Models as games: a novel approach for 'gamesourcing' parameter data and communicating complex models

1 Summary

1. Models have become indispensable tools in conservation science in the face of increasingly rapid loss of biodiversity through anthropogenic habitat loss and natural resource exploitation. In addition to their ecological components, accurately representing human decision-making processes in such models is vital to maximise their utility. This can be problematic, as such socio-ecological models because increasingly complex, and thus both challenging to communicate and parameterise.

2. Games have a long history of being used as science communication tools, but are less widely used as data collection tools, particularly in videogame form. This is surprising, given many parallels between models and videogames. We here propose a novel approach to (1) aid communication of complex socio-ecological models, and (2) "gamesourcing" human decision-making data, by explicitly casting an existing modelling framework as an interactive videogame. NICE!

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3. We present players with a natural resource management game as a front-end to the modelling framework GMSE. Players actions replace a model algorithm involving management decisions about a population of wild animals which graze on crops, and can thus lower agricultural yield. A number of (non-player) farmers respond to the player's management, taking actions that may affect their yield as well as the animal population. Players are asked to set their own management goal (e.g. maintain the animal population at a certain level or improving yield), and make decisions accordingly. Trial players were also asked to provide any feedback on both gameplay and purpose.

May need to explain how the non-player responses are determined briefly ie. model algorithm

4. We demonstrate the utility of this approach by collecting and analysing game play data from a small sample of trial plays, in which we systematically vary two model parameters, and allowing trial players to interact with the model through the game

interface. As an illustration, we show how variations in land ownership and the number of farmers in the system affects decision-making patterns as well as population trajectories (extinction probabilities).

5. We discuss the potential and limitations of this model-game approach in the light of trial player feedback received, focusing in particular on (1) concerns about perceived lack of realism and potential adverse effects on external validity of decision-making, and (2) potential issues with audience bias and player sampling. Player feedback further highlights the parallels between games and models, and in particular the need for clear communication of model limitations and assumptions. We conclude that videogames provide an effective means to do so, and that although they provide a promising means to collect data on human decision-making, it is vital to carefully consider both external validity and potential biases when doing so.

Probably need to briefly state how trial players were selected

2 Introduction

In recent years, the use and application of models has become widespread and indispensable in conservation science, ranging from demonstrating the likely effects of climate change (IPCC 2021) to supporting the understanding of fundamental processes in natural resource management (e.g. Fryxell et al. 2010; Cusack et al. 2020). Given the continued rapid global loss of biodiversity (Ceballos et al. 2015; Ceballos, Ehrlich, and Dirzo 2017), understanding the mechanisms and consequences of such loss is vital. Although a number of drivers of biodiversity loss have been identified (e.g. Maxwell et al. 2016), one of the most prevalent and widespread ones is human exploitation of habitats and natural resources, both directly (e.g. through hunting or habitat loss to agriculture) or indirectly (e.g. through international trade in natural resources) (e.g. Wilting et al. 2017). Because resource use is fundamentally driven by economic and social processes, it has long been recognised that accurate predictions thereof is reliant as much on understanding resource dynamics as it is on understanding human behaviour and decision-making (Milner-Gulland 2012; Schlüter et al. 2012). Thus, the development of socio-ecological models in which natural resource dynamics and human decision making interact is becoming increasingly urgent.

Cutting-edge modelling approaches have made significant progress towards this goal. For example, Orach, Duit, and Schlüter (2020) used an agent-based model to show how coalitions of interest groups can stabilise natural resource dynamics, whereas Cusack et al. (2020) used a novel agent-based modelling framework (Duthie et al. 2018) to assess the effect of lobbying on species extinction risk. Although such modelling efforts represent significant progress in modelling complex socio-ecological systems, their increased complexity poses two, interlinked, challenges. First, models are often difficult to communicate clearly to non-specialist audiences in the first place, and this challenge increases with model complexity (Grimm et al. 2006). This is particularly important for models for resource use in socio-ecological systems, as they are often specifically intended for use by managers or stakeholders who may lack technical expertise. Much has been said about improving the uptake of models in such settings (e.g. Addison et al. 2013; Schuwirth et al. 2019; Will et al. 2021), and detailed documentation of the purpose, organisation and predictions has been highlighted as particularly important (Grimm et al. 2020). Even so, often the evidence for practical uptake of many models is limited (Addison et al. 2013; Zasada et al. 2017). Second, their complexity implies the need for extensive data to parameterise them effectively. In terms of socio-ecological systems, while data to parameterise the ecological component are often relatively easily available, the human decision-making components are often based on limited theory and lack a general empirical basis (Groeneveld et al. 2017). Not only may this lead to limited predictive power, a perceived lack of empirical basis may negatively affect their acceptance by stakeholders (cf. model "quality" as in Kolkman et al. 2016). To maximise the adoption of complex socio-ecological models as management tools, both appropriate representation of human decision-making and effective communication are therefore key.

Games have a long history of being in research (Sandbrook, Adams, and Monteferri 2015; Chabris 2017; Redpath et al. 2018) including as tools to aid the communication of complex ideas and processes to non-specialists (Garcia, Dray, and Waeber 2016; Tan et al. 2018; Fjaellingsdal and Kloeckner 2019), with online and video games recently becoming popular (**REF**). Given this long history, it is striking that the parallels between videogames in particular and models are not discussed more widely. All models are abstract representations of environments, actors and relationships, with inputs (parameters) and outputs (predictions or inferences). Similarly, all games present a player with an environment in a given state (parameters), including one or more actors, which can take actions (inputs) to affect the environment for a given effect (outputs). It is worth stressing that every game has an underlying model that defines the state of the environment, relationships between objects in this environment, and inputs and outputs available to the player. However, while games are by definition designed with player (user) interaction in mind, models rarely have user-facing or even user-friendly interfaces, and running or adapting them to specific circumstances usually relies on technical expertise. Casting models as games provides an opportunity to effectively improve the communication and understandability of even relatively complex models. Inputs and outputs may be presented in a visual way and tweaked depending on the type of audience, and both potential applications and limitations of the model can be demonstrated effectively.

I am sold! :)

In addition, presenting a model as a game provides an opportunity to empirically collect data on how stakeholders make decisions in the modelled environment. Games have already been widely used for data collection to answer specific questions (e.g. Meinzen-Dick et al. 2016; Villamor and Badmos 2016; S. Rakotonarivo et al. 2021; O. S. Rakotonarivo et al. 2021) on what affects decision-making in socio-ecological systems. A less well-explored potential of using this approach is using in-game decisions directly as a “big data” source to improve the parameterisation of the underlying model itself. Many existing models represent human decision-making by relatively crude algorithms (e.g. fully rational utility maximisation) despite widespread recognition that this does not reflect real-world decision-making (Groeneveld et al. 2017). By presenting real-world stakeholders with in-game decisions that would otherwise be taken by a predefined algorithm, large data sets of actions and outcomes may be collected. Given a large enough sample of players and in-game conditions, such data might then be used to train decision-making algorithms that better reflect human decision-making in natural resource management[1]. It is notable that this "gamesourcing" or "Gamorithm" (Sipper and Moore 2020) approach has already been widely used in a number of other fields (e.g. crowdsourcing accurate protein-structure models (Khatib et al. 2011), and classification of fluorescence microscopy images (Sullivan et al. 2018)), but remains rare in conservation science (but see van den Bergh et al. 2021). Thus, model-games can be considered "virtual laboratories" (Duthie et al. 2021) to not only test specific hypotheses or predictions, but potentially also as an effective method to source data to parameterise the underlying models, based on in-game decisions by real humans.

We here aim to illustrate the potential for this model-game approach, both in terms of aiding model communication as well data collection for improved parameterisation, by introducing Animal&Farm (A&F). We developed A&F as a simple interactive game front-end for a complex socio-ecological modelling framework (GMSE), in which the player acts as the manager of a virtual environment in which a population of wild grazing animals (the natural resource) may adversely affect farming yield, with farmers acting to maximise their yield and potentially hunting the animals. We argue that by acting as an interface between users (i.e. players) and a complex underlying model with many components and assumptions, such a game can simultaneously (1) aid the communication and useability of the underlying model and (2) can be used to gather data to improve the parameterisation of such models. We first briefly summarise the underlying modelling framework, its potential and limitations. Second, we describe both the structure of A&F itself as well as its database back-end. Third, we outline how this approach may be used to collect data on player decision-making in simulated *in silico* experiments, and present some example results of doing so; noting that these findings are intended as illustrative only. Finally, using test player feedback as a basis, we discuss both the limitations of this approach as well as its wider potential.

[1] Note that there are of course limitations to this, and that data on decisions made would only be relevant to the context of the game (i.e. internally valid in the game context). Wider external validity depends on a number of factors; we discuss limitations in more detail below.

3 Outline of approach

A&F is available to play online.

Overall, it consists of two main components; (1) the underlying model(s) describing the wild grazing animal ("resource") population dynamics, the observation of this population, and farmer ("user" or stakeholder) actions, all implemented using the GMSE framework as described below; and (2) the game interface for the underlying model, which allows the player to set management actions (specifically, costs for user actions) that would otherwise be determined by the management model in the default GMSE set up.

3.1 Underlying model: GMSE

We used the Generalised Management Strategy Evaluation (GMSE) modelling framework to model the socio-ecological system underlying A&F. The GMSE R package (**REF**) was designed as a flexible solution for parameterising systems that model the management, observation, exploitation and population dynamics of a natural resource (e.g. a population of hunted wildlife). In this section, we summarise the basic functionality of GMSE as relevant to the present manuscript; for a full description see Duthie et al. (2018) and Nilsson et al. (2021) (the latter containing an appendix with the full ODD model description).

3.1.1 Basic introduction of GMSE principles and structures

GMSE consists of four submodels (Figure 1a): (1) the **resource model**, an individual-based model for an animal population situated on a landscape modelled as 100x100 square cells; (2) the **observation model** which represents the process of observations (including a degree of uncertainty) of the animal population, feeding into (3) the **manager model** which uses the observation of the animal population to make management decisions, involving costs set for agents in (4) the **user model**, representing a number of agents (farmers) that each own a part of the landscape. In each time step, both manager and user agents are allocated a (fixed) budget. The users (farmers) may allocate their budget to taking one of several potential actions (here:

hunting animals, scaring animals of their land, or tending crops - they may only take these actions on their own land).

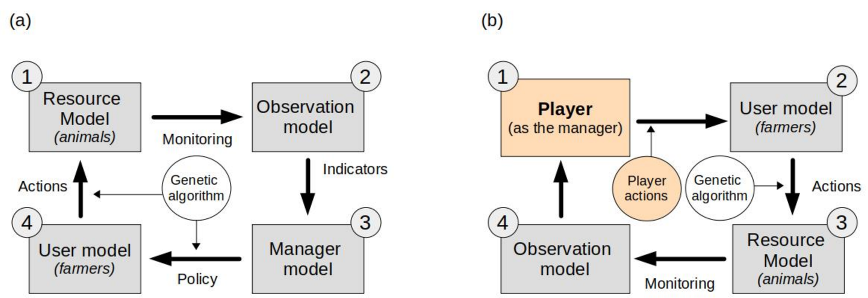

Figure 1. The basic structure of (a) the GMSE modelling framework and its default order of operations with the genetic algorithm (GA) modelling the decision-making process of both users and manager, and (b) the adaptation of the GMSE framework to accomodate the model-game approach presented here. The grey boxes represent the various GMSE submodels, with the arrows representing the process links between them. The yellow boxes and circles are the adapted components in the model-game adaptation, with player interaction replacing the manager model in GMSE, and the underlying GA for the manager - the GA is still used to make user decisions. Grey circles indicate the order of operations in each.

The goal for the manager is to maintain the animal population to a desired level (the management target, normally set externally as a model parameter). It does so by controlling the cost for user (farmer) actions in the following time step: e.g. higher costs for hunting is likely to decrease the number of animals hunted, limiting negative effects on the population and thus making population increases more likely, decreasing scaring cost may increase the number of users choosing scaring. Users (farmers) aim to maximise agricultural yield from their land; yield equals 1 per cell owned per time step, but yield is decreased by the presence of animals on a cell (e.g. through grazing) and may be increased by tending crops (one of the possible three actions). Through this, users have an incentive to control the number of animals of their land, either through allocating budget to hunting or through scaring. The former permanently reduces the number of animals present, the latter has a certain probability of moving an animal away from

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the user's land, for the duration of the time step. Users can only take actions on land that they own.

Costs for actions (by the manager) or actions taken (by the users) are chosen using a genetic algorithm (GA), a heuristic optimisation algorithm which mimics the choice of decision as evolution by natural selection; a large number of possible decisions are iteratively compared by assessing their outcome, with the decision that maximises a given utility function (yield for users, and minimising distance to population target for the manager) identified as the "fittest." The GA is run separately for each agent (manager and all users) in each time step.

In the default resource (animal) model in GMSE, the animal population is modelled as a form of logistic growth, with a small amount of added random mortality per time step and death caused by hunting; for more detail see below and in Duthie et al. (2018). In each time step, each animal moves a given distance in a random direction, and feeds from the cell it is present in. In the current model, neither movement nor population growth rate is affected by agricultural yield.

It is worthwhile stressing that in the current GMSE implementation, using the GA, both agent types (users and the manager) essentially have only a single goal they each aim for. Users (farmers) aim to maximise their yield, whereas the manager aims to minimise deviation from a given population target - neither can balance multiple competing objectives. This is unlikely to be reflective of real conservation scenarios, where it is common for conservation managers to at least recognise other aims if not take these explicitly into account when setting policy , and other stakeholders in the system (e.g. farmers) commonly having some interest in conservation objectives (**REF?**). Human decision-making in such scenarios in inevitably about balancing these different objectives, but parameterising algorithms that mimic such processes without reference to long-term data is very challenging (**REF?**). Addressing this issue was a key motivation for the development of the model-game approach presented here.

3.2 Animal&Farm

3.2.1 Structure as relating to GMSE

In the default implementation of GMSE 0.6.2.0, a single time t step consists of a series of calls to the resource model, observation model, management model and user model, in that specific order; in other words, a time step ends after user actions have been chosen (by the GA) and implemented (Figure 1b). To allow players to assess the environment and interactively choose management actions, A&F uses a modified version of GMSE.

A&F uses a development version of GMSE (v. 0.6.2.0, implemented in R version 4.1.0 (2021-05-18), code available here in which the management model is replaced by user (player) inputs, and the order of operations is altered to accommodate this. To initialise each game session, four time steps are run using the default GMSE implementation; i.e. in these time steps the management decisions are chosen by the default GA, and the resource, observation and user models are run using the parameters as defined for the given scenario (see 4.2 below). These time steps are followed by a "partial" time step where only the resource and observation models are run, skipping the management and user models. As a result, at the end of these initial time steps (`init_man_control()`), the simulated system has five population and observation time steps and is ready for the next choice of management action at $t = 5$, pending the first player input. This is done both to set up all the required GMSE data structures using existing code, as well as to provide the player with a short time series on which to base management decisions going forward.

The current GMSE simulations used by A&F simulates a landscape of 100x100 cells, divided into farms owned by 4-12 farmers (stakeholders; the precise number and land distribution is randomly varied per session, see 4.2 below). Farmers can take three possible actions; tending crops, hunting (culling) animals, or scaring animals off their land. All submodels used in A&F are currently the default GMSE models (with the exception of the management model in time steps $t > 5$, where the player assumes control over the management decisions (see below). Thus, we only give brief details here, for full details and descriptions of all models, see Duthie et al.

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(2018) and Nilsson et al. (2021) for further details). The **animal population** model uses the logistic growth form with $N_o = 1000$, $\lambda = 0.3$ and $K = 5000$, meaning that in the absence of any management the population is likely to increase from the initial population size (1000) to carrying capacity (5000). The **observation model** uses the default GMSE model (density-based sampling of a subset of the environment); only *observed* numbers of animals are available to the manager to base decisions on (and thus population trajectory plots in the game interface reflect observations only, which are subject to an unknown level of uncertainty). Both the **management model** (in the initialisation steps) and **user model** use the GA algorithms with default parameter settings. User (farmer) budgets are set to 1500 units per time step, manager budgets to 1000 units (both for the initial 5 time steps and the subsequent game play). The users (farmers) aim to maximise yield from their land, their annual budget is reset each year and is unaffected by yield. Yield is positively affected by tending crops, and may be negatively affected by the presence of grazing wild animals - thus hunting or scaring may offset any potentially negative effects on yield. Note that the choice of models and parameter values here serve as an example only; it is expected that future implementations and development of A&F will focus on specific research questions / case studies, and will adjust models and parameter settings accordingly (see Discussion).

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Each following A&F time step then consists of (1) user input, taking the place of the default management model, in which the player can assess the environment using outputs provided (see below) and choose management actions (costs for user actions), and, (2) and once the player confirms their choice, a modified GMSE time step including sequential calls to the default user, resource and observation models (`gmse_apply_UROM()`) (Figure 1b).

3.2.2 User interface

The user interface for A&F is a web application is coded in R, using `Shiny` (1.6.0), and packages `shinyjs` (2.0.0), `shinyBS` (0.61), and `waiter` (0.2.2).

On starting a new game session, the player is presented with a series of introductory screens explaining the background, flow and objective of the game , after which they are asked to enter a player name, which is stored and used to show player scores as the end of a session, compared to previous sessions by other players.

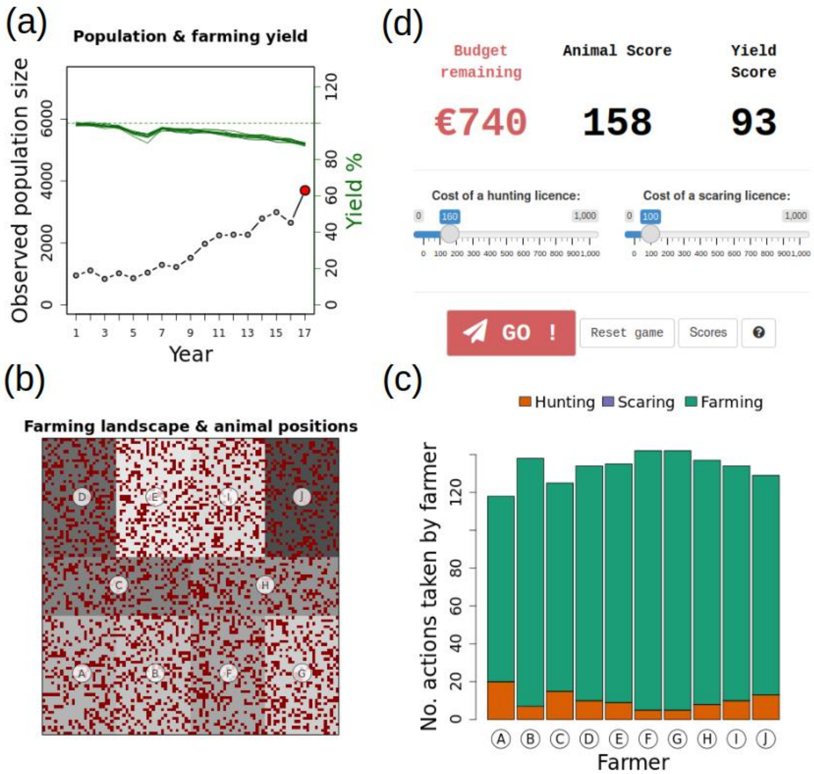

Figure 2. The Animal & Farm main game interface, showing (a) animal (resource) population trajectory and yield per farmer, (b) the farming landscape with animal positions as red dots and farm ownwership indicated by the grey shades, (c) actions taken by farmers in the previous game round, and (d) user inputs inluding a budget report and costs set for actions.

The main game screen consists of four components (Figure 2). First, a trajectory plot (Figure 2a) showing (1) observed animal population numbers and (2) agricultural yield for each farmer in each time step, up to time t (at the start of the game this will show five observations from the initialisation steps described above). Agricultural yield is expressed as a % of "maximum unaffected yield," i.e. yield in the absence of damage from wildlife or investment in tending crops. Second, a plot of the landscape (Figure 2b) showing the distribution of farm ownership as well as the position of animals at time t. Third, a bar plot of the number of actions taken by each farmer at time t (Figure 2c). Fourth, a report of the current management budget available (not allocated), player scores (see 3.2.3 below), and player inputs (Figure 2d). The player (manager) inputs consist of two sliders, setting the cost for two out of the three actions available[2] to farmers in time $t + 1$: killing animals (presented as the cost of a hunting licence) and scaring animals off their land (presented as the cost of a scaring licence). Management budget allocated to one of these cannot be allocated to another, and any budget not allocated is not rolled over to the next time step. The third action available to farmers (tending crops) cannot be directly[3] affected by the manager (player), so no input is available for this .

The game progresses to the next time step $t + 1$ once the player confirms their choice of cost inputs. At this point (1) the user, resource and observation models are run using the updated action costs set by the player, (2) selected environment state data are stored in the database (See 3.2.3 below), and (3) trajectory, landscape and action plots are updated and budget allocation is reset. The current implementation of A&F continues for a maximum of 20 time steps (following the initial five) at which point the game session is ended and the player is presented with a scoreboard. If the resource population reaches extinction, the game session is also terminated.

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[2] A&F currently focuses only on hunting animals, scaring animals or tending crops as available actions to farmers; this may be expanded in the future to other actions available in GMSE.

[3] It can be affected *indirectly* by setting the cost for the two actions prohibitively high, so that tending crops becomes more likely to be most beneficial to maximising yield (the farmer's goal).

3.2.3 Game objective, scores and scoreboard

Other than preventing extinction of the animal population, A&F does not have a particular game objective; instead, the player is asked to make management decisions reflecting their preference of animal population and agricultural yield trajectory. The player is, however, presented with two scores which allows them to assess their performance relative to their own previous game sessions as well as those of other players.

The scores are arbitrarily defined to reflect performance in terms of the animal population ("animal score," A_t) on the one hand, and overall agricultural yield ("yield score," Y_t) on the other. Both scores can be interpreted as the mean % of the initial (i.e. at time $t = 5$) true size of the animal population N_t and landscape yield y_t, with y_t calculated as the mean yield over all landscape cells at time t .

$A_t = \left(\sum \frac{N_t}{N_{t=5} \cdot t}\right) \cdot 100$ and $S_t = \left(\frac{\sum_{t=5}^{T} y_t}{t}\right) \cdot 100$ where $t \geq 5$ and T the total number of time steps for the game session.

Both scores are intitialised as $A_t = S_t = 100$ when the game is first initialised, to ensure score development over a session can be interpreted as a change from that baseline.

Players can choose to either balance both scores, or score highly on one or the other. They are updated and displayed on each time step, and the final scores are displayed on a score board after the final time step ($t = 25$, so after 20 time steps played) is complete, or once the animal population goes extinct. The scoreboard is a top 10 "leaderboard" of scores over all sessions played by all players to date; if the current player's score is not included in the top 10, it is displayed at the bottom of the board with the correct rank relative to other players.

3.2.4 Data collection & database

Game play data (e.g. session variables, player inputs, environment state variables) are stored in a MySQL relational database. Database structure is summarised in **Fig X** and a full list of parameter values stored and their description is listed in **Table X**. The current version of A&F stores only a subset of GMSE parameters (**Table X**); this may be easily extended in the future by

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adding additional fields to the relevant database table and ensuring the database interface functions append the extra parameters. For any GMSE parameters that are not stored currently, the default GMSE parameter values are used.

In summary, six main tables are used to store data (see **XXX** for a full description). Tables are linked by the unique session ID present in each table.

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- `run`

  Holding player name, start- and end times for the session and a flag for whether or not the animal population reached extinction or not (single record per session).

- `run_par`

  Holding all game parameters for the GMSE simulation for a session. As per section **XXX**, in the example application presented here, the majority of these will be constants, with only `ownership_var` and `remove_pr` varying per session.

- `scores`

  Holding the number of time steps achieved per session and the animal and yield score.

- `gdata`

  A record per time step for each session, recording the true and observed population state, the number of actions of each type taken, and the costs set by the manager (player), as well as the total yield in the environment.

- `yield`

  The yield achieved by each farmer in each time step, per session.

Records in tables `run`, `run_par` and `scores` are only updated at the start and end of each session, whereas `gdata` and `yield` are the "live" tables that are appended to at each time step during a game session. End times are recorded for each session where the player either reaches $t = 25$, manually resets the game during a session, or as the animal population reaches extinction; i.e. when this field remains blank (`NULL`), it means that a session was not terminated “normally,” i.e. by the browser being closed manually or timing out due to inactivity.

4 Example application

4.1 “Sandbox” for *in silico* experiments

The combination between the underlying modelling framework, game interface and the database back-end, provides a platform to collect data on player interaction with the models in a range of simulated environments. This might include *in silico* tests of the effect of specific variability in the environment on simulat~~ion~~ed animal population extinction, or collecting “big data” on player decision-making given a set of (more or less) variable parameters in terms of population, observation or user (farmer) models. For example, a user of the platform may be interested in testing how human decision-making varies depending on the extent of observed variation in either the ecological (e.g. more or less uncertainty in animal population trajectories) or social (e.g. higher or lower variability in land ownership or sizes of farmer budgets) parts of the modelled system. Data from such experiments may then be combined with debriefing interviews with players to further investigate what may drive such decision-making (e.g. S. Rakotonarivo et al. 2021). Alternatively, by collating large amounts of decision-making data under varying parameter settings as well as the outcome of each game session (e.g. animal population extinction and/or trajectories), it may be possible to develop algorithms that can make decisions that are most likely to lead to a desired outcome (e.g. minimising extinction probability while maintaining agricultural yield, or maximising one or the other score). While the genetic algorithm for manager decision-making currently implemented in GMSE is effective, it does not currently balance multiple objectives, nor does it necessarily accurately reflect variability in real-life decision-making processes. Parameterising an alternative algorithm directly based on empirical decision-making data has the potential to address these shortcomings.

4.2 Example scenario & method

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4.2.1 Rationale & methods

We here illustrate one aspect of this potential by collecting decision-making data from a small sample of test players, during a short period. We chose to focus on a scenario that systematically varies two parameters, farmer land ownership distribution o_v and the number of farmers (stakeholders, s). While inequity in land ownership is commonplace and of interest to conservation strategies (**REF**), the current manager decision-making algorithm implemented in GMSE cannot explicitly take the extent of such variation in account. Thus, collecting empirical data on how decisions and resultant population trajectories may be affected by variable land distribution is important.

(I've just seen it's explained here)

Each new game session is initialised with a random draw of one of three possible values of o_v, representing low, moderate and high variability in land ownership (resulting landscape patterns illustrated in **Fig X**) and one of nine possible values of s, i.e. 4-12 farmers. In addition to this variability, each session also has a small amount of random population mortality ($0.05 \leq r_d \leq 0.2$), sampled from a uniform distribution. Although the landscape ownership distribution is clearly shown to the player throughout the game (**see XX above**), the player is not told explicitly that ownership will vary before a session starts, or what the extent of this variability will be. This was done to ensure that a player would not selectively abort sessions. Other than this scenario-based parameter variation, game play progresses as described above, with the player able to make management decisions (setting costs for farmer actions) over 20 time steps following the initial five.

We circulated a link to the game with scenarios configured as above to a sample of 45 contacts working in conservation science and practical conservation and management, covering a range of academic institutions, research institutes, NGO's and government. Contacts were also asked to share the link with any potentially interested contacts. The main aim was to (1) obtain feedback on the model-game set up, and (2) collect example data to illustrate the potential of the approach, with specific emphasis on how communication of it may be improved in the future. An accompanying covering letter explained this aim, the background to the work, and a request to respond with any feedback. Note that the data collected here should not be interpreted as comprehensive research on a specific question, and is intended as illustrative only.

4.2.2 Ethics

The work described here was approved by the University of Stirling's General University Ethics Panel (GUEP), project no. 2519. While the game link is publicly accessible, it was not publicised beyond the direct contacts described above. On accessing the link, players are presented with a series of introductory screens explaining the background and purpose of the game, followed by a digital consent form, which has to be agreed to by ticking a confirmation tick box, before a new session can be started. No personally identifiable data are collected or stored, other than a player nickname - the latter is only requested so that scores can be shown in context and compared to other players; however this can be left as a default placeholder, and players explicitly told that this is not expected to be their real name. Player nicknames are replaced by random identifiers prior to further data processing.

4.3 Illustrative results

woah!

Between 21 July 2021 and 19 August 2021, we collated data on 76 play session by 28 unique players[4]. Sessions lasted 4.5 on average (0.2 - 179.4 minutes). As per the scenario set up, these sessions were roughly equally distributed between land ownership variability o_v (0, 0.25 or 0.5, N = 21 [28%], 32 [42%], and 23 [30%], respectively) and number of stakeholders s (4-12).

The animal population reached extinction in 23 out of the 76 sessions (30.3%). Extinction probability appeared to be higher at both higher levels of land ownership variability ($o_v = 0.25$ and $o_v = 0.5$), particularly so at intermediate ($o_v = 0.25$) levels (Figure 3a). Differences in

[4] Strictly speaking, unique player *names*. It is possible for the same player to play under multiple different player names. See Discussion for further details.

I'm wondering if folk (skim readers) may still think these are research results - depending on the journal, maybe having them in a box, or something like that, to clearly distinguish them as illustrative??

extinction probability with variability in farmer (stakeholder) number was less pronounced (Figure 3b).

These extinction probabilities were reflected in the animal population trajectories in each parameter scenario. Figure 4 shows trajectories per level of landownership variability, with cases where the population reached extinction highlighted in red. Both higher levels of variablility ($o_v = 0.25$ and $o_v = 0.5$) show fewer cases with rapid increasing trends.

Management actions taken by the players (over time, $t > 5$) are summarised in Figure 5. It is notable that when land ownership variability was higher ($o_v = 0.5$), chosen costs for hunting licences appeared to be more stable (i.e. less variable), particularly toward the end of playing sessions (Figures 5c vs. 5a-b). It should be noted that this may in part be an artifact of somewhat lower sample size at higher time steps (because in some sessions the population would have gone extinct part way through a session). On average, hunting licence costs also appeared to be set lower overall at higher land ownership variability. By comparison, costs set for scaring licences appeared to more stable over time (Figures 5d-f).

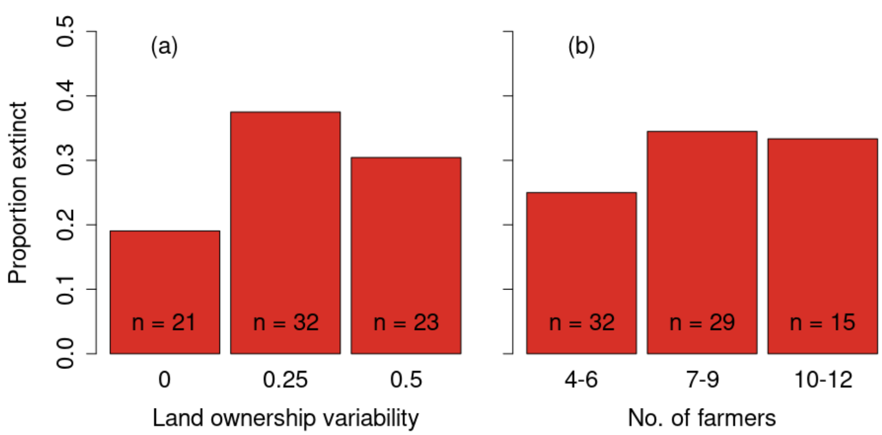

Figure 3. Proportion of game sessions where animal population reached extinction, as a function of (a) land ownership variability and (b) the number of farmers (stakeholders) in the game session.

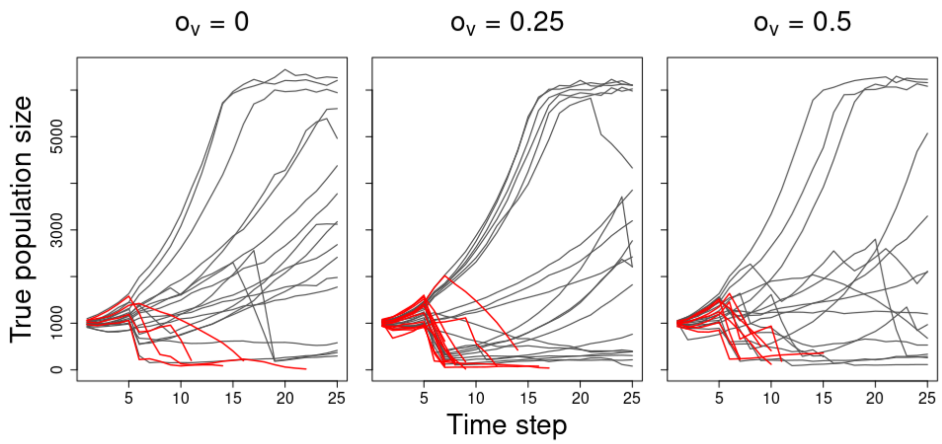

Figure 4. Animal population trajectories per game session, split by levels of land ownership variability. Trajectories highlighted in red are sessions where the population reached extinction.

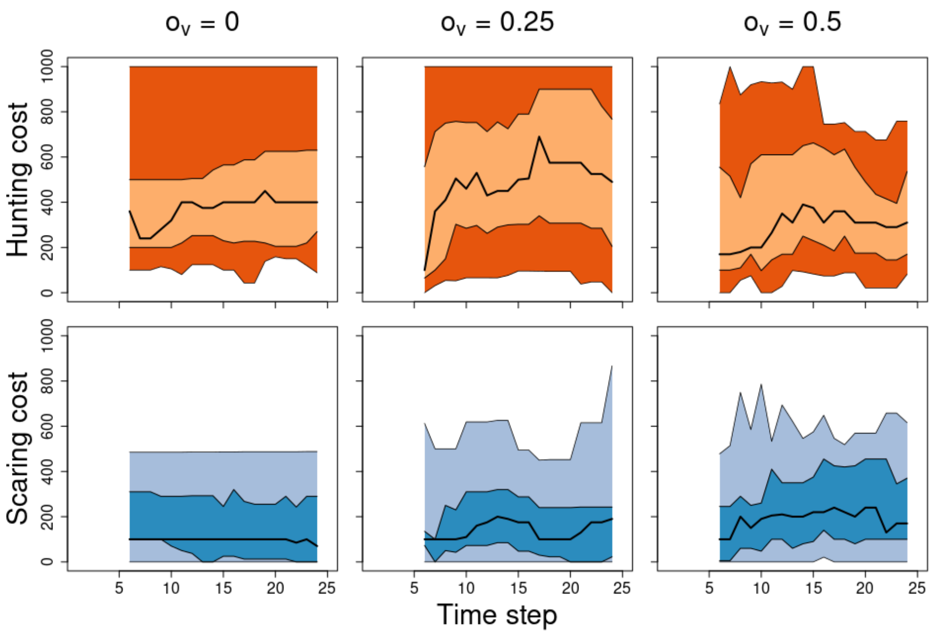

Figure 5. Summary of player management actions (costs set for hunting- and scaring licences) over time, per ownership variability scenario. Solid black line is the mean cost per time step, with lighter and darker polygons representing the 25-75% and 2.5% and 97.5% quantiles of the cost distribution per time step.

5 Discussion

We have here outlined a framework for using an interactive game (A&F) as an interface to a socio-ecological model for natural resource management. The game interface allows players that are not familiar with the underlying model to interact directly and easily with it, with game play decisions directly reflecting parameter settings in the models. We argue that not only does this provide a convenient communication/education tool with respect to both the specific model and models in general, it also provides a tool to both perform *in silico* experiments on human decision-making in given natural resource management scenarios, as well as collect large amounts of data that may be used to improve the model parameterisation. It is worth stressing that we are here specifically referrring to model-games as data-collection tools, as opposed to exclusively as communication- or educational tools.

5.1 Potential

We illustrated the potential of this approach by presenting data from a small number of trial game play sessions: we showed that subtle variation in farmer land ownership can lead to noticeably different resource population trajectories and manager (player) decision-making patterns. While the data shown here should be taken as illustrative only, it highlights the potential to easily run a range of *in silico* experiments with direct relevance to real-world questions. For example, observation uncertainty and its consequences on decision-making is a perennial topic in conservation management (Nuno, Bunnefeld, and Milner-Gulland 2013). While real-world experiments on this would be extremely challenging and costly, GMSE provides a suitable modelling framework in which observation uncertainty can be manipulated, with A&F providing the platform to run controlled experiments with real-world stakeholders. This approach could extend to many if not all of the 74 parameters currently controllable by users in GMSE, ranging from variability in demography or behaviour of the natural resource, to user (farmer) behaviour or variability, and wider environmental change or stochasticity. The game interface and player interaction would remain the same, with only the underlying architecture and database back end requiring minor tweaks to accommodate the extra parameter variation.

In addition to use as an experimental tool, this approach also has great potential for use as a way to source large amounts of decision-making data which may then be used to re-parameterise the underlying models, to better reflect real-world decision making. Given a large enough sample of play sessions with a range of parameter combinations and outcomes, it may be possible to train machine learning algorithms on data collected from this approach, to represent human decision-making under a wide range of conditions. Such algorithms would potentially reflect a range of subtleties of the decision-making process, e.g. balancing multiple objectives in the presences of e.g. social, financial, and organisational constraints. Algorithms implemented in existing

Does this need a reference?

modelling approaches (without reference to empirical data) including GMSE, are very limited in how they can represent such "non-rational" decision-making.

5.2 Some limitations and potential solutions

5.2.1 "The game is unrealistic"

I'm not sure they're necessary (don't want to make it sound too negative...)

There are clearly a number of limitations to the model-game approach, particularly in terms of directly using "game-sourced" data to (re)parameterise underlying models. One concern was raised by several trial players, and can be summarised as the game or game play lacking "realism," or crucially, lacking aspects or features or real life, or the player's experience of the conservation problem (**INSERT QUOTES?**). This may be seen as particularly problematic if such data collected is subsequently used to adjust model parameterisation; i.e. if the game world is not seen as sufficiently realistic, it may be argued that player behaviour cannot be taken as realistic (i.e. perceived lack of realism leading to lack of external validity, (Jackson 2012; Levitt and List 2007)), and therefore any reparameterisation would be (at best) biased. While a very important point, it is interesting to note that strictly speaking, this point relates to the *underlying model* as opposed to the game or the game interface itself. That is, concerns about the lack of "features" or assumptions made are as true of any model as they are of the game representation of it, and indeed they are applicable to all models ("*all models are wrong*," (Box 1979)). Indeed, this in itself highlights the value of the model-game approach, in that it helps the user (i.e. player) to fully understand the model's structure, assumptions, and consequent limitations: particularly given complex socio-ecological models, it can be challenging to effectively communicate the full scope of features and limitations (Grimm et al. 2006, 2020). By casting the model as a game, users are put in the center of the modelling process, and any limitations are likely more apparent, more quickly. Recognition of this, particularly by those lacking technical modelling expertise is vital when such models are put to applied use: all models are abstractions of reality and their utility ("*some models are useful*," (Box 1979)) depends on careful application and recognition of this.

Very well argued in this section!

5.2.2 “Humans are biased”

An additional limitation of “gamesourcing” data either in experimental settings or for parameterising models, is the potential for the sampled decision-making data to be biased, e.g. in terms of players or their motivations. For example, either intentionally or unintentionally, it may be that players are sampled from a limited subset; e.g. all players may have a single professional background such as conservation science, or the nature of the game (framing) may selectively attract a subset of the public. As a consequence, decision-making may not be representative of a wider population of potential players (e.g. more biased towards conservation rather than social objectives). While this is an important potential issue, we argue that such issues can be avoided by carefully controlling player recruitment, and subsampling of data collected in different sampling regimes, depending on the research question. This may be achieved, for example, by using game play session codes, separating game sessions for a specific experiment from “open” play sessions (**REF Izzy’s game**).

Oh yay! Though I wonder it actually written anything to reference... argh!

Similar bias may occur if some players play the game with widely different motivations (e.g. Levitt and List 2007): e.g. playing to “win,” simply maximise a single score, or deliberately attempt to achieve undesirable outcomes. Indeed, it should be stressed that the scores used in the example implementation presented here are to some extent entirely arbitrary, and the choice of scoring system (including algorithms to calculate them) may inherently bias the decision-making data collected, depending on player motivations. There are a number of ways in which this issue can be addressed. First, in fully implementing this model-game approach, it will be vital to collect player data through pre- or post-game questionnaires, including on e.g. professional background, social- and ecological atttitudes (as in e.g. S. Rakotonarivo et al. 2021; O. S. Rakotonarivo et al. 2021), which can be used to control for any potential motivational biases in decision-making data. It should be noted that the current example implementation of A&F allows for anonymous play, and that collection of player personal data would require both further ethical approval as well as additional infrastructure (i.e. unique player names through codes or accounts). Second, it should be stressed that in setting up A&F, we were careful not to steer players to play to maximise any specific objective (**INCLUDE PHRASE ON GAME GOAL**

IN INTRO SCREENS). Careful framing of the game (either in open play or in more limited experimental settings) in terms of game objectives, and ensuring that this matches the objective of the particular application, is vital to avoid goal bias.

5.3 Concluding remarks

Provided that the limitations outlined above are taken into account, and the given application is carefully considered, we believe that the approach outlined here has great potential to advance both the understanding and capability of complex socio-ecological models for natural resource management. As previous work has already shown, games and in particular videogames provide a great tool to increase public engagement with quantitative models, and we here highlight how this could be extended to provide effective, flexible and powerful tools for data collection.

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6.1

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