GMSE: an R package for generalised management strategy evaluation

Supporting Information 4

A. Bradley Duthie[1,3], Jeremy J. Cusack[1], Isabel L. Jones[1], Jeroen Minderman[1], Erlend B. Nilsen[2], Rocío A. Pozo[1], O. Sarobidy Rakotonarivo[1], Bram Van Moorter[2], and Nils Bunnefeld[1]

[1] Biological and Environmental Sciences, University of Stirling, Stirling, UK [2] Norwegian Institute for Nature Research, Trondheim, Norway [3] alexander.duthie@stir.ac.uk

Fine-tuning simulation conditions using `gmse_apply`

Here we demonstrate how simulations in GMSE can be more fine-tuned to specific empirical situations through the use of `gmse_apply`. To do this, we use the same scenario described in Supporting Information 3; we first recreate the basic scenario run in `gmse` using `gmse_apply`, and then build in additional modelling details including (1) custom placement of user land, (2) parameterisation of individual user budgets, and (3) density-dependent movement of resources. We emphasise that these simulations are provided only to demonstrate the use of GMSE, and specifically to show the flexibility of the `gmse_apply` function, not to accurately recreate the dynamics of a specific system or make management recommendations.

We reconsider the case of a protected waterfowl population that exploits agricultural land (e.g., Fox and Madsen, 2017; Mason et al., 2017; Tulloch et al., 2017; Cusack et al., 2018). The manager attempts to keep the watefowl at a target abundance, while users (farmers) attempt to maximise agricultural yield on the land that they own. We again parameterise our model using demographic information from the Taiga Bean Goose (*Anser fabalis fabalis*), as reported by Johnson et al. (2018) and AEWA (2016). Relevant parameter values are listed in the table below.

Table 1: GMSE simulation parameter values inspired by Johnson et al. (2018) and AEWA (2016)

Parameter	Value	Description
`remove_pr`	0.122	Goose density-independent mortality probability
`lambda`	0.275	Expected offspring production per time step
`res_death_K`	93870	Goose carrying capacity (on adult mortality)
`RESOURCE_ini`	35000	Initial goose abundance
`manage_target`	70000	Manager's target goose abundance
`res_death_type`	3	Mortality (density and density-independent sources)

Additionally, we continue to use the following values for consistency, except in the case of `stakeholders`, where we reduce the number of farmers to `stakeholders = 8`. This is done to for two reasons. First, it speeds up simulations for the purpose of demonstration; second, it makes the presentation of landscape ownership easier (see below).

Table 2: Non-default GMSE parameter values chosen by authors

Parameter	Value	Description
`manager_budget`	10000	Manager's budget for setting policy options
`user_budget`	10000	Users' budgets for actions

Parameter	Value	Description
`public_land`	0.4	Proportion of the landscape that is public
`stakeholders`	8	Number of stakeholders
`land_ownership`	TRUE	Users own landscape cells
`res_consume`	0.02	Landscape cell output consumed by a resource
`observe_type`	3	Observation model type (survey)
`agent_view`	1	Cells managers can see when conducting a survey

All other values are set to GMSE defaults, except where specifically noted otherwise.

Re-creating `gmse` simulations using `gmse_apply`

We now recreate the simulations in Supporting Information 3, which were run using the `gmse` function, in `gmse_apply`. Doing so requires us to first initialise simulations using one call of `gmse_apply`, then loop through multiple time steps that again call `gmse_apply`; results of interest are recorded in a data frame (`sim_sum_1`). Following the protocol introduced in Supporting Information 2, we can call the initialising simulation `sim_old`, and use the code below to read in the relevant parameter values.

```
sim_old  <- gmse_apply(get_res = "Full", remove_pr = 0.122, lambda = 0.275,
                       res_death_K = 93870, RESOURCE_ini = 35000,
                       manage_target = 70000, res_death_type = 3,
                       manager_budget = 10000, user_budget = 100000,
                       public_land = 0.4, stakeholders = 8, res_consume = 0.02,
                       res_birth_K = 200000, land_ownership = TRUE,
                       observe_type = 3, agent_view = 1, converge_crit = 0.01,
                       ga_mingen = 200);
```

Note that the argument `get_res = "Full"` causes `sim_old` retain all of the relevant data structures for simulating a new time step and recording simulation results. This includes the key simulation output, which is located in `sim_old$basic_output`, which is printed below.

```
## $resource_results
## [1] 34237
##
## $observation_results
## [1] 34237
##
## $manager_results
##          resource_type scaring culling castration feeding help_offspring
## policy_1             1      NA     509         NA      NA             NA
##
## $user_results
##         resource_type scaring culling castration feeding help_offspring
## Manager             1      NA       0         NA      NA             NA
## user_1              1      NA     191         NA      NA             NA
## user_2              1      NA     190         NA      NA             NA
## user_3              1      NA     191         NA      NA             NA
## user_4              1      NA     191         NA      NA             NA
## user_5              1      NA     190         NA      NA             NA
## user_6              1      NA     190         NA      NA             NA
## user_7              1      NA     190         NA      NA             NA
## user_8              1      NA     190         NA      NA             NA
```

```
##         tend_crops kill_crops
## Manager         NA         NA
## user_1          NA         NA
## user_2          NA         NA
## user_3          NA         NA
## user_4          NA         NA
## user_5          NA         NA
## user_6          NA         NA
## user_7          NA         NA
## user_8          NA         NA
```

We can then loop over 30 time steps to recreate the simulations from Supporting Information 3. In these simulations, we are specifically interested in the resource and observation outputs, as well as the manager policy and user actions for culling, which we record below in the data frame `sim_sum`. The inclusion of the argument `old_list` tells `gmse_apply` to use parameters and values from the list `sim_old` in the new time step.

```
sim_sum_1 <- matrix(data = NA, nrow = 30, ncol = 5);
for(time_step in 1:30){
    sim_new                 <- gmse_apply(get_res = "Full", old_list = sim_old);
    sim_sum_1[time_step, 1] <- time_step;
    sim_sum_1[time_step, 2] <- sim_new$basic_output$resource_results[1];
    sim_sum_1[time_step, 3] <- sim_new$basic_output$observation_results[1];
    sim_sum_1[time_step, 4] <- sim_new$basic_output$manager_results[3];
    sim_sum_1[time_step, 5] <- sum(sim_new$basic_output$user_results[,3]);
    sim_old                 <- sim_new;
}
colnames(sim_sum_1) <- c("Time", "Pop_size", "Pop_est", "Cull_cost",
                         "Cull_count");
print(sim_sum_1);
```

```
##       Time Pop_size Pop_est Cull_cost Cull_count
##  [1,]    1    32649   32649       849        922
##  [2,]    2    32176   32176       953        825
##  [3,]    3    32449   32449       974        809
##  [4,]    4    33218   33218      1009        778
##  [5,]    5    37392   37392       997        787
##  [6,]    6    38510   38510       998        786
##  [7,]    7    40035   40035       987        794
##  [8,]    8    41742   41742      1001        785
##  [9,]    9    43703   43703       995        791
## [10,]   10    45901   45901       993        793
## [11,]   11    48305   48305       994        793
## [12,]   12    50905   50905       998        786
## [13,]   13    53632   53632       984        800
## [14,]   14    56316   56316      1006        779
## [15,]   15    59405   59405      1003        785
## [16,]   16    62388   62388      1000        786
## [17,]   17    65620   65620       993        793
## [18,]   18    69096   69096       995        789
## [19,]   19    73265   73265        10      29160
## [20,]   20    47254   47254      1010        778
## [21,]   21    49745   49745       991        793
## [22,]   22    52113   52113      1006        781
## [23,]   23    54944   54944      1001        785
```

```
## [24,]   24   57797   57797      994       793
## [25,]   25   60994   60994     1000       786
## [26,]   26   64048   64048     1007       780
## [27,]   27   67489   67489     1002       785
## [28,]   28   71478   71478       10     29137
## [29,]   29   45231   45231     1010       778
## [30,]   30   47487   47487      989       794
```

The above output from `sim_sum_1` shows the data frame that holds the information we were interested in pulling out of our simulation results. All of this information was available under the list element `sim_new$basic_output`, but other list elements of `sim_new` might also be useful to record. It is important to remember that this example of `gmse_apply` is using the default resource, observation, manager, and user submodels. Custom submodels could produce different outputs in `sim_new` (see Supporting Information 2 for examples). For default submodels, there are some list elements that might be especially useful. These elements can potentially be edited *within the above loop* to dynamically adjust simulations.

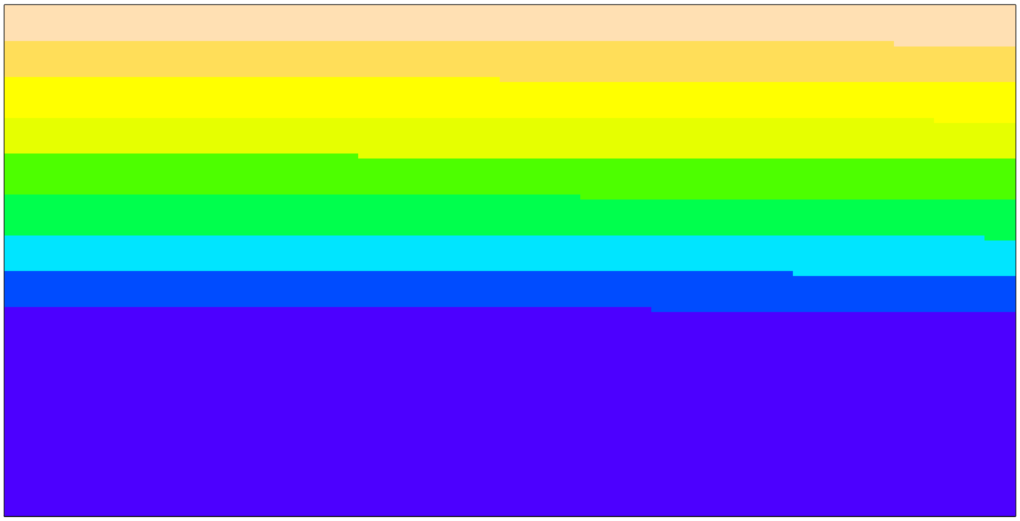
- `sim_new$resource_array`: A table holding all information on resources. Rows correspond to discrete resources, and columns correspond to resource properties: (1) ID, (2-4) types (not currently in use), (5) x-location, (6) y-location, (7) movement parameter, (8) time, (9) density independent mortality parameter (`remove_pr`), (10) reproduction parameter (`lambda`), (11) offspring number, (12) age, (13-14) observation columns, (15) consumption rate (`res_consume`), and (16-20) recorded experiences of user actions (e.g., was the resource culled or scared?).
- `sim_new$AGENTS`: A table holding basic information on agents (manager and users). Rows correspond to a unique agent, and columns correspond to agent properties: (1) ID, (2) type (0 for the manager, 1 for users), (3-4) additional type options not currently in use, (5-6), x and y locations (usually ignored), (7) movement parameter (usually ignored), (8) time, (9) agent's viewing ability in cells (`agent_view`), (10) error parameter, (11-12) values for holding marks and tallies of resources, (13-15) values for holding observations, (16) yield from landscape cells, (17) budget (`manager_budget` and `user_budget`).
- `sim_new$observation_vector`: Estimate of total resource number from the observation model (`observation_array` also holds this information in a different way depending on `observe_type`)
- `sim_new$LAND`: The landscape on which interactions occur, which is stored as a 3D array with `land_dim_1` rows, `land_dim_2` columns, and 3 layers. Layer 1 (`sim_new$LAND[,,1]`) is not currently used in default submodels, but could be used to store values that affect resources and agents. Layer 2 (`sim_new$LAND[,,2]`) stores crop yield from a cell, and layer 3 (`sim_new$LAND[,,3]`) stores the owner of the cell (value corresponds to the agent's ID).
- `sim_new$manage_vector`: The cost of each action as set by the manager. For even more fine-tuning, individual costs for the actions of each agent can be set for each user in `sim_new$manager_array`.
- `sim_new$user_vector`: The total number of actions performed by each user. A more detailed breakdown of actions by individual users is held in `sim_new$user_array`.

Next, we show how to adjust the landscape to manually set land ownership in `gmse_apply`.

1. Custom placement of user land

By default, all farmers in GMSE are allocated the same number of landscape cells, which are simply placed in order of the farmer's ID. Public land is produced by placing landscape cells that are technically owned by the manager, and therefore have landscape cell values of 1. The image below shows this landscape for the eight farmers from `sim_old`.

```r
image(x = sim_old$LAND[,,3], col = topo.colors(9), xaxt = "n", yaxt = "n");
```

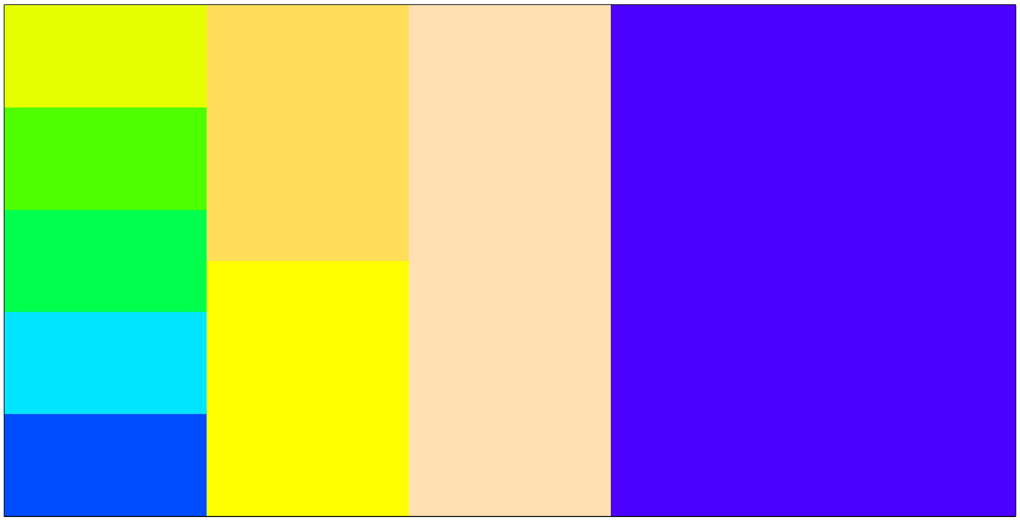


We can change the ownership of cells by manipulating `sim_old$LAND[,,3]`. First we initialise a new `sim_old` below.

```
sim_old  <- gmse_apply(get_res = "Full", remove_pr = 0.122, lambda = 0.275,
                       res_d4eath_K = 93870, RESOURCE_ini = 35000,
                       manage_target = 70000, res_death_type = 3,
                       manager_budget = 10000, user_budget = 10000,
                       public_land = 0.4, stakeholders = 8, res_consume = 0.02,
                       res_birth_K = 200000, land_ownership = TRUE,
                       observe_type = 3, agent_view = 1, converge_crit = 0.01,
                       ga_mingen = 200);
```

Because we have not specified landscape dimensions in the above, the landscape reverts to the default size of 100 by 100 cells. We can then manually assign landscape cells to the eight farmers, whose IDs range from 2-9 (ID value 1 is the manager). Below we do this to make eight different sized farms.

```
sim_old$LAND[1:20,   1:20,  3] <- 2;
sim_old$LAND[1:20,  21:40,  3] <- 3;
sim_old$LAND[1:20,  41:60,  3] <- 4;
sim_old$LAND[1:20,  61:80,  3] <- 5;
sim_old$LAND[1:20,  81:100, 3] <- 6;
sim_old$LAND[21:40,  1:50,  3] <- 7;
sim_old$LAND[21:40, 51:100, 3] <- 8;
sim_old$LAND[41:60,  1:100, 3] <- 9;
sim_old$LAND[61:100, 1:100, 3] <- 1; # Public land
image(x = sim_old$LAND[,,3], col = topo.colors(9), xaxt = "n", yaxt = "n");
```



The above image shows the modified landscape stored in `sim_old`, which can now be incorporated into simulations using `gmse_apply`. We can think of all the plots on the left side of the landscape as farms of various sizes, while the blue area of the landscape on the right is public land.

2. Parameterisation of individual user budgets

Perhaps we want to assume that farmers have different budgets, which are correlated in some way to the number of landscape cells that they own. Custom user budgets can be set by manipulating `sim_old$AGENTS`, the last column of which (column 17) holds the budget for each user. Agent IDs (as stored on the landscape above) correspond to rows of `sim_old$AGENTS`, so individual budgets can be directly input as desired. We can do this manually (e.g., `sim_old$AGENTS[2, 17] <- 4000`), or, alternatively, if farmer budget positively correlates to landscape owned, we can use a loop to input values as below.

```
for(ID in 2:9){
    cells_owned             <- sum(sim_old$LAND[,,3] == ID);
    sim_old$AGENTS[ID, 17] <- 100 * cells_owned;
}
```

The number of cells owned by each farmer is therefore listed in the table below.

ID	1	2	3	4	5	6	7	8	9
Budget	10000	40000	40000	40000	40000	40000	1e+05	1e+05	2e+05

As with `sim_old$LAND` values, changes to `sim_old$AGENTS` will be retained in simulations looped through `gmse_apply`.

3. Density-dependent movement of resources

Lastly, we consider a more nuanced change to simulations, in which the rules for movement of resources are modified to account for density-dependence. Assume that geese tend to avoid aggregating, such that if a goose is located on the same cell as too many other geese, then it will move at the start of a time step. Programming this movement rule can be accomplished by creating a new function to apply to the resource data array `sim_old$resource_array`. Below, a custom function is defined that causes a goose to move up to 5 cells in any direction if it finds itself on a cell with more than 10 other geese. As with default GMSE simulations, movement is based on a torus landscape.

```
avoid_aggregation <- function(goose_table, land_dim_1 = 100, land_dim_2 = 100){
    goose_number <- dim(goose_table)[1]    # How many geese are there?
    for(goose in 1:goose_number){          # Loop through all rows of geese
        x_loc  <- goose_table[goose, 5];
        y_loc  <- goose_table[goose, 6];
        shared <- sum(goose_table[,5] == x_loc & goose_table[,6] == y_loc);
        if(shared > 10){
            new_x <- x_loc + sample(x = -5:5, size = 1);
            new_y <- y_loc + sample(x = -5:5, size = 1);
            if(new_x < 0){ # The 'if' statements below apply the torus
                new_x <- land_dim_1 + new_x;
            }
            if(new_x >= land_dim_1){
                new_x <- new_x - land_dim_1;
            }
            if(new_y < 0){
                new_y <- land_dim_2 + new_x;
            }
            if(new_y >= land_dim_2){
                new_y <- new_y - land_dim_2;
            }
            goose_table[goose, 5] <- new_x;
            goose_table[goose, 6] <- new_y;
        }
    }
    return(goose_table);
}
```

With the above function written, we can apply the new movement rule along with our custom farm placement and custom farmer budgets to the simulation of goose population dynamics.

Simulation with custom farms, budgets, and goose movement

Below shows an example of `gmse_apply` with custom landscapes, farmer budgets, and density-dependent goose movement rules.

```
# First initialise a simulation
sim_old  <- gmse_apply(get_res = "Full", remove_pr = 0.122, lambda = 0.275,
                       res_death_K = 93870, RESOURCE_ini = 35000,
                       manage_target = 70000, res_death_type = 3,
                       manager_budget = 10000, user_budget = 10000,
                       public_land = 0.4, stakeholders = 8, res_consume = 0.02,
                       res_birth_K = 200000, land_ownership = TRUE,
                       observe_type = 3, agent_view = 1, converge_crit = 0.01,
                       ga_mingen = 200, res_move_type = 0);
# By setting `res_move_type = 0`, no resource movement will occur in gmse_apply
# Adjust the landscape ownership below
sim_old$LAND[1:20,   1:20,  3] <- 2;
sim_old$LAND[1:20,  21:40,  3] <- 3;
sim_old$LAND[1:20,  41:60,  3] <- 4;
sim_old$LAND[1:20,  61:80,  3] <- 5;
```

```r
sim_old$LAND[1:20,  81:100, 3] <- 6;
sim_old$LAND[21:40,  1:50,  3] <- 7;
sim_old$LAND[21:40, 51:100, 3] <- 8;
sim_old$LAND[41:60,  1:100, 3] <- 9;
sim_old$LAND[61:100, 1:100, 3] <- 1;
# Change the budgets of each farmer based on the land they own
for(ID in 2:9){
    cells_owned            <- sum(sim_old$LAND[,,3] == ID);
    sim_old$AGENTS[ID, 17] <- 10 * cells_owned;
}
# Begin simulating time steps for the system
sim_sum_2 <- matrix(data = NA, nrow = 30, ncol = 5);
for(time_step in 1:30){
    # Apply the new movement rules at the beginning of the loop
    sim_old$resource_array  <- avoid_aggregation(sim_old$resource_array);
    # Next, move on to simulate (old_list remembers that res_move_type = 0)
    sim_new                 <- gmse_apply(get_res = "Full", old_list = sim_old);
    sim_sum_2[time_step, 1] <- time_step;
    sim_sum_2[time_step, 2] <- sim_new$basic_output$resource_results[1];
    sim_sum_2[time_step, 3] <- sim_new$basic_output$observation_results[1];
    sim_sum_2[time_step, 4] <- sim_new$basic_output$manager_results[3];
    sim_sum_2[time_step, 5] <- sum(sim_new$basic_output$user_results[,3]);
    sim_old                 <- sim_new;
}
colnames(sim_sum_2) <- c("Time", "Pop_size", "Pop_est", "Cull_cost",
                         "Cull_count");
print(sim_sum_2);
```

```
##       Time Pop_size Pop_est Cull_cost Cull_count
##  [1,]    1    33736   33736       772         74
##  [2,]    2    34021   34021       882         64
##  [3,]    3    35040   35040       937         61
##  [4,]    4    36538   36538       948         60
##  [5,]    5    42054   42054       958         60
##  [6,]    6    44004   44004       989         59
##  [7,]    7    46454   46454       987         60
##  [8,]    8    49267   49267      1004         52
##  [9,]    9    52325   52325       975         60
## [10,]   10    56050   56050       999         53
## [11,]   11    60032   60032       980         60
## [12,]   12    63945   63945       985         60
## [13,]   13    67892   67892       996         56
## [14,]   14    72191   72191       427        136
## [15,]   15    76750   76750       431        137
## [16,]   16    81631   81631       413        140
## [17,]   17    87006   87006       444        131
## [18,]   18    93120   93120       418        138
## [19,]   19    99563   99563       421        138
## [20,]   20   101705  101705       430        137
## [21,]   21   102557  102557       429        135
## [22,]   22   102719  102719       416        139
## [23,]   23   103107  103107       440        134
## [24,]   24   103163  103163       420        138
## [25,]   25   103493  103493       422        138
```

```
## [26,]   26   103366  103366        432         135
## [27,]   27   103154  103154        413         140
## [28,]   28   103538  103538        416         139
## [29,]   29   103444  103444        428         137
## [30,]   30   103897  103897        428         137
```

Conclusions

In this example, we showed how the built-in resource, observation, manager, and user sub-models can be customised by manipulating the data within the data structures that they use. The goal was to show how software users can work with these existing sub-models and data structures to customise GMSE simulations. Software users seeking even greater flexibility (e.g., replacing an entire built-in submodel with a custom submodel) should refer to the Supporting Information 2 that introduces `gmse_apply` more generally. Future versions of GMSE are likely to expand on the built-in options available for simulation; requests for such expansions, or contributions, can be submitted to GitHub.

References

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