

III. Capture-Recapture for group-structured, “multi-session” or stratified populations



Group structure or stratified populations

- Examples
 - Sex
 - Location (e.g., trapping grid)
 - Time (year)
- Exactly like “model Mh” with finite mixture except we have information on which group captured individuals belong to
- Thus the groups have biological context



Sex specificity of model parameters

Two ways to formulate the model in BUGS:

1. As an additive covariate:

$$\text{logit}(p[i]) = \alpha_0 + \alpha_1 * X_{\text{sex}}[i]$$

$X_{\text{sex}}[i] = 1$ if male, 0 if female (dummy variable)

2. Index variables:

$$\text{logit}(p[i]) = \alpha_0[X_{\text{sex}}[i]]$$

$X_{\text{sex}}[i] = 1$ if female

2 if male

Key technical issues:

- X_{sex} is missing for M-n individuals in our augmented data set.
- Put a prior distribution on it....just like Model Mh
- X_{sex} can be missing for some captured individuals

SEX SPECIFICITY

Prior distribution for a 2-class variable:

$$\Pr(X_{\text{sex}} = 1) = f \quad (\text{estimate the parameter } f)$$

then

$$\Pr(X_{\text{sex}} = 0) = 1 - f$$

f = “prob. that an individual in the population is female”

Implies class specific population size:

$$N_1 \sim \text{Bin}(N, f) \quad \text{and} \quad N_2 = N - N_1$$

GENERAL CASE

- > 2 classes, could be space or time groupings
- The class membership probabilities are a prior distribution on the discrete class variable

SEX SPECIFICITY

- R work session

MULTI-YEAR DATA

- If we have data from multiple years (or “sessions”) we can use the exactly same model but treat year as a class variable to allocate the augmented individuals into years.

- For this model we stack the data from each year:

```
Y <- rbind(Y1, Y2, Y3, Y4, Y5)
```

```
## T=5 years Yt = nind[t] x K
```

A sex-structured data set
is just:

```
Y<- rbind(Ymale, Yfemale)
```

Then apply data augmentation to the matrix Y

- This is a primitive form of an open model in which **individual identity is ignored across years**, $N[t]$ are independent parameters then

MULTI-YEAR DATA

- $\text{year}[i]$ = year to which individual i belongs. This has T possible values then
- In BUGS the model looks like this:

```
year[i] ~ dcat(probs[])
```

```
probs[t] <- 1/T
```

- We could also model the categorical probabilities directly as a function of time or explicit covariates :

```
log(mu[t]) = beta0 + beta1*x[t]
```

```
probs[t] <- mu[t] / sum(mu[])
```

Multinomial logit

OVENBIRD STUDY

The R package “`secr`” has the ovenbird data

```
library(secr)  
data(ovenbird)
```

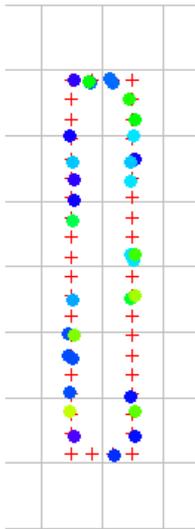
This is based on 44 mist nets operated for 5 years.

Distracting problems to deal with:

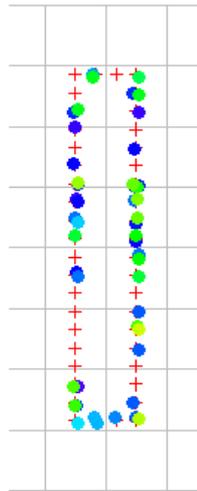
- 1. One individual died on capture
- 2. Year 1 had $K=9$ reps, other years had $K=10$

OVENBIRD STUDY

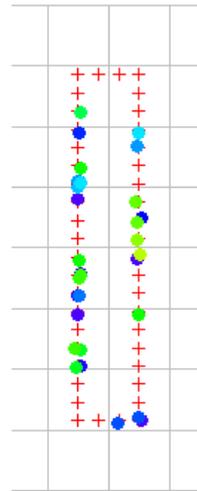
2005
9 occasions, 35 detections, 20 animals



2007
10 occasions, 52 detections, 26 animals



2009
10 occasions, 33 detections, 16 animals



- 44 nets (+ signs)
- Captures marked with circles
- Individuals marked with colors
- 5 year study, only 3 years shown here

OVENBIRD STUDY

- Data are SPATIAL encounter histories
- Mist-nets: individual can only be captured in 1 trap per occasion (unlike Fort Drum bear data)
- $y[i,j] = \text{TRAP OF CAPTURE}$. Ordinary CR models operate on binary data (captured or not)
- For now we will throw out the spatial information. Just change trap of capture to “1”

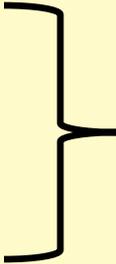
The “year as a class variable” model

```
psi ~ dunif(0,1)

for(t in 1:5){
  p[t] ~ dunif(0,1)
  probs[t] <- 1/5  ## uniform distribution on year membership
}
for(i in 1:M){
  year[i] ~ dcat(probs[])
  z[i] ~ dbern(psi)

  for(k in 1:K){
    mu[i,k] <- z[i]*p[year[i]]*(1-isdead[i,k])*sampled[k,year[i]]
    Ystacked[i,k] ~ dbern( mu[i,k] )
  }
}

for(t in 1:5){
  N[t] <- sum(inyear[,t])
  for(i in 1:M){
    inyear[i,t] <- equals(year[i],t)*z[i]
  }
}
```



**N[t] are derived parameters
Have to compute number of
Individuals in each year**

YEAR AS A CLASS VARIABLE

By treating year as a class variable:

- We have to recover $N[t]$ by creating a frequency distribution of the year variable.
- Also note that the joint prior distribution for $N[1], \dots, N[t]$ is

$$(N[1], N[2], \dots, N[T]) \sim \text{Multinomial}(M; \text{probs}[1:T])$$

Roughly the same as saying $N[t] \sim \text{Poisson}(\text{lambda})$

Reference: Royle, J. A., & Converse, S. J. (2014). Hierarchical spatial capture–recapture models: modelling population density in stratified populations. *Methods in Ecology and Evolution*, 5(1), 37-43.

MULTI-YEAR DATA/OPEN POPULATIONS

Many ways to analyze multi-year data sets:

- Treat “year” as a class variable: $\text{year}[i] \sim \text{dcat}(\text{psi}[\text{year}])$
- **Day 3** of the workshop “open population models”
 - T-fold data augmentation -- Input the data as a 3-d array “individual x replicate x year” with each year augmented independently
 - Still regards individuals as independent across years
 - Fully dynamic model: preserve individual identity across years.

SUMMARY PART III

- Discrete classes are common in capture-recapture studies (sex is the typical one also year as a class variable is a special type of open model)
- Technical problem is that class is unknown for uncaptured individuals
- We solve this by putting a prior distribution on class membership
- In BUGS this is easy...?
- Model follows naturally from Model Mh, the finite-mixture version, but with information about which class

SUMMARY PART III

- Year (or other temporal period) can be treated as a class variable to model variation in N (and density) across time
- This casts the model as a basic stratified population model analogous to models with sex-specificity
- “multi-session” models in “secr” do a similar thing but not exactly the same thing.