SIMSEA: A Multiagent Architecture for Fishing Activity in a Simulated Environment

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Keywords: Multiagents, Finite-state Machines, Muti-criteria Decision-making.

Abstract: Understanding fishermen decision-making proccess, plays a key role in predicting the impacts of the fishing activity in the marine ecosystems. Simulating fishing activity using multiagent based approaches provides tools that assist decision-makers in order to pursuit sustainable fishing activity. In this paper we present a multiagent architecture for the fishing activity where geo-referenced resources and fishing agents with different profiles are used to model and simulate the complexity of human fishing activity. A first implementation of the model (via NetLogo), along with gathered results, provides insights into the capability to build a research tool for fisheries management.

1 INTRODUCTION

Fishing activity has been under scrutiny mainly because of the over-fishing and its impact in marine ecosystems as well as in the economy of fishing communities. Different research tools have been used to understand the exploitation of the marine ecosystems, including trophic web and biogeochemical simulation models, despite the considerable problems in tuning and validating complex numerical models with field data (Pitcher et al., 2007; Morato et al., 2016). Multiagent systems have been increasingly used in the context of what is being defined as a coupled human and natural systems or CHANS systems (An, 2012). In these systems it is usually aggregated a GIS representation, making interaction more representative of the real world and socio-economic models, re-focusing attention in ecosystem analysis from the ecology of 'nature' to the important influence of people (An, 2012). With regard to the scenario being studied, different levels of complexity must be considered and all of them must be somehow incorporated in the model (Pitcher et al., 2010).

In this paper we present the SIMSEA, a multiagent architecture for simulating fishing activity in a geo-referenced scenario where simulated human decision-making agents with different profiles are used to explore the complexity of human decision-making. Profiles contribute to increase the diversity of behaviours of these agents, tuning their decisions by using a multi-criteria decision-making process. In this paper we resport on the first implementation of a model in NetLogo (Tisue and Wilensky, 2004) applied to the scenario of demersal fishing activity in Azores archipelago (NE Atlantic). Agents have different roles in the model, they are either static or dynamic, representing different entities such as vessels, ports and fishing grounds (areas where fishing activity occurs). The model uses a multi-criteria decision-making mechanism applied on the top of a finite-state machine to model agents' behaviour which simulate human decision-making. Moreover, the concept of risk aver-

Cascalho, J., Trigo, P., Cruz, M., Mendes, A., Giacomello, E., Ressurreição, A., Dentinho, T. and Morato, T.
SIMSEA: A Multiagent Architecture for Fishing Activity in a Simulated Environment.
DOI: 10.5220/0007393502020209
In *Proceedings of the 11th International Conference on Agents and Artificial Intelligence (ICAART 2019)*, pages 202-209
ISBN: 978-989-758-350-6

sion is used to create behaviour diversity among these agents. A set of agents with different profiles described as *optimistic*, *pessimistic* or *middle* are used to tune the behaviour of these agents. To the best of our knowledge, this is the first study focused on the simulation of fishing activities in the Azores using Agent-Based Systems.

The paper is organized as follows: In section 2 a background and related work is presented. Then, in section 3, a description is made of the architecture proposed. In sections 4 and 5, the implementation and the running experiment using NetLogo are discussed. Finally, in section 6, the conclusions are presented.

2 BACKGROUND AND RELATED WORK

Previous work on multiagent based simulation demonstrated the utility of these tools applied to different areas (Abar et al., 2017) . DISPLACE (Bastardie et al., 2015; Bastardie et al., 2013) is an agent based simulation tool applied to the fishing activity, calculating the income and evaluating the best vessels' trajectory under spatial constraints. It includes a geo-referenced dynamic model of the resources (i.e. fishing stocks) and the vessels have a simple decision-making process based on a finite-state machine architecture. This model is used essentially to evaluate the costs/benefits of agents' decisions predicting also what are fishing captures in different scenarios. Soulié and Thébaud (2006), also developed a multiagent bio-economic model to analyze the consequences of regulatory measures, such as temporary fishing bans on the allocation of fishing effort between target species and areas, and the potential economic impacts of these measures.

The models produced in the context of the CHANS systems are often based on production rule systems i.e. systems that use rules *if-then-else*, and some deliberative capabilities to fulfil goals however without explicit deliberation or cognitive processes. One of the reasons pointed out by some authors is the fact that simpler models are better suited if the objective is to predict the behaviour of an organization as a whole instead of predicting with accuracy a behaviour at the individual or small group level (Balke and Gilbert, 2014). Although SIMSEA is intended to analyse the global behaviour of a set of entities, it also has the goal to address a small group of agents following specific constraints related to the location and availability of resources. So, it is expected to provide decision-making methods that increase the capability of the simulation to address the diversity of behaviours related to the fishing activity.

Usually when human decision-making is part of the simulated model of an agent, the concept of being rational (Kennedy, 2012) is addressed. A rational agent has consistent and well-defined preferences across all available decisions options and chooses the option that meets its preferences best, taking into account all relevant information. Usually, the bounded rationality, a concept of rationality more close to human decision-making, is adopted. If an agent has a bounded rationality, he takes a decision based on his limited information and cognitive capabilities in his limited processing time (Groeneveld et al., 2017). A rational decision-making is often associated to maximizing expected utility. So, bounded rational agents are the ones that provide answers to problems maximizing the utility measured in that specific contexts and within their own limitations. Maximization utility is usually addressed as a multi-criteria decision problem, where enriched methodologies are used, implying the selection of the best compromise solution that usually depends on the preferences of the decision-maker (Tomic et al., 2011). In SIMSEA, agents modelling human behaviour use a multi-criteria decision-making mechanism. Moreover, to increase the diversity of behaviours, it was decided to adopt the concept of risk aversion/ risk seeking as a way to express agents with different behaviours and characterize their profiles as optimistic vs. pessimistic. Several authors have been considering these same concepts as a way to describe how agents' beliefs have consequences in their behaviour. In particular, in a financial crisis scenario, an optimistic behaviour corresponds to an agent that overestimates their information and capacities (Said et al., 2018). Other authors use the risk aversion perspective to create agents with different behaviours (Magessi and Antunes, 2013). In this case, they may have a high predisposition for risk, called a risk-demander, or a low predisposition for risk, a risk-fearful.

3 MODELS ARCHITECTURE

SIMSEA is intended to simulate fishing activity. The architecture is organized in three layers where each one is associated to different entities with specific purposes. The rationale behind the creation of the three layers is the following:

- The bottom layer refers to the geo-physical environment with information gathered from geographic information systems (GIS). This data is fixed along the simulation.

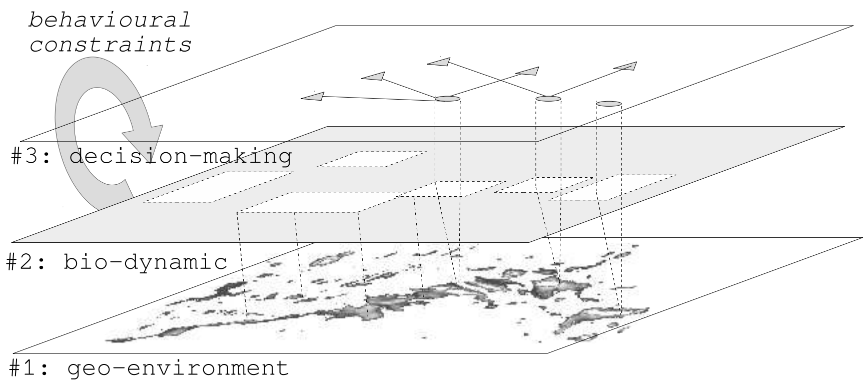

Figure 1: Different layers in SIMSEA architecture: The bottom layer corresponds to physical features (e.g. bathymetry, water temperature, etc); the mid layer includes the bio-dynamic features (eg. fish biomass index) and identifies fishing areas; the top layer includes fixed (i.e. fishing grounds and ports) and moving agents (e.g. vessels).

- The mid layer corresponds to fishery resources, attributing a value of available fish biomass for each fishing ground. This data can be obtained from the biology and behaviour of the species considered in the model or from other type of experts' data related to the amount of resources in the different fishing areas of the scenario.
- The top layer includes the static and moving agents (e.g. fishing grounds, ports and vessels) and their (economic and social) interaction.

Agents in the model have different levels of complexity. For example, vessels movements are the result of fishermen decision-making and, so, it must be added decision-making capabilities to these agents whereas fishing grounds are just reactive agents toward constraints imposed to the model i.e. closing a fishing ground to the fishing activity. As depicted in figure 1, constraints to the agents' behaviours with respect to the bio-dynamics (e.g. stock more or less abundant) and the interaction between agents (e.g. a port closes with adverse weather conditions) are also part of the model.

3.1 Simulated Environment

The simulated environment corresponds to the bottom and mid layers in the model. At the bottom layer it is defined the geo-referenced physical area for the scenario where data on bathymetry, mean temperature, etc, may be allocated. The mid layer adds biological information related to the fishery resources, e.g. fishing stock for different species and the variation of recruitment for the species captured (Bastardie et al., 2013).

Table 1: High level description of agents using Backus-Naur Form.

$Agent ::= < agentType, agentFeatureSpace, agentDecisionSpace >$
$agentType ::= VESSEL \mid FISHGROUND \mid PORT$
$agentFeatureSpace ::= VESSEL_{FeatureSpace} \mid FISHGROUND_{FeatureSpace} \mid PORT_{FeatureSpace}$
$agentDecisionSpace ::= VESSEL_{DecisionSpace} \mid FISHGROUND_{DecisionSpace} PORT_{DecisionSpace}$
$VESSEL_{FeatureSpace} ::= < geoRefLocal, velocity, workingPeriodMax, workingPeriodMin, restingPeriod, catchRate, fishingDistanceMax, fishingDistanceMin\ fishingPriceMax, fishingPriceMin, fishingCostMax, fishingCostMin, size, registeredPort, portOrigin, portDestination\_vector, fishingGround\_vector, profile\_vector >$
$VESSEL_{DecisionSpace} ::= < DECISION_{portDestination}, DECISION_{fishingGround} >$
$PORT_{FeatureSpace} ::= < geoRefLocal, state, constraintDestination, destination\_vector >$
$PORT_{DecisionSpace} ::= < DECISION_{portState}, DECISION_{constraintDestination}, DECISION_{constraintQuota}, DECISION_{constraintFishing} >$
$FISHINGGROUND_{FeatureSpace} ::= < geoRefLocal, state, biomassIndex >$
$FISHGROUND_{DecisionSpace} ::= < DECISION_{FishGroundState} >$

3.2 Agency Model

Agents main properties are summarized as follow (table 1):

- Agents make decisions supported by a set of features, some related to their own properties, others as a result of environment perception.
- Each agent can be of the type *VESSEL*, *FISHGROUND* or *PORT*:

(a) *VESSEL* and *PORT* types model human behaviours.

(b) *FISHGROUND* type is used to model the dynamics associated to fishing on a specific fishing ground.

- Feature space contains the set of features for each agent type in the model.
- Decision space has a set of higher level functions defined in the decision-making context as multi-criteria decision-making mechanism or as constraint decisions based on rules applied to some scenario.

Table 2 describes the details of the features associated to each agent. Agents are implemented through finite-state machines (Adam et al., 2017) and the decision-making functions are called in specific agents' states. In the example discussed in section 4, only the decision-making function related to getting to the fishing ground is implemented. The other types are the ones that result from rules imposed to the scenario. These rules model decisions concerning the management of resources by local government authorities [1].

FISHGROUND and *PORT* types can be on a *open* or *closed* state. The decision to open or close a port can be autonomous (e.g. weather conditions) while the decision to close or open a fishing area may occur from constraints defined in the scenario to be studied. Destination constraints are imposed by rules (e.g. Demersal fishing activity restricted 3 nm from shore). *FISHGROUND* type uses an index of relative abundance of fish (biomass index) which determines the catch for each vessel in that specific area.

Table 2: Lower level description of agents using Backus-Naur Form.

$velocity$ ::= nm/h
$workingPeriod$ ::= #hours-at-fishing
$restingPeriod$ ::= #hours-at-port
$fishingMaxDistance$ ::= max-distance
$fishingMinDistance$ ::= min-distance
$size$ ::= $size\_A \| size\_B$
$portDestination\_vector$ ::= [] |[$portDestination_1, portDestination_2, ...$]
$fishingGround\_vector$ ::= [] |[$fishingGround_1, fishingGround_2, ...$]
$catchRate$ ::= kg/h
$DECISION_{portDestination}$ ::= $multi\_criteria\_decision\_function(portDestination\_vector)$
$DECISION_{fishingGround}$ ::= $multi\_criteria\_decision\_function()$
$DECISION_{portState}$ ::= $multi\_criteria\_decision_function()$
$DECISION_{constraintDestination}$ ::= $constraint\_decision\_function(fishingGround\_vector)$

[1] In future models, these rules can be modelled as part of *governance* agents.

3.3 Decision-making

Two main concerns guided the implementation of decision-making. First we needed to use a decision mechanism with enough complexity to tackle a simulation where agents model human decision-making. Secondly, we were looking for a way to identify different profiles among agents that took decisions, expecting that these agents' behaviours could be biased to a more or less aversion to risk behaviour. Based on these two concerns, we decided to follow a multi-criteria approach with the following components:

- A set o $a_1 \ldots a_k$ alternatives (options) for each agent's decision.
- A set of criteria, $c_i, \ldots c_n$, defined for each alternative;
- A set of weights $w_i \ldots w_n$ which represents the relative importance each criterion has for the agents;
- A set of $f_1, \ldots f_n$ evaluation criteria.

Naturally, each criterion has a possible different domain from the other criteria and care should be taken in eliminating the scaling-effects of the used criteria.

More formally, we define a multi-criteria problem as:

$$decision = argmax_{a_i \in A}\{f_1(c_1, a_x), ... f_n(c_n, a_x) | a_x \in A\} \quad (1)$$

where A is a finite set of alternative actions, c_i, $i = 1, \ldots, n$ are n criteria, w_i, $i = 1 \ldots, n$ are the associated weights denoting the relative importance of each criterion and $f_1, \ldots, f_n$ are the evaluation criteria for each a_x. This means that as an output of the decision, the option based on the evaluation of multiple criteria applied to each alternative in A must be the best option that maximizes the result.
Each $f_i(c_i, a_x)$ is calculated as follows:

- $V_{c_i}(a_x)$ is calculated for each criterion c_i, $i \in \{1, \ldots, n\}$
- $f_i(c_i, a_x) = sgn(c_i) * V_{c_i}(a_x)$, $sgn(c_i) \in \{-1, 1\}$

To make the final decision, an utility function is calculated for each a_x, $x \in \{1, \ldots, k\}$ as depicted in equation 2.

$$\begin{aligned} U(a_x) = &< w_1, w_2, ..., w_n > * \\ &< f(c_1, a_x), f(c_2, a_x), ..., f(c_n, a_x) >^T \end{aligned} \quad (2)$$

The option a_x with highest utility is, then, selected. Note that $sgn(c_i)$ expresses the signal of the criteria, maximizing or minimizing the contribution of c_i to the utility.

As mentioned before, the output of the function V_{c_i} must be a universal comparable value. One possibility is to consider the value of a cost/gain for each

V_{c_i} e.g. the cost in *euros/km* of a vessel's trip. This was the solution that was tested in the simulation (see section 4). However there are other options like the ones that use preference functions that sum up the contribution of the option a_x that represents the intensity of a preference when compared to the other options (Tomic et al., 2011). In this case the contribution to utility is the result of comparison with other options instead of having an universal comparable value. This option is expected to be tested in future experiments.

Finally, selecting from a set of options a_x can also be constrained by rules specifying which set of options can be considered. So, for each decision, a constraint should be taken into account following the rules which are applied to the original set of options a_x, returning a sub-set of options (equation 3).

$$New\_A = constraints(A),\ New\_A \subset A \quad (3)$$

4 IMPLEMENTATION OF SIMSEA IN NetLogo

NetLogo (Tisue and Wilensky, 2004) is a free software platform founded in multiagent programming language and modelling environment for simulating complex natural and social phenomena. With NetLogo the modeller can give instructions to hundreds or thousands of independent *agents* specifying how they should behave and interact with one another. NetLogo is being used to build an endless variety of simulations, allowing to explore the behaviour of individuals under various conditions and the patterns that emerge from their interactions. The moving agents are called *turtles* and move over a two-dimensional grid of *patches* which may also execute instructions and interact with turtles and other patches. The execution cycle of instructions in NetLogo is made by calling all the agents in the model by a *supervisor agent* called the *observer*. NetLogo includes a tool for running the simulation experiments, dubbed *Behaviour Space*, that allows *parameter sweeping* i.e. systematically testing the behaviour of a model across a range of parameter settings.

Netlogo have been considered as one of the tools that supports simulation at a medium-scale of scalability (Abar et al., 2017). The fact that the development effort is easy and that the high level language used to model the agents facilitates the interaction between researchers with different backgrounds, led us to implement a first prototype in NetLogo. The following features were used in the model tested:

- The scenario of the experiment is the archipelago of Azores, NE Atlantic;
- A multi-criteria decision-making mechanism is used to select a fishing ground for vessels of a specific size, located at ports in one of the archipelago islands;
- Two criteria for selecting a fishing ground are applied: the distance from the port of origin and the fish biomass index;
- A profile is defined by weighting the two criteria differently.

A description of the environment and how the vessels make decisions is explained in the following sections.

4.1 Environment

The environment is defined by the combination of a geo-referenced physical area, the bathymetry and a biomass index. Depth was obtained as bathymetric data composite using multiple sources: *GEBCO_08*, grid (*MOMARGIS v*2, *DOPUAz*), multi-beam surveys (GMRT grids), point and contour data digitized from nautical charts in the vicinity of the islands.

In the SIMSEA model geo-referenced physical area of the scenario represents the archipelago of the Azores and respective fishing areas within the Exclusive Economic Zone (EEZ). A value of bathymetry is added to each cell of the grid (corresponding to an area $0.14km^2$) used in the scenario.

The biomass index is a measure of relative biomass of fish, and the model use it to represent the biomass of fish in the different fishing areas. In the present model it is assumed that the value is static for each simulation. A range of values from 1 to 9 was arbitrarily attributed to the index, and randomly associated to each fishing area.

Vessels moving in the environment know both the bathymetry of each patch and the location of the different fishing grounds. In the simulation, it was considered the fishing of the most valuable commercial fish species in the Azores, the blackspot seabream *Pagellus bogaraveo* (Menezes et al., 2013).

4.2 Agent's Decisions

The decision-making mechanisms were modelled only for agents of the *VESSEL* type when they select a specific fishing ground.

$$U(a_{fg}) = w_d * f(c_d, a_{fg}) + w_b * f(c_b, a_{fg}) \quad (4)$$

Two criteria c_d and c_b, are used to calculate the utility for each fishing ground option (see equation 4). The first corresponds to the distance from port origin to the fishing ground, measured as a mean distance between the closest patch and the most distant patch of a specific fishing ground area from the port. It has a negative contribution to the final result as depicted in equation 5. The second criterion is the index of biomass of the fishing ground area and has a positive contribution as depicted in equation 6. The maximum value corresponds to the patches where it is expected to capture more fish.

$$f(c_d, a_{fg}) = -V_{c_d}(a_{fg}) = -fuel\_price * distance(a_{fg}) \quad (5)$$

$$f(c_b, a_{fg}) = +V_{c_b}(a_{fg}) = +fish\_price/kg * biomass\_index(a_{fg}) \quad (6)$$

With the help of the equation 4, three different profiles are identified, based on the *risk aversion* concept (Mandrik and Bao, 2005). The first one, *optimistic*, assumes that it will always be rewarding to select the spot with the highest biomass index discarding the distance from the port. In this case, the weight w_b = 1, meaning that it takes into account only the index of biomass criterion. The second one, *pessimistic*, selects the closest spot, because it assumes that it will be never captured enough fish to compensate the trip cost. In this case, the weight w_d = 1. Finally, the *middle* profile corresponds to the fisherman that weighs equally the two criteria evaluating the cost of long distances versus the gains of fish catches.

5 RUNNING THE EXPERIMENT

To test SIMSEA model, two experiments were run with different fishing price i.e. the Exp. 1 with lower price and the Exp. 2 with a higher price. An experiment comprised four simulations, each one with a random distribution of biomass index and with a set of profiles covering all the possible types of fishermen behaviour. Moreover, each simulation was run for different sets of optimistic vessels, pessimistic vessels, middle vessels and for a set of half of vessels optimistic and a half pessimistic (mixed).

The experiment intended to test the capabilities of the model. The values used for the different parameters are not yet validated and some of them are only reference values.

5.1 Input Variables

Table 3 describes the input variables tested in the simulation. Each experiment had four simulations, each one setting a random distribution of biomass index. A simulation run for a time limit of 240 hours, corresponding to 10 days and was repeated 25 times for each profile. The moving agents representing vessels were divided in two categories according to vessel length, namely size A to simulate vessels with 0-9 m in length and size B to simulate vessels with size superior to 9 m. The variables fuel price and working and resting period, had different values according to the vessel type.

The two categories of boats were proscribed to fish within 3 nautical miles from shore and size A boats were also prohibited to travel beyond 30 nautical miles.

The vessels move along a grid of patches and capture quantities of fish proportional to the fish biomass present in a given area.

Table 3: Input variables tested in the SIMSEA.

Experiment		**Exp. 1**	**Exp. 2**
N.º simulations		4	4
N. runs by profile	Optimistic	25	25
	Pessimistic	25	25
	Mixed	25	25
	Middle	25	25
Working Period (h)		A (6-12) B (12-120)	A (6-12) B (12-120)
Resting Period (h)		A (10) B (8)	A (10) B (8)
Fuel price ($euros/nm$)		A (4) B (7)	A (4) B (7)
Fish price ($euros/kg$)		8	15
Biomass index		Random	Random

The profile is related to the choices made by fishermen to select a specific fishing area. The profiles optimistic, pessimistic and middle were present in both experiences. The choice of fishing grounds was dependent on the evaluation made within each profile.

The simulation run for the cases where all vessels A and B were optimistic (w_b=1), pessimistic (w_d=1), middle (w_b=0.5 and w_d=0.5) or mixed (half of the vessels pessimistic, the other half optimistic). Such behavioural diversity was expected to represent the different behaviours of fishermen.

Fuel price per nautical mile (nm) was determined for each vessel type according to the vessels characteristics. Fuel price was calculated by multiplying the vessel speed by the vessel consumption per mile and this value by the current fuel price for fisheries in the region (0.58 Euros). The price of the fish was established according to the annual average value in the auction for blackspot seabream.

5.2 Experimental Results

Figure 2 and 3 shows cost vs. gain of fishing resulting from the simulation, for both Vessel A and B types. In both figures it is possible to observe that Vessel A has the points restricted to a specific range cost. This result may be related to the fact that A are prohibited to travel beyond 30 nautical miles. Nevertheless, vessels of both types reach the break even in the two experiments, showing that restrictions do not rule out the possibility of vessels having profit. It is also worth of notice the higher gain variability from experiment 2, with higher fish prices when compared with experiment 1, as expected.

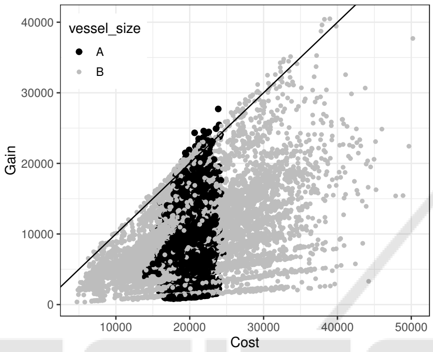

Figure 2: Cost vs gain for Vessel A (black dot) and Vessel B (grey dots) types. Gains are calculated from the sale of the captured fish using the lowest fish sale price.

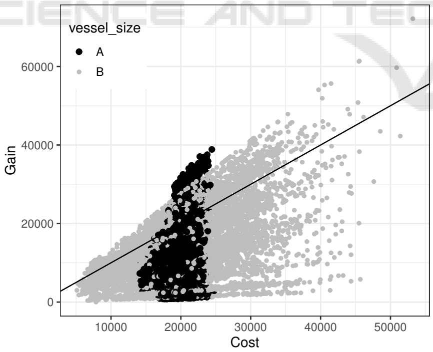

Figure 3: Cost vs gain for Vessel A (black dot) and Vessel B (grey dots) types. Gains are calculated from the sale of the captured fish using the highest fish sale price.

The estimation of mean profit for the types of agent profile and fish biomass distribution index led to major differences in values, as demonstrated in figure 4. This figure shows the importance of distribution of biomass for the final results of the experiments. It also shows that the different profiles have significant differences in revenue outcomes, providing an insight of the sensitivity of the model towards these two parameters

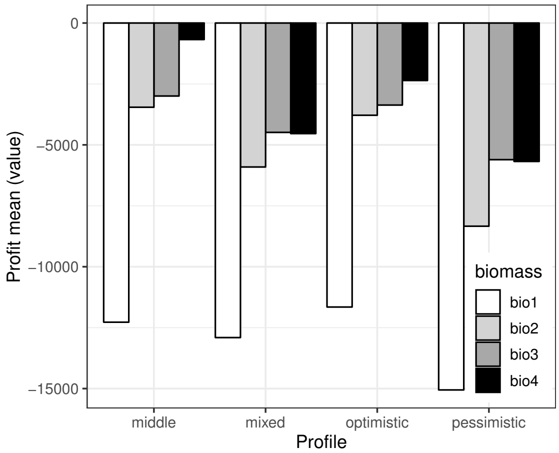

Figure 4: Mean profit per agents profile on experiment 2. The four colors distinguish the biomass scenarios.

These experiments confirm the complexity of the simulation model and the high influence of results for the controlled factors as agent's profile, vessel type and fish biomass distribution.

6 CONCLUSION

In this paper we present SIMSEA, a multiagent simulation system to support decision management related to fishing activity. A three layer architecture aggregates the data from GIS and the data from fishing resources to feed the agents, representing the entities in the simulated context.

The NetLogo implementation provided insights on how the model reacts to the diversity of data. The experiment used profiles and a randomized set of initial parameters to study the output patterns. These features and data were responsible for a diversity of outputs for each category of vessel's size and for the different profiles. As a first approach testing the model, it is possible to identify that fishing profit may be influenced by agent profile and the variability associated to the distribution of biomass index. As expected the profiles that target fishing areas with higher biomass index are those that obtain a higher revenue, even when they ignore the cost associated to the distance.

Further work must be done to improve the decision model. Improvements can be obtained by adding a dynamic fishing stock model, by increasing the space of decision in the *VESSEL* and *PORT* agents' types and, at the same time, testing other multi-criteria decision-making mechanisms, such as the ones based on comparing preferences.

ACKNOWLEDGEMENTS

This work was funded by FEDER (85%) and by the Azorean Regional Funds (15%), trough the Operational Program Azores 2020, in the scope of the project ACORES-01-0145-FEDER-000049. We thank Luis Rodrigues and Hugo Diogo for sharing the data used in this study, and the anonymous reviewers for their valuable comments and suggestions. AR acknowledges Fundação para a Ciência e Tecnologia (FCT), through postdoctoral grant (SFRH/BPD/102494/2014) and the strategic project UID/MAR/04292/2013 granted to MARE.

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