Exploring Anthropogenic Activities and Management Decisions Using a Novel Environmental Agent Based Model

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Abstract*—Lake whitefish (*Coregonus clupeaformis*) are an ecologically, economically, and culturally important species to the native and non-native fishers of Lake Huron, Canada. Studying the effects of anthropogenic activity on lake whitefish is of utmost importance to ensure this species remains viable in its environment for sustainable harvest. One analysis tool that is frequently used for ecological population risk assessments are agent-based models (ABMs), in which the population is represented as a network of heterogeneous individual agents that interact with one another and their environment. However, in an ABM that incorporates a high level of biological detail to model a large population moving within a spatial environment over time, significant computation is required to manage, manipulate, and store the relevant data for each agent over successive time iterations. We introduce a new approach to ABMs known as environmental ABMs (enviro-ABMs) to reduce this computational expense and simulation runtime. Specifically, we divide the environment into a collection of spatially indexed cells and treat each of these as a single agent, allowing fish to move from one contiguous cell to another. This reduces the computational requirements to a limited number of active cells. In addition to more predictable computational requirements, this method keeps all fish sorted by age and location for efficient mortality, spawning, and harvest operations, and reduces the amount of computational overhead needed. Applying the enviro-ABM to our case study in Lake Huron, we demonstrate how it can be used to model anthropogenic activities and stressors that may affect lake whitefish, and how the model can be used to facilitate fisheries management decision making. While the model is applied specifically to the case of whitefish in Lake Huron, it can be generalized to conduct risk assessment for other species in a variety of habitats.

I. Introduction

Agent-based models (ABMs) were orginally developed to simulate the interaction between autonomous agents and their surrounding environment [1]. Representing a population as a collection of heterogeneous interacting agents can produce insights and relationships that are not present in representative-agent models, where the population is viewed as a homogeneous aggregate. Typically, ABMs are able to simulate hundreds or thousands of autonomous agents all performing under a set of predefined rules [1]. In order for agents to behave autonomously with independent decisions, some parts of agents' behaviour are defined stochastically: for example, the choice of whether to move in one direction or another. The study of spatially relevant movement, mortality, spawning, and interaction can all be incorporated in ABMs [1]. Additionally, environmental conditions, anthropogenic factors (such as power plants and harvest), predator-prey interactions, system -wide assumptions, and carrying capacity may all be included in ABM modeling [1].

With a large set of parameters, it is quickly apparent that the level of complexity in an ABM is high. Although ecological models are generally complex, they must be capable of producing meaningful results from a supplied set of parameters in order to perform population risk assessment. Finding a set of parameters to produce results consistent with historical data can be difficult and requires techniques to determine how the simulation output varies when altering the parameters [2], [3]. The level of computation required for simulations with a large environment, high level of detail, or high population size is taxing on a computer's resources and can create lengthy simulation run-times. A tool like this could become very useful if the underlying software could improve computational efficiency so simulations could be completed within a reasonable time frame. This would allow researchers to rapidly find an accurate parameter set then efficiently run simulations of various scenarios of interest.

We propose here, the alteration of ABMs into Environmental Agent Based Models (we will refer to it as enviro-ABMs from here on), wherein we treat the environment as the agent which, contrary to traditional ABMs, use the animal as the agent. Our transformation of traditional ABMs seeks to provide high quality simulation data production while allowing for highly reduced runtimes. The data generated from simulations could be used for statistical analysis in the domain of fisheries management for sustainable life under water. Presented here are the methods used for the development of this model and a qualitative analysis of a case study. The case study considers a commercial fishery important to a local

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indigenous community for demonstrating the initial capability of the model as a management tool.

II. Methods

In an analysis procedure similar to traditional ABMs, enviro-ABMs can be a useful tool for population risk assessment [4], [5]. The behaviour of any ecosystem is immensely complex with significant codependency between many uncontrollable or unknown variables. The unknown behaviour of each individual autonomous agent presents difficulties when estimating the input parameter set. For this reason, it is important to use as much available data applicable to agent behaviour as possible with the intent of modelling observed population distributions [6], [7]. Additionally, this makes it nearly impossible to accurately predict how the population of any species will respond to anthropogenic imposed changes in habitat. The predicted effects are exceptionally important for decisions concerning sustainable fisheries management for obvious reasons.

In this particular case, we apply the enviro-ABM and begin simulations for risk assessment of the lake whitefish population in Lake Huron [8]. The intention of performing the risk assessment is to determine how the collaboration of various local anthropogenic activities affect the lake whitefish population. We can vary a single parameter to create one scenario, and by running many simulations for each scenario of interest, it's possible to compare the scenarios and quantitatively measure the total effect to improve fishery management decisions.

A. General Properties of an Enviro-ABM

Many aspects of the enviro-ABM are analogous with traditional ABMs. Like traditional ABMs, enviro-ABMs input a carrying capacity and use discrete time steps to update agent location, spawning, and mortality. The major difference between ABMs and enviro-ABMs is how individual agent data are stored during a simulation. Rather than storing a collection of agents with individual properties calculated at birth, enviro-ABMs use spatial environment locations storing the total number of agents from each cohort and stochastically calculate the individual properties as required (Figure 1). Storing the total number of agents by environment location and cohort has the benefit of agents always being sorted by location and age for optimized calculations and efficient parameter access. When iterating through sorted agents, some operations are only required once and can be applied to other agents to avoid redundant computation.

B. Environment

Habitat types were chosen by using Lake Huron bathymetry data [9]. Lake depth helps predict mortality rates from increased predation, as well as preferred habitat and spawning depths [10]–[12].

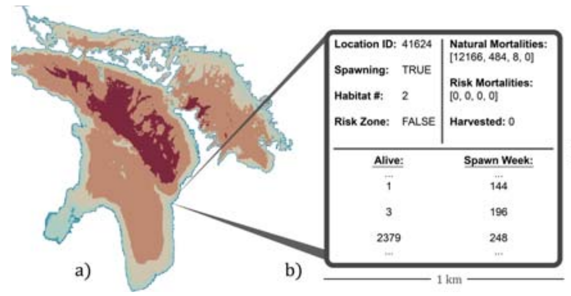

Fig. 1. a) A matrix density plot of the environment used in simulations and the habitat type (distinguished using Lake Huron Bathymetry data) of each cell, and b) an illustration of how each individual environmental agent stores data.

C. Lake Whitefish Biological Properties

Similar to traditional ABMs, enviro-ABMs split agents into life stages (even though exact age in weeks of each agent is known) with distinct biological properties used for modelling individual behaviour [10]. Our model incorporates four life stages for lake whitefish: egg, larvae, juvenile, and adult [11].

D. Spawning

Spawning locations are approximated by the collaboration of results from two independent reports. The first report gave information pertaining to the spawning depths preferred by lake whitefish, and their natural habitat locations [10]. Noting, that this information is in reference to Lake Huron, located within Ontario, Canada; and Michigan in the United States. Our second source comes from local fishery reports [13]. Important to the model is the spawning seasons, which are are from September through December [10].

E. Mortality

1) Natural mortality: Natural mortality for each individual agent is dependent on their age and location.

2) Harvest: Reported lake whitefish yield is used to model total harvest. The observed seasonal effects are accounted for by randomly selecting harvest locations from in-season harvesting zones [14], [15].

3) Other Anthropogenic Activity: Anthropogenic effects of the cooling water intake from a local power plant is included in the model. The total impact of local entrainment and impingement in Lake Huron is not known, so various scenarios are based on a past study of Lake Michigan lake whitefish entrainment and impingement [16]. Thermal plume is not explicitly included in the model, but slightly increased agent mortality rates are experienced near cooling water dispersion areas consistent with previous experiments [10].

F. Movement

During the winter months, adult lake whitefish move toward shallow water for breeding and inhabit deeper waters once the temperature rises [11]. Previous reports have shown that all stages of lake whitefish have a tendency to follow the currents present within Lake Huron [12], [17], [18].

III. Analysis

Management teams responsible for sustainability of any wildlife stock can benefit from prediction tools. Models aimed at using realistic assumptions and providing scalable results are a necessity for running simulations of various scenarios for population risk assessment. Inference of future production requires historical harvest and population data of their fish stock. Our focus is on lake whitefish, so our model is seeded using data pertaining to this species of fish.

As previously mentioned, this model is applied using a case study of the fishery of lake whitefish in Lake Huron to determine the impact of increasing anthropogenic effects. Whitefish experience heavy harvest by the local fishers in addition to the thermal plume and cooling water intake impingement and entrainment from a power plant along the coast of this fishery. Knowing the spatial distribution of lake whitefish in the area, it is apparent that broods of lake whitefish may be directly affected as their spawning grounds overlap with regions of the power plan. Members of fishery management teams have the intent of maintaining a sustainable stock of fish. Thus, it is possible that they would seek to understand the potential effects caused by this power plant on their fish stock.

Knowing the historical data for the fish stock prior to the installation of the power plant allows for the generation of a population baseline; that is, a set of population data over time which has not been exposed to the effect of fishing, climate change, power plants, or any other anthropogenic activity over time. We present both the "perfect world" scenario outlined above, and a scenario that adds extra mortality through the addition of an anthropogenic effect. This anthropogenic effect is presented as an isolated effect caused by a power plant, the effects of harvesting fish, and finally the combination of both.

Each simulation splits fish into four graduating life stages: eggs, larvae, juveniles and adults. Graduation occurs at a specified number of weeks and is captured by a growth vector: $[19, 52, 104, 0]$. Each element in the growth vector represents the total number of weeks since agent spawning until the next life stage. Adults do not graduate to a new life stage so adult growth is not required. The adult ages are chosen because of the stage structured submodel [19]. Adult fish stages are split from two years to "age8plus", which encompasses all lake whitefish of eight years or older.

The simulation begins with injecting agents into the environment with a stock vector and a corresponding stock age vector. The initial stock used was: $[15000, 125000, 10000, 7000, 5000, 2000]$ and $[0, 19, 52, 104, 4 * 52, 8 * 52]$ respectively. Each entry in the stock and stock age vectors represent the total number of agents and their age in weeks. Additionally, carrying capacity was chosen based on a normal distribution with a mean of 300000 and standard deviation of 30000 across the entire period of 100 years so the carrying capacity varies between each year. For the scenario involving anthropogenic activity, there is the addition of the risk mortality vector: $[1.0, 1.0, 1.0, 1.0]$. The risk mortality rate is stochastically

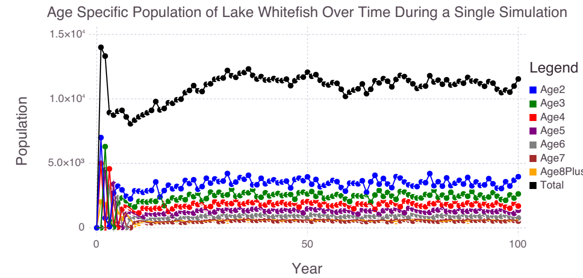

Fig. 2. The results of a single simulation of a Non-anthropogenic simulation using the FishEBM model. This plot illustrates the age specific population total of adults during the entire simulation.

applied to agent stages one through four, in ascending order left to right, for agents coming into contact with risk locations. The maximum mortality rate is chosen for all agents to study the largest potential effect of impingement and entrainment at risk locations. Parameters related to brood size, catchability, movement, and mortality are also included.

Figure 2 illustrates a graph of adult lake whitefish population over a simulation period of 100 years. Each line represents a specific age class of adult fish. The specific ages are chosen because of the stage structured submodel incorporated in this model [19]. The visible spike in initial population of the simulation is attributed to the initial stock of agents, which is why it is essential to run simulations over a long period of time. This implies assumptions must be made about the initial stock of fish for reproducible and realistic results. In this case, it was higher than the simulation's carrying capacity allowed for, so there was an initial decrease in the total adult population. Over time the model will periodically correct for this spike through all layers of mortality and spawning leading to a relatively stable population. A better set of stock parameters closely related to a resulting adult population distribution could reduce the initial population fluctuations. As expected, the population totals and spatial distribution of agents in the simulation are not perfectly periodic due to the uncertainty of autonomous agent behaviour.

Using the enviro-ABM model a fisheries management team could now apply a new anthropogenic effect (such as the power plant intake or increased harvest fishing) to perform risk assessment and determine if the added effects in the presence of one another have an additive or multiplicative impact on the population. Risk assessment requires a comparison between scenarios with nearly identical parameters and only varying the parameter values we would like to investigate. Figure 3 contains a plot of a set of total populations of four independent scenarios over a period of 100 years within our model. Scenario 1 is the original simulation from figure 2 and is assumed to be a perfect world with little or nonexistent anthropogenic activity. Scenario 2 is a similar scenario to the first simulation but exposes the agents to a specified intensity of harvesting. Scenario 3 expands scenario 1's simulation to include the effect of power plant cooling water intake. Lastly, scenario 4 combines the effects of both harvesting and

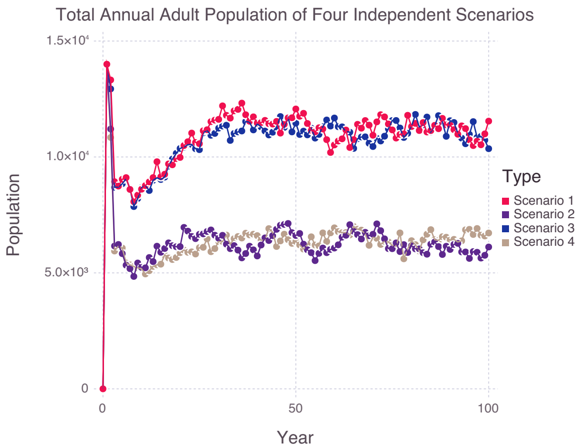

Fig. 3. Simulation results from the enviro-ABM model for four independent scenarios. Scenario 1 is the original simulation with little or nonexistent anthropogenic activity. Scenario 2 introduces harvest. Scenario 3 introduces power plant cooling water intake. Scenario 4 combines the effects of scenario 2 and 3.

anthropogenic activity in the second and third scenario.

As illustrated in Figure 3, simulations that included harvest (scenarios 2 and 4) have a reduced adult population relative to the simulations without harvest (scenarios 1 and 3), but the overall population trend of scenarios 2 and 4 is too similar to draw qualitative conclusions from. In this instance, using the parameters provided, harvesting definitely has an impact on total population over the 100 year period. There is insufficient information to judge the potential impact of the cooling water intake on the simulated fish stock. This is not a shortcoming of the model itself as we simply demonstrate a glimpse at some of the available information that this model can provide. For example, the model records the total harvest by age and harvest zone, spawning total by location, and type of mortality for each life stage during every time step. Tracking the total harvest and cause of mortality grants the ability to study various anthropogenic activities on Lake Huron lake whitefish. Further research is required to investigate a variety of anthropogenic scenarios where model outputs will be used to evaluate individual and cumulative effects on the fish populations, providing fisheries managers further tools for evaluating management decisions.

From a computational perspective, observations of the per scenario run-time provided rough estimates of the typical total simulation times across each scenario. For the large population scenarios, we observed typical run times centered around the 4 hour mark; while, low population scenarios were centered around the 2 hour mark. Our traditional agent-based model had run-times centered around the 24 hour mark across both scenario types. This represents a significant increase in simulation speed from the ABM to the enviro-ABM model.

IV. Conclusion

This study is applied to the lake whitefish fishery in Lake Huron to investigate possible complications introduced by local anthropogenic effects. The model was specifically designed to simulate the inclusion of anthropogenic activity including harvest as well as impingement and entrainment of lake whitefish from power plant cooling water intake. We have demonstrated the basic capability of our novel enviro-ABM design and we believe it is not limited to just the case study we provided. On a general level, this enviro-ABM serves as a fast generator of trends for any ecosystem of interacting autonomous agents it is needed for. A major success of the enviro-ABM is the improved computational performance. On top of the improved computational performance in comparison to traditional ABMs, there is no loss of information during calculations when using an enviro-ABM instead of a traditional ABM. Using the spatially indexed environment as an agent benefits a fisheries management team by granting the ability to rapidly test many scenarios to study results with a modern ecological model without long computation time or limiting the detail included in the model. One limitation of the enviro-ABM approach is the stochastic calculations for information on individual agents. With a low population or very small environment it would likely be beneficial to use a traditional ABM because individual agent properties have a larger effect on the simulation results. In the future, we would like to extend this model to include additional anthropogenic effects, such as spatially limited thermal plume. If possible, tailoring the current case study to improve the simulation of early life stages and including predator prey dynamics would likely improve overall simulation quality. We feel that enviro-ABMs could be implemented as a useful tool for assisting with critical decisions pertaining to sustainable management of ecosystems.

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