# Estimating abundance in small populations using pedigree reconstruction

Sarah Croft<sup>1</sup>, Richard Barker<sup>1</sup>, Mik Black<sup>2</sup>, Jamie Sanderlin<sup>3</sup> and Matt Schofield<sup>1</sup>

<sup>1</sup>Department of Mathematics and Statistics, University of Otago

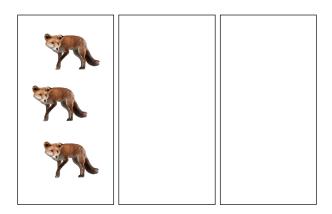
> <sup>2</sup>Department of Biochemistry, University of Otago

<sup>3</sup>Rocky Mountain Research Station, USDA Forest Service

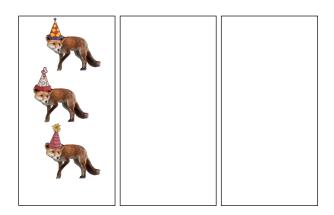
Biometrics in the Bush Capital, November 2025



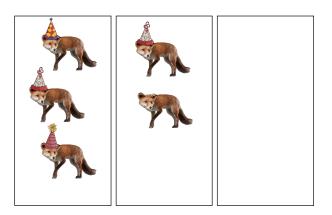




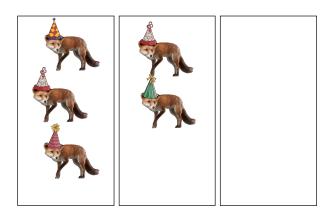




















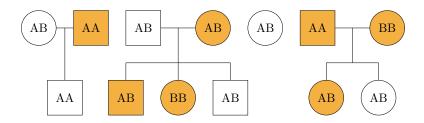
## Close-Kin Mark-Recapture

- Bravington et al. (2016)<sup>1</sup> defined a pseudo-likelihood model, identifying the number of kinship pairs within the sample from the genetic data
- The model can be fit to dead recoveries without previous observation of the individual
- Rather than a physical tag a genetic sample is taken from each observed animal



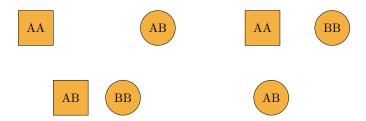
## The population's pedigree

Consider two time periods, with a founder generation and one offspring period, and we observe the highlighted individuals.



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## Model assumptions and restrictions

#### We assume:

- 1. The population is geographically closed
- 2. All individuals born before the study began are defined as founders and their parents are undefined
- 3. All individuals born during the study must have a female and male parent within the super population
- 4. Births are defined as individuals who were born within the period and survived until the start of the next time period

Let  $b_0$  be the number of founders. We define

$$b_0 \sim \mathsf{Pois}(\lambda_0)$$
 (1)

$$s_i \sim \mathsf{Bern}(\omega) \text{ for } i \in 1, ..., b_0$$
 (2)

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Using the properties of a Bernoulli marked Poisson we define  $b_{00}$  and  $b_{01}$  as the number of male and female founders respectively where

$$b_{00} \sim \mathsf{Pois}(\lambda_0(1-\omega)) \tag{3}$$

$$b_{01} \sim \mathsf{Pois}(\lambda_0 \omega)$$
 (4)



#### For time period 1 then:

1. Each female founder i mates with probability  $\zeta$  and under random mating then

$$M_{1i} \sim \mathsf{Cat}\left((1-\zeta, \frac{\zeta}{b_{00}}, ..., \frac{\zeta}{b_{00}})'\right)$$
 (5)

with sample space  $\{0, 1, ..., b_{00}\}$ .

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2. Let the number of offspring born to a mated female i, be independent Poisson random variables with parameter  $\lambda_1$ . Each of the offspring are female with probability  $\omega$  then

$$b_{10} \sim \mathsf{Pois}\bigg(\lambda_1(1-\omega)\sum_{i=1}^{b_{01}}I(M_{1i}>0)\bigg)$$
 (6)

$$b_{11} \sim \mathsf{Pois}igg(\lambda_1\omega\sum_{i=1}^{b_{01}}I(M_{1i}>0)igg)$$



#### For time period 1 then:

3. The mother of an offspring h is a Categorical random variable such that

$$r_h \sim \mathsf{Cat}\Bigg(I(\mathbf{M_1} > 0) \bigg(\frac{1}{\sum_{i=1}^{b_{01}} I(M_{1i} > 0)}, ..., \frac{1}{\sum_{i=1}^{b_{01}} I(M_{1i} > 0)}\bigg)'\Bigg)$$
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where  $r_h = i$  if female i is the mother of h.

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- 4. Each founder survives until the start of period 2 with probability  $\phi_1$ .
- 5. If a founder dies between the start of period 1 and 2 they are recovered with probability  $\pi_1$ .



We can generalise the model to K periods. For  $j \in \{1,...,K\}$ :

• 
$$M_{ji} \sim \mathsf{Cat} \left( \left( 1 - \zeta, \frac{\zeta}{A_{j0.}}, ..., \frac{\zeta}{A_{j0.}} \right)' \right)$$
 if  $A_{j1i} = 1$ 

• 
$$b_{j0} \sim \mathsf{Pois}\bigg(\lambda_j(1-\omega)\sum_{i=1}^{A_{.1}}I(M_{ji}>0)\bigg)$$

• 
$$b_{j1} \sim \mathsf{Pois}\bigg(\lambda_j \omega \sum_{i=1}^{A_{.1}} I(M_{ji} > 0)\bigg)$$

- $r_h \sim \operatorname{Cat} \left( I(\mathbf{M_j} > 0) \left( \frac{1}{\sum_{i=1}^{A,1} I(M_{ji} > 0)}, ..., \frac{1}{\sum_{i=1}^{A,1} I(M_{ji} > 0)} \right)' \right)$  for all h born in j.
- $d_i \sim \mathsf{Cat}(\xi_t)$  where i is born in period t and  $\xi_t$  is a function of  $\phi$ .
- $x_i \sim \text{Bern}(\pi_j)$  where i died in period j.





We model a founder's genotype at L independent loci by

$$G_{il} \sim \mathsf{Cat}(\gamma_l), \ l \in \{1, ..., L\}$$
 (9)

and a non-founder i born in j with mother  $r_i$  and father  $M_{jr_i}$  by

$$G_{il} \sim \mathsf{Cat}\left(\left(\frac{1}{4}, \frac{1}{4}, \frac{1}{4}, \frac{1}{4}\right)'\right)$$
 (10)

with sample space

$$\mathcal{G}_{il} = \{ (G_{r_i1}, G_{M_{jr_i}1}), (G_{r_i2}, G_{M_{jr_i}1}), (G_{r_i1}, G_{M_{jr_i}2}), (G_{r_i2}, G_{M_{jr_i}2}) \}$$
 (11)



#### **Implementation**

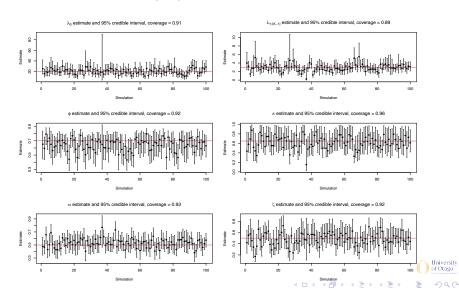
- 1. Update  $B_{js}$  for  $j\in\{0,1,...,K-2\}$  and  $s\in\{0,1\}$  using a Metropolis-Hastings split-merge reversible jump
- 2. Update  $B_{K-1,s}$  for  $s \in \{0,1\}$  using a Metropolis-Hastings reversible jump
- 3. Update all other variables using either Metropolis-Hastings reversible jump moves or Gibbs sampling



#### Simulation results

#### We simulated 100 pedigrees with true parameters values:

$$\theta = (K, \lambda_0, \lambda_{1:(K-1)}, \phi, \pi, \omega, \zeta) = (4, 20, 3, 0.7, 0.65, 0.5, 0.5)$$
(12)



#### Continuing work

- Test on real data
- Speed up algorithm:
  - Marginalising over unobserved branches of the pedigree
  - Joint updates for genotype
- Explore adjustments to the model required to allow for inbreeding



#### Thanks!

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