Using artificial intelligence to improve decision-making in conservation conflicts

Ten-week report

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Contents

1 Context

1.1 Conservation

At the beginning of what could be a new mass extinction episode (LACKS REF), preserving biodiversity is a central concern for humanity. Human survival depends on the services ecosystems provide, including pollination, soil enrichment, water treatment, and carbon dioxide fixation (REF). Additionally, the role of nature in human well-being is increasingly being recognized as important (REF). A key for ensuring ecosystem sustainability is the maintenance of biodiversity, which enables quick and dynamic responses to change (REF). Moreover, this biodiversity is often an inspiration for technological innovations. Thus, conservation of biodiversity have become a leading field in ecology.

According to ... Definition of conservation. (to complete tomorrow morning)
Conservation can be applied in many different ways. It can be preventive, by establishing protected areas to preserve intact ecosystems from human impact (Wilgen and Biggs, 2011; Bainbridge, 2017), or to restore already damaged ecosystems (Rumpff et al., 2011). It can also be applied in reaction to a ongoing problem without preventing contact, *e.g.* culling control by monetary incentives (Mason et al., 2017; Cusack et al., 2018). Another example is offsetting, which is balancing "local habitat destruction by restoring, enhancing and/or protecting similar but separate habitat" (Gordon et al., 2011). There are many other examples, but genuinely successful implementation of conservation is scarce because of the numerous challenges it faces (Keith et al., 2011; Wilgen and Biggs, 2011).

The systems conservation deals with are highly complex and densely interconnected, including ecology, sociology, agronomy and climatology simultaneously. They exhibit most of the characteristics of wicked problems, including "*numerous interacting elements lacking any central control, non-linear interactions between elements, constant change which is seldom reversible, and no clearly defined boundaries*" (Game et al., 2013). In such systems, it is often impossible to isolate the causes of changes, and the response to a conservation action is lost in other signals from a myriad of uncontrollable external factors. Thus, monitoring a system's response to a policy over time can be very expensive, time consuming, and possibly intractable if the number of possible variables affecting conservation is large. This results in conservation policies often lacking data to account for their effectiveness, or to understand failuree (Keith et al., 2011). Furthermore, management is based on estimations of populations, which accuracy varies according to the technique (Bunnefeld et al., 2011). To summarize, conservation faces uncertainty at many levels.

This inability to predict the system's response to a change in the conservation policy can result in a reluctance to change, and in the maintain of inadequate conservation policies (Peterson et al., 2005; Keith et al., 2011). Moreover, it often takes place in a political context, and can be significantly slowed, even blocked, by divergent political interests or lobbies for groups that would not benefit from the conservation policies (Keith et al., 2011). Unexpectedly but fortunately, there is little evidence that bigger budgets make conservation easier or more effective (Game et al., 2013).

All the above led to the question: how to conduct efficient conservation, while dealing with these discouraging barriers and embracing uncertainty?

1.2 Adaptive management

Adaptive Management (AM) suggests to update dynamically the management policy according to the system's behaviour. This way, conservation can be better fitted to the system, and acting regularly allow to acquire informations on its response to change. Therefore, managers can learn

Figure 1: The cases of conservation conflicts on which the ConFooBio project is focused.

heuristically from the system, and react effectively. Although AM also relies on the monitoring of some selected variables, their choice can adapt to the problems detected after each policy updating. LACKS REF

A major concern in current conservation is that, even if a policy effectively protects a species from going extinct, mismanagement can lead populations to reach problematical numbers for human livelihood.

1.3 Conflicts

This is when conflicts arise, as "*two or more parties with strongly held opinions clash over conservation objectives and [...] one party is perceived to assert its interests at the expense of another*" (definition from Redpath et al. (2013)). ConFooBio (Conflicts between Food security and Biodiversity) is a gathering of well monitored cases of conservation conflicts (see figure 1), in which conservation objectives are threatening to the local inhabitants farming activity. In these conflicts, the divergence of stakeholders interests makes conservation more challenging, as people impacted by a protected population's growth are more likely to defect protection policies. That is why meeting every stakeholder interests is essential for a management policy to be sustainable (Redpath et al., 2013).

Management Strategy Evaluation is a framework that describes the process of Adaptive Management in the situation of conservation conflicts. It decomposes the problem in four main parts: manager's policy updating, user's harvest strategy, the species population and the mode of estimation of the population (see figure 2). This structure isolates uncertainty at four main levels: decision-making under uncertainty for managers and users, the population's response, and its estimation. Also, the circular structure is adapted to the heuristic updating of management policy.

With such divergent interests, reaching a consensus on a target for the population can be

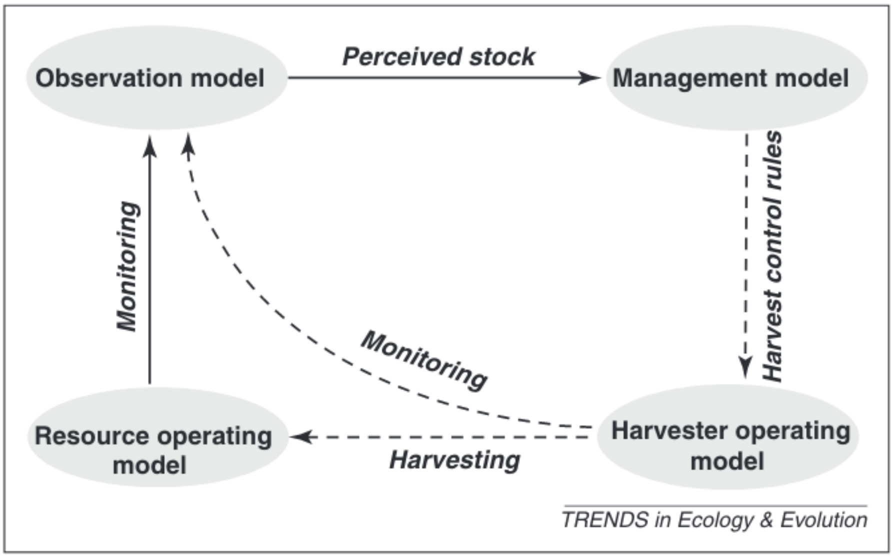

Figure 2: Flow diagram for the management strategy evaluation framework. This comprises a resource operating model (simulating the 'true' population biology of the species), the observation model to monitor the species (with error) and the management model, using the perceived stock to create and implement the harvest control rules. (Bunnefeld et al., 2011)

an unproductive process, and prevent the situation from changing in a more equitable way (Peterson et al., 2005). Unlike consensus-based approach, placing manager and user into two different parts recognizes different interests and expectations for conservation, and describes a goal-oriented behaviour. It was successfully implemented in fisheries, and than applied on terrestrial animals conservation (Bunnefeld et al., 2011, 2013).

1.4 Modelling

Since an accurate prediction of these socio-ecosystems' response is hardly possible, any conservation frameworks benefits from a modelling approach. Indeed, conceptual models allow for the rapid exploration of different scenarios under certain hypotheses, thus being very useful decision-helping tools.

For example, Rumpff et al. (2011) used a Bayesian network to model the transitions between the possible state of a landscape according to a policy, to plan for the restoration of different protected areas previously damaged by human activity. The book from Schlüter et al. (2012) threw the stones of socio-ecological modelling in order to manage conservation involving human compliance (an extensive list of studies using modelling in conservation is presented in chapter 2.1). But, the high diversity of models highlights the lack of common framework, to which MSE is a strong candidate. In the conclusion, the authors also stated that a proper modelling framework for conservation conflicts needs human decision-making modelling, because unforeseen defection is one of the main causes for failures.

Game Theory (GT), introduced by John Von Neumann and Oskar Morgenstern in 1944 in the book "The Theory of Games and Economic Behavior", is the leading framework for decision-making modelling. Myerson (1997) describes GT as follows: "*the study of mathematical models of conflict and cooperation between intelligent rational decision makers [which choices] affect one another welfare*". *Games* are simplified vision of actual conflicts, because the actual complexity is unreachable, and can prevent from understanding the fundamental issues of conflict. As any other scientific work, game models deliberately omit less relevant details of actual situation to allow the study of particular phenomenon in the scope of a particular question.

In these games, players act in order to maximise the expected value of the game's outcome, the so-called *utility*. Utility is not necessarily quantified as a monetary pay-off, it can be seen in many different ways, e.g. time, effort saved, well-being, happiness, *etc*, and even a mix of them).

Game theoretical perspective can provide insights about: "the strategies different stakeholders will likely adopt given their objectives, [...] the range of possible outcomes, [...] and whether an optimal or satisfactory solution for all stakeholders can be reached simultaneously" (Colyvan et al., 2011). It was first used in Biology in Maynard-Smith and Price (1973) to investigate the evolution of animal strategies in con-specific fights. Colyvan et al. (2011) investigated theoretical applications of the four main types of games (simple, chicken, stag and prisoner games) to Adaptive Management, but its actual implementation for conservation purposes is fairly novel. Glynatsi et al. (2018) modelled the conflict over rhinos protection and illegal poaching for ivory as a common-pool resource problem, to assess which proportion of rhinos should be de-horned to minimize their killing, according to poacher being unconditional or selective killers.

And finally, a model developed on MSE framework, including decision-making modelling within Game Theory, was introduced in Duthie et al. (2018).

2 GMSE

2.1 Formalisation of MSE framework

GMSE is a formalisation of MSE framework, assigning each part a mathematical model. It aims at exploring the long-term consequence of a given management strategy, in order to test its effectiveness, and highlight potential problems managers would not have thought of. GMSE can be used both for research (Cusack et al., 2018), and application to conservation conflict cases (Bainbridge, 2017).

Concerning the mathematical models, the population changes at each time step according to a spatially explicit, individual-based, population dynamic model. Each individual is born, moves, and dies according to probabilities drawn in defined laws to account for the uncertainty linked with population dynamics.
The population is monitored according to different definable techniques, some of which includes probabilities of detection, thus accounting for the uncertainty about the accuracy of monitoring.
The manager model can be parametrized to reflect its conservation goals. It uses the information from the monitoring to set a policy. A policy is a set of possible actions associated with a cost for their performing. The manager has a given budget, and implementing a policy implies a cost for him/her.
The user model is individual-based, and each user can be parametrized to reflect its interests concerning the population. There can be several users, and they are modelled independently. Each has a given budget, and acts according to the number of actions she/he can perform according to their cost set by the manager, in order to achieve his/her goal (figure 3).

According to MSE framework, a policy is effective when, after the chosen period of management:

- The population (i) does not go extinct and (ii) stabilizes around the conservation target.
- The users' yield reaches a satisfactory percentage.
- All users have comparable yield percentages.

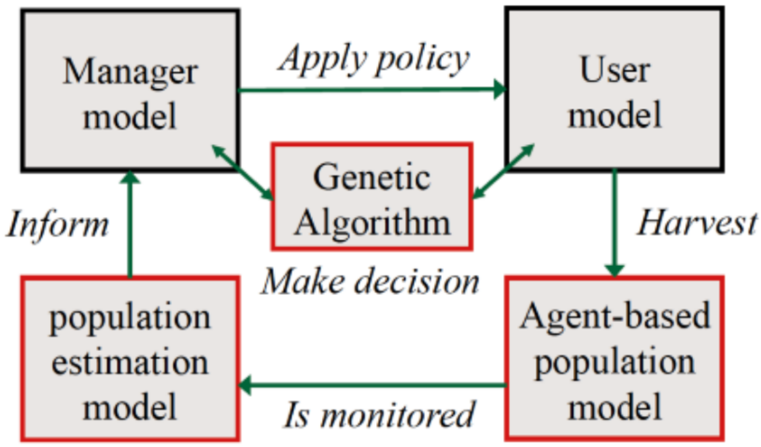

Figure 3: Flow chart of GMSE current version. Red outlines indicate stochastic models.

- The spatial distribution of the resource is equitable between users' lands.

If these condition are fulfilled, there should not be any reason left for conflict to persist.

2.2 Decision-making artificial intelligence

The manager's and the users' decision are made by calling a Genetic Algorithm (GA) - a form of Artificial Intelligence (AI). Initially, GA were used to model the evolution of allele frequencies in a population under stochastic recombination and mutation. It has previously been used in combination with an individual-based model in a ant collective foraging model, where the parameter governing the interaction rules was allowed to evolve according to a GA. (Hamblin, 2013) Although this algorithm was not exactly successful in mimicking evolution, it inspired a new kind of Artificial Intelligence.

In GMSE, a population of random strategies (a list of costs associated to actions) of a given size is initiated, and then allowed to evolve through stochastic mutation and crossing-over. Each strategy's fitness to the decision-maker criteria is assessed, and the fittest are allowed to reproduce. The process is repeated until the increase in fitness between the current fittest stategy and the previous one falls under a defined threshold.

It is particularly well fitted to human decision-making in this context, because due to the complexity of the problem, the decision-maker does not know in advance the best choice, but can judge if a choice is better than another. Furthermore, humans are usually not able to explore all the possibilities to choose the best one, they rather select the best among the one they could think of.

3 Research Questions

I will focus on an actual case study of conservation conflict to keep GMSE development into a down-to-earth situation, and parametrize simulations with actual measures from the field. I chose the case of conflict over geese population and farming on the Isle of Islay (Scotland) as it is a well documented case, with very accessible data within the team.

3.1 Case study: Geese

Geese endangered status was recognised during the 1940's, and is believed to result from a combination of hunting for food and sport, systematic persecution and the disruption of the

Second World War. In the 1980's, all geese species population numbers increased significantly, most likely as a consequence of improved protection, paired with land-use and climate change (Mason et al., 2017). But this rise in population started a conflict with farmers in Special Protection Areas, as geese were intensely grazing their crops. The first arrangements between the state and these farmers concerning geese control were made in the early 1990's, in the form of payments from government for farmers to allow undisturbed grazing on certain areas, and scare them away in others areas. Yet, some populations are still increasing, and farmers started to consider the compensation too low for the damages caused. But Scottish government refused to increase them for financial reasons (Bainbridge, 2017).

This case is particularly adapted to work on the development of GMSE, because it is a small-scale case of conservation conflict, involving a handleable number of neighbouring users, that are very likely to interact in different interesting ways. It is already a case of interest for Scottish National Heritage (SNH), and part of the ConFooBio project, so the goose population, along with the updates in the conservation policy, have been regularly monitored for years. Furthermore, this situation could clearly benefit from the results of this project, and would be an interesting way to test once again the applicability of GMSE to actual cases.

3.2 How does flexibility in policy updating frequency affect geese management strategy efficiency?

Optimal growth in finances, or plant, sometimes includes doing nothing. More precisely, to invest less resources than usual in buying (balancing consumption and capital investment) or reproduction (less investment in seeds or flowers and more in root stock or growth, waiting for a less unsuitable or competitive time) for a certain amount of time. Since the problems conservation is dealing with are often irreversible, managers are used to invest financial resources in acting as soon as they get them. Indeed, the complexity of conservation problems results in temporal heterogeneity, so acting can be more efficient at certain moments than others, if the possible outcome outweigh the increase in threat to the protected species in the meantime. Thus, finding the best time to act could lead to more efficient management strategies (Iacona et al., 2017).

Currently in GMSE, a parameter sets the number of the manager's interventions per time step, and according to Duthie et al. (2018), the number of extinctions over several simulations decreases exponentially with increasing frequency of manager intervention. But does it means acting as soon as possible is an efficient strategy?

To answer this, I will implement a 'doing nothing' option in GMSE, as a bypass of policy updating under certain conditions at a given time step. The most intuitive condition would be the deviation of estimated population from the manager's target. For now, the manager updates the policy whenever he/she is meant to, even if the estimated population is only a few individuals away from the target. To loosen this condition, I will implement an action threshold A based on D, the ratio of estimated population to manager's target. If at this time step, $|1 - D| < A$, the policy will not be updated, meaning that the manager would act only if the population exceeds or goes under its target by a certain value set by A.

First, A will have a fixed value along the conservation scheme period. To quantitatively assess the effect of this strategy on management efficiency, I will select a set of relevant values for A, and run multiple simulations for each of them - probably a hundred replicates per A values. For each A value, I will gather different informations from the simulations, according to the MSE criteria for an efficient management strategy:

- The number of simulations in which the goose population went extinct, divided by the number of replicates, to estimate a probability of extinction.

- The mean deviation of the actual goose population from conservation target over the conservation scheme period, averaged over all the replicates.
- The mean total crop yield percentage across the conservation scheme period, averaged over all the replicates.
- The mean variability in crop yield percentage across the different users, averaged over all the replicates.
- The mean variability in the number of geese per land unit across the different users, averaged over all the replicates.

I will use these measures to compare the effectiveness of the management strategy according to the value of A, and eventually highlight the most efficient one.

I have also thought of another way to find an optimal value for A, involving a more dynamic way to set it during the conservation scheme period. The value of A could be a Gaussian or a stair function of a variable describing the situation ($|1-D|$ for example, see figure **??**, a schema of the link function, will be done tomorrow), centred on a maximum value for A. That way, if the situation is concerning at this time step, it could mean that the previous A value was too high, thus the manager can adjust it to react more sensibly from now on.

I will run multiple replicates for different parameters values for the link-function between A and the variable describing the situation. From the simulation output, I will assess the evolution of the mean A value over the replicates at each time step, along the conservation scheme period. This will eventually show the emergence of an optimal value for the action threshold according to the link-function's shape and parameters.

Finally, an interesting feature to add to this exploration would be the ability for the manager to save some budget for next time step if she/he decided not to act this time step. I could assess the efficiency of the policy according to different percentages of budget saving, with the same method as previously.

3.3 How to manage geese population efficiently taking into account interactions between stakeholders?

The main research goal of this project is to allow the decision-making AI to consider interactions between agents. In GMSE current version, the users act independently, regardless of their neighbours' behaviour. This is very unlikely, as seen in the role-play games performed in Redpath et al. (2018). Also, Game Theory explicitly showed how crucial was the ability to know the other players' strategy to get the most out of the game's outcome. I will take advantage of answering the first research question to get familiar with the case study, as well as GMSE code, in order to find out what kind of interactions are at play here, and how to implement them within the existing structure of the software. After that, I will be able to assess how it affects the way managers make policies.

3.4 Next challenges

GMSE being a completely novel software, there are still many ways to keep on developing it.

From a computational point of view, computing time increases greatly with the number of stakeholders, due to the individual-based approach crossed with the systematic calling of the Genetic Algorithm. This could be improve using parallel computing. With the adapted software and code language, this technique allows to make many similar tasks simultaneously instead of in sequentially, thus highly increasing the throughput (number of operations per time unit).

Furthermore, it is now complicated to speak about AI without including Machine Learning, yet Genetic Algorithm is not a structure that can be trained. To turn the decision-making AI into a learning structure, the team thought about a Neural Network (NN) in the shape of a map. Given a variety of inputs, the NN would be able to output a land-use decision map. The NN would be trained with data from numerous behavioural games performed within the ConFooBio project. Once coded, this new version of GMSE could be compared to the previous one in terms of ability to manage conservation conflicts.

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