# GMSE: an R package for generalised management strategy evaluation

Supporting Information 4

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## 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 |
| `public_land` | 0.4 | Proportion of the landscape that is public |

| Parameter | Value | Description |
|---|---|---|
| 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] 34000
##
## $observation_results
## [1] 34000
##
## $manager_results
##          resource_type scaring culling castration feeding help_offspring
## policy_1             1      NA     504         NA      NA             NA
##
## $user_results
##         resource_type scaring culling castration feeding help_offspring
## Manager             1      NA       0         NA      NA             NA
## user_1              1      NA     193         NA      NA             NA
## user_2              1      NA     192         NA      NA             NA
## user_3              1      NA     192         NA      NA             NA
## user_4              1      NA     194         NA      NA             NA
## user_5              1      NA     193         NA      NA             NA
## user_6              1      NA     192         NA      NA             NA
## user_7              1      NA     194         NA      NA             NA
## user_8              1      NA     192         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    32625   32625       504       1538
##  [2,]    2    31484   31484       506       1534
##  [3,]    3    30929   30929       493       1573
##  [4,]    4    30803   30803       499       1554
##  [5,]    5    33720   33720       498       1559
##  [6,]    6    33877   33877       529       1465
##  [7,]    7    34326   34326       491       1580
##  [8,]    8    34805   34805       508       1526
##  [9,]    9    35340   35340       505       1537
## [10,]   10    36108   36108       514       1511
## [11,]   11    37105   37105       496       1563
## [12,]   12    38066   38066       506       1533
## [13,]   13    39081   39081       513       1515
## [14,]   14    40157   40157       495       1563
## [15,]   15    41265   41265       524       1481
## [16,]   16    42592   42592       521       1493
## [17,]   17    43861   43861       513       1511
## [18,]   18    45088   45088       506       1533
## [19,]   19    46433   46433       516       1504
## [20,]   20    47989   47989       520       1494
## [21,]   21    50021   50021       498       1559
## [22,]   22    51658   51658       491       1580
## [23,]   23    53582   53582       513       1513
## [24,]   24    55561   55561       514       1509
```

```
## [25,]   25    57858   57858       507       1529
## [26,]   26    60036   60036       512       1516
## [27,]   27    62311   62311       506       1532
## [28,]   28    64749   64749       513       1512
## [29,]   29    67411   67411       517       1504
## [30,]   30    70568   70568       505       1535
```

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.

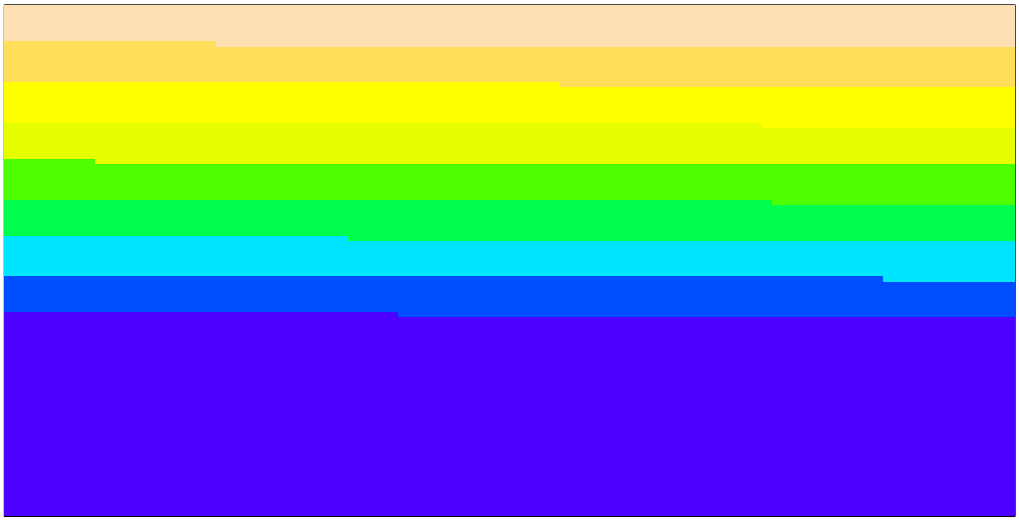
- `sim_new$resource_array`: A table holding all information on resources. Rows correspond to discrete resources, and columns correspond to resource properties: (1) ID, (2-4) types (not currently in use), (5) x-location, (6) y-location, (7) movement parameter, (8) time, (9) density independent mortality parameter (`remove_pr`), (10) reproduction parameter (`lambda`), (11) offspring number, (12) age, (13-14) observation columns, (15) consumption rate (`res_consume`), and (16-20) recorded experiences of user actions (e.g., was the resource culled or scared?).
- `sim_new$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`.

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

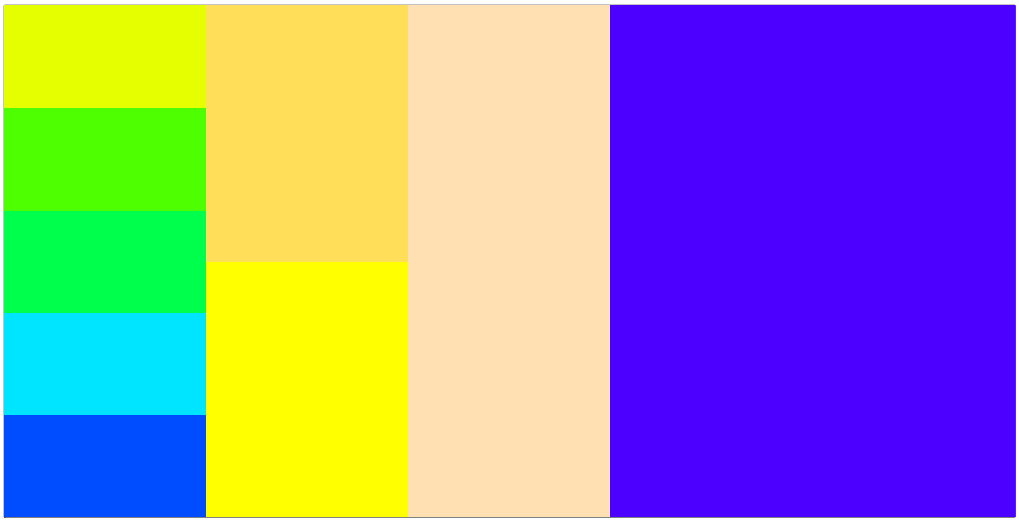


We can change the ownership of cells by manipulating `sim_old$LAND[,,3]`. First we initialise a new `sim_old` below.

```
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;
```

```
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    33620   33620       513        111
##  [2,]    2    33816   33816       490        120
##  [3,]    3    34739   34739       505        111
##  [4,]    4    36304   36304       509        111
##  [5,]    5    41674   41674       491        119
##  [6,]    6    43617   43617       520        110
##  [7,]    7    46169   46169       515        111
##  [8,]    8    49132   49132       511        111
##  [9,]    9    52443   52443       511        111
## [10,]   10    56014   56014       513        111
## [11,]   11    59949   59949       504        112
## [12,]   12    63784   63784       523        109
## [13,]   13    67877   67877       489        119
## [14,]   14    72200   72200       512        111
## [15,]   15    76883   76883       510        111
## [16,]   16    82196   82196       510        111
## [17,]   17    87852   87852       507        111
## [18,]   18    93850   93850       511        111
## [19,]   19   100042  100042       516        111
## [20,]   20   101802  101802       495        119
## [21,]   21   102685  102685       506        112
## [22,]   22   102709  102709       518        110
## [23,]   23   102855  102855       508        111
## [24,]   24   102943  102943       520        110
## [25,]   25   103237  103237       509        111
```

```
## [26,]   26   103487  103487       516        111
## [27,]   27   103524  103524       499        114
## [28,]   28   103597  103597       512        111
## [29,]   29   103872  103872       515        111
## [30,]   30   103828  103828       517        111
```

# 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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