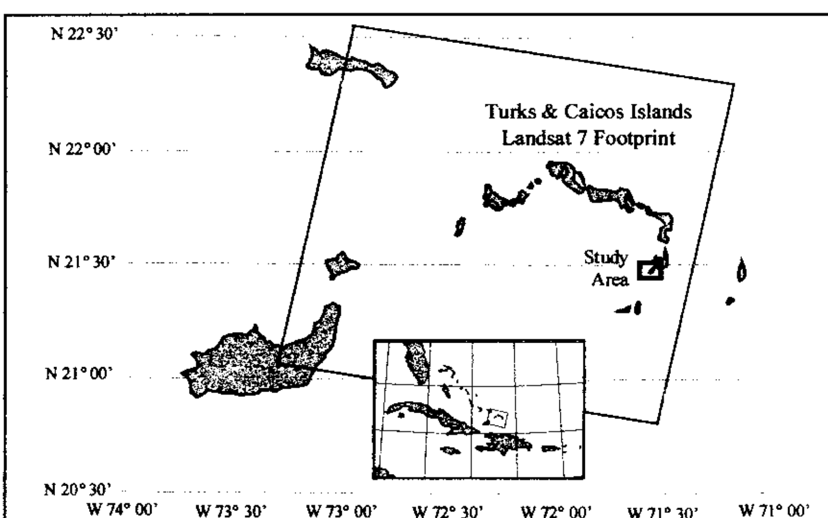

Figure 1. Landsat 7 Footprint in relation to the Turks and Caicos Islands study site

A sub-scene of the eastern Caicos Bank was geometrically registered (RMS error = 14.5 - m, about one-half pixel) using 1:10,000 topographic maps of the region and Idrisi32 image processing software (Eastman 1999). Geometric registration warps the 2-dimensional satellite image of the 3-dimensional surface of the earth to make it coincide with mapping systems. A study area of 301 columns by 251 rows (68 km^2, 30 m resolution), including all of EHLCR, was selected from the registered sub-scene. Masks were applied to land, exposed sand, and deep-water, leaving submerged banks and reefs for spectral analysis.

For the pilot model, we used digital numbers (DNs) that measure at-sensor reflectance at the satellite rather than calibrated surface reflectance (i.e., corrected for atmospheric disturbance); the patterns for DN and surface reflectance should be closely correlated. Because water rapidly absorbs infrared radiation, most of the work done in this project utilizes visible light from Bands 1 (blue), 2 (green) and 3 (red).

Scatterplots were used to plot the reflectance of combinations of Bands for the entire image without reference to spatial location. Figure 2 shows the scatter plot for Band 3(red) versus Band 1(blue) reflectance.

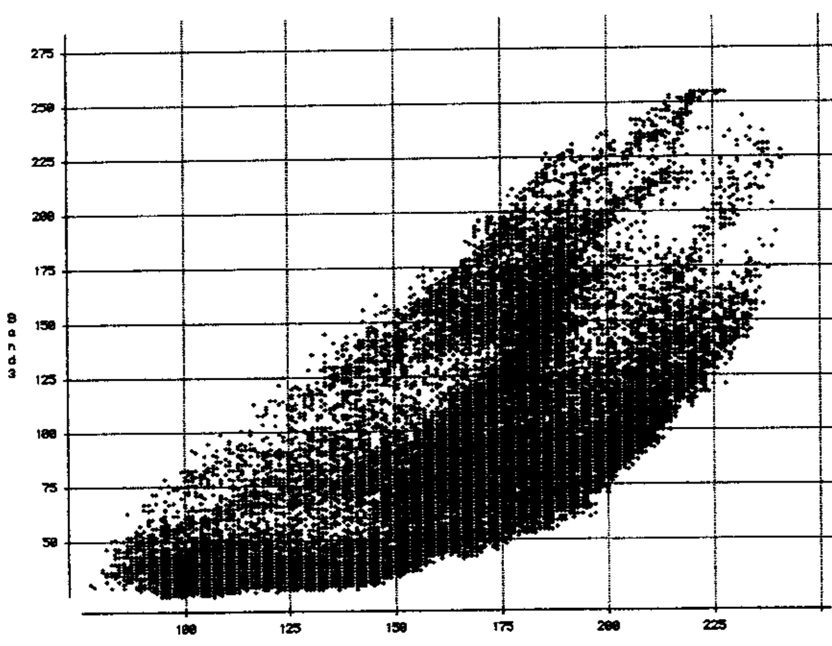

Figure 2. Scatterplot of Band 3 (red = light) versus Band 1 (blue = dark)reflectance as measured by digital numbers (DNs)

The use of scatterplots underlies Spectral Mixture Analysis (SMA) (e.g. Schweik and Green 1999). In SMA extreme 'end members' are defined – those points at the most extreme fringes of the scatterplots – as areas of 'pure' habitat type and used to classify other intermediate pixels as some linear combination of the end members. Using Datadesk software (Velleman 1997), it is possible to locate particular pixels or groups of pixels from the scatterplot in a spatial image of the study area, thus making it possible to associate particular habitat types with specific ranges of Bands 1 and 3 DNs. In our preliminary habitat classifications, we found that certain distinct habitat types tended to be closely grouped in the Band 3 vs Band 1 scatterplot. After exploratory analyses, we partitioned the scatterplot into 18 zones (Table 1), each of which is thought to represent a different type of habitat that is meaningful for the pilot ABM.

Fine-scale partitions in the areas of low reflectance were used to distinguish important differences between a variety of reef, seagrass and gorgonian-sponge habitats. The classification also shows algal plain and patches very well and distinguishes known fine-scale habitats crucial for conch nurseries and juvenile rearing (Danylchuk et al. in press). The classification will undergo further refinement and accuracy assessment in the near future.

Figure 3 shows a gray-tone image of the classified EHLCR study site. Each of the 75,551 pixels in the image was classified as one of the 18 habitat types or as masked area. This spatially referenced habitat data was exported from Idrisi32 to a text file, and subsequently imported into the Swarm modeling platform to construct the environmental base of the agent-based conch model.

Agent-Based Model Development using Swarm

The Swarm project was started at the Santa Fe Institute in 1994 and the first public simulation toolbox made available in 1995. Swarm is a collection of software libraries in the object oriented programming language, Objective-C, and now available for models written in Java. Swarm provides a platform for developing and documenting computer experiments that use collections of independent agents that interact in discrete space and time.

Diverse users in the natural and social sciences have developed the Swarm libraries, which can, according to Steffanson (1997), be broadly organized as classes of objects that:

i) Build spatial environments for agent interaction and handling information;
ii) Automate data collection and analyze data output visually or statistically;
iii) Maintain objects (e.g., conch, fishers) in structured collections (e.g., arrays) that can be readily manipulated (e.g., sorted, ranked, culled);
iv) Schedule periodic events at variable time-steps or to be triggered dynamically;
v) Probe simulation objects during simulations (e.g., how many conch are in a particular pixel grid) and adjust parameter values; and
vi) Generate random numbers that facilitate Monte Carlo analyses and random seeds that can be used to control the replicability of simulation runs.

Table 1. Partitions zones for scatterplot of Band 3/Band 1reflectance (measured by digital numbers, DN) and preliminary habitat type classifications

	Band 3 DN	Band 1 DN	Preliminary habitat type
1	$10 \leq B3 \leq 32$	$10 \leq B1 \leq 116$	Dense and/or deep seagrass
2	$33 \leq b3 \leq 55$	$10 \leq B1 \leq 88$	Medium-dense seagrass
3	$44 \leq B3 \leq 55$	$89 \leq B1 \leq 102$	Medium seagrass
4	$33 \leq B3 \leq 43$	$89 \leq B1 \leq 102$	Light seagrass (or deep reef)
5	$33 \leq B3 \leq 55$	$103 \leq B1 \leq 116$	Deep gorgonian-sponge
6	$10 \leq B3 \leq 55$	$117 \leq B1 \leq 142$	Shallow gorgonian-sponge
7	$10 \leq B3 \leq 55$	$143 \leq B1 \leq 300$	Mid-depth algal plain
8	$56 \leq B3 \leq 104$	$10 \leq B1 \leq 116$	Dense red algae
9	$56 \leq B3 \leq 104$	$117 \leq B1 \leq 147$	Red algae/shallow coral
10	$56 \leq B3 \leq 104$	$148 \leq B1 \leq 175$	Sand/algal plain
11	$56 \leq B3 \leq 104$	$176 \leq B1 \leq 300$	Shallow algal plain
12	$105 \leq B3 \leq 188$	$10 \leq B1 \leq 161$	Very shallow algal plain
13	$105 \leq B3 \leq 130$	$162 \leq B1 \leq 200$	Sand
14	$105 \leq B3 \leq 130$	$204 \leq B1 \leq 300$	Shallow sand 1
15	$131 \leq B3 \leq 188$	$162 \leq B1 \leq 203$	Shallow sand 2
16	$131 \leq B3 \leq 188$	$204 \leq B1 \leq 300$	Exposed sand
17	$189 \leq B3 \leq 300$ $212 \leq B3 \leq 300$ $251 \leq B3 \leq 300$	$10 \leq B1 \leq 220$ $10 \leq B1 \leq 226$ $10 \leq B1 \leq 300$	Exposed sand
18	$189 \leq B3 \leq 211$ $212 \leq B3 \leq 250$	$221 \leq B1 \leq 300$ $227 \leq B1 \leq 300$	Exposed sand/shell debris

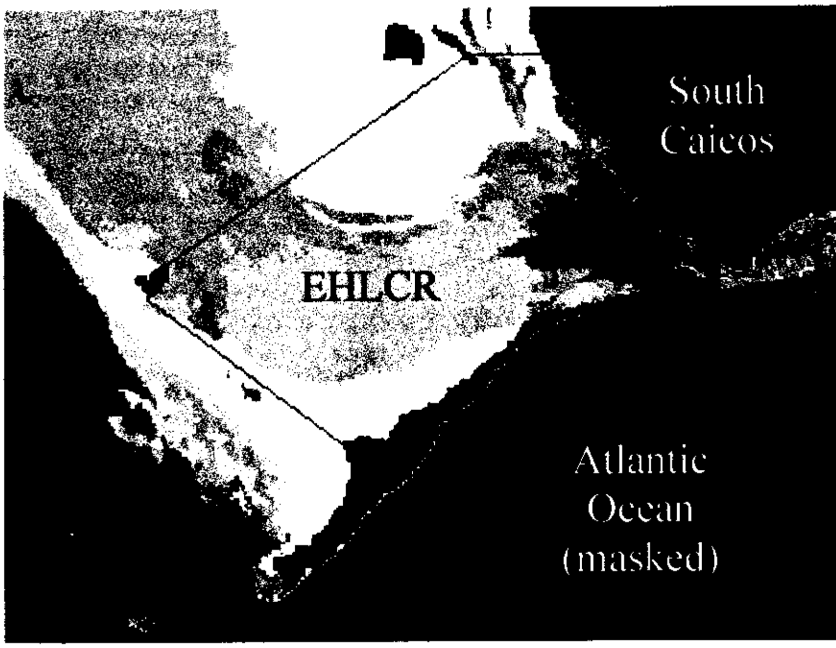

Figure 3. Gray-scale image of habitat classification (black = land/sea mask; classes 1 - darkest gray to 18 - white) at the South Caicos study site

In developing a Swarm model, the modeler's role is to define the types of objects and agents in the model, the behavior of each type of agent, and how the system is observed. Agent behaviors are designed following the recommendations of Railsback (2001), considering such issues as which behaviors should be forced to reproduce observed behaviors vs. emerging from a mechanistic representation of the causal processes. We attempt to capture the key processes driving agent behaviors using very simple representations of the processes. To date, only habitat cells and adult conch have been designed in detail. In the pilot conch model, we have defined the following important objects and agents.

Habitat Cells — are based on the 30-m ETM+ pixels described above. Habitats cells model food production and keep track of food consumption by conch and the resulting food availability; at any time step when food consumption by conch exceeds food production, food availability in the following time step is reduced. Predation risks also vary among habitat cells as a function of the relative predator abundance and quality of hiding cover for conch.

Conch — are the primary model agents. Larval dispersion and settlement are not currently modeled, although it would be feasible to integrate water flow, larval dispersal and habitat-specific settlement in the future. Conch behaviors that are simulated include feeding and growth, habitat selection, and mortality. Because conch traits change over their life cycle, three life stages of conch are simulated using different assumptions for each:

i) *Juveniles* — enter the model when they emerge after spending their first year buried in sand. Juveniles are vulnerable to predation by fish, and use all energy intake for growth. Habitat is selected to maximize the individual's probability of surviving to adulthood. This probability decreases in risky habitat and increases with growth rate because rapid growth reduces the time until adulthood is reached.

ii) *Adults* — are sexually mature conch not in the spawning period. Predation is assumed to be a negligible risk, so fishing mortality is the only important source of mortality. Energy intake is used for gamete production and habitat is selected to maximize gamete production. Adults decide when to become spawners by maximizing their expected reproductive success, a function of their probability of surviving until the next spawning season and the expected gamete production.

iii) *Spawners* — are conch during reproductive activity. Habitat is selected to obtain good spawning habitat and to maximize the probability of finding mates.

Fishers — are agents representing people that fish for conch. Fisher behavior is simple in the pilot model: we assume that fishers are simple profit maximizers that need only be concerned with conch harvests and variable operating costs (i.e., fuel). Much more complicated behaviors are possible in expanded models (e.g., accounting for risk preferences).

The Fishery Manager — is an agent that represents the agencies setting and enforcing fishery management rules. A number of potential management rules are easily modeled. For example, MPA boundaries can be changed to examine the effects of different MPA configurations on adult emigration of conch to adjacent commercial fishing grounds. In addition, policies such as TACs, minimum size limits, input taxes or subsidies, and export taxes can be modeled and compared. In addition, probes can be used to simulate field sampling programs, enabling the *fishery manager* to undertake virtual fishery science, setting policies to meet objectives with less than complete information.

Several tools are provided for observing the simulations. The main animation window shows all the habitat cells, colored by their habitat type. Individual conch (and, eventually, fishing boats) appear as dots but the resolution is too coarse to observe conch movement. A higher-resolution window can be opened to observe conch within a selected subset of habitat cells; in these windows cells are colored by food availability and conch are represented by line segments indicating their location, size, and movement direction. In addition, summary information (e.g., total conch abundance by life stage; number of conch using each habitat type) can be obtained via output files or screen graphs.

Model Parameterization

Model parameterization is in process, and is based on a variety of scientific studies of feeding, movement and mortality (e.g., Stoner and Ray 1993, Stoner et al. 1995. Stoner and Glazer 1998). Key processes that seem important in modeling feeding include: larger conch can consume more food because they can move faster and forage over a wider path; conch adjust their feeding distance with the availability of food; and food competition can affect foraging behavior and intake. Three main sets of parameters need to be defined – feed use and growth; movement; and mortality risk.

Feeding — Conch (1) use food (detritus, algae, seagrass) that is produced slowly, and (2) have limited movement compared to the 30 m grid cell size, thus making it unrealistic that they compete for food at a daily time step. The approach we are adapting is to assume a constant rate of food production, with accumulation and depletion of food over time, subject to constraints of a zero lower limit and some set upper limit. If the conch in a cell consume more food than is produced in a day, then food availability on the next day is lower. This allows food production and competition to occur over times longer than a one-day time step.

Movement — We assume that adult conch move a distance determined by the feeding model, and travel in the direction toward highest potential net energy intake. Avoiding mortality risks is not included in the movement decision because we assume in the pilot model that survival of adult conch does not vary with habitat.

Movement is simulated after feeding in the model's daily schedule. Therefore, the distance moved is a function of food availability in the habitat cell where the conch starts its movement. If food is relatively scarce, this distance will be equal to the variable *AdultForageSpeed* (m/d); if food is abundance and the conch can obtain its maximum daily food intake in less distance, then the distance needed to obtain maximum food intake is used.

Potential movement destinations are each of the eight cells adjacent to the conch's current cell, plus the conch's current cell. This approach assumes that adult conch are capable of sensing gradients in food availability in all directions. We do not necessarily assume that a conch "knows" habitat conditions in adjacent cells. We do assume that the conch can detect local gradients in habitat conditions, and that such local gradients are represented by the differences among adjacent cells.

The best destination is the cell offering the highest net energy intake. The conch calculates the net energy intake it would receive in each potential destination cell, using the feeding methods described above. If any of the eight adjacent cells offers higher net energy intake than the conch's current cell, then that cell becomes the best destination; otherwise, the current cell is the best destination.

Mortality — We model natural mortality as a stochastic function of each conch's state and its habitat: the daily probability of survival is a function of conch state and habitat. On each simulation day, a random number is drawn from a uniform distribution between zero and one, for each type of mortality simulated. If the random number is greater than the survival probability, the conch is assumed dead of that type of mortality.

Following the evidence that natural mortality of adult conch is low (Appeldorn 1988), in the pilot model we simply assume a constant daily survival rate that is independent of habitat, energy status, and age. This daily survival rate is specified by the adult conch parameter *adultSurvivalProb*. A value of can be selected using *adultSurvivalProb* = 0.5[exp(1/(n*365))], where n is the mean survival time, in years, after conch achieve adulthood. We now use a mean survival time of 8 y, so *adultSurvivalProb* is 0.99976.

DISCUSSION AND CONCLUSIONS

A pilot ABM of queen conch in the EHLCR has been developed and is undergoing parameterization and calibration. The use of Landsat 7 ETM+ satellite imagery has allowed the classification of the 68 km^2 study area into 18 distinct habitat types based on spectral reflectance characteristics in the blue and red wavelengths. The 30 m resolution is useful as it allows differentiation of habitat zones as small as a few hectares, which may play particularly important roles in conch population dynamics within the MPA (Danylchuk et al. in press).

Methods for validating (testing the realism of) and analyzing (learning from) ABMs are quite different from the methods typically used for conventional fishery stock assessment models. Model validation and analysis are closely linked and focus on the question of whether the agent behaviors included in the ABM produce realistic patterns of individual- and system-level dynamics (Railsback in press). Agents must be shown to exhibit realistic behavior patterns before results for the entire fishery model can be considered valid.

Epstein (1999) argues for a criterion of generative sufficiency in ABMs. That is, are micro-level specifications (i.e., rules of behavior) sufficient to generate the macro-level outcomes of interest (i.e., conch distribution, age structure, etc.)? If more than one set of behavioral rules is sufficient to generate outcomes similar to those observed in the field, then the ABM can point to important experimental research questions that need to be addressed.

Behavior of model agents will be validated and analyzed by conducting a series of simulation experiments that examine the extent to which observed behavior patterns are reproduced. Alternative representations of key behaviors can be compared to determine which best reproduce observed patterns. Examples of patterns that could be used for validation and analysis of conch behavior include:

i) Relative abundance of conch in various habitat types, and how it varies with conch life stage;
ii) Migration timing and direction in juveniles and spawners; and
iii) How conch ages and size at adulthood varies with food availability and growth.

The integration of the Swarm model and the Idrisi32 image processing and GIS software also offers the opportunity for model validation using advanced spatial statistics (e.g., Cressie 1993). Over 4.8 ha of EHLCR have been surveyed by CMRS using integrated line and belt transects (Danylchuk et al. in press). In addition, the Turks and Caicos Department of Environment and Coastal Resources (DECR) has engaged in extensive surveys farther afield in commercial fishing grounds using the same methodology (Clerveaux and Danylchuk in press). In total, over 400 field sites have been sampled to date, allowing for statistical comparisons of conch distribution in the field and in the ABM. The work underway in the TCI queen conch fishery should lead to new MPA modeling methodologies and insights as the model is further developed in the future.

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