# FISH 621 Laboratory #4: Advanced Mark-Recapture

Curry Cunningham 2022

## Instructions

The purpose of this lab is to:

- Explore how we can use information provided by a Schnabel multi-event mark-recapture experiment to estimate abundance, and derive confidence intervals for those estimates.

If you have a question during the lab, please un-mute yourself and ask, or type it into the chat box. There is a high likelihood that someone else has the same question. It is more fun if we all learn together in our distance-learning world.

I have posted the lecture slides to the ***Canvas site***, so you can reference this material as you work through the lab.

This and all other labs will be graded based on your attendance and participation.

## Lab Contents

- **621_Lab 4_Advanced Mark Recapture.pdf** (this file)
- **621_Lab 4_ Advanced Mark Recapture.R** R script with exercises.
- **Simple Schnabel.csv** Example Schnabel mark-recapture dataset

## Exercise 2: Schnabel Experiment

As we have seen in lecture we can extend our simple Petersen mark-recapture experiment to include multiple survey periods in which some number of individuals are captured ($n_i$), of which some number are marked ($m_i$), and some component is of the unmarked individuals ($u_i = n_i - m_i$) are marked, and all fish are released. This means that our total number of marks in the population at the start of sampling period $i$ ($M_i$) likely increases across time (or at least doesn't decrease).

Based on this Schnabel-type experiment there are several alternative estimators for abundance:

- Mean Petersen estimator
- Mean Chapman estimator
- Schnabel estimator

We will explore these estimators based on simulated and real data, as well as the related methods for approximating confidence intervals.

- Chapman-ized estimators
  - $N_i^* = \frac{(M_i+1)(n_i+1)}{(m_i+1)} - 1, v_i^* = \frac{(M_i+1)(n_i+1)(M_i-m_i)(n_i-m_i)}{(m_i+1)^2(m_i+2)}$
- Each of these $s-1$ abundance estimates is approximately ***unbiased***, so the mean
  - $\bar{N}^* = \sum_{i=2}^{s} N_i^*/(s-1)$
    - Is approximately ***unbiased*** and ***less variable*** than the individual estimates

- There are two methods for estimating variance
  - Theoretical (uses estimated variances)
    - $v_1^* = \sum_{i=2}^{s} v_i^*/(s-1)^2$
  - Empirical (uses squared deviations)
    - $v_2^* = \sum_{i=2}^{s} \frac{(N_i^*-N^*)^2}{(s-1)(s-2)}$

- Confidence intervals require the typical large-sample normality assumption
  - Resulting in $N^* \pm t_{s-2} se^*$, where $se^* = \sqrt{v^*}$
    - Using either of the variance estimation methods

- The Schnabel MLE for abundance is
  - $N' = \frac{\sum n_i M_i}{\sum m_i} = \frac{\lambda}{m}$
    - $\lambda = \sum n_i M_i$
    - $m = \sum m_i$
- Chapman's improvement for reduced bias
  - $N'' = \frac{\lambda}{m+1} = \frac{\sum n_i M_i}{\sum (m_i)+1}$
- A $(1-\alpha)\times 100\%$ confidence interval for abundance
  - Using a normal approximation to the Poisson distribution
    - $\lambda \times \frac{2m+z_{\alpha/2}^2 \pm z_{\alpha/2}\sqrt{4m+z_{\alpha/2}^2}}{2m^2}$

## Exercise 3: Schumacher-Eschmeyer Regression Method

We have seen that the data from a Schnabel-type mark-recapture experiment can also be fit into the context of a weight regression to estimate abundance based on the slope of that regression. In this exercise we will explore how this is done in practice.

# 3. Schumacher-Eschmeyer Regression Method

Captures: $n_i$
Recaptures: $m_i$
Total marks: $M_i$

- Regression through the origin
  - $y_i = \beta M_i + e_i$ , where…
    - $y_i = m_i / n_i$
    - $\beta = 1/N$
    - $e_i \sim Normal(0, \sigma_i^2)$
  - $\tilde{\beta} = \frac{1}{\tilde{N}} = \frac{\sum_{i=2}^{s} m_i M_i}{\sum_{i=2}^{s} n_i M_i^2}$, therefore $\tilde{N} = \frac{1}{B}$

Correct!!!

| Period ($i$) | Captures ($n_i$) | Recaptures ($m_i$) | New Marks ($u_i$) | Total Marks ($M_i$) | $m_i M_i$ | $n_i M_i^2$ |
|---|---|---|---|---|---|---|
| 1 | 20 | 0 | 20 | 0 | 0 | 0 |
| 2 | 20 | 4 | 16 | 20 | 80 | 8,000 |
| 3 | 20 | 3 | 17 | 36 | 108 | 25,920 |
| 4 | 20 | 2 | 18 | 53 | 106 | 56,180 |
| 5 | 20 | 4 | 16 | 71 | 284 | 100,820 |
| 6 | 20 | 3 | 17 | 87 | 261 | 151,380 |
| 7 | 20 | 3 | 17 | 104 | 312 | 216,320 |
| 8 | 20 | 5 | 15 | 121 | 605 | 292,820 |
| 9 | 20 | 4 | 16 | 136 | 544 | 369,920 |
| 10 | 20 | 3 | 17 | 152 | 456 | 462,080 |
| Total | | 31 | | | 2,756 | 1,683,440 |

$$\tilde{\beta} = \frac{\sum_{i=2}^{s} m_i M_i}{\sum_{i=2}^{s} n_i M_i^2}$$

$$\tilde{\beta} = \frac{2{,}756}{1{,}683{,}440}$$

$$\tilde{\beta} = 0.001637$$

$$\tilde{N} = \frac{1}{\tilde{\beta}} = 610.8$$