Proceedings of the 10th International Workshop on Simulation for Energy, SustainableDevelopment & Environment,005
19th International Multidisciplinary Modeling & Simulation Multiconference

2724-0061 © 2020 The Authors.
doi: 10.46354/i3m.2022.sesde.005

Agent-based modelling of a small-scale fishery in Corsica

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Abstract

In this work we introduce a new multi-stock, multi-fleet, multi-species and bioeconomic model for the complex system of a small-scale fishery. The objective is to study fisheries in order to ensure the renewal of the stock of biomass. This stock represents both a means of subsistence for fishermen but also contributes to food security. We model the system as a *Multi-Agent System* using both *Cellular Automata Model* (*CAM*) and *Agent-Based Model* (*ABM*) computational modelling approaches. *CAM* are used to describe the environment and the dynamics of resources. *ABM* are used to describe the behaviour of fishing activities. The main interest of the conceptual model lies in the proposed laws and in its capacity to organize hierarchically all the local interactions and transition rules within the simulated entities. We report preliminary results showing that our modelling approach facilitates software parameterization for the specific requirements implied by the context of a small-scale fishery. The main results of this work consist in the creation of a computer modelling structure CAM and ABM, which constitutes a preliminary for an optimized resources management. In a future development, we will improve the behavior of economic agents in order to consider the complexity of their decision making.

Keywords: Fishery modelling, Multi-Agent System, NetLogo pattern.

1. Introduction

The deterioration of fishery ecosystems as a consequence of human activity implies the need to develop an effective and sustainable management of fisheries. Hence, there is a need to efficiently manage halieutic resources over time. This regulation cannot be carried out in a uniform way across the globe due to the differences between all the ecosystems.

The development of a sustainable management requires an accurate study of the location's characteristics so as to set appropriate management rules. Given its evolution, computer technology is a promising tool to understand and predict the behaviour of dynamical complex systems. Through computer simulations, *Information Technology (IT)* tools allow to study numerous cases so as to develop sustainable fishery management and maintain biodiversity in the ecosystems considered. In this preliminary work, we present a conceptual model for the design of a small-scale fishery system in the form of a *Multi-Agent System* (*MAS*) based on both *Cellular-Automata Model* (*CAM*) and *Agent-Based Model* (*ABM*) computational modelling approaches (Hogeweg, 1988). As stated in (Lindkvist et al., 2020), "small-scale fisheries consist of an intricate network of individuals, institutions and communities. They are also part of a wider mesh of international trade, tourism and technological change. This complexity makes it hard to develop sustainable policies that would be easily applicable." Traditional fishery models in economics are based on strong hypotheses regarding both the fishermen's decision-making and population dynamics in space. They are based on emphasised analytical solutions in terms of equilibrium conditions leading to adopt simplifying assumptions such as representative agent approach, a perfect rationality of economic agents, the absence of interactions amongst agents and an instantaneous adjustment to equilibrium. On the other hand, modelling a complex fishery system using computational modelling approaches looks promising to embrace complexity and overcome issues caused by the paucity of information (Lindkvist et al., 2020). In this paper, we develop a *MAS* of the spatio-temporal dynamics of a small-scale fishery to deal with the limitations in traditional bioeconomic fishery models. The *MAS* deals with heterogeneous behaviours both in economic agents' decision-making and in population dynamics in space, shaped by many interacting components. To achieve our modelling purpose, our main assumption is that the complex multi-scale dynamic system is based on a set of local interactions and transition rules organised hierarchically within enough simply entities to be simulated on traditional computers. We obtain an effective model to produce modular and scalable experimentation that can serve as a guide for specific management scenarios. The following sections of this paper are organised as follows: in a second part, we present the state of the art in both the literature of economics and the literature of complex systems. In a third part, we define the dynamic complex system of a fishery. In a fourth part, we review the modelling concepts that underlie this work. In a fifth part, we present the conceptual model and its bioeconomic dynamics. In a sixth part, we detail the main components of the resulting computer model. An example of computer simulation is presented in the seventh part. General preliminary results are commented and discussed in an eighth part. Finally, we conclude and present research perspectives in the last part.

2. State of the art

The economic literature on fisheries developed significantly in the 1950s. The first major works in the field were from (Gordon, 1954) and (Schaefer, 1957), who are considered as the first authors of bioeconomic models for the regulation of fishery resources. They applied these models to the issues of resource over-exploitation by developing the *maximum sustainable yield* concept. Since these pioneering works, many advances have been made thanks to the contributions of game theory and spatial economics. In this case, agents are considered as perfectly rational individuals (which implies to model fishermen as individuals able to perfectly apprehend all the impacts resulting from the activity of fellow fishermen). These various impacts are assimilated to negative externalities (Pigou, 1932) that result from the fact that the exploitation of the fishery resource by one agent affects the actions of other fishermen. Indeed, through the fishing activity, the stock of resources deteriorates, which affects all fishermen, each of them seeing their own stock reduced. This effect was examined by (Levhari and Mirman, 1980) in a *Cournot duopoly* in which these authors examine a cod war between Iceland and Great Britain and highlight this conflict's inherent economic implications.

Further improvements in the modelling scope were achieved thanks to the introduction of dynamics. Several authors, among them (Dockner et al., 1989), (Clark, 1990), (Dockner et al., 2000), (Van Long, 2010), (Long, 2011), (Benchekroun and Van Long, 2002), (Jørgensen and Zaccour, 2007), (Benchekroun, 2008), (Colombo and Labrecciosa, 2018) and (Benchekroun et al., 2020), studied the applications of dynamic and differential game theories to the management of fishery resources. For the basic analytical framework, dynamic and differential games adopt assumptions that are similar to those used by static games. Thus, there is a set of perfectly rational players, each seeking to maximise their own objective. However, these models have some limitations. Notably, in the real world, fishermen have no perfect knowledge of the state of biomass stocks or their migration. It is therefore unrealistic to assume that these negative externalities are perfectly taken into consideration and that fishermen are perfectly rational. Moreover, the optimum cannot be reached without perfect information. Finally, the heterogeneities between fishermen are poorly considered in this kind of model - if considered at all.

Concerning the spatial approach, space is generally considered as homogeneous in the economic literature. The consideration of its heterogeneous nature led the authors to focus on the impact of biological characteristics on fishing and species recruitment. The resource is not uniformly distributed in space, due to the fact that some fishing patches are more fertile and have higher growth rates than others. Furthermore, fishery resources are not static and migrate in time and space. These migration phenomena are modelled in the following contributions: (Tuck and Possingham, 2000), (Sanchirico and Wilen, 1999), (Sanchirico and Wilen, 2001) and (Smith et al., 2009). Although these works brought forward significant advances regarding the issue of over-exploitation of fishery resources, they suffer from certain limitations. The decisions regarding locations by fishermen are the result of an economic computation allowing the optimisation of their rent. In accordance with the rent dissipation hypothesis in the Gordon and Smith models, fishermen determine the location of their activity according to the relative profitability of fishing patches until the rent is dissipated over all patches. This is due to the adoption in these models of an "open access" fishing hypothesis over the whole space, which is unrealistic, as is the optimisation of the rent.

Because of all the limitations in these models, we focus in this work on the spatio-temporal modelling of the complex fishery system using agents. The use of agents will allow us to gradually introduce the complexity inherent to this kind of system (Arthur, 2014), (Tesfatsion, 2017). The fishery's complex system is composed of a large number of heterogeneous entities. The behavioural descriptions that can result from it require modelling multiple interactions between many entities. The modelling process primarily involves conceptual and computer models formulations which are performed by modellers. The use of

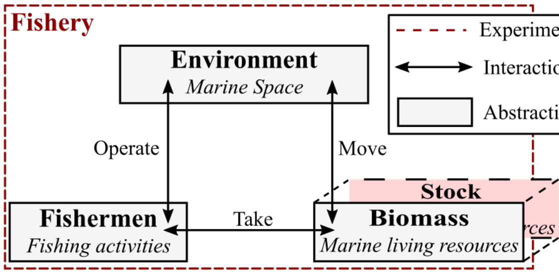

Figure 1. Illustration of the complex fishery system (Idda et al., 2020).

agents will allow us not to limit our scope to the study of an equilibrium, and also to understand the different interactions between agents. On the other hand, fishermen are no longer supposed to be perfectly rational and homogeneous, which means that we can simulate scenarios in the "digital world" closer to the behaviour of fishing activity in the "real world".

Modelling a complex fishery system in the form of an *ABM* has been developed over the recent years (Carrella et al., 2019), (Bailey et al., 2019), (Cenek and Franklin, 2017), (Carrella et al., 2020), and (Burgess et al., 2020). In these *ABM*, authors develop algorithms for decision-making processes within fishing agents. (Carrella et al., 2019) used 13 different (mostly adaptive) strategies in their POSEIDON *ABM* to evaluate the outcome on fishermen's profits. They have shown that the bandit strategy is the most effective in their case. Nevertheless, in their *ABM*, agents are not heterogeneous, which limits the scope of their result. (Carrella et al., 2020) compared predicted to observed fishing models. They find that *ABM* with adaptive agents perform better predictions. On the other hand, when the *ABM* assumes that fishermen are maximisers, profits will be overestimated. Although these *ABM* provide important insights, they include a limited consideration of space and heterogeneity of the different agents, as well as the economic model in which fishermen interact. One of the main difficulties faced by the modeller stems from the treatment of different scales of time and space. Spatial scales are particularly difficult to model because most fish species are highly mobile.

3. The complex fishery system

Fishery science refers to a complex bioeconomic system characterised by a natural or artificial aquatic environment exploited by industrial, artisan and recreational fishers. This general definition is the experimental frame from which the dynamics of the system are usually observed (Bommel et al., 2000).

On figure 1, we consider three main entity categories: - the *environment*, the locus of stakeholders movements and interactions; - the *biomass* exploited for economic purposes and that generally evolves according to a *global population law*; - *fishermen* operating in the environment and interacting by harvesting biomass from different *stocks* (patches in the environment). Consequently, in a computer simulation it is a matter of representing a set of hierarchically interconnected entities, localised in space and time, representing "a very large number of fish, a fragmented space and fishermen"(Bousquet, 1995, p. 150). The difficulty of modelling this kind of system is accentuated by the fact that the observations of this system require perspectives belonging to different disciplinary fields, and consequently the different modellers perceive this system in very different ways. Only recognised unifying concepts such as *CAM* and *ABM* allow to work in this direction.

4. Modelling concepts

4.1. MAS paradigm

As often reported in the literature, when dealing with the simulation of the spatio-temporal dynamics of a complex system of a set of autonomous and interacting constituents, the *MAS* paradigm is particularly well suited. This paradigm implies to consider the complex system through the prism of a set of subsystems that can be static or dynamic, connected and hierarchically organised. These are subsystems which interact in a unique environment which for the observer constitutes a *MAS*. The strength of the *MAS* perspective lies in its capacity to formulate the explanation of the behavioural dynamics of the complex system considered, as the result of a set of autonomous constituents called *agents*. Agents here are individual entities that interact in the *environment* according to *interaction links*. These agents are therefore the key concepts from the point of view of *MAS* and are generally sufficient to formulate an agent-based conceptual model. Thus, the conceptual model of a *MAS* is the abstract representation of a complex system in which clearly identified entities, called agents, interact with each other as well as with an environment. The interaction mechanisms linked to these interactions can be of different natures and evolve over time.

They are generally expressed in the form of *interaction rules* which describe the mechanisms of interaction between agents and which are clearly stated. The modelling process based on the *MAS* paradigm is illustrated in figure 2. In computer simulation science, the *MAS* paradigm is nowadays considered as one of the best methods for modelling complex dynamic systems. It is the source of two major modelling processes: one leading to the formulation of *CAM* and the other leading to the formulation of *ABM* (Bonabeau, 2002).

4.2. Cellular Automata

Cellular Automata (*CA*), initially proposed by *Stanislas Ulam* (1909-1984) and by *John von Neumann* (1903-1957) in the late 1940s, are multicomponent conceptual models that are generally organised at two levels of abstraction (Innocenti et al., 2016). A first level of abstraction called "local" or "micro" is structured according to a regular grid of com-

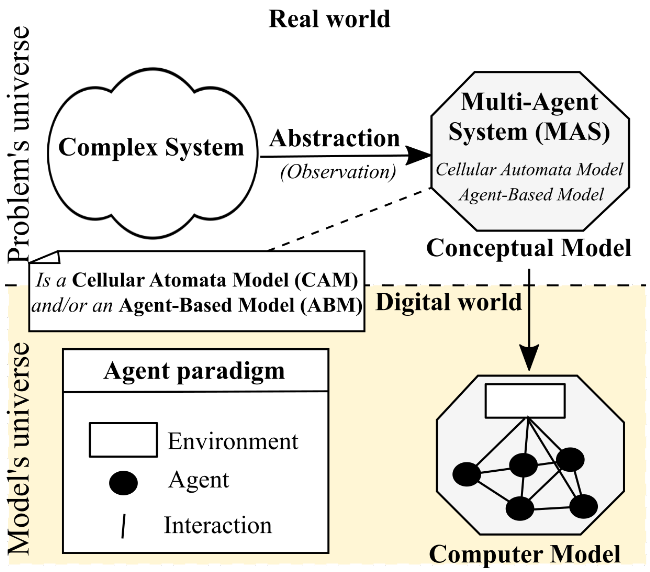

Figure 2. Formulation of a conceptual model according to the *MAS* paradigm, based on (Innocenti et al., 2020).

ponents. A second level of abstraction called "global" or "macro" is considered to observe the outputs of the model through the composition of the "local states" of these components. In a *CA*, the components are called cells and each of them has a finite state that can evolve over time according to a deterministic or stochastic transition rule. During the simulation process, at each time step, the same transition rule is applied simultaneously to all the cells in the grid. It generates a new population of cells whose states entirely depend on the states of the previous generation. The computation of the state of a cell at time *t+1* is a function of the state of this cell at time *t* and of the states of the finite subset of cells *N* called *neighborhood*. In this paper, the *CA* model essentially provides the conceptual foundation used to represent marine space.

4.3. Cellular Automata Models

CAMs are specialisations of the basic *CA* conceptual model. Thus, in a *CAM* the fixed agents of the environment play a prominent role in the mechanisms of interaction. The vast majority of these models are based on the specification of interactions between *agents* that can extend over several *levels of abstraction*, generally two or three. We consider *CAMs* as an increasing specialisation of the basic *CA*, where space and time are discrete and interactions are always local but where the environment, cells and interactions are more developed than in *CA*. Nowadays, they are usually used as conceptual tools to model spatial spreading dynamics as observed in some complex systems in physics (Rui et al., 2018), biology (Schimit, 2021), as well as in economics (Chen et al., 2019). Formally, they group together in the same entity more complex variations of the basic conceptual model of the *CA*. However, the definition of local transition rules in discrete space must remain quite simple to implement, even in the case a large number of components distributed on several abstraction levels. Moreover, the simulation of executable *CAMs* makes it possible to exploit the computing parallel (GPGPU and multi-core processors) and distributed computer hardware architectures (Innocenti et al., 2009). Finally, as *CAM* inherit the characteristics of *CA*, they also benefit from the emergence phenomenon which appears during some of the simulation experiments. It should be noted that the *CA* model and its *CAM* extensions also offer many technical benefits: they are adapted to *Object Oriented Programming* (*O.O.P.*). They also allow the production of computational models through the expression of modular and scalable components.

4.4. Agent-Based Models

ABMs are *CAM* extensions that have additional agents that can move in the environment. Their basic components are *fixed agents* and *mobile agents*. The environment is also considered as an agent. Figure 3 illustrates schematically the difference between a conceptual *CAM* model and an *ABM* type.

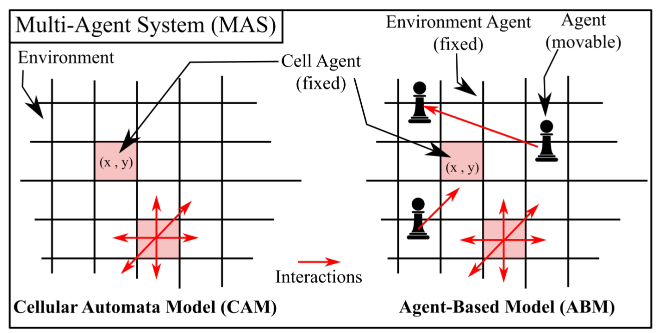

Figure 3. *MAS*: *CAM* versus *ABM* (Innocenti et al., 2019).

In life sciences, *ABMs* are called "Individual-Based Models" (*IBMs*). *CAMs* and *ABMs* often benefit from an intrinsic capacity to describe many phenomena from the reality with great realism, mainly through the expression of transition rules formulated on very simple mathematical bases. The scientific literature presents the good performance of these models in many cases. Thus, the *ABM* allows to apprehend the complexity of a natural system according to a reductionist modeling process, easier to conceptualise. In the case of fisheries, they allow to use simplified formulations of a local economic behavior. They are based on the description of local autonomous entities and interactions, leaving the modeller to observe the behaviour of the system as a whole, from the appearance of new properties, not known a priori, through the emergence phenomenon.

5. Conceptual modelling

In this model we chose to focus on the interaction between fish population dynamics (ecological dynamics) and fleet dynamics associated with fishing decision processes (economic dynamics), as is usually the case in fishery science (Bousquet, 1995). In a fishery model conceptualised as a *MAS*, the entities of interest, i.e. economic agents (fishermen) and biological agents (biomass, fish), are spatially distributed in an environment consisting of fixed cells (*CAM*). Some of the agents are modelling individuals who move and interact in the fishery environment, especially considering different temporal granularity (*ABM*). The integration of the economic rules of fishing is obtained through the formulation of interaction rules between fishing agents (and biological agents) in subsets of cells describing different fishing patches (stocks).

5.1. Agents' biological dynamics

Our biological agents are based on a metapopulation model defined as a group of subpopulations distributed in spatially discrete habitats and interconnected via dispersion rates. Since the spatial dynamics of the population is described in a *CAM*, the evolution of the biomass in discrete time $B_{N,\omega,t}$ of different patches of the discrete space N is given by:

$$\begin{aligned} B_{i,\omega,t+1} = B_{i,\omega,t} + F(B_{i,\omega,t}) - H(B_{i,\omega,t}, E_{i,p,t}) \\ +D(B_{i,\omega,t}, \sum_{\substack{m=1\\ m\neq i}}^{8} B_{m,\omega,t}) \end{aligned} \tag{1}$$

Index i corresponds to a fishing patch, $i = \{1, ..., N\}$. Index m corresponds to the adjacent cells that constitute a patch i. Index ω represents the different fish species present in the patch i. $p = \{1, ..., P\}$ is the set of fishermen agents in the model.

$F(B_{i,\omega,t})$ is the instantaneous biomass evolution function in a patch i, such that:

$$F(B_{i,\omega,t}) = r(B_{i,\omega,t})(1 - \frac{B_{i,\omega,t}}{K_i}) \tag{2}$$

This corresponds to the logistic function of the (Verhulst, 1838) model in which r is the intrinsic growth rate and K_i is the carrying capacity in the patch i.

We assume that the fishing function $H(B_{i,\omega,t}, E_{i,p,t})$ in i can be represented in linear form. It depends on the fishing effort $E_{i,p,t}$ in i and the quantity of biomass $(B_{i,\omega,t})$ in i. q_p is the catchability coefficient of a fishing agent p. This coefficient describes the level of technology of the agent, i.e. the higher q_p, the greater the quantity of biomass caught for the same level of effort. Furthermore, we assume that all species fished can be caught with the same fishing gear. Thus, the fishing effort and the catchability coefficient are not dependent on the species ω. So, we express H, such that:

$$H(B_{i,\omega,t}, E_{i,p,t}) = \begin{cases} q_p B_{i,\omega,t} \sum_{p=1}^{P} E_{i,p,t} \; si \; Z_t = Z_i \\ 0 \; otherwise \end{cases} \tag{3}$$

where $Z_i = [px_i; py_i]$ and $Z_t = [px_t; py_t]$ respectively represent the coordinates of the patch i and of the fishing agent p.

A fisherman agent only fishes if it reaches the patch i it chose during its internal decision process. Biomass migration occurs in Moore's neighborhood from the corresponding 8 adjacent cells, i.e.:

$$D(B_{i,\omega,t}, \sum_{\substack{m=1\\ m\neq i}}^{8} B_{m,\omega,t}) = In_{i,t} - Out_{i,t} \tag{4}$$

With

- $In_{i,t} = d_{m,i,t} \sum_{\substack{m=1\\ m\neq i}}^{8} B_{m,\omega,t}$
- $Out_{i,t} = d_{i,m,t} \sum_{\substack{m=1\\ m\neq i}}^{8} B_{i,\omega,t}; m = \{1, ..., 8\}$

$In_{i,t}$ corresponds to the entries in the patch i at a percentage $d_{m,i,t}$ and $Out_{i,t}$ represents the exits from the patch i to the 8 cells of the neighborhood at a percentage $d_{i,m,t}$.

Departures from a patch must coincide with arrivals in the destination patch, as long as the K carrying capacity of the destination patch has not been reached. Otherwise, the excess biomass is considered zero at destination in the patch.

Temporal granularity Δt of the model (time step) corresponds to one hour, which makes it possible to take into account the fleet's travel time in a more refined way. Furthermore, we assume that a fishing trip does not exceed 24 hours. In other words, we only consider fishing campaigns of the "small-scale" type (artisan fishing). Our model can be adapted to be extended seamlessly to other types of fishing (coastal fishing, offshore fishing or large-scale fishing) by adapting temporal granularity. We assume that during a trip a fisherman only exploits one patch per fishing decision from the home port. A fisherman has a fixed effort that he entirely deploys in the chosen fishing patch. The decision process related to the choice of a fishing patch is exclusively based on the location of this fishing patch.

5.2. Agents' economic dynamics

The computation of the fishing rent of a fishing agent is given by:

$$R(B_{i,\omega,t}, E_{i,p,t}) = \sum_{\omega=1}^{\Omega} [p_\omega H(B_{i,\omega,t}, E_{i,p,t})] \\ -c_p H(B_{i,\omega,,t}, E_{i,p,t})^2 - \gamma S_i \tag{5}$$

with $p_\omega \geq 0$ corresponding to the sale price of ω species. We assume that the selling price of a given species is a regional price. Since biomass is considered to be homogeneous throughout the entire territory, its selling price is also identical. This assumption is usual in bioeconomic models in which a world price is generally assumed for simplification purposes.

There are two components in the cost function. (1) $c_p H(B_{i,\omega,t}, E_{i,p,t})^2$ represents the direct fishing cost. This cost is assumed to be quadratic and convex. Thus, an increase in fishing is associated with a higher cost at an increasing rate, due to the fact that a large fishery implies a decrease in the biomass stock which becomes more and more costly to harvest. (2) γS_i represents the portion of the cost related to the travel of a fishing agent. It is assumed to be linear with the distance S_i travelled to reach the chosen patch i (number of cells to reach the patch i from the home port of the fishing agent).

Furthermore, we assume that if a fisherman fails to earn a positive rent, he leaves the market after a certain number of periods (fixed at three months). The logic movement of a fisherman agent is illustrated in figure 4.

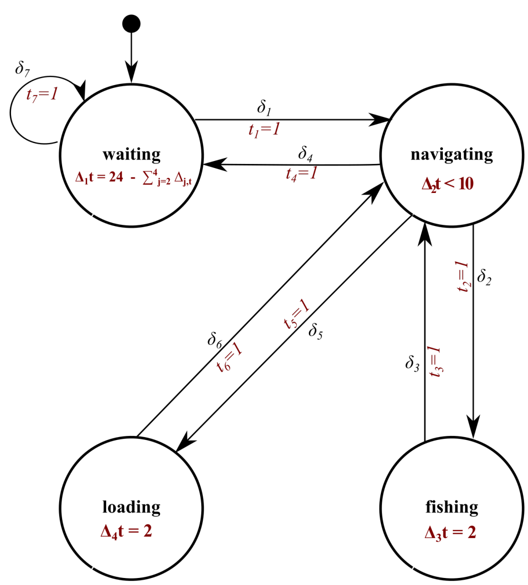

Figure 4. Status diagram of the fishing agents.

The travel logic of the fishing agents is modelled according to four finite states of activity over a period corresponding to the working week of the French legislation such as:

- *Waiting* → *Waiting*: activity state *Waiting* symbolises periods of fishing inactivity related to the presence of the fishing agent in the home port (e.g. when leaving and after returning from a fishing activity). Between two trips, the period of inactivity of a fishing agent is given by: $\Delta_{1,t} = 24 - \sum_{j=2}^{4} \Delta_{j,t}$.
- *Waiting* → *Navigating*: activity state *Navigating* corresponds to the agent's travel activity from his home port to the target fishing patch or vice versa. The behaviours related to this state of activity imply taking into account travel times between home ports and fishing patches. We assume that the fishing agents' travel time does not exceed 24 units of time and remains strictly inferior to 10 units of time, i.e. $\Delta_{2,t} < 10$.
- Fishing : this state corresponds to the fishing activity, time of setting the nets in the patch *i*. The fishing time $\Delta_{3,t}$ is fixed at two time steps.
- Loading : the latter is the time of nets removal. This time is given by $\Delta_{4,t} = 2$.

Each state transition is done in one hour, i.e. in one time step.

As for the four sequences mentioned above, they are repeated every week with the following recurrence:

- *Waiting* → *Navigating* → *Fishing* → *Navigating*: This sequence takes place at each restart of the activity, i.e. on the first day of each week. At the beginning of a week of fishing, each fisherman leaves the home port to reach the fishing patch they have chosen, throw nets and then return to the home port.
- *Waiting* → *Navigating* → *Loading* → *Navigating* → *Fishing* → *Navigating*: This sequence is repeated over the next four days/outings. Fishermen leave the home port, go to the first fishing patch, take up their nets, go back to the second fishing patch, throw their nets again and return to the home port.
- *Waiting* → *Navigating* → *Loading* → *Navigating*: This sequence corresponds to the last fishing day of the week. Fishermen leave the home port for their previous fishing patch, take up their nets and return directly to the port.
- *Waiting*: This last one represents a day of rest for fishermen. They stay in the home port for one day.

The fishing automaton can be represented by the following state-transition table:

Current state	Input	Next state	Output
Waiting	δ_1	*Navigating*	Move
Navigating	δ_2	*Fishing*	Throwing of the nets
Fishing	δ_3	*Navigating*	Move
Navigating	δ_4	*Waiting*	Return to home port
Navigating	δ_5	*Loading*	Recover the fish
Loading	δ_6	*Navigating*	Move
Waiting	δ_7	*Waiting*	Nothing

6. Computer model

6.1. Design patterns and Netlogo pattern

The Design Pattern (*DP*) concept comes from *A pattern language: towns, building, construction* dealing with the work of building architects *Christopher Alexander*, *Sara Ishikawa* and *Murray Silverstein*. These authors worked on architectural design in the 1970s and defined the notion of *pattern*, such as: "*Each pattern describes a problem which occurs over and over again in our environment, and then describes the core of the solution to that problem, in such a way that you can use this solution a million times over, without ever doing it the same way twice.*" This sentence defines a *DP* as the description of a recurring problem associated to its solution, a specific context, an architecture and the expression of the associated *generic solution*. However, it is only in 1995 that the use of *DP* boomed with *O.O.P.* and the famous work by "*GoF*"(*Gang of Four*) of *Erich Gamma*, *Richard Helm*, *Ralph Johnson* and *Jhon Vlissides* (Johnson et al., 1995). Since then, the use of *DP* has progressively been spreading and allowed the unambiguous expression of generic and reusable computer code. Thus, *DP* will make it possible to disseminate good design practices, in particular those related to the *know-how* of specialists on the basis of a precise language and vocabulary that is common to all designers and developers. Many books dealing with *DP* have been published, including (Hunt, 2016; Buck and Yacktman, 2010; Buschmann et al., 1996). In computer simulation, *DP* offer the opportunity to capitalise on valuable knowledge acquired from the *know-how* of experts in the field.

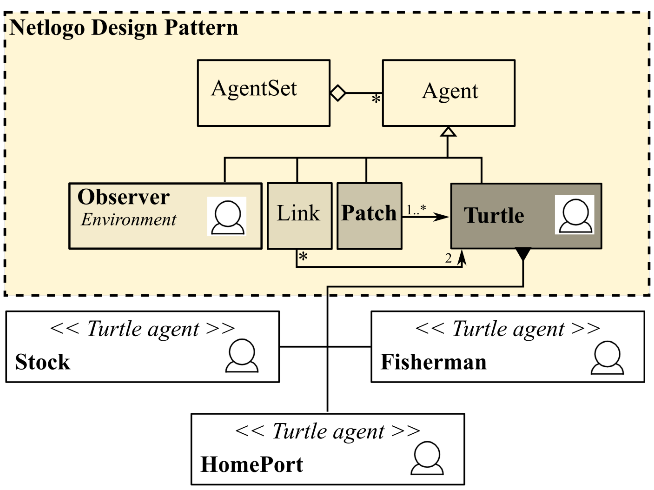

Figure 5. The main agents of the computer model.

The *NetLogo Design Pattern* is derived from the generic *ABM* proposed by *Uri Wilensky* and implemented in the *NetLogo* simulation environment (Wilensky and Rand, 2015; Tisue and Wilensky, 2004). It provides a simple and efficient mechanism for simulating the behaviour of agents in *CAMs* or *ABMs* with four categories of abstract components: an omniscient observer (*Observer*), cells (*Patches*), turtles (*Turtles*) and links (*Links*). In this pattern, the *Observer* component is a single agent whose role consists in observing the environment and giving orders to other various agents of the model (whether mobile or not). *Patches* are agents which model fixed locations in space. For example, they can implement the cells of a *CAM* (Innocenti et al., 2016). *Turtles* are mobile agents that move on the *patches* of the environment, as for example on the cells of an *ABM* (Innocenti et al., 2020). Links are special agents that are used to link *Turtles* agents together. They are essentially used to integrate conceptual models based on *graphs* into agent-based computer models. According to the *Netlogo Design Pattern*, we describe the agents of our *ABM* in the light of the three groups of generic agents: *observer*, *patches* and *turtles*. For that, as mentioned on figure 5, *turtle agents* will have to be specialised using the inheritance mechanism of *O.O.P* (Banos et al., 2015). Thus, using the *NetLogo* simulation environment this process will be very much simplified.

6.2. Agents organisation

In our *ABM*, the *fishery* consists of *fishing patches* (*Stock agents*) which are composed of one or many *locations* (*Patch agents*). *Patch agents* are linked to *Stock agents* and produce the *biomass* from each species each year. Particular *patches* are placed in the environment at the boundary of a stock determining the outer edges of the *Moore neighborhoods* of a stock location. *Fishermen agents* are at the source of the biomass harvesting behaviour in *stocks*.

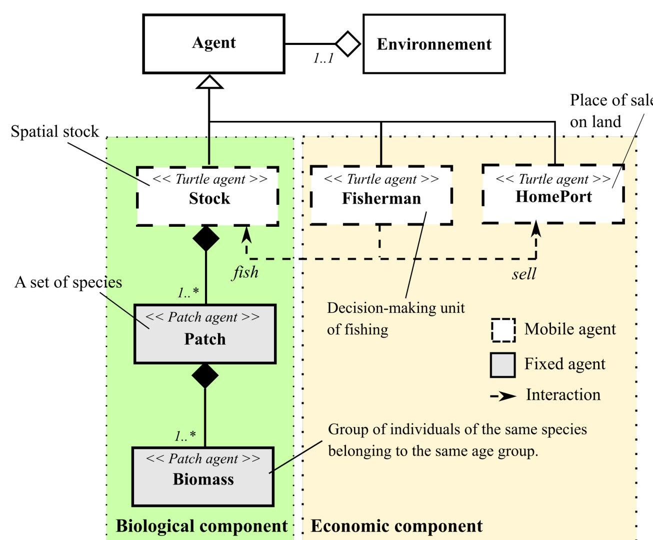

Figure 6. Organisation and interactions of the objects of the computer model.

The interactions and organisation of agents in the computer model are illustrated in figure 6. We define 5 specialised classes of agents and three classes of mobile agents:

Stock, *Fisherman* and *HomePort* agents (inheritance from turtles) as well as two classes of fixed agents *Patch* and *Biomass* agents. *Stock* agents are defined in order to organise the temporality of the biomass growing evolution during the discrete time simulation phase.

7. Materials and Methods

7.1. Netlogo simulation platform

By organising the computer model's objects according to the *Netlogo Design Pattern*, it is easy to very quickly prototype an executable *ABM* that can be run on the *Netlogo* simulation environment (Tisue and Wilensky, 2004). *Netlogo* is also an effective tool for setting and visualising the results from observation. It also facilitates the calibration process from experimental data. We can thus verify the validity of the modelling hypotheses by quickly implementing them (Prunetti et al., 2021; Beauchemin et al., 2018).

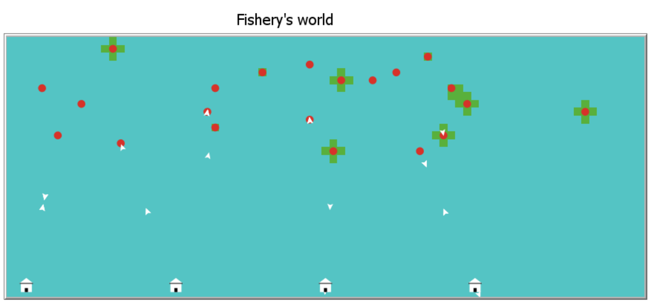

Figure 7. The digital world of the executable model under Netlogo.

Figure 7 is an illustration of the parameterisation of the model in *Netlogo* with 5 fish population species, 10 fishermen (white arrows), 4 home ports (white houses) and 21 stocks (red circles).

7.2. Simulation algorithm

The context of the study is the marine resources management in Corsica, where artisan fishing is the most widely spread. Indeed, Corsica only has 195 professional reported fishing units among which 182 are small units ("Petits Métiers Côtiers", PMC) called "pointus" (pointed-shaped fishing boats), 5 are longliner units (PML), and 8 are large trawlers (CHA). Fishing activity takes place along the entire coastline of Corsica, up to 3 nautical miles away from the shore, and along 1,045 km of coasts. Fishing areas are grouped in four corporations ("prud'homie"): Ajaccio/Propriano/Cargèse, Bonifacio, Bastia/Cap Corse and Balagne. In this work, the agents' transitions are simulated sequentially, performing the main steps depicted in Figure 8.

Each day, fisherman agents proceed to a fishing action in stock agents. Fishermen agents only relate fish in authorised locations, i.e. stock agents that are assigned to them, as in Corsica where the fishing areas are regulated at a local level by the fishermen corporations. The species renewing occurs once in a year.

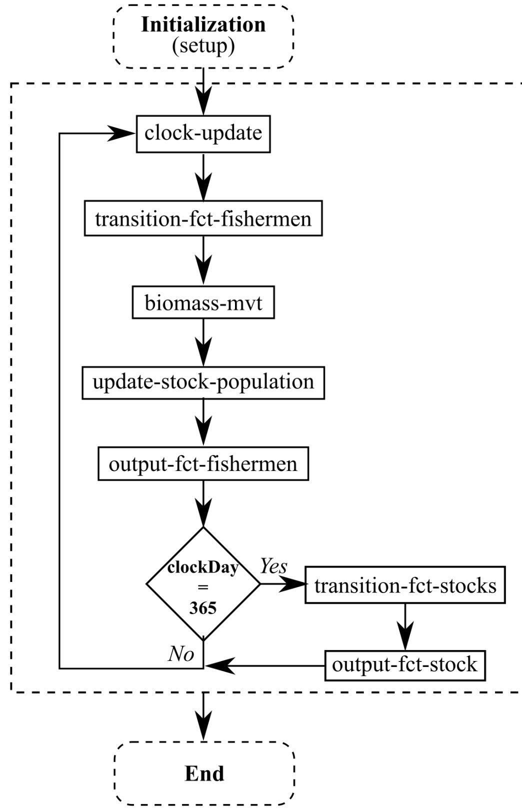

Figure 8. The Discrete-Time Simulation algorithm.

8. Results and Discussion

We have reported here preliminary results showing that our modelling approach facilitates software parameterisation for specific requirements implied by the Corsican coastal fisheries context. Unlike other fields of study, when it comes to gain experimental data on fisheries, only observations of a real system allow to acquire this data. This mainly relates the observation of fishing activity provided by fishermen (fishing form, logbook data, sell sheet, etc.) or observations acquired by sampling throughout research campaigns. In this work, we have partly received this data in the context of the *Moonfish* research project (University of Corsica, 2016) that we initiated in 2016 and from the literature (Le Manacha et al., 2011). In the future, we hope to be able to integrate this data further into the model to improve it and remove random parameters. Experimental data will be acquired later during scientific field campaigns and will help to improve the computer model. This data can also provide calibration elements for the computer model.

9. Conclusion

In this preliminary work, we have presented a multi-stock, multi-fleet, multi-species and bioeconomic model for small-scale fisheries. As an example, Corsican coastal fisheries are described as a *MAS*. The model's structure complies with both *CAM* and *ABM* computational modelling approaches. Discrete time simulations are performed with the *NetLogo* simulation environment to evaluate our model's capabilities and deficiencies. Regarding the improvement of the behaviour of economic agents, our next step will consist in considering decision-making processes based on bandit-like reinforcement learning (Sutton and Barto, 2018). On the basis of the work of (Hanaki et al., 2018), we will use multi-armed bandit-like reinforcement strategies to determine the location chosen by fishermen for their fishing activity based on conditional probabilities.

10. Acknowledgements

This work supports one of the research themes of the BIODIVCORSE Project (BIODIVCORSE Explorer la biodiversité de la Corse) funded by the Collectivity of Corsica. We would also like to thank Antoine Belgodere for his patience with regard to our "noisy" meetings.

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