

# **Autoregressive Models for Capture-Recapture Data: A Bayesian Approach**

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Paper and software available at  
[www.stat.colostate.edu/~jah](http://www.stat.colostate.edu/~jah)

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## **What factors affect animal survival?**

Historically, survival probabilities were modeled as as fixed constants.

More recently Burnham and others have begun to consider survival probabilities as realizations of a random process.

We model survival as a function of environmental factors and allow for a time series correlation structure between survival probabilities.

We develop methodology for

- Open population mark-recapture models (Cormack-Jolly-Seber Model)
- Band recovery models

## Band Recovery Model

Animals are captured, banded and released.  
Hunters report when bands are recovered.

Some notation:

$R_i =$  # banded animals released at time  $t_i$

$m_{ij} =$  # animals recovered at time  $t_j$   
out of the  $R_i$  animals released at time  $t_i$

$I =$  # capture occasions when banding  
is performed

$J =$  # occasions when bands are recovered

$(m_{i1}, \dots, m_{iJ}) \sim$   
Multinomial ( $R_i, p = f(\text{survival, recovery})$ )

## Likelihood for Band Recovery Model

$$\mathcal{L}(\phi, \lambda; \mathbf{R}, \mathbf{m}) = \prod_{i=1}^I \left( \begin{matrix} R_i \\ m_{ii}, \dots, m_{iJ} \end{matrix} \right) \xi_i^{v_i} \prod_{j=i}^J \left\{ \lambda_j \prod_{k=i}^{j-1} \phi_k \right\}^{m_{ij}}$$

where

- $\xi_i$  is the probability that an animal is never recovered after release at  $t_i$
- $v_i$  is the number of animals captured at  $t_i$  and never subsequently recovered
- $\lambda_j$  is the probability that a marked animal, alive at  $t_j$ , is harvested between time  $t_j$  and  $t_{j+1}$  and reported to the banding agency.
- $\phi_k$  is the probability that an animal survives from time  $t_k$  to  $t_{k+1}$  given that it is alive at time  $t_k$

## A Random Effects Model for Survival Probabilities

We consider a generalized linear model for the probability that an animal survives from time  $t_j$  to time  $t_{j+1}$  of the form

$$g(\phi_j) = \mathbf{X}'_j \boldsymbol{\beta} + \epsilon_j, \quad j = 1, \dots, J,$$

where

- $g$  is an appropriate link function to constrain survival between 0 and 1
- $\mathbf{X}_j$  is a  $P \times 1$  matrix of environmental covariates for capture occasion  $j$
- $\boldsymbol{\beta}$  is a  $P \times 1$  vector of regression coefficients
- $(\epsilon_1, \dots, \epsilon_J)' \sim N(\mathbf{0}, \boldsymbol{\Sigma})$

## Covariance Matrix for the Survival Model

The covariance matrix,  $\Sigma$ , can be any general form.

Here we consider an  $AR(m)$  model which implies that the  $\epsilon_j$  error terms are realizations from the stochastic process

$$\epsilon_j = \sum_{k=1}^m \rho_k \epsilon_{j-k} + z_j, \quad j = 1, \dots, J,$$

where  $z_j \sim \text{i.i.d. } N(0, \sigma^2)$  and  $\rho = (\rho_1, \dots, \rho_m)$  is a set of parameters.

The stationary  $AR(m)$  model

- allows for positive or negative correlation between survival probabilities that decreases with an increasing separation in time
- imposes constraints on  $\rho$  (see paper for details)

## Parameter Estimation

Parameter estimation via maximum likelihood or quasi-likelihood is challenging in this context. We adopt a Bayesian approach.

For the Bayesian approach, we assume that the parameters  $\beta$ ,  $\sigma^2$ ,  $\rho$ , and  $\lambda$  are independent *a priori*.

The posterior distribution of the parameters and random effects is then given by

$$\begin{aligned} \pi(\beta, \sigma^2, \rho, \epsilon, \lambda | \mathbf{m}, \mathbf{R}, \mathbf{X}) &\propto \mathcal{L}(\beta, \epsilon, \lambda; \mathbf{m}, \mathbf{R}, \mathbf{X}) \\ &\times \pi(\beta)\pi(\sigma^2)\pi(\rho)\pi(\lambda) \\ &\times |\Sigma|^{-1/2} \exp \left\{ -\frac{\epsilon' \Sigma^{-1} \epsilon}{2} \right\} \end{aligned}$$

## A modified Gibbs Sampler

We show that conditional distributions of the parameters are given by

$$f(\beta_l | \beta_{-l}, \sigma^2, \rho, \epsilon, \lambda, D) \propto \prod_{i=1}^I \xi_i^{v_i} \prod_{j=i}^J \left\{ \prod_{k=i+1}^{j-1} \phi_k \right\}^{m_{ij}} \pi(\beta_l)$$

$$f(\lambda_l | \lambda_{-l}, \beta, \epsilon, \sigma^2, \rho, D) \propto \prod_{i=1}^I \xi_i^{v_i} \prod_{j=i+1}^J \lambda_j^{m_{ij}} \pi(\lambda_l)$$

$$f(\epsilon_l | \epsilon_{-l}, \beta, \sigma^2, \rho, \lambda, D) \propto \prod_{i=1}^I \xi_i^{v_i} \prod_{j=i}^J \left\{ \prod_{k=i+1}^{j-1} \phi_k \right\}^{m_{ij}} N(\mu_l / \eta_l, \sigma^2 / \eta_l),$$

where for an AR(2) error process, for example,

$$\mu_l = \begin{cases} \rho_1 \epsilon_2 + \rho_2 \epsilon_3 & l = 1 \\ \rho_1 (\epsilon_1 + \epsilon_3) + \rho_2 (\epsilon_4 - \rho_1 \epsilon_3) & l = 2 \\ \rho_1 (1 - \rho_2) (\epsilon_{l-1} + \epsilon_{l+1}) + \rho_2 (\epsilon_{l-2} + \epsilon_{l+2}) & l = 3, \dots, J-2 \\ \rho_1 (\epsilon_J + \epsilon_{J-2}) + \rho_2 (\epsilon_{J-3} - \rho_1 \epsilon_J) & l = J-1 \\ \rho_1 \epsilon_{J-1} + \rho_2 \epsilon_{J-2} & l = J \end{cases}$$

$$\eta_l = \begin{cases} 1 & l = 1 \text{ and } J \\ 1 + \rho_1^2 & l = 2 \text{ and } J-1 \\ 1 + \rho_1^2 + \rho_2^2 & l = 3, \dots, J-2 \end{cases}$$

$$f(\rho | \beta, \epsilon, \sigma^2, \lambda, D) \propto \left( \prod_{j=1}^m K_j \right)^{-1} \exp \left\{ -\frac{1}{2\sigma^2} \sum_{j=1}^J (\epsilon_j - \nu_j)^2 / K_j \right\} \pi(\rho)$$

$$f(\sigma^2 | \beta, \epsilon, \rho, \lambda, D) \propto \sigma^{-J} \exp \left\{ -\frac{1}{2\sigma^2} \sum_{j=1}^J (\epsilon_j - \nu_j)^2 / K_j \right\} \pi(\sigma^2)$$

where  $K_j$  is a function of  $\rho$ .

## Northern Pintails

Study of female Northern Pintail ducks in California for banding years 1955 – 1983.

Birds were banded in January of each banding year.

No yearly environmental covariates were available, but we considered the possibility of a trend in survival probabilities over time via the model

$$\text{logit } \phi_j = \beta_0 + \beta_1(j - 14) + \epsilon_j \quad j = 1, \dots, 27$$

So the covariate vector  $\mathbf{X}_j = (1, j - 14)$  for  $j = 1, \dots, 27$ .

We also consider the logit model without a slope parameter.

## Choosing the order for the AR process

We chose an AR(2) model for these data, so the error terms follow the stochastic process

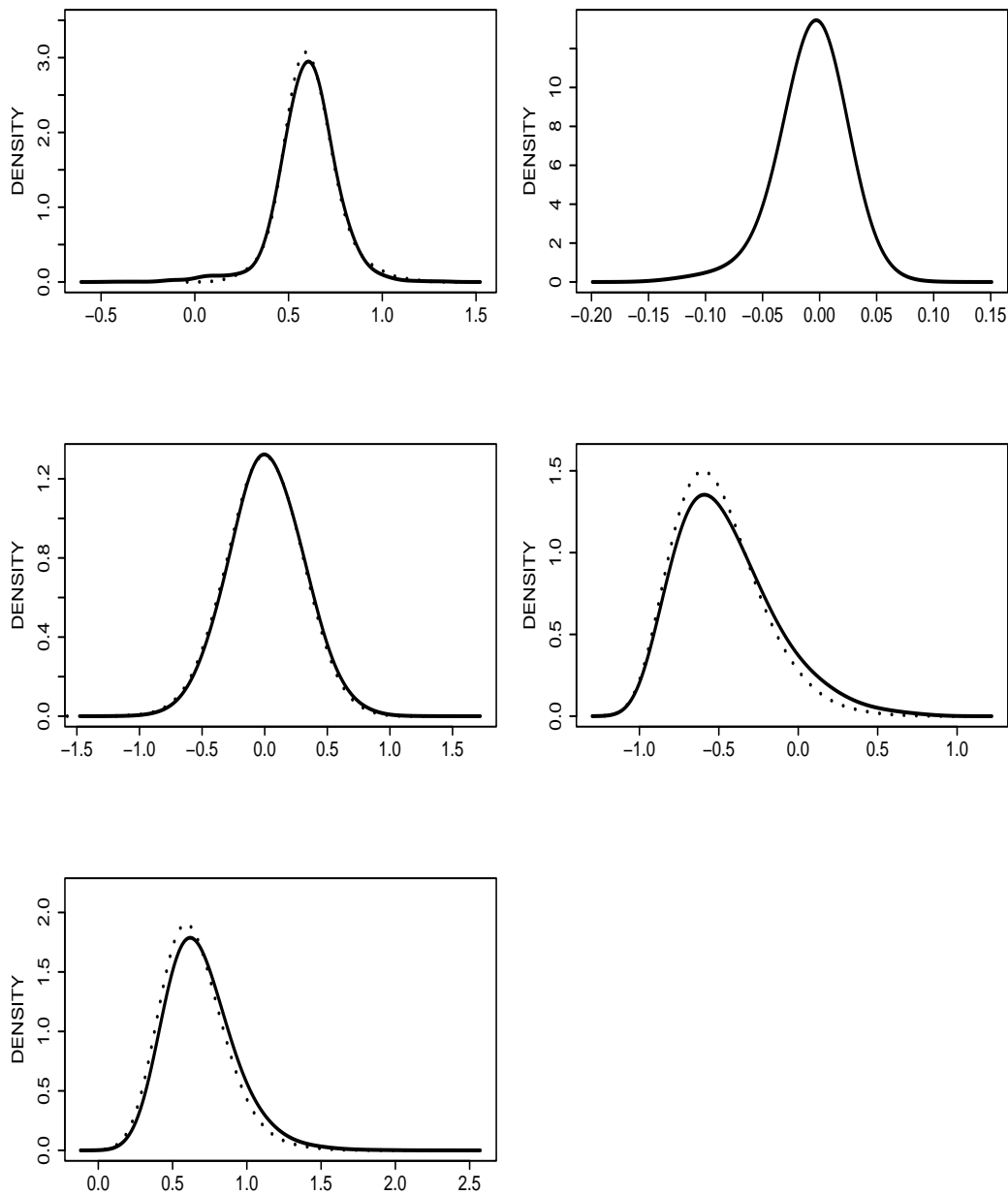
$$\epsilon_j = \rho_1 \epsilon_{j-1} + \rho_2 \epsilon_{j-2} + z_j, \quad j = 1, \dots, 27$$

The AR order was chosen based on a correlogram of the maximum likelihood estimates of yearly survival probabilities from the program MARK.

## Prior distributions for the parameters

$$\begin{aligned} (\beta_0, \beta_1)^T &\sim N\left(\mathbf{0}, \frac{1}{0.01} \mathbf{I}\right) \\ \sigma^{-2} &\sim \Gamma(0.001, 0.001) \\ \rho_2 &\sim U(-1, 1) \\ \rho_1 | \rho_2 &\sim U(-(1 - \rho_2), 1 - \rho_2) \\ \lambda_j &\sim \text{i.i.d. } U(0, 1) \quad j = 1, \dots, 28 \end{aligned}$$

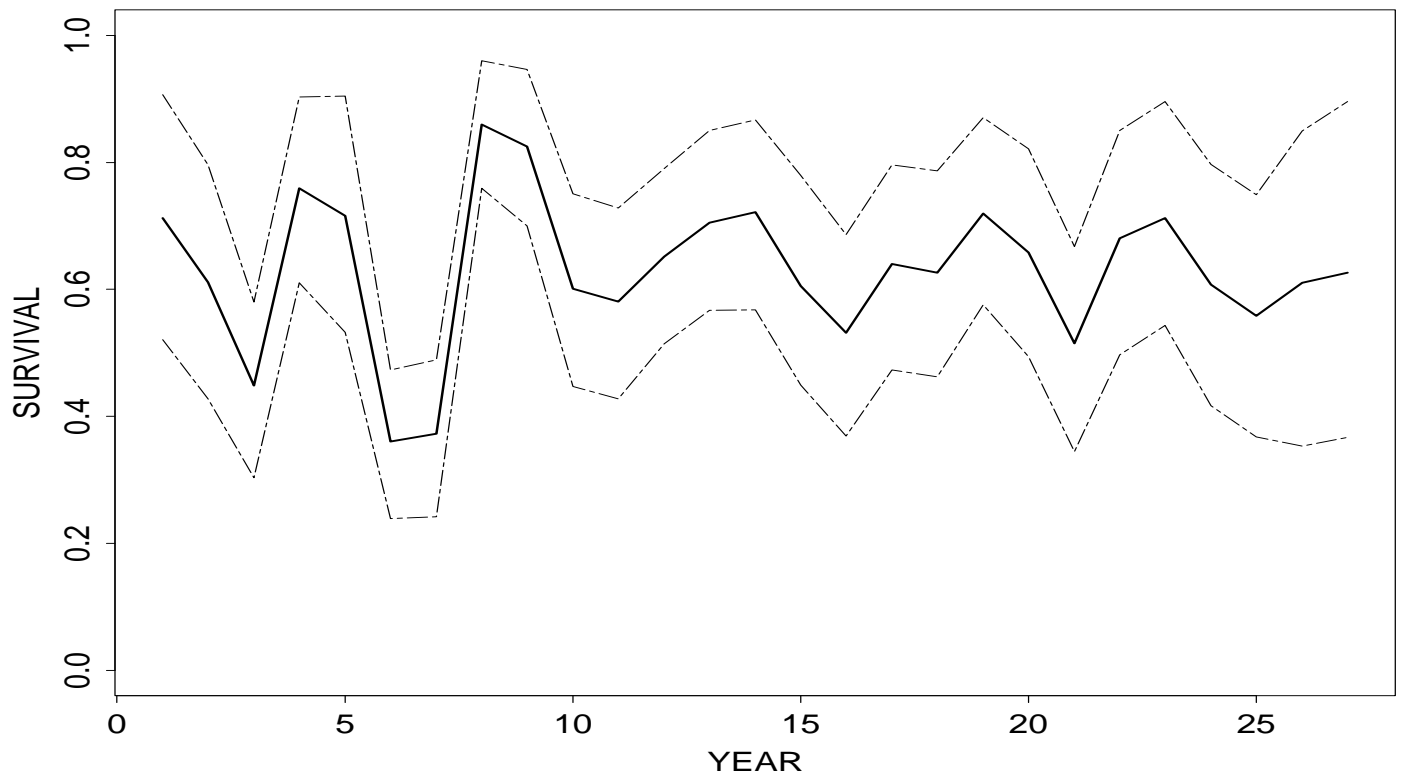
MCMC sampling was carried out using winBUGS.



**Figure 1.** Marginal Posterior Densities.

Solid line = linear time trend model

Dotted line = model with no linear time trend



**Figure 2.** Yearly survival estimates for Northern Pintails (model with no linear time trend). The solid line is the estimated posterior mean survival and the dashed lines represent a 90% HPD interval.

## Conclusions

The time series modeling of capture-recapture data can provide additional insights to the survival process.

Extensions and related models include

- Random effects models for recovery parameters
- Multivariate AR process

Other issues include model selection and model uncertainty:

- Which covariates?
- Which link function?
- Which order for the AR process?

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