**Methods**

*GMSE*

GMSE is designed to simulate dynamic decision-making by stakeholders in a social-ecological system (Duthie et al., 2018). The stakeholders are a) the “manager” who represents an appropriate authority, for example a protected area manager or a natural resource manager, and b) the “users” who represent independent actors such as farmers or hunters. Additionally, there is a natural “resource” population, for example animals or trees, that requires management. In each simulation, the manager is attempting to get the resource population as close to a pre-determined value as possible, and the users are trying to maximise their utility on the landscape. Simulations in GMSE are comprised of four submodels that govern the social-ecological system, each of which can be individually parameterised (Figure 1). The submodels are (1) the natural resource model which is used to simulate the biological population within the system. The natural resource model can simulate complex spatially explicit biological populations that have individual traits such as age, and population-level traits such as carrying capacity and related density-dependent mortality. Because individuals within the population have discrete traits there is inherent stochasticity within the population. (2) The observation model represents the observation process, and the associated error, whereby the manager estimates the size of the natural resource population. The manager sets policy based on the estimates rather than the actual population size, thus introducing uncertainty that exists in the real world. The submodel has four methods available which mimic commonly used biological monitoring techniques. (3) the manager model which uses the genetic algorithm (GA, see below) to develop management policies that attempt to reduce deviation of the natural resource population from the target population size. The manager achieves this by dynamically altering the cost of actions for the users thereby increasing or decreasing the ability of the users to act on the resources. (4) The user model, in which after the manager has set the policy, each user calls the GA to develop a strategy for that time step that maximises their utility (e.g., maximises their yield) given the constraints imposed by the manager. Users can choose to act on the natural resources (e.g., cull or scare) which can affect the resource population (e.g., if they choose to cull) or the landscape cell (e.g., if they choose to scare, forcing resources onto another cell). These changes then feed into the natural resource submodel in the next time step. For detailed explanations of the submodels, see Duthie et al (2018) and the documentation for the GMSE R package.

The primary approach to altering system dynamics is via the manager and user budgets. These parameters are relative rather than absolute and therefore the values are less important than the relationship between them. Generally, when the manager has a high relative budget, they have a greater ability to set policies that will influence the resource population in the desired way. For example, if the resource population is below the target, a manager with a relatively high budget can increase the costs of culling for the users, thus reducing the users’ ability to cull, and in turn allowing the resource population to recover. Conversely, if users have a relatively high budget, then they are more likely to be able to afford to take actions such as culling, even if the manager is setting the costs as high as possible. The budgets, and the associated dynamics, can be used to replicate various real-world systems and scenarios such as conservation conflicts, power dynamics, and lobbying (Cusack et al., 2020; Duthie et al., 2018; Nilsson et al., 2019).

*Genetic algorithm*

The GA is the core process by which the manager develops policy and users decide upon actions. The GA mimics the process of natural selection whereby each call to the GA results in several possible strategies being initialised. Multiple iterations then allow cross-over and mutation between the initialised strategies, ensuring that budgets are not exceeded. Each subsequent iteration of strategies is selected via a fitness function and a tournament. This process results in adaptive, but not necessarily optimal, strategies for the manager and the users. In each simulation time step the GA is called by the manager and each of the users to simulate decision-making. The GA first takes the manager’s budget constraints, user action histories, and the predicted consequences of each action on the resource population and develops a strategy for the manager to reduce deviation from the target resource population size. Once the manager’s policy is established users will individually call the GA to decide upon actions that maximise their utility (e.g., agricultural yield). Users can choose from several options depending on the parameters set by the researcher. These include tending their crops or acting on the natural resources (e.g., cull, scare), all of which will have some effect on their yield. Their ability to act on the natural resource is governed by both the user budget, and the manager’s policy, in each time step.

Diagram

Description automatically generated

**Figure 1. Conceptual flow diagram showing the four submodels and the genetic algorithm, and how they interact in a single time step in GMSE. Figure taken from Duthie et al., (2018).**

*Model parameterisation*

Landscape

In this study we have used the GMSE modelling framework to explore the effects of different investment strategies and funding models available to a conservation manager on forest resources, in the context of finite funds and increasing anthropogenic pressure caused by an increasing human population. We simulated a forested landscape of 100 × 100 cells, where we assumed one cell was equivalent to 1 hectare, resulting in a landscape of 10,000 ha (or 100 km2). We allocated 30 “users” to the landscape, which in this case represented 30 villages or communities, each which had an equal area of spatially explicit land upon which they could act. This resulted in each village having 333.33 ha (3.33 km2) of land. We assumed the users represented agricultural communities whose primary livelihood is farming. We simulated scenarios over 50 time steps, which we assumed represented 50 years.

Resource population

The flexibility of GMSE allows for the biological resource to represent a population of a wide range of taxa. In this study we assumed the resources were trees, that the manager’s goal was to protect as many trees as possible from being felled (i.e., maintain the resource population at the starting value), and that the users were able to increase their agricultural yield by felling trees on their land. We tested the landscape with a tree density that was realistic for a tropical forested landscape (50 trees ha-1, n = 1,125,000), but because the number of users on the landscape was relatively low, due to each user representing a community rather than an individual farmer, the absolute number of trees felled was too low to see clear differences between scenarios. We therefore reduced the total number of trees to 100,000 to ensure trends in felling were clear to see. Trees were randomly distributed across the landscape, reflecting natural variation. The population dynamics of trees is difficult to capture over a 50-year time period due to slow growth and recruitment relative to animals. Furthermore, we wanted to eliminate any “noise” around the deforestation signal so that the only driver of forest loss was the effect of user actions on the trees. Therefore, despite high flexibility within GMSE for simulating realistic population dynamics, we removed the effects of natural recruitment or natural deaths (density-dependent and density-independent), resulting in a static population (excluding the effects of the users). If trees were present on a landscape cell, they reduced the agricultural yield that could be harvested by the user. Each tree reduced the cell’s yield by 8%, with the cumulative reduction in yield governed by the exponential function:

Where *y* is the yield of the cell when trees are present, *Yr* is the % reduction in yield for a single tree, and *Rt* is the number of trees remaining on the cell. Therefore, if there are 50 trees on a given cell, the cell’s yield is 1.5% of the total possible yield. If there are 25 trees remaining on a given cell then the cell’s yield increases to 12.4%, and so on.

Users

GMSE allows for each user to represent an individual actor or agent, who makes decisions about their actions based on individual circumstances. However, the number of users on a landscape cannot be changed during a simulation, and so to simulate increasing human populations we assumed that each user represented a village or community rather than an individual. We assumed that a population increase in a real-world community would result in increased human and financial resources, and increased demand for land (e.g., for housing and agriculture). These combined effects would increase the community’s desire and ability to clear forest land. This allowed us to employ the user budget to simulate population increases. The user budget is the primary parameter that governs a user’s ability to take actions, such as felling trees. Therefore, a user budget that increases during the simulation represents an increase in the user’s power to act, thus simulating population increases. The land ownership parameter for all simulations was set to TRUE, resulting in each community having a spatially explicit area of land upon which they could act. When users own their land, they use the GA to try and maximise their yield in each time step (rather than trying to increase their harvest of the biological resource, as is the case when land ownership = FALSE). The only actions the users were permitted to take were 1) tend crops, and 2) fell trees. The decision about which action to take in each time step was governed by trade-offs in cost versus benefit (computed within the GA). The parameter which defined how much a user could increase their yield by tending their crops was set to 0.01 (1%). This contrasts with the parameter governing the yield reduction for a single tree (8%, see section above). Different ranges of these parameters were tested for sensitivity (Table Sx), with the final values chosen to deliberately ensure that felling trees would have a much higher positive effect on yield than simply tending crops. This was both to reflect the fact that in the real world expanding agricultural area will generally increase yield more than tending existing agricultural land, and to simulate strong exogenous drivers of deforestation that are found around the world, particularly in the tropics (Ceddia 2019, Davis et al 2015).

Manager

In our study, the manager represents a person or organisation that has a remit to conserve forest land and the authority to set and implement policy that affects the ability of users to take actions. We set the resource population target (which the manager tries to maintain) at the same value as the starting number of trees, and because there was no natural tree regeneration (natural population increase), the manager’s goal is to reduce forest loss as much as possible in every time step. These parameters were set to simulate a conservation landscape in which there is pressure on forest resources, and authorities are trying to reduce all forest loss. This could, for example, represent a protected area which contains both forest and local communities. In each time step the manager called the GA and identified a policy, which was reflected in the cost for users to fell trees, that attempted to reduce forest loss as much as possible. We assumed the manager’s budget reflected the actual budget of the authority, and could represent a monetary budget, available non-monetary resources (e.g., law enforcement resources), or a combination of these. In each of the different scenarios, the manager’s budget varied according to the funding scenario we were simulating.

*Scenarios*

We designed 5 scenarios with dynamic manager budgets that simulated different funding regimes (Table 1, Figure 2) that a manager or authority with responsibility over a conservation landscape may encounter in the real world. Before running the final 5 scenarios we tested several null scenarios to ensure the landscape was operating as expected (Supporting Information). Due to the nature of the GA (i.e., identifying one out of multiple possible near-optimal solutions), and that each actor on the landscape calls the GA in each time step, stochasticity is explicitly built into the simulations. Therefore, each simulation was run 100 times to quantify variation in results. The manager budget, user budget, number of felling actions, the cost of felling actions, and the number of trees remaining at each time step were extracted for each replicate simulation. For each parameter, the 50, 2.5, and 97.5% percentiles across all replicates were calculated and used to represent the mean, and lower and upper confidence intervals, respectively. For all scenarios in which the manager budget displays some level of increase (scenarios 2 to 5, Table 1, figure 2), we ensured that the total cumulative budget was equal across all scenarios. This was to eliminate the possibility of one scenario outperforming another simply because the manager had access to a greater total budget over the simulation period. In all scenarios we assumed the same level of human population increase over time, and so for each scenario the user budget increases linearly with the same starting point and slope (Table 1, figure 2). The absolute values for the user budget are arbitrary and can be set in such a way as to meet the objectives of the study. We tested various starting values and slopes for the user budget, increasing the parameter values until the absolute number of trees felled was sufficient to see clear differences between scenarios.

The manager and user budgets are not equal nor necessarily proportional, as they are used in very different ways (Duthie et al 2018). Therefore, equal budgets (e.g., if both manager and user budgets were set to 500) do not necessarily equate to equal power to affect the system. The differences in manager and user budgets relative to each other is what governs the differences and changes in power to affect the system. It is important to recognise the incomparability between the absolute values of the manager and user budgets, and therefore to differentiate the two parameters in this study we will refer to the user budget as “community resources”.

All simulations were conducted using the R package GMSE (Duthie et al 2018, v0.6.2.0), and all associated analyses described below were conducted in R (v4.0.4, R Core Team, 2021).

Scenario 1

This scenario assumed that the manager budget does not change over the simulation period (Figure 2). This scenario was designed to represent a conservation landscape in which the authority has a regular and predictable budget over time with which to invest in policy, but one which does not increase or decrease in response to changing threats or grant cycles. This scenario could represent a government-funded landscape which has a finite but regular budget that is not reliant on short-term grants.

Scenario 2

This scenario assumed that the budget available to the manager starts low but increases with increasing pressure on the landscape (Figure 2). This scenario could represent a statutory authority in a conservation landscape in which the authority is provided regular and predictable budget increases with which to invest in policy. In this scenario the management authority is not reliant on short-term grants. The shape of the manager budget (starting point, slope) was calculated to ensure that the total cumulative budget was equal to scenarios 3 to 5.

Scenario 3

This scenario assumed that the budget available to the manager increases and decreases in a regular and predictable way, regardless of the changing pressure on the landscape (Figure 2). This scenario was designed to replicate a conservation landscape in which the management authority is largely reliant on regular grant cycles. The scenario assumes that the authority conducts successful fundraising at regular intervals, and thus has a varying yet predictable budget with which to invest in policy implementation. The cycle length (i.e., the wavelength) is approximately 5 years, reflecting larger grants that are often provided by statutory funding agencies or international bodies. These large, longer-term grants require a high investment in staff time to apply for, and high administrative capacity to manage once implemented, and so are generally won by large, international organisations, government agencies, or collaborations between such partners, where the required resources already exist. To simulate this funding cycle, we produced a sine wave of the form:

Where *MB* is a vector of resulting manager budget values, and *t* is a vector of time steps (1:50).

Scenario 4

This scenario assumed that the budget available to the manager increased and decreased in unpredictable and irregular ways (Figure 2). This was to simulate a conservation landscape in which the management authority relies on grant funding for policy implementation, and so applies for a range of different grants which vary in size and duration and is not necessarily successful at any given time. This scenario could reflect any number of conservation landscapes around the world, where project budgets are subject to the success of funding applications, resulting in variable and unpredictable resources for project activities and policy implementation. To simulate this scenario, we produced a set of three random sine waves by randomly sampling values between 0.01 and 0.08 for the fundamental frequency, between 1 and 5 for the wave frequency, between 1 and 150 for the wave strength (amplitude), and between 0 and 180 for the wave delay. The three sine waves were then combined using an Inverse Fourier Transform to produce a random complex wave (ref?). Each of the 100 replicates produced a different complex wave (Figure 2 shows 10 examples, see Supporting Information for all the waves used in the simulations). The Inverse Fourier Transform took the form:

Where *trj* is the trajectory of the random complex wave, *acs* is the additive constant signal, *cs* is the component strength, *cf* is the component frequency, *w* is *2 × π × F0*, where *F0* is the fundamental frequency, *t* is the duration of the wave, and *cd* is the component delay.

Scenario 5

This scenario is a more extreme example of scenario 4 and was to test the effect of increased variation and uncertainty in manager budgets on deforestation and system dynamics. We increased the range of the available values from which the fundamental frequency and component strength could be sampled from, thus increasing the potential amplitude of each wave, and making the changes in wave frequency more extreme (figure 2 shows 10 examples, see Supporting Information for all the waves used in the simulations). To simulate this scenario, we produced a set of three random sine waves by randomly sampling values between 0.01 and 0.2 for the fundamental frequency, between 1 and 5 for the wave frequency, between values 1 and 300 for the wave strength (amplitude), and between 0 and 180 for the wave delay.

Standardisation

For scenarios 2 to 5 we standardised the manager budgets to a total cumulative budget over the 50 time steps of 25,000, using:

where *x* is the vector of manager budget values produced in the above sections.

Maximum harvest under maximum conflict

The maximum harvest under maximum conflict (MHMC) was calculated for each time step in each scenario to improve our understanding of the power dynamics between the manager and the communities. The MHMC is a single value for each time step that is based on the manager and user budgets at that time step. It is the maximum number of trees a user can harvest if the manager uses all of their budget to reduce culling, and the user uses all of their budget to cull. The manager uses 10 budget points to increase the cost of culling by 1. There is always a minimum cost of an action of 10. Therefore, the cost of an action for the user, assuming the manager is using all of their budget to increase the cost of the action, will be:

Where *nUA* is the number of user actions (i.e., the number of trees felled), *CR* is the community resources (user budget), and *MB* is the manager budget.

**Table 1. details of the five scenarios**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Scenario** | **Description** | **Manager budget** | |  | **Community resources** | | |
| **Starting value** | **Total cumulative budget** |  | **Starting value** | **Slope** | **Total cumulative resources** |
| 1 | Manager budget remains constant (i.e., does not increase) over time. Community resources increases linearly | 500 | 25,000 |  | 2000 | 75 | 191,875 |
| 2 | Manager budget increases linearly, reflecting a regular and predictable increase in resources over time. Community resources increase linearly | 126.9 | 25,000 |  | 2000 | 75 | 191,875 |
| 3 | Manager budget increases and decreases in a predictable way, reflecting reliable funding cycles. Community resources increases linearly | 499.3 | 25,000 |  | 2000 | 75 | 191,875 |
| 4 | Manager budget increases and decreases unpredictably, reflecting unreliable and unpredictable funding streams over time. Community resources increase linearly | Variable | 25,000 |  | 2000 | 75 | 191,875 |
| 5 | Manager budget increases and decreases unpredictably, reflecting unreliable and unpredictable funding streams over time. Community resources increase linearly | Variable | 25,000 |  | 2000 | 75 | 191,875 |

Chart

Description automatically generated

**Figure 2. Manager budgets and community resources (user budget) for the five scenarios. Scenarios 4 and 5 have different manager budgets for each replicate simulation, and so this figure shows 10 examples for each.**