Week 2: Simple models of growth and mortality

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LBSAT Workshop - Fall 2022

Load libraries and clear console

```
library(TropFishR)
library(fishmethods)
library(MLZ)
library(TMB)
library(dplyr)

graphics.off()
rm(list=ls(all=TRUE))
```

Exercise 1: von Bertalanffy growth and Beverton-Holt length-based catch curve - Yellow Perch example

In the Excel spreadsheet provided ("Simple LB catch curves in Excel.xls"), navigate to the red "Yellow Perch vonB" tab. Estimate the vonB parameters and lc given the yellow perch length and age data provided.

Why use only the female data?

Now navigate to the red "BH Length-based catch curve YP" tab. Estimate yellow perch Z and F with a Beverton-Holt length-based catch curve using the growth info you just generated and the catch at length data provided.

Using the "YPlens.csv" dataset provided, estimate vonB length at age growth model parameters in R using the function "growth" from fishmethods.

How do these estimates compare with your Excel-based estimates?

```
YPdat=read.csv("YPlens.csv")
colnames(YPdat)=c("age","length")
growmod=growth(intype=1,unit=1,size=YPdat$length,age=YPdat$age,
calctype=1,wgtby=1,error=1,Sinf=300,K=0.3,t0=-1)
growmod$vout
```

Exercise 2: Estimation of Z using Beverton-Holt method and simulated length-frequency data in TropFishR package

Load and inspect the dataset named synLFQ2 that is associated with the TropFishR package. Note that numbers caught in each of 3 years are summarized across 11 length bins and that catch is associated with the mid-points of length bins (\$midLengths). Linf and K used to simulate this data are provided.

```
data(synLFQ2)
synLFQ2
```

Estimate Z for all 3 years using the Z_BevertonHolt function. Note that in this package, "Lprime_tprime" is the mid-point of the bin in which animals are fully recruited. Lc = Lprime_tprime - binwidth/2. Compare your R-based estimate of Z for 1960 with the estimate in the Excel spreadsheet example from lecture.

Is there a trend in \mathbb{Z} ?

```
Z1960=Z_BevertonHolt(synLFQ2, catch_columns = 1, Lprime_tprime = 47.5)
Z1970=Z_BevertonHolt(synLFQ2, catch_columns = 2, Lprime_tprime = 47.5)
Z1980=Z_BevertonHolt(synLFQ2, catch_columns = 3, Lprime_tprime = 47.5)

Z1960$Z
Z1970$Z
Z1970$Z
Z1980$Z
BHests=c(Z1960$Z,Z1970$Z,Z1980$Z)
BHests
```

Exercise 3: Estimation of Z using Powell-Wetherall method and simulated length-frequency data in TropFishR package

Using the reformatted synLFQ2mod dataset generated using the top three lines of code below, estimate Z and Linf for all 3 years and compare relative Zs. Note the "point and click" selection of min and max length bins part of the identify function is a bit touchy. You may need to copy and paste each year's catch curve code individually in the console to get the graphics window to pop up properly.

Compare your R-based estimate of Z for 1960 with the estimate in the Excel spreadsheet example from lecture.

What does Z/K tell us about the stock? Is there a trend in Z given the K provided?

```
synLFQ2mod=synLFQ2[-c(1,5)]
synLFQ2mod$t0=0
synLFQ2mod$catch=synLFQ2$catch[]

dev.new()
PW1960=powell_wetherall(synLFQ2mod,catch_columns=1)
PW1970=powell_wetherall(synLFQ2mod,catch_columns=2)
PW1980=powell_wetherall(synLFQ2mod,catch_columns=3)
PWests=c(PW1960$ZK*PW1960$K,PW1970$ZK*PW1980$K,PW1980$ZK*PW1980$K)
```

Exercise 4: Estimation of Z using a length-converted catch curve and simulated length-frequency data in TropFishR package

Using the reformatted synLFQ2mod dataset again, estimate Z using a length-converted catch curve and the "catchCurve" function for all 3 years and compare relative Zs. Again, the "point and click" selection of min and max length bins part of the identify function is a bit touchy. You may need to copy and paste each year's catch curve code individually in the console to get the graphics window to pop up properly.

Where is this function getting information about dt? Is there a trend in Z?

```
LC1960 <- catchCurve(synLFQ2mod,catch_columns=1)
LC1970 <- catchCurve(synLFQ2mod,catch_columns=2)
LC1980 <- catchCurve(synLFQ2mod,catch_columns=3)
LCests=c(LC1960$Z,LC1970$Z,LC1980$Z)
```

Exercise 5: Graph all 3 sets of Z estimates

Create an object containing the years and combine Z estimates from all 3 methods in the same object. Plot them on the same graph.

How do these estimates of Z compare? Why might they differ? What do these analyses indicate might be happening to this stock? What would you tell managers of this stock?

Exercise 6: Explore non-equilibrium mean length-based mortality estimators using MLZ package

For this exercise, you will example a dataset for Silk Snapper. I've provided example code, but feel free to deviate if you want to explore alternative models with different number of time periods in which Z changes.

Load the dataset using the data command. Plot the relative length frequencies by year.

Do you notice any trends?

Explore changes in length over time using the modal length function.

Are there obvious time periods in which modal length changed? If so, after what year(s) did the change(s) seem occur?

```
modal_length(SS.dataset, breaks = seq(80, 830, 10))
```

Assuming Lc=310mm, calculate annual mean length and associated sample size using the calc_ML command and inspect your handiwork.

Again, do you notice any trends?

```
SS.dataset@Lc <- 310
SS.dataset <- calc_ML(SS.dataset)
summary(SS.dataset)
```

Run a likelihood profile with the appropriate number of change points given the pattern you see in the data (ncp=#distinct Z periods -1) using the profile_ML function. The lowest negative log likelihood value should be associated with the most likely change point(s) given the data.

Which change point(s) have the lowest NLL? Does the likelihood profile support your choice of change points?

Remember the main assumptions of a catch curve. What are the three most likely potential causes of changes in mean length? What questions would you ask the data providers before proceeding to estimate Z using these data?

```
profile_ML(SS.dataset, ncp = 1)
profile_ML(SS.dataset, ncp = 2)
```

Next, estimate mortality using the ML function with the appropriate number of change points (ncp).

```
est <- ML(SS.dataset, ncp = 2)
plot(est)
summary(est)</pre>
```

Run a model with one more and one less change point. Compare Akaike's Information Criterion (AIC) among the models using the compare_models function. (A lower AIC indicates a better model fit to the data after taking into account the number of independent variables. Essentially, AIC indicates which model explains the most amount of variation in the data using the fewest variables).

How does your model compare?

```
model1 <- ML(SS.dataset, ncp = 0)
model2 <- ML(SS.dataset, ncp = 1)
model3 <- ML(SS.dataset, ncp = 2)
compare_models(model1, model2, model3)</pre>
```

Remember, your model is only as good as your assumptions! Examine the sensitivity of your model estimates to changes in Lc using the sensitivity Lc function.

Does Lc matter in this situation?

```
Lc.vec <- seq(250, 350, 10)
sensitivity_Lc(SS.dataset, model2, Lc.vec)</pre>
```