

## Combining longitudinal data and pedigree information to assess heritability of survival

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# Context

- Quantitative genetics for assessing the ability of a trait to respond to natural selection.
- Recently proposed for wild animal and plant populations.
- Applications in evolutionary ecology, management and conservation biology.
- **Heritability: Proportion of the total phenotypic variance that can be ascribed to additive genetic variance.**
- For (demographic) parameters strongly related to fitness, we expect low heritability.
- But, predictions not so clear in wild populations.

# Where are we?

- **Animal models**: mixed models incorporating genetic, environmental and other factors.
- **Capture-recapture models**: assess demographic parameters with  $p < 1$  and individual variability.

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- **Capture-recapture models**: assess demographic parameters with  $p < 1$  and individual variability.
- *The idea of combining Animal and Capture-recapture models is in the air (O'Hara et al. 2008; Cam 2009).*

The idea is in the air (1), O'Hara et al. 2008

## The idea is in the air (2), Cam 2009

"Estimating the genetic basis of quantitative traits can be tricky for wild animal populations in natural environments: environmental variation often obscures the underlying evolutionary patterns (...) **[The animal model has] been applied to estimation of heritability in life history traits, either in the rare study populations where detection probability is close to 1, or without considering the probability of detecting animals that are alive and present in the study area** (recapture or resighting probability). Applications of the animal model to demographic parameters (fitness components) (...) where detection probability is  $< 1$  require **trans-disciplinary efforts**"

## Where are we?

- Animal models: mixed models incorporating genetic, environmental and other factors.
- Capture-recapture models: assess demographic parameters with  $p < 1$  and individual variability.
- The idea of combining Animal and Capture-recapture models is in the air (O'Hara et al. 2008; Cam 2009).

### Main objective

A unified model combining pedigree information and capture-recapture data to assess heritability of survival in natural conditions.

# Plan

- 1 Capture-recapture animal model: CRAM
- 2 Bayesian inference using MCMC
- 3 The Blue tits as a case study
- 4 What's next?



# Outline

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# State-space model

## Definition:

A state-space model describes the evolution of two time series running in parallel, one referred to as the state process and the other as the observation process (Buckland et al. 2004).

# State–space model for capture–recapture data

- Define  $X_{i,t} = \begin{cases} 1 & \text{if } i \text{ is alive at time } t \\ 0 & \text{if } i \text{ is dead at time } t \end{cases}$

## State equations – survival process:

$$X_{i,t+1} | X_{i,t} \sim \text{Bernoulli}(X_{i,t} \cdot \phi_{i,t})$$

- Define  $Y_{i,t} = \begin{cases} 1 & \text{if } i \text{ captured at time } t \\ 0 & \text{if } i \text{ non-captured at time } t \end{cases}$

## Observation equations – detection:

$$Y_{i,t} | X_{i,t} \sim \text{Bernoulli}(X_{i,t} \cdot p_{it})$$

- Clark et al. (2005), McCarthy (2006), Gimenez et al. (2007), Royle (2008) (...)

# Threshold model to deal with discrete traits

Survival was related to a continuous underlying latent variable  $l_{i,t}$ , which, given  $X_{i,t} = 1$ , satisfied:

$$X_{i,t+1} = \begin{cases} 1 & \text{if } l_{i,t} > \kappa, \\ 0 & \text{if } l_{i,t} \leq \kappa. \end{cases}$$

where  $\kappa$  is a threshold value.

Distribution for the so-called liability  $l_{i,t}$

We assumed  $l_{i,t} \sim N(\mu_{i,t}, \sigma_\epsilon^2)$ .

# Threshold model to deal with discrete traits

# What is the link between survival and liability?

- Recall:  $l_{i,t} \sim N(\mu_{i,t}, \sigma_\epsilon^2)$

$$\begin{aligned}\phi_{i,t} &= \Pr(X_{i,t+1} = 1 | X_{i,t} = 1) \\ &= \Pr(l_{i,t} > \kappa) \\ &= F\left(\frac{\mu_{i,t} - \kappa}{\sigma_\epsilon}\right)\end{aligned}$$

where  $F$  is the cumulative function of a  $N(0, 1)$

- For identifiability reasons, and without loss of generality, we fixed  $\sigma_\epsilon$  to 1 and  $\kappa$  to 0.

## Relationship between survival and liability

We have:  $\phi_{i,t} = F(\mu_{i,t})$

- $F^{-1}$  is usually referred to as the probit function.

# Towards a capture–recapture animal model (CRAM)

- Recall:  $\phi_{i,t} = F(\mu_{i,t})$  where  $F \sim N(0, 1)$

Plug the animal model in the capture-recapture model:

$$\text{probit}(\phi_{i,t}) = F^{-1}(\phi_{i,t}) = \mu_{i,t} = \eta + b_t + e_i + a_i$$

- $\eta$  is a constant term for the mean survival on the probit scale,
- $b_t$  is a yearly effect with  $b_t \sim N(0, \sigma_t^2)$ ,
- $e_i$  is an individual non–genetic value with  $e_i \sim N(0, \sigma_e^2)$ ,
- $a_i$  is a genetic value, with  $\mathbf{a} \sim MN(0, \sigma_a^2 \mathbf{A})$ ,  $\sigma_a^2$  is the genetic additive variance and  $\mathbf{A}$  the additive genetic relationship matrix.  $\mathbf{A}$  is built up from the pedigree (e.g.  $A_{\text{individual, itself}} = 1$ ,  $A_{\text{offspring, parent}} = 0.5$ ).

# Calculating heritability

- Recall:  $\text{probit}(\phi_{i,t}) = \eta + b_t + e_i + a_i$ .
- Decomposing components of variance in survival.
- The proportion of variance explained by the additive genetic variance  $\sigma_a^2$ .

The heritability is thus obtained as:

$$h^2 = \frac{\sigma_a^2}{\sigma_t^2 + \sigma_e^2 + \sigma_a^2 + 1}.$$



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# Estimation via MCMC

- A priori distributions:
  - $p \sim U(0, 1)$ ,
  - $\eta \sim N(0, 100)$ ,
  - $\sigma_e, \sigma_a$  and  $\sigma_b \sim U(0, 10)$ .
- Parameters of the MCMC runs:
  - 2 chains,
  - 5000 iterations as a burn-in,
  - 15000 iterations after the burn-in,
  - thinning every 10th iterations,
  - inference using 1000 remaining iterations.
- Checking convergence:
  - visual inspection of mixing and posterior distributions,
  - calculate the BGR statistic ( $\hat{R} < 1.2$ ).
- Implementation:
  - call OpenBUGS from R (block-updating!).

# Is heritability "significant", i.e. $\sigma_a^2 \neq 0$ ?

- Introduce binary variables to have labels on models (Congdon 2005, Royle 2008).
- $\sigma$  is in the model if  $w_\sigma = 1$ , and is not if  $w_\sigma = 0$ .
- For example,  $\{w_{\sigma_e} = 0, w_{\sigma_a} = 1\}$  is a model with genetic variance only:  $\text{probit}(\phi_{i,t}) = \eta + b_t + a_i$ .
- Calculate the posterior probability of a given model using the mean number of iterations spent in this given model.
- All models containing  $\sigma_a$  give  $h^2 \neq 0$ .

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## Details on capture-recapture data

- Blue tits – Study site in Corsica.
- 1979 – 2007  $\Rightarrow$  29 years of monitoring.

# Information on pedigree

- Characteristics of the (social) pedigree:
  - 654 individuals,
  - 218 fathers (sires),
  - 215 mothers (dams),
  - 12 generations.
- Dependence among individuals.
- Complex relationships over several generations.

# Mixing for variance terms

# Mixing for mean survival and detection probabilities



# Posterior distribution of the detection probability $p$

- Recall: prior is  $U(0, 1)$ .
- Mean = 0.767,  
Median = 0.769,  
Credible interval =  
[0.707, 0.822].

# Posterior distribution of the mean survival $F(\eta)$

- Recall: prior on  $\eta$  is  $N(0, 100)$ .
- Mean = 0.569,  
Median = 0.569,  
Credible interval =  
[0.493, 0.650].

# Posterior distribution of the temporal variance $\sigma_t^2$

- Recall: prior is  $U(0, 10)$ .
- Mean = 0.307,  
Median = 0.301,  
Credible interval =  
[0.105, 0.558].

# Posterior distribution of the non-genetic variance $\sigma_e^2$

- Recall: prior is  $U(0, 10)$ .
- Mean = 0.105,  
Median = 0.089,  
Credible interval =  
[0.005, 0.284].

# Additive genetic variance $\sigma_a^2$ posterior distribution

- Recall: prior is  $U(0, 10)$ .
- Mean = 0.122,  
Median = 0.110,  
Credible interval =  
[0.006, 0.308].

# Posterior distribution of the heritability $h^2$

- Mean = 0.018,  
Median = 0.011,  
Credible interval =  
[0.000, 0.077].

# Model selection 'à la Congdon–Royle' favored...

Model	Posterior probability
0	0.960
$\sigma_e^2$	0.019
$\sigma_a^2$	0.020
$\sigma_e^2, \sigma_a^2$	0.001

**Table:** The posterior model probabilities associated with different models for the tits data.

# Model selection with DIC

Model	Posterior probability	DIC (pD)
0	0.960	857.6 (437.2)
$\sigma_e^2$	0.019	860.2 (441.9)
$\sigma_a^2$	0.020	875.6 (456.7)
$\sigma_e^2, \sigma_a^2$	0.001	848.4 (433.7)

Table: The posterior model probabilities and the DIC values associated with different models for the tits data.



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# Discussion

- Combination of two existing models: animal and capture–recapture models.
- Key role of the liability.
- What if  $p$  is assumed to be 1?

# Perspectives

- Extension to other parameters (age at first reproduction (Swans) – PhD S. Cubaynes; dispersion (Flycatchers) – post-doc (?) with B. Doligez).
- Simulation study to:
  - check that we are able to detect heritability,
  - explore data requirements (sample size, power),
  - decide which model selection procedure to use, and
  - make sure we have no bugs in the code.
- MCMC or numerical integration (Gimenez and Choquet, submitted; R. Choquet's talk tomorrow morning).
- Goodness-of-fit testing?

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# Modelling individual histories with state uncertainty

- **What?** Multievent capture–recapture workshop.
- **How?** See <http://www.cefe.cnrs.fr/biom/Workshops/>.
- **When?** November 16-20, 2009.
- **Where?** Southern France, Montpellier (good and lots of food too).
- **Who?** R. Pradel, R. Choquet, J.–D. Lebreton, O. Gimenez, L. Rouan, and....



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# Reparameterizing $\mathbf{a}$ for improving MCMC

- Henderson (1976): in  $\mathbf{a} \sim N(\mathbf{0}, \sigma_a^2 \mathbf{A})$ , we can write  $\mathbf{A} = \mathbf{TDT}'$  where  $\mathbf{T}$  is a matrix gathering the fraction of genes of animal  $i$  inherited by animal  $j$  (sparse).
- We can rewrite  $\mathbf{a}$  as  $\mathbf{a} = \sigma_a \mathbf{TD}^{\frac{1}{2}} \boldsymbol{\gamma}$  where  $\boldsymbol{\gamma} \sim N(\mathbf{0}, \mathbf{Id})$
- Quaas (1989): we use a recursive algorithm to calculate  $\mathbf{v} = \mathbf{Ts}$ , in which we write:  $\mathbf{s} = \mathbf{D}^{\frac{1}{2}} \boldsymbol{\gamma}$  and therefore we deduce:  $\mathbf{a} = \sigma_a^2 \mathbf{v}$
- We have:  $v_i = D_{ii}^{\frac{1}{2}} \cdot \gamma_i + \frac{v_{si} + v_{di}}{2} \quad \forall i = 1 \dots N$  where the indices  $si$  and  $di$  are for the sire and dam of individual  $i$ .
- See Damgaard (2007) and Waldmann (2009).



# Identifiability issues in the threshold model

- Apply constraints to make the threshold model identifiable, namely  $\kappa = 0$  and  $\sigma_\epsilon^2 = 1$
- Any non-zero  $\kappa$  will be offset by a corresponding shift in the intercept.
- Multiply both sides of  $l_{i,t} = \eta + b_t + e_i + a_i + \epsilon_{i,t}$  by  $c > 0$ . We note that  $\theta = (\theta, \sigma_t^2, \sigma_e^2, \sigma_a^2)$  fits the data as well as  $\theta^* = (c\theta, c^2\sigma_t^2, c^2\sigma_e^2, c^2\sigma_a^2)$ . Setting  $\sigma_\epsilon^2$  to any positive constant will pin down the latent variable (and hence  $\eta, \sigma_t^2, \sigma_e^2$ , and  $\sigma_a^2$ ), and the value 1 is chosen for convenience.