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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 key aspects of natural resource management under conditions of uncertainty.
2. We present the R package GMSE, which generalises MSE using a game-theoretic approach, applying genetic algorithms to simulate adaptive decision-making management scenarios between stakeholders with competing objectives under complex social-ecological interactions and uncertainty.
3. GMSE models can be agent-based and spatially explicit, incorporating a high degree of realism through mechanistic modelling of links and feedbacks among stakeholders and with the ecosystem; additionally, user-defined sub-models can also be incorporated as functions into the broader GMSE framework.
4. We show how GMSE simulates a social-ecological system using the example of an adaptively managed waterfowl population on an agricultural landscape; simulated waterfowl exploit agricultural land, causing conflict between conservation interests and the interest of food producers maximising their 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; Ceballos et al., 2017; O'Connell, 2017). Conservation of biodiversity can be complicated by the immediate need to use natural resources and land area for human livelihood (e.g., food production), causing real or perceived conflicts between biodiversity conservation and food security. This creates a challenging situation for the management of many natural resources (Redpath et al., 2015). Given increasing human population size (Crist et al., 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 sustainable use of natural resources under the rising demand for food production (Fischer et al., 2017).

To effectively manage natural resources, an adaptive approach allows managers to iteratively update their models and respond flexibly to changing conditions (Keith et al., 2011). This approach is especially effective when considering all aspects of the social-ecological system being managed, including the dynamics of resources, monitoring, and the decision-making processes of stakeholders (Bunnefeld et al., 2011; Bunnefeld and Keane, 2014). Management strategy evaluation (MSE) is a modelling framework, first developed in fisheries, 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 et al., 2011; Punt et al., 2016). Nevertheless, MSE models developed hitherto have been limited in their ability to model human decision-making (Fulton et al., 2011; Dichmont and Fulton, 2017); manager decisions are typically based on fixed rules, and user behaviour likewise remains fixed over time instead of dynamically responding to changing resource availability

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and management decisions (Schlüter et al., 2012; Melbourne-Thomas et al., 2017). Here we introduce generalised management strategy evaluation (GMSE), which incorporates a game-theoretic perspective to model the goal-oriented, dynamic decision-making processes of stakeholders.

The R package 'GMSE' is a flexible modelling tool to simulate all key aspects of natural resource management. GMSE offers a range of parameters to simulate resource dynamics and management policy options, and includes genetic algorithms to dynamically model stakeholder (manager and user) decision-making. Genetic algorithms find adaptive solutions to any simulated conditions given stakeholder-specific goals, allowing GMSE to model scenarios of conservation conflict.

GMSE allows researchers to address adaptive management questions *in silico* through simulation. Simulations can be parameterised with initial conditions derived from empirical populations of conservation interest to predict key social-ecological outcomes (e.g., resource extinction, agricultural yield) given uncertainty. The sensitivity of these outcomes to different management options (e.g., population target, policies available, observation methods, budget constraints, etc.) can thereby inform management decisions, even given competing management objectives caused by conservation conflict (e.g., Strand et al., 2012; Redpath et al., 2013; Sundt-Hansen et al., 2015; Pozo et al., 2017; Fox and Madsen, 2017). Additionally, GMSE can be used to explore general questions concerning management theory such as the following: How is population persistence affected by management frequency or observation intensity? How does variation in user actions affect the distribution of resources or landscape properties? How do asymmetries in stakeholder influence (i.e., budgets) affect resource dynamics?

GMSE model structure

GMSE builds off of the MSE framework (Figure 1). The workhorse function `gmse` runs simulations using four predefined submodels, which can be parameterised to fit various case studies; more tailored submodels can also be defined using the `gmse_apply` function (see below). (1) A population of discrete resources (e.g., a managed species) with individual traits (e.g., location, age) is modelled on a spatially-explicit landscape and can simulate resource birth, movement, interaction with the landscape, and death; the discrete nature of resources causes demographic stochasticity, and therefore uncertainty. This sub-model is unique in not relying on other sub-models because ecological dynamics can be simulated in the absence of observation and management. (2) Observation is modelled in one of four ways: resource counting on a subset of landscape cells (e.g., Nuno et al., 2013), marking and recapturing a fixed number of resources, and resource counting across the whole landscape either one linear transect or one rectangular block at a time (during which resources might move). Sampling error from all observation types generates a range of uncertainties that depend on monitoring effort. (3) Managers analyse data collected from observations to estimate resource abundance, then compare this estimate with their pre-defined target abundance. Policy is developed by calling the genetic algorithm (see below), which works within a manager's constraints to find costs for user actions on the resource (e.g., culling, scaring, etc.) that minimise deviation from the target abundance, as informed by the predicted consequences of each action on resource abundance and user action histories. After a suitable policy is found, (4) users perform actions that affect resources or landscape cells. Users 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 user has found an adaptive strategy, user actions affect resources and landscape cells, feeding back into the resource sub-model.

Genetic Algorithm

Game theory is the formal study of strategic interactions, and can therefore be applied to modelling stakeholder actions and addressing issues of cooperation and conflict in conservation (Colyvan et al., 2011; Lee, 2012; Kark et al., 2015; Adami et al., 2016; Tilman et al., 2016). In game-theoretic models, agents adopt strategies to make decisions that maximise some type of payoff (e.g., utility, biological fitness). Agents are constrained in their decision-making, and realised pay-offs depend on decisions made by other agents. In simple models, it is

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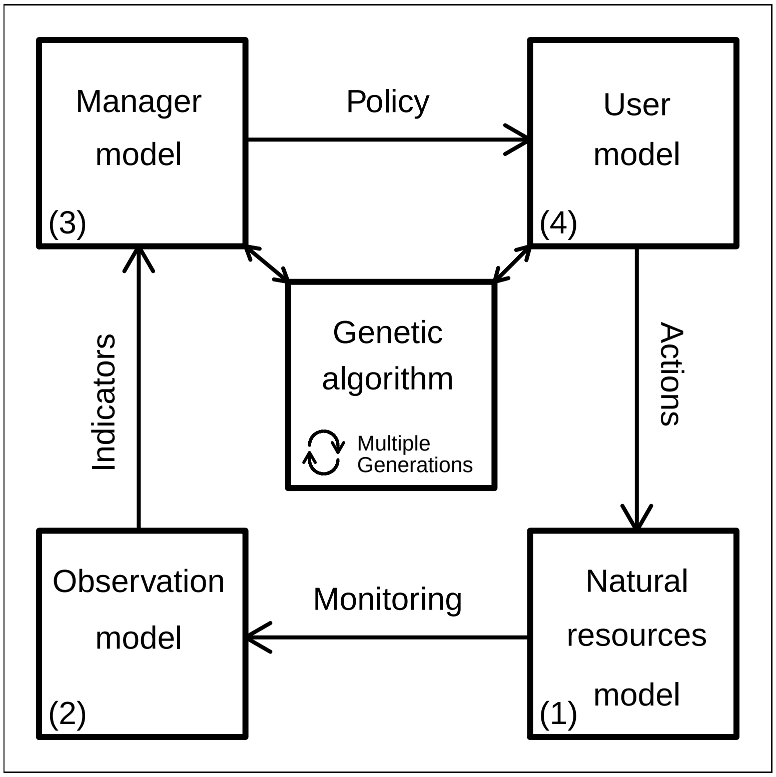

Figure 1: Description of one time step of the generalised management strategy evaluation framework, which is comprised of four separate sub-models.

often useful to assume that agents are perfectly rational decision-makers, then find optimal solutions for pay-off maximisation mathematically. But models that permit even moderately complex decision-making strategies or pay-off structures often include more possible strategies than are mathematically tractable (Hamblin, 2013). In these models, genetic algorithms, which mimic the process of natural selection (mutation, recombination, selection, reproduction), can find adaptive (i.e., practical, but not necessarily optimal) solutions for game strategies (e.g., Balmann and Happe, 2000; Tu et al., 2000; Hamblin, 2013).

Consistent with the MSE approach (Bunnefeld et al., 2011), GMSE does not attempt to find optimal strategies or solutions for agents (stakeholders). Instead, genetic algorithms are used to heuristically find an adaptive strategy for each stakeholder in each time step (see Supporting Information 1 for details). Critically, all stakeholders involved in resource conservation are constrained in their decision-making; managing and using resources takes effort (e.g., time or money), and effort expended in developing or enforcing one policy (for managers) or performing one action (for users) will be effort not expendable elsewhere (Milner-Gulland, 2011; Müller-Hansen et al., 2017; Schlüter et al., 2017). In finding strategies, GMSE models this trade-off by setting a fixed budget for managers and users. Allocations from a manager's budget can be used to increase the cost it takes a user to perform an action (i.e., 'policy'), and allocations from a user's budget can be used to perform the action at the cost set by the manager. Hence, stakeholders can have incomplete control over resource use and express competing management objectives.

In each new call of the genetic algorithm, a unique population of managers or users with random strategies is temporarily initialised. In each generation of the genetic algorithm, these strategies crossover and mutate; when this results in strategies that are over-budget, expenditures 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

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in the population then becomes the stakeholder's new strategy. Overall, a single call of the genetic algorithm thereby simulates the process of thinking and decision-making for one manager or user.

GMSE arguments and output

Simulations using the default GMSE sub-models described above 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 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, and a summary of results can be obtained using `gmse_summary`). An example below shows how simulations are set and interpreted.

Argument	Default	Description
time_max	100	Maximum time steps in simulation
land_dim_1	100	Width of the landscape (horizontal cells)
land_dim_2	100	Height of the landscape (vertical cells)
res_movement	20	Distance (cells) a resource can move in any direction (for movement rules, see res_move_type)
remove_pr	0	Density-independent probability of resource mortality during a time step
lambda	0.3	Poisson rate parameter for resource offspring number produced during a time step
agent_view	10	How far managers can see on the landscape for resource counting when observe_type = 0
res_birth_K	10000	Carrying capacity applied to the number of resources added during a time step
res_death_K	2000	Carrying capacity applied to the number of resources removed during a time step
res_move_type	1	Type of resource movement (default is up to res_movement cells in any direction)
observe_type	0	Type of resource observation (default is density-based; i.e, counting a subset on the landscape)
fixed_mark	50	For mark-recapture observation (observe_type = 1), number of marked resources
fixed_recapt	150	For mark-recapture observation (observe_type = 1), number of recaptured resources
times_observe	1	For density-based observation (observe_type = 0), landscape subsets viewed during observation
res_consume	0.5	Pr. of a landscape cell's value reduced by the presence of a resource in a time step
max_ages	5	The maximum number of time steps a resource can persist before it is removed
minimum_cost	10	The minimum cost of a user performing any action
user_budget	1000	A user's budget per time step for performing any number of actions
manager_budget	1000	A manager's budget per time step for setting policy
manage_target	1000	The manager's target resource abundance
RESOURCE_ini	1000	The initial abundance of resources
scaring	FALSE	Resource scaring is a policy option
culling	TRUE	Resource culling is a policy option
castration	FALSE	Resource castration is a policy option
feeding	FALSE	Resource feeding (increases lambda) is a policy option
help_offspring	FALSE	Resource helping (increases offspring number) is a policy option
tend_crops	FALSE	Users can increase landscape cell values
tend_crop_yld	0.2	Proportional increase per landscape cell from tend_crops action
kill_crops	FALSE	Users can decrease landscape cell values to zero
stakeholders	4	Number of users in the simulation
land_ownership	FALSE	Users own land and increase utility indirectly from landscape instead of resource use
manage_freq	1	Frequency (in time steps) with which managers revise and enact policy
public_land	0	Proportion of land that is public (un-owned by users) if land_ownership = TRUE

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

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An example of resource management

Here we illustrate the usefulness of GMSE by considering the case study of a protected population of waterfowl that exploits agricultural land causing a conservation conflict with farmers (e.g., Fox and Madsen, 2017; Mason et al., 2017; Tulloch et al., 2017). Managers attempt to keep the abundance of waterfowl at a target level, while farmers attempt to minimise the damage inflicted on their crops (e.g., Madsen et al., 2017). Using GMSE, we can 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. We consider a population of waterfowl with an initial abundance and manager target abundance of 1000, but whose carrying capacity is 2000. Waterfowl consume and destroy all crop yield upon arrival to a landscape cell. In each time step, waterfowl are observed on a subset of cells, then managers extrapolate from density per cell to estimate total population size. Managers then use these estimates to set costs of culling and scaring (non-lethal) waterfowl for five 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 = 5, observe_type = 0,
            res_death_K = 2000, manage_target = 1000, RESOURCE_ini = 1000,
            user_budget = 1000, manager_budget = 1000, res_consume = 1,
            scaring = TRUE, plotting = FALSE);
```

```
## [1] "Initialising simulations ... "
## [1] "Generation  33 of  100"
## [1] "Generation  66 of  100"
## [1] "Generation  99 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 (manager and user decisions can also be interpreted using the `plot_gmse_effort` function).

```
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 shows the landscape broken down by resource position and farmer land 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 observation uncertainty (compare black and blue lines in 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 farmers 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 1/2). Farmers responding to policy are interested only in minimising 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.

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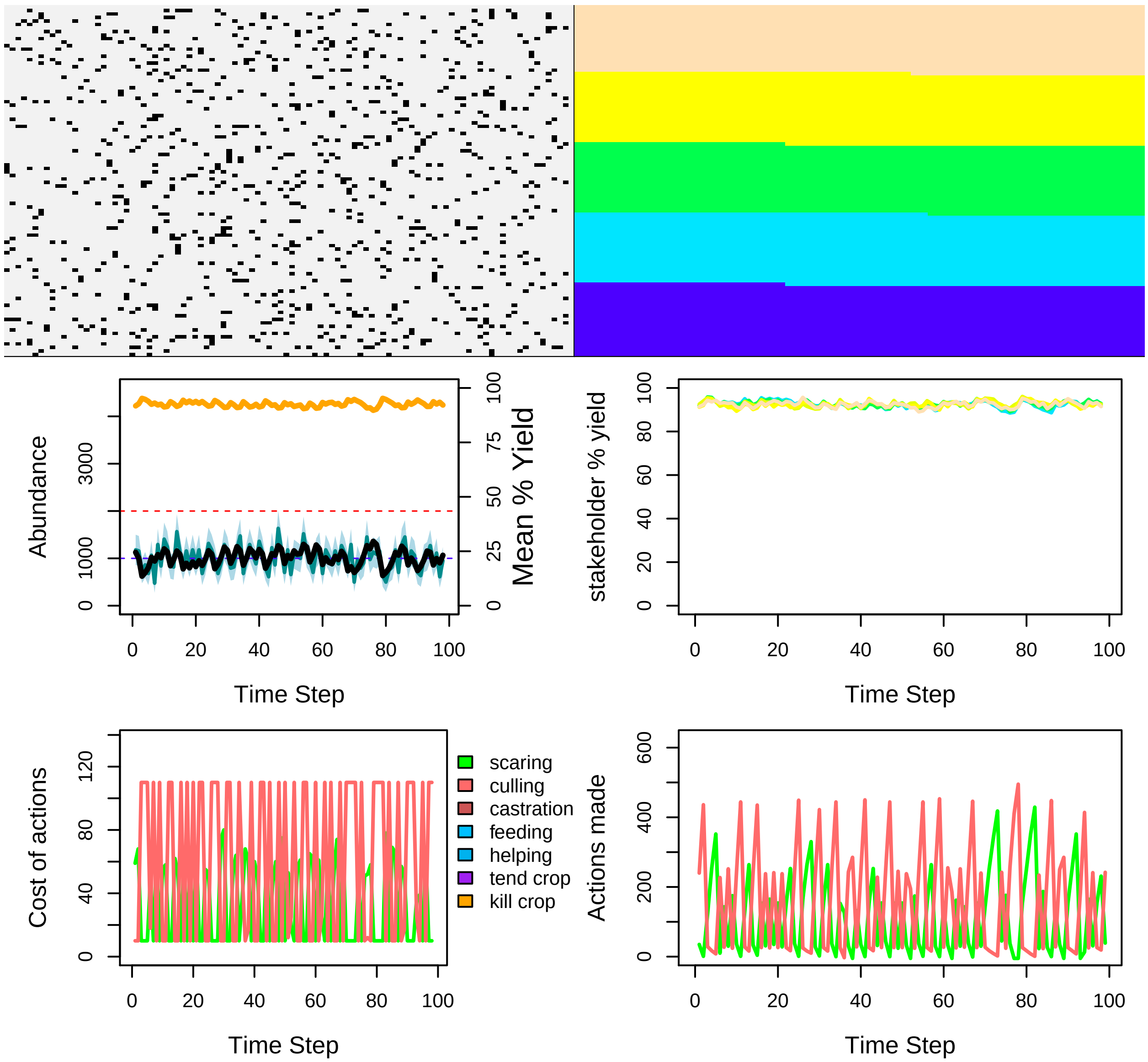

Figure 2: Results of an example simulation illustrating the management of a protected resource that exploits the land of five farmers. The upper left panel shows locations of resources (black dots) on the landscape in the final time step of the simulation. The upper right panel shows the same landscape broken down into five differently coloured regions, which correspond to areas of land owned by each of the five farmers. 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), 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 farmers 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 farmers over time (some actions might be unsuccessful if resources are unavailable on a farmer's land to cull or scare, so, e.g., culling actions might be larger than resources actually culled).

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Graphical User Interface (GUI)

The function `gmse_gui` opens GMSE in a browser and allows simulations to be run for most `gmse` parameter options using the package 'shiny' (Chang et al., 2017). Figures from `plot_gmse_results` and `plot_gmse_effort`, and tables from `gmse_summary` are provided as GUI output.

Custom defined sub-models

The function `gmse_apply` allows custom resource, observation, manager, or user sub-models to be integrated into the GMSE framework. Any type of sub-model (e.g., numerical, individual-based) is permitted by defining a function with appropriately specified inputs and outputs; where custom functions are not provided, `gmse_apply` runs default GMSE sub-models used in `gmse`. Any parameter options available in `gmse` or in custom functions can be passed directly to `gmse_apply`, thereby allowing for high flexibility in model specification. For example, a simple logistic growth function can be integrated as a resource sub-model to replace the default `resource` function.

```
logistic_res_mod <- function(X_0, K = 2000, gr = 1){
    X_1 <- X_0 + gr * X_0 * ( 1 - X_0/K );
    return(X_1);
}
sim <- gmse_apply(res_mod = logistic_res_mod, X_0 = 1000, gr = 0.3, stakeholders = 5);
```

The `gmse_apply` function simulates a single GMSE time step, and therefore must be looped for simulations over multiple time steps. Within loops, GMSE arguments can be redefined to simulate changing conditions (e.g., change in policy availability or stakeholder budgets, see Supporting Information 2), thereby allowing many management scenarios to be simulated *in silico*.

Availability

The GMSE package can be downloaded from CRAN (https://cran.r-project.org/package=GMSE) or GitHub (https://github.com/bradduthie/gmse). GMSE is open source under GNU Public License.

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