GMSE: an R package for generalised management strategy evaluation

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# Abstract

1. Management strategy evaluation (MSE) is a powerful tool for simulating all aspects of natural resource management under conditions of uncertainty.

2. We present the R package GMSE, which generalises MSE using a game-theoretic approach to simulate adaptive management scenarios under complex social-ecological interactions and uncertainty.

3. GMSE is agent-based and spatially explicit, and incorporates a high degree of realism and uncertainty through mechanistic modelling of the social-ecological system.

4. We show how GMSE simulates a social-ecological system using the example of a waterfowl population that is adaptively managed; simulated waterfowl exploit agricultural land, causing conflict between conservation interests and the interest of stakeholders (farmers) in maximising crop yield.

5. The R package GMSE is open source under GNU Public License; source code and documents are freely available on GitHub.

# Introduction

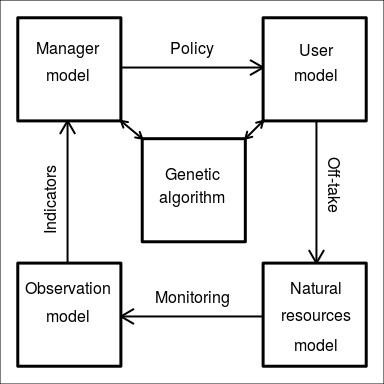
Many global natural resources, including the biodiversity on which critical ecosystem services depend, are in a state of severe decline (Dirzo et al. 2014; Hautier et al. 2015; G. Ceballos, Ehrlich, and Dirzo 2017; O’Connell 2017). Conservation of biodiversity can be complicated by the immediate need to use natural resources and land area for human food production, causing real or perceived conflicts between conservation and food security and creating a challenge for the management of many natural resources (Redpath et al. 2015). Given an increasing human population (Crist, Mora, and Engelman 2017), the number and intensity of such conflicts are likely to increase into the twenty first century. Effective management tools are therefore needed for the long-term maintenance of natural resources under the rising demand for food production.

To effectively manage natural resources, an adaptive approach allows managers to iteratively update their models of resource dynamics and respond flexibly to changing conditions. This approach is especially effective when considering all aspects of the socio-ecological system being managed, including the dynamics of resources, monitoring, and the decision-making processes of managers and stakeholders (Bunnefeld, Hoshino, and Milner-Gulland 2011; Bunnefeld and Keane 2014). Management strategy evaluation (MSE) is a modelling framework for simulating all of these aspects of resource management in a way that uniquely considers the uncertainties inherent to every stage of the management process (Bunnefeld, Hoshino, and Milner-Gulland 2011; Punt et al. 2016). Nevertheless, MSE remains limited in its ability to model human decision-making; manager decisions are typically based on simple rules, and stakeholder behaviour remains fixed over time instead of dynamically responding to changing resource availability and management decisions. Here we introduce a generalised management strategy evaluation (GMSE), which incorporates a game-theoretic perspective to model the goal-oriented, dynamic decision-making processes of managers and stakeholders.

The GMSE R package is a flexible, highly mechanistic, agent-based modelling tool to simulate all aspects of natural resource management. GMSE considers a range of parameters to simulate resource dynamics and management policy options, and uses genetic algorithms to dynamically model manager and stakeholder decision-making. Genetic algorithms allow managers and stakeholders to find adaptive solutions to any simulated conditions given unique agent goals, allowing GMSE to model scenarios of conservation conflict.

# GMSE model structure

GMSE builds off of the traditional MSE framework, which includes four sub-models, each of which runs once in a single time step of the broader model (Figure 1). (1) A natural resources sub-model considers a population of discrete resources with individual traits (e.g., location, age) on a spatially-explicit landscape. This sub-model can include processes of resource birth, movement, interaction with the landscape, and death. The discrete nature of resource demographics naturally gives rise to stochasticity, and therefore uncertainty. Although the resource sub-model can interact with other sub-models, it is unique in not relying on them because ecological dynamics can be simulated in the absence of observation and management. (2) An observation sub-model simulates the process of data collection performed by a manager to estimate resource abundance. Four types of data collection are permitted, including exhaustive resource counting on a subset of landscape cells (e.g., Nuno, Bunnefeld, and Milner-Gulland 2013), marking and recapturing a fixed number of resources, and exhaustive sampling of the whole landscape iteratively (during which resources might move). Imperfect sampling from all of these mechanisms of data collections generates observation uncertainty. (3) A manager sub-model simulates a manager's analysis of collected data to estimate resource abundance, then compares this estimated abundance with the manager's target abundance. Policy is developed by calling the genetic algorithm (see below), which works within a manager's constraints to find costs for stakeholder actions (e.g., culling, scaring, etc.) that minimise resource deviation from the target abundance, as informed by the predicted consequences of stakeholder actions and stakeholder action histories. After an adaptive policy is found, (4) a user sub-model is run that allows each stakeholder to perform actions that affect resources or landscape cells. Stakeholders respond to policy individually, each calling the genetic algorithm to find actions that maximise their own utilities (e.g., maximise resource use or landscape yield) within their imposed constraints. Once each stakeholder has found an adaptive strategy, stakeholder actions affect resources and landscape cells, feeding back into the resource sub-model.



*Figure 1: Description of the generalised management strategy evaluation framework*

## Genetic Algorithm

Game theory is the standard tool for understanding conflict between rational agents, and is therefore the appropriate tool for modelling manager and stakeholder actions and addressing issues of cooperation and conflict in conservation (Colyvan, Justus, and Regan 2011; Lee 2012; Kark et al. 2015; Adami, Schossau, and Hintze 2016; A. R. Tilman, Watson, and Levin 2016). A game-theoretic approach is compatible with agent-based modelling (An 2012; Tesfatsion et al. 2017), but given the number of possible strategies available to agents, identifying optimal strategies is often intractable. Instead, genetic algorithms, which mimic the process of natural selection (mutation, recombination, selection, reproduction), are useful to find adaptive solutions for game strategies (e.g., Balmann and Happe 2000; Tu, Wolff, and Lamersdorf 2000; Hamblin 2013).

In keeping with the MSE approach (Bunnefeld, Hoshino, and Milner-Gulland 2011), GMSE does not attempt to find optimal strategies or solutions for managers or stakeholders. Instead, within each time step of a simulation (Figure 1), a new genetic algorithm is called for each agent to heuristically find strategies that are well-adapted to achieving agent goals. Hence for the manager and each stakeholder, a unique population with a random set of possible values affecting policy or actions, respectively, is initialised. In each generation of the genetic algorithm, strategies crossover and mutate; when this results in strategies that are over-budget, values are iteratively decreased at random until budget constraints are satisfied. A fitness function then evaluates each strategy in the population, and a tournament is used to select the next generation of strategies (Hamblin 2013). The genetic algorithm terminates when a minimum number of generations has passed and the increase in the fitness of the fittest strategy between the current and previous generation is below some threshold. The highest fitness strategy in the population then becomes the agent's strategy in the current time step.

## GMSE arguments and output

Simulations are run using the gmse() function, which offers a range of options for setting parameter values (see Table 1 for some select examples). Output of gmse() is an exhaustive list that includes all resources and observations, all manager and stakeholder decisions and actions, and all landscape properties in each time step of the simulation. Results are most easily interpreted visually, so a summary of simulation dynamics is plotted by default (the plot can also be called using the plot\_gmse\_results function). An example below shows how simulations are set and interpreted.

< SEE PDF FOR TABLE 1 >

*Table 1: Select parameter values for initialising generalised management strategy evaluation simulations*

# An example of resource management

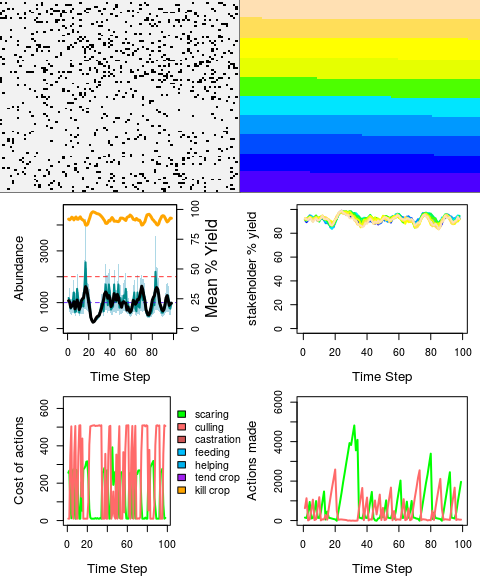
Here we consider the example of a managed natural resource whose abundance affects a group of stakeholders by temporarily decreasing the value of stakeholder land. This scenario could be interpreted in multiple ways; we consider a protected population of waterfowl that exploits agricultural land causing a conservation conflict with farmers (e.g., Tuvendal and Elmberg 2015; Anthony D. Fox et al. 2016; Anthony D Fox and Madsen 2017). Managers in this example might want to keep the abundance of waterfowl at a target level, while farmers might want to minimise the damage inflicted on their crops. Using GMSE, it is possible to simulate waterfowl population dynamics, along with the continued monitoring and policy set by managers, and the actions that farmers take to protect their crop yields given the constraints of policy. Here we consider a population of waterfowl with an initial abundance and manager target abundance of 1000, but whose carrying capacity (applied to mortality) is 2000. Waterfowl consume and destroy all crop yield upon arrival to a landscape cell. Managers estimate population size in each time step using mark-recapture techniques, and use their estimates to set costs of culling and scaring (non-lethal) waterfowl (i.e., 'policy') for ten farmers. Farmers attempt to reduce the negative impact of waterfowl on the cropland that they own, working within the constraints of culling and scaring costs and their budget for performing these actions.

sim <- gmse(land\_ownership = TRUE, stakeholders = 10, observe\_type = 1,   
 res\_death\_K = 2000, manage\_target = 1000, RESOURCE\_ini = 1000,   
 user\_budget = 5000, manager\_budget = 5000, res\_consume = 1,   
 scaring = TRUE, fixed\_mark = 50, fixed\_recapt = 300,   
 plotting = FALSE);

## [1] "Initialising simulations ... "  
## [1] "Generation 12 of 100"  
## [1] "Generation 24 of 100"  
## [1] "Generation 34 of 100"  
## [1] "Generation 44 of 100"  
## [1] "Generation 55 of 100"  
## [1] "Generation 66 of 100"  
## [1] "Generation 76 of 100"  
## [1] "Generation 86 of 100"  
## [1] "Generation 96 of 100"

Parameters in gmse() not listed are set to default values. By plotting the output with plot\_gmse\_results, simulation results can be interpreted visually.

plot\_gmse\_results(res = sim$resource, obs = sim$observation, land = sim$land,   
 agents = sim$agents, paras = sim$paras, ACTION = sim$action,   
 COST = sim$cost);



*Figure 2: Results of an example simulation illustrating the management of a protected resource that exploits the land of 10 stakeholders. The upper left panel shows locations of resources (black dots) on the landscape in the final time step of the simulation. The upper right panel shows the same landscape broken down into 10 differently coloured regions, which correspond to areas of land owned by each of the 10 stakeholders. The middle left panel shows the actual abundance of resources (black solid line, and the abundance of resources as estimated by the manager (blue solid line; shading indicates 95 percent confidence intervals of a mark-recapture analysis), over time. The horizontal dotted red and blue lines show the resource carrying capacity enacted on adult mortality and the manager's target for resource abundance, respectively. The orange line shows the total percent yield of landscape cells. The middle right panel shows total percent yield of landscape cells for each individual farmer, differentiated by colour, where line colours correspond to areas of the landscape in the upper right panel. The lower left panel shows the cost of stakeholders performing actions over time, as set by the manager. The lower right panel shows the total number of actions attempted to be performed by all stakeholders over time (some actions might be unsuccessful if resources are unavailable on a stakeholder's land to cull or scare, so, e.g., culling actions might be larger than resources actually culled).*

Figure 2 shows the landscape broken down by resource position and stakeholder ownership in the upper left and right hand panels, respectively. The waterfowl population fluctuates around the manager's target size of 1000, but the manager's estimate of population size deviates from its actual size due to uncertainty caused by the observation process (compare black and blue lines the middle left panel). Because the waterfowl have a direct negative effect on landscape yield, total landscape yield (orange line of the middle left panel), along with the yield of individual farmers (right middle panel), is low when waterfowl abundance is high, and vice versa.

Only the estimates of population size from the observation model are available to the manager, so policy change at any time step is driven primarily by the deviation of the currently estimated population size from the manager's target and the actions of farmers in the previous time step. Hence, when the population size is estimated to be below (above) the manager's target, the manager increases (decreases) the cost of culling and decreases (increases) the cost of scaring. Because the manager does not know in advance how stakeholders will react to policy change, they assume a proportional response in total actions with respect to a change in cost (e.g., doubling the cost of culling will decrease stakeholder culling by ). Farmers responding to policy are interested only in mitigating waterfowl's exploitation of their crops, so they will either cull or scare to remove the waterfowl from their land, depending on which option is more effective (i.e., cheaper). This is reflected in the bottom left versus right panels of Figure 2; when managers decrease culling costs relative to scaring, farmers respond with more total culling, and vice versa. Farmer decisions then affect waterfowl distribution and abundance, impacting future crop yield and policy.

# Utility of GMSE simulations

GMSE incorporates feedback between resource dynamics, management policy, and stakeholder actions over time given multiple sources of uncertainty. By simulating complex systems of adaptive management in GMSE, it is possible to gain new insights into questions relevant to conservation. One obvious application of our software is to parameterise simulations with initial conditions similar to those from empirical populations of conservation interest. Running replicate simulations using empirically derived starting conditions could facilitate the prediction of key social-ecological outcomes (e.g., resource extinction, agricultural yield) given uncertainty, and the sensitivity of such outcomes to different management options (e.g., population target, policies available, observation methods, etc.), realised through results from replicate simulations, could inform management decisions.

Additionally, GMSE might be useful for developing adaptive management theory by allowing researchers to explore general questions concerning management *in silico* through simulation. Such questions might include the following: How is population persistence affected by management frequency or observation intensity? How does variation in stakeholder actions affect the distribution of resources or landscape properties? How do asymmetries in manager and stakeholder influence (i.e., budgets) affect resource dynamics? All of these questions can be explored through simulation using GMSE.

# Future development

The GMSE package is under continued development to include additional features that will be of interest to conservation biologists, managers, and the general public. Such features will include multiple (interacting) resource types and sub-types (e.g., structured populations), improved manager and stakeholder decision-making and prediction based on multiple time steps of simulation history, incorporation of empirical data (e.g., landscape features), and a browser-based graphical user interface. Additionally, future versions of GMSE will allow software users to take the place of managers or stakeholders in decision-making during simulations (replacing the genetic algorithm as desired), facilitating the collection of data to test sociological hypotheses and further improve the realism of the genetic algorithm (for a preliminary example of this, see the 'hunt' argument in the gmse() function). Code underlying GMSE is publicly available on GitHub < <https://github.com/bradduthie/gmse> > and highly modular, meaning that GMSE model components (black boxes in Figure 1) can be developed freely and independently, then integrated into the broader GMSE framework. The GMSE R package is therefore a versatile and collaborative tool with widespread applications for adaptive resource management.X

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