Lecture 10

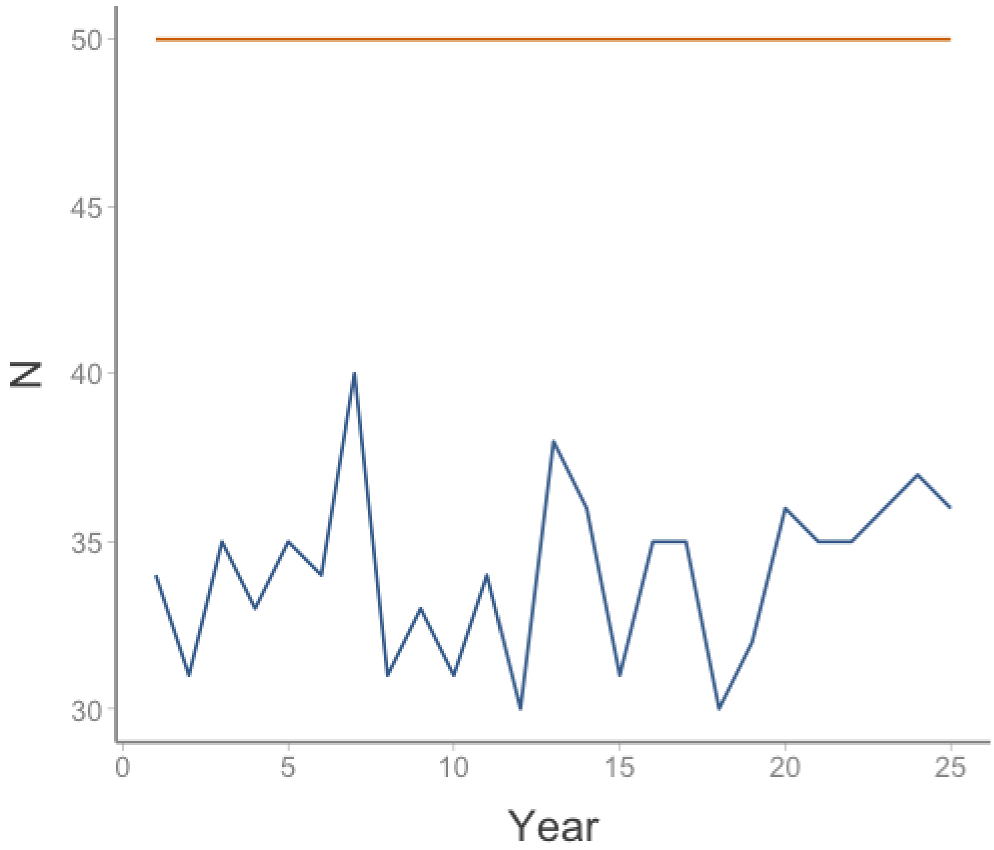
Estimating abundance: N-mixture models

WILD6900 (Spring 2020)

Readings

> Kéry & Schaub 383-411
>
> Powell & Gale chp. 18

Systematic bias in state-space models



State-space models

Produce unbiased estimates of N **only** when false-positives and false-negatives cancel each other out on average

Produce unbiased estimates of population **indices** (Np) if detection probability has no pattern ove time

Do **not** produce unbiased estimates of N or Np if their are temporal patterns in detection probability or false-positive rates

Estimating abundance

Unbiased estimates of N require estimating p

Many methods available:

- Mark-recapture
- Removal sampling
- Distance sampling
- Double observer
- N-mixture models

Estimating abundance

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- Mark-recapture
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- Double observer
- **N-mixture models (Royle 2004)**

N-mixture models

N-mixture models

The basic idea

- $\mathbf{J}$ sites surveyed
  - Each site has an expected abundance λ
  - State model:

$$N_j \sim Poisson(\lambda)$$

- Each site is surveyed $\mathbf{K}$ times
  - During each visit, probability p of detecting each individual
  - Observation model:

$$y_{j,k} \sim binomial(N_j, p)$$

N-mixture models

The data

Site	N	Visit1	Visit2	Visit3	Visit4	Visit5
1	**3**	0	1	1	2	0
2	**5**	4	2	2	2	1
3	**1**	0	0	1	0	0
4	**1**	0	0	0	1	1

N-mixture models

JAGS code

```
model{
  # Priors
  lambda ~ dgamma(0.01, 0.01)
  p ~ dbeta(1, 1)

  # Likelihood
  for(j in 1:J){
    ## State model
    N[j] ~ dpois(lambda)

    ## Observation model
    for(k in 1:K){
      y[j, k] ~ dbinom(p, N[j])
    } # end k loop
  } # end j loop

} # end model
```

N-mixture models

Extensions

1) Covariates and random effects

$$log(\lambda_j) = \alpha_0 + \alpha_1 x_j + \epsilon_j$$

$$\epsilon_j \sim normal(0, \tau)$$

$$logit(p_{j,k}) = \beta_0 + \beta_1 x_j + \beta_2 x_{j,k}$$

N-mixture models

Extensions

1) Covariates and random effects

2) Open N-mixture model (Dail & Madsen 2011)

$$N_{j,1} \sim Poisson(\lambda)$$

$$N_{j,t} = S_{j,t} + G_{j,t}$$

$$S_{j,t} \sim binomial(N_{j,t-1}, \phi)$$

$$G_{j,t} \sim Poisson(\gamma N_{j,t-1})$$

N-mixture models

Extensions

1) Covariates and random effects

2) Open N-mixture model (Dail & Madsen 2011)

3) Other distributions

- negative binomial, zero-inflated Poisson, multinomial

N-mixture models

Extensions

1) Covariates and random effects

2) Open N-mixture model (Dail & Madsen 2011)

3) Other distributions

4) Integrated N-mixture models

- Integrated N-mixture/known fate model (Schmidt et al. 2015)
- Integrated N-mixture/distance sampling model (Hostetter et al. 2019)

Assumptions of the N-mixture model

1) Poisson and binomial distributions are true descriptions of state/observation processes

2) Abundance at each site is random and independent of abundance at all other sites

3) Population is closed between surveys

4) Observers do not double count individuals

5) All N individuals have the same detection probability p

Advantages and disadvantages of the N-mixture model

Advantages

- Count data is "cheap" to collect (relative to mark-recapture)
- Does not require auxillary information (distance, double observer, etc.)
- Analysis is straightforward

Disadvantages

- Count data has less information about p than mark-recapture data
- Requires lots of replication
- Trade-off between temporal replication and spatial replication
- Inference can be sensitive to violating assumptions

Controversy

Barker et al. (2017)

- Mark-recapture data provides auxillary information about p without reference to N
- Without auxillary information about p, count data cannot distinguish between N-mixture model or other possible models of N

Controversy

Barker et al. (2017)

Kery (2017)

- No issues with identifiability of Poisson N-mixture model based on 137 bird data sets from 2,037 sites
- Some parameters not identifiability with negative binomial model (especially with small sample sizes)
  - problematic because NB often selected based on AIC

Controversy

Barker et al. (2017)

Kery (2017)

Link et al. (2018)

- Estimates from N-mixture models sensitive to violation of double counting and constant λ/p
- Small violations unlikely to be detected using goodness-of-fit tests but can influence inference about N