Fisheries example integrating FLR

GMSE: an R package for generalised management strategy evaluation (Supporting Information 5)

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Integration and simulation with fisheries

Early development of management strategy evaluation (MSE) models originated in fisheries (Polacheck et al., 1999; Smith et al., 1999; Sainsbury et al., 2000). Consequently, fisheries-focused software for MSE has been extensively developed, including R libraries that focus on the management of species of exceptional interest, such as the Atlantic Bluefin Tuna (*Thunnus thynnus*) (ABFTMSE; Carruthers and Butterworth, 2018b,a), and Indian Ocean Bigeye (*T. obesus*) and Yellowfin (*T. albacares*) Tuna (MSE-IO-BET-YFT; Kolody and Jumppanen, 2016). The largest of all such libraries is the Fisheries Library in R (FLR), which includes an extensive collection of tools targeted for fisheries science. The FLR library has been used in over a hundred publications (recent publications include Jardim et al., 2018; Mackinson et al., 2018; Utizi et al., 2018), and includes an MSE framework for evaluating different harvest control rules.

As part of the ConFooBio project, a central focus of GMSE is on simulating the management of animal populations of conservation interest, with a particular emphasis on understanding conservation conflict; further development of GMSE is expected to continue with this as a priority, further building upon the decision-making algorithms of managers and users to better understand how conflict arises and can be managed and mitigated. Hence, GMSE is not intended as a substitute for packages such as FLR, but the integration of these packages with GMSE could make use of GSME's current and future simulation capabilities, and particularly the genetic algorithm. Such integration might be possible using the `gmse_apply` function, which allows for custom defined submodels to be used within the GMSE framework, and with default GMSE submodels. Hence, GMSE might be especially useful for modelling the management of fisheries under conditions of increasing competing stakeholder demands and conflicts. We do not attempt such an ambitious project here, but instead show how such a project could be developed through integration of FLR and `gmse_apply`.

Here we follow a Modelling Stock-Recruitment with FLSR example, then integrate this example with `gmse_apply` to explore the behaviour of a number of simulated fishers who are goal-driven to maximise their own harvest and a manager that aims to keep the fish stocks at a predefined target level. The core concept in GMSE is that manager can only incentivise fishers to harvest less or more by varying the cost of fishing (through e.g. taxes) given a set manager budget; please note that the manager cannot force the fisher to follow any policy. Based on the cost of fishing, the fisher can then given their own budget decide whether to invest in fishing or keep the budget. This concepts represents a nartural resource managmeent and conservation conflict, where one party aims to maximise their livelihood (fisher) and the other aims to keep a population at a sustainable level and prevent it from going extinct. Importantly, the manager does not have full control over fishers but can set policies to incentivise sustainable behaviour. We emphasise that this example is provided only as demonstration of how GMSE can potentially be integrated with already developed fisheries models, and is not intended to make recommendations for management in any population.

Integrating with the Fisheries Library in R (FLR)

The FLR toolset includes a series of pacakges, with several tutorials for using them. For simplicity, we focus on a model of stock recruitment to be used as the population model in `gmse_apply`. This population model will use sample data and one of the many available stock-recruitment models available in FLR, and a custom function will be written to return a single value for stock recruitment. Currently, `gmse_apply` requires that submodels return subfunction results either as scalar values or data frames that are structured in the same way as GMSE submodels. But interpretation of scalar values is left up to the user (e.g., population model results could be interpreted as abundance or biomass; manager policy could be interpreted as cost of harvesting or as total allowable catch). For simplicity, the observation (i.e., estimation) model will be the stock reported from the population model with error, and the manager model will be a total allowable catch calculated from the stock-recruitment relationship that accounts for the number of fishers in the system. The user model, however, will employ the full power of the default GMSE user function to simulate user actions. We first show how a custom function can be made that applies the FLR toolset to a population model.

Modelling stock-recruitment for the population model

Here we closely follow a tutorial from the FLR project. To build the stock-recruitment model, the `FLCore` package is needed (Kell et al., 2007).

```
install.packages(c("FLCore"), repos="http://flr-project.org/R");
```

To start, we need to read in the `FLCore` and GMSE libraries.

```
library(FLCore);
```

```
## Loading required package: lattice
```

```
## FLCore (Version 2.6.7, packaged: 2018-04-17 09:12:42 UTC)
```

```
library(GMSE);
```

For a simplified example in GMSE, we will simulate the process of stock recruitment over multiple time steps using an example stock-recruitment model. The stock-recruitment model describes the relationship between stock-recruitment and spawning stock biomass. The sample that we will work from is a recreation of the North Sea Herring (`nsher`) dataset available in the `FLCore` package (Kell et al., 2007). This data set includes recruitment and spawning stock biomass data between 1960 and 2004. First, we initialise an empty `FLSR` object and read in the recreated herring data files from GMSE, which contains recruitment (`rec.n`) and spawning stock biomass (`ssb.n`)

```
newFL   <- FLSR(); # Initialises the empty FLSR object
data(nsher_data);  # Called from GMSE library (not from FLCore)
```

The recruitment (`rec.n`) and spawning stock biomass (`ssb.n`) data need to be in the form of a vector, array, matrix to use them with `FLQuant`. We will convert `rec.n` and `ssb.n` into matrices.

```
rec.m        <- as.matrix(rec.n);
ssb.m        <- as.matrix(ssb.n);
```

We can then construct two `FLQuant` objects, specifying the relevant years and units.

```
Frec.m       <- FLQuant(rec.m, dimnames=list(age=1, year = 1960:2004));
Fssb.m       <- FLQuant(ssb.m, dimnames=list(age=1, year = 1960:2004));
Frec.m@units <- "10^3";
Fssb.m@units <- "t*10^3";
```

We then place the recruitment and spawning stock biomass data into the `FLSR` object that we created.

```
rec(newFL)     <- Frec.m;
ssb(newFL)     <- Fssb.m;
range(newFL)  <- c(0, 1960, 0, 2004);
```

The FLCore package offers several stock-recruitment models. Here we use a Ricker model of stock recruitment (Ricker, 1954), and insert this model into the FLSR object below.

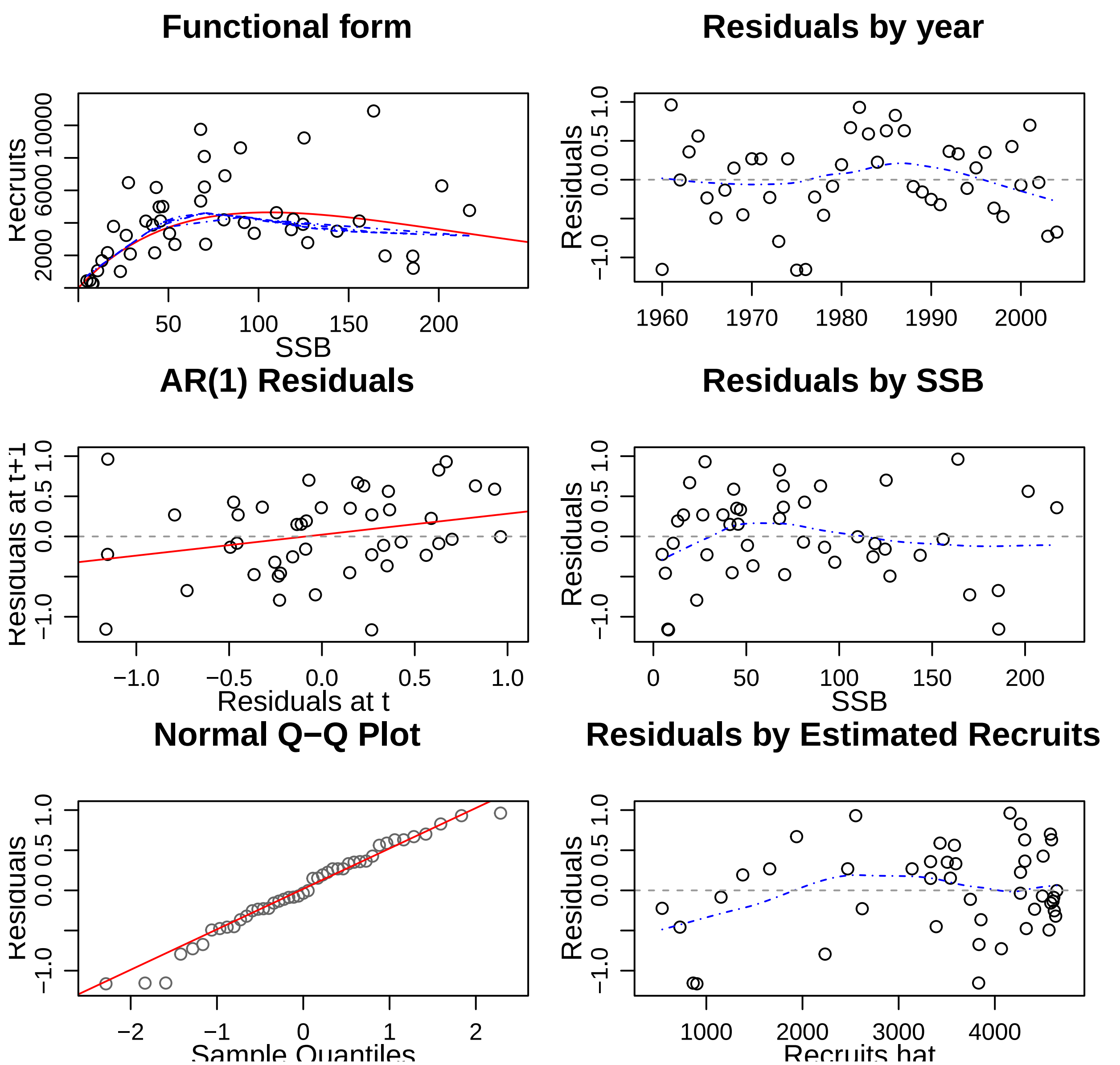
```
model(newFL) <- ricker();
```

Parameters for the Ricker stock-recruitment model can be estimated with maximum likelihood.

```
newFL <- fmle(newFL);
```

Diagnostic plots, identical to those of the modelling stock-recruitment tutorial for the nsher_ri example, are shown below.

```
plot(newFL);
```



We now have a working example of a stock-recruitment model, but for our integration with `gmse_apply`, we will want a function that automates the above to simulate the process of updating the stock-recruitment model. We do this using the custom function created below.

```
update_SR_model <- function(rec_m, ssb_m, years){
    Frec_m       <- FLQuant(rec_m, dimnames=list(age = 1, year = years));
    Fssb_m       <- FLQuant(ssb_m, dimnames=list(age = 1, year = years));
    Frec_m@units <- "10^3";
    Fssb_m@units <- "t*10^3";
    rec(newFL)   <- Frec.m;
    ssb(newFL)   <- Fssb.m;
    range(newFL) <- c(0, years[1], 0, years[length(years)]);
    model(newFL) <- ricker();
    newFL        <- fmle(newFL);
    return(newFL);
}
```

The above function will be used within another custom function to predict the next time step of recruitment.

```
predict_recruitment <- function(rec_m, ssb_m, years, new_ssb){
    newFL <- update_SR_model(rec_m, ssb_m, years);
    a     <- params(newFL)[[1]] # Extract 'a' parameter of the Ricker model
    b     <- params(newFL)[[2]] # Extract 'b' parameter of the Ricker model
    rec   <- a * new_ssb * exp(-b * new_ssb); # Predict the new recruitment
    return(rec)
}
```

In `gmse_apply`, we will use the `predict_recruitment` function above as the resource (i.e., operational) model. The `new_ssb` reads in the new spawning stock biomass, which will be calculated from the built-in GMSE `user` model.

Integrating `predict_recruitment` with `gmse_apply`

The FLR project includes libraries that can be used to perform a management strategy evaluation (MSE) under fisheries-focused observation, manager, and user models. We will not recreate this approach, or integrate any other submodels into GMSE as was done for the population model above, although such integration of submodels should be possible using similar techniques. Our goal here is to instead show how the `predict_recruitment` model created above can be integrated with `gmse_apply`, which can then make use of the genetic algorithm to predict the fishers' behaviour.

We will use a custom observation model, which will simply estimate recruitment with some fixed error.

```
obs_ssb <- function(resource_vector){
    obs_err <- rnorm(n = 1, mean = 0, sd = 100);
    the_obs <- resource_vector + obs_err;
    return(the_obs);
}
```

Hence, we can now feed the data from `rec.m` and `ssb.m` through `predict_recruitment`, which will return a value for new recruitment, and this new value can in turn be fed into `obs_ssb` to predict recruitment with some error. We also need a new spawning stock biomass `new_ssb`, which we can just initialise with the biomass from the last year in `ssb.m`

```
ssb_ini <- ssb.m[length(ssb.m)];
new_rec <- predict_recruitment(rec_m = rec.m, ssb_m = ssb.m, years = 1960:2004,
```

```r
                                   new_ssb = ssb_ini);
obs_rec <- obs_ssb(new_rec);
```

An initial run of these models gives values of 3835.21 for `new_rec` and 3961.67 for `obs_rec`. We are now ready to use the built-in manager and user submodels in `gmse_apply`. We will assume that managers attempt to keep a recruitment of 5000, and that there are 4 independent fishers [stakeholders in gmse_apply says 10, is that a difference?] who attempt to maximise their catch. We assign a user budget of `manager_budget = 10000`, and all other values are set to GMSE defaults. In the built-in GMSE functions, the manager will use the estimate of recruitment based on `obs_rec` and use it to set the cost of harvesting (`culling` in GMSE).

```r
yrspan       <- 1960:2004;
rec.m        <- as.matrix(rec.n);
ssb.m        <- as.matrix(ssb.n);

sim <- gmse_apply(res_mod = predict_recruitment, obs_mod = obs_ssb,
                  rec_m = rec.m, ssb_m = ssb.m, years = yrspan,
                  new_ssb = ssb_ini, manage_target = 5000, stakeholders = 10,
                  manager_budget = 10000);
print(sim);
```

```
## $resource_results
## [1] 3835
##
## $observation_results
## [1] 3856.055
##
## $manager_results
##          resource_type scaring culling castration feeding help_offspring
## policy_1             1      NA     442         NA      NA             NA
##
## $user_results
##         resource_type scaring culling castration feeding help_offspring
## Manager             1      NA       0         NA      NA             NA
## user_1              1      NA       2         NA      NA             NA
## user_2              1      NA       2         NA      NA             NA
## user_3              1      NA       2         NA      NA             NA
## user_4              1      NA       2         NA      NA             NA
## user_5              1      NA       2         NA      NA             NA
## user_6              1      NA       2         NA      NA             NA
## user_7              1      NA       2         NA      NA             NA
## user_8              1      NA       2         NA      NA             NA
## user_9              1      NA       2         NA      NA             NA
## user_10             1      NA       2         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
## user_9          NA         NA
```

```
## user_10         NA         NA
```

The resource and observation results above are interpreted in terms of recruitment, while the manager results are interpreted in terms of the cost of harvesting a unit of spawning stock biomass and the user results are interpreted in terms of how much biomass was harvested. Note in the run of `gmse_apply` that the arguments for our custom resource and observation models (`predict_recruitment` and `obs_ssb`, respectively) are read directly in as arguments of `gmse_apply` itself. The `gmse_apply` function will figure out which subfunctions custom arguments should go to, then update these arguments as needed over the course of a single run of `gmse_apply`.

Simulation with `gmse_apply` over multiple time steps

We are now ready to loop the `gmse_apply` function over multiple time steps. To do this, we will update the `rec.m` and `ssb.m` matrices after each time step, simulating 20 years into the future. The population model `predict_recruitment` will use these data to dynamically update parameters of the Ricker model, as might occur in an empirical fishery that is being monitored. We will use the results from the observation model to update recruitment for the new year in `rec.m`. For simplicity, spawning stock biomass prior to harvest will be randomly sampled from a value in last 10 years (i.e., from `ssb.m` between 1994 and 2004), but more realistic models could relate this spawning stock biomass to recruitment and environmental variables from a prevoius year; spawning stock biomass will be decreased after harvest based on user actions. The GMSE initialisation and simulation is below.

```r
# This code initialises the simulation ------------------------------------------
yrspan       <- 1960:2004;
rec.m        <- as.matrix(rec.n);
ssb.m        <- as.matrix(ssb.n);
ssb_ini      <- ssb.m[length(ssb.m)];
sim_old      <- gmse_apply(res_mod = predict_recruitment, obs_mod = obs_ssb,
                           rec_m = rec.m, ssb_m = ssb.m, years = yrspan,
                           new_ssb = ssb_ini, manage_target = 3500,
                           stakeholders = 10, manager_budget = 10000,
                           get_res = "Full");
# The code below simulates 20 time steps ----------------------------------------
sim_sum  <- matrix(data = NA, nrow = 20, ncol = 6); # Hold results here
for(time_step in 1:20){
    # Update the relevant parameter values as necessary -----------------------
    rand_ssb        <- sample(x = ssb.m[35:45], size = 1);
    harvest         <- sum(sim_old$basic_output$user_results[,3]);
    new_rec_m       <- c(sim_old$rec_m, sim_old$observation_vector);
    new_ssb_m       <- c(sim_old$ssb_m, rand_ssb - harvest);
    sim_old$rec_m   <- matrix(data = new_rec_m, nrow = 1);
    sim_old$ssb_m   <- matrix(data = new_ssb_m, nrow = 1);
    sim_old$years   <- c(sim_old$years, time_step + 2004);
    sim_old$new_ssb <- sim_old$ssb_m[length(sim_old$ssb_m)];
    # Run a new simulation in the loop: custom functions are always specified -
    sim_new  <- gmse_apply(get_res = "Full", old_list = sim_old,
                           res_mod = predict_recruitment, obs_mod = obs_ssb);
    # Record the results in sim_sum -------------------------------------------
    sim_sum[time_step, 1] <- time_step + 2004;
    sim_sum[time_step, 2] <- sim_new$basic_output$resource_results[1];
    sim_sum[time_step, 3] <- sim_new$basic_output$observation_results[1];
    sim_sum[time_step, 4] <- sim_new$basic_output$manager_results[3];
    sim_sum[time_step, 5] <- harvest;
```

```
    sim_sum[time_step, 6] <- sim_new$new_ssb;
    # Redefine the old list -------------------------------------------------
    sim_old               <- sim_new;
}
colnames(sim_sum) <- c("Year", "Recruitment", "Recruit_estim", "Harvest_cost",
                       "Harvested", "SSB");
print(sim_sum);
```

```
##       Year Recruitment Recruit_estim Harvest_cost Harvested      SSB
##  [1,] 2005        4133      4020.005          511        20 165.5799
##  [2,] 2006        3303      3100.690          520        10  40.6133
##  [3,] 2007        4629      4776.838          571        10 115.2627
##  [4,] 2008        4208      4356.721          529        10 160.1926
##  [5,] 2009        3988      3912.199          492        10 175.5799
##  [6,] 2010        4336      4491.473          494        20 150.1926
##  [7,] 2011        2347      2362.962          557        20  24.8673
##  [8,] 2012        2994      3032.592          660        10  34.8673
##  [9,] 2013        4629      4674.325          550        10 115.2627
## [10,] 2014        4208      4259.621          544        10 160.1926
## [11,] 2015        3303      3454.684          492        10  40.6133
## [12,] 2016        2347      2370.866          556        20  24.8673
## [13,] 2017        4339      4266.281          679        10  71.3340
## [14,] 2018        4328      4312.658          589        10  70.7603
## [15,] 2019        4629      4536.300          525        10 115.2627
## [16,] 2020        4082      4072.970          512        10  60.6639
## [17,] 2021        4328      4302.660          477        10  70.7603
## [18,] 2022        2399      2379.841          507        20  25.5913
## [19,] 2023        4339      4400.963          487        10  71.3340
## [20,] 2024        2399      2336.650          479        20  25.5913
```

The above output from `sim_sum` reports the recruitment (resource or operational model), recruitment estimate (observation error model), management set harvest cost (harvest control model), user harvested numbers (implementation model) and spawning stock biomass (SSB) simulation results. This example simulation demonstrates the ability of GMSE to integrate with fisheries libraries such as FLR through `gmse_apply`. In addition to being a useful wrapping function for MSE submodels, `gmse_apply` can therefore be used to take advantage of the genetic algorithm in the GMSE default manager and user models. This flexibility will be retained in future versions of `gmse_apply`, allowing custom resource and observation models that are built for specific systems to be integrated with an increasingly complex genetic algorithm simulating various aspects of human decision-making.

Conclusions

GMSE is a general, flexible, tool for simulating the management of resources under situations of uncertainty and conflict. Management Strategy Evaluation (Bunnefeld et al., 2011; Punt et al., 2016), the framework upon which GMSE is based, had its origin in fisheries management (Polacheck et al., 1999; Smith et al., 1999; Sainsbury et al., 2000), and here we showed one example of how GMSE could be integrated with the core package of the Fisheries Library in R.

Future versions of GMSE will continue to be open-source and developed to avoid unecessary dependencies (GMSE v.0.4.0.3 requires only base R). Key goals including (1) providing highly general and useful default `resource`, `observation`, `manager`, and `user` submodels for a variety of MSE modelling tasks, (2) keeping these submodels highly modular so that they can be developed in isolation given standardised data structures, and (3) allowing these modular submodels to be integrated with custom defined submodels as flexibly as possible using `gmse_apply`. Contributions in line with these goals, and suggestions for new features, can be made on GitHub.

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