Modeling Fine-Scale Abundance Dynamics:

A Dual Frequentist and Bayesian Approach Applied to Common Birds

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Breeding Bird Surveys

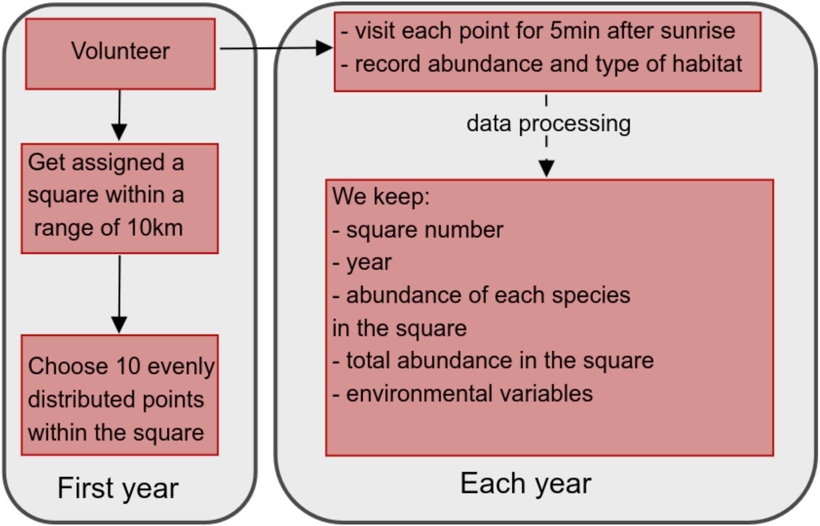
Meadow pipit (*Anthus pratensis*)

From Charles J. Sharp

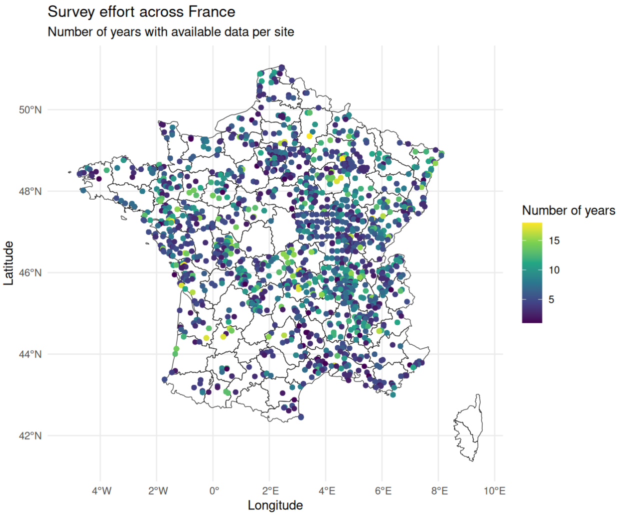
Breeding Bird Surveys (BBS) are long-term, large-scale, international avian monitoring programs designed to track the status and trends of bird populations.

Key features: standardized protocol, geographical and temporal coverage.

French BBS program (STOC)



What's in the data?



Environmental variables

For each observed point, we retrieve:

- Climate variables during spring (minimum and maximum temperature, total rain);
- Land uses in the square (% of agricultural, forest and urban land);
- Indices on how the agricultural land is fragmented 10km around the observation.

Goals

1. Give a method to estimate future abundance of birds at a local scale.
2. Find which environmental variables induce changes in abundance.

Birth and death model

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The transition to a new state $\mathcal{P}'$ is governed, by:

- birth probability: $b(\tau_x \theta, \tau_x \mathcal{P})$
- death probability: $d(\tau_x \theta, \tau_x \mathcal{P})$

with τ_x a shift operator.

Effort rate

The observers form a random set in $\mathbb{R}^2$, $E = (E(x), x \in \mathbb{R}^2)$, that is independent of $\mathcal{P}$ and θ.

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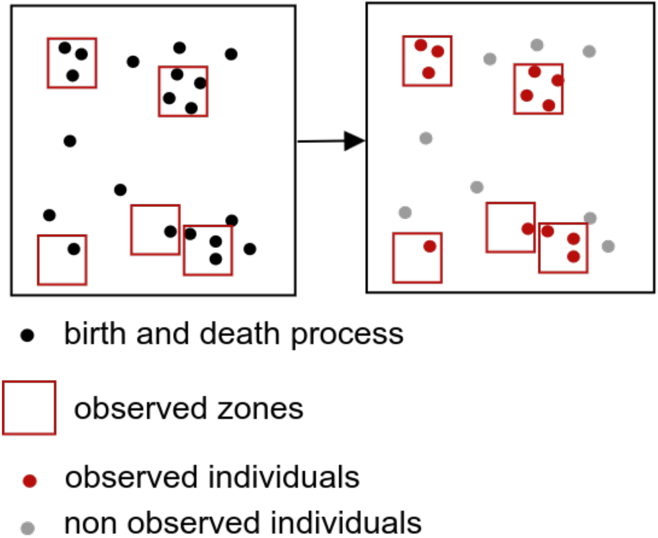
Example

$E_0 = \bigcup_e B(e, \rho)$ initial observed zone with e the location of the observers and ρ the (random) range of observation
To go to the next state of observed zone:

- each point is removed with constant rate;
- new points arrive according to a homogeneous Poisson process

Representation of the model



(Non) stationarity assumptions

- No temporal stationarity nor equilibrium
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Given a population $\mathcal{P}_0$ and covariates $\theta = (\theta(x), x \in \mathbb{R}^2)$. We want to predict next year abundance around x:
$N_1(x) = \#\{\mathcal{P}_1 \cap B(x, \rho)\}$

Estimator

Let $(\theta', \mathcal{C})$ be a deterministic configuration of interest.

$$\hat{N}_n^{(\theta',\mathcal{C})} := \frac{1}{\sum_{x_j \in E} k(\tau_{x_j}(\theta, \mathcal{P}_n), (\theta', \mathcal{C}))} \sum_{x_i \in E} N_1(x_i) k(\tau_{x_i}(\theta, \mathcal{P}_n), (\theta', \mathcal{C}))$$

where $\mathcal{P}_n := \mathcal{P} \cap [-n/2, n/2]^2$ and k is a similarity function.

Convergence results

If $\mathcal{P}$ is a log Gaussian Cox process then it has exponential mixing correlations.

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Proposition

$$\left(\mathrm{Var}\left(\hat{N}_n^{(\theta',\mathcal{C})}\right)\right)^{-1/2}\left(\hat{N}_n^{(\theta',\mathcal{C})} - \mathbb{E}[\hat{N}_n^{(\theta',\mathcal{C})}]\right) \xrightarrow{d} \mathcal{N}(0,1)$$

Proof with a theorem from BYY 2026+

How does it work with a toy data set ?

Square	Year	Abundance	Environmental variables	**Abundance next year**
10295	2003	5	🦜🦜 🪿 🪿 🌡️☀️🌲	2
11158	2006	1	🪿 🪿 🌧️🌡️ 🌽	4
20204	2015	6	🐦🐦🐦☀️❄️ 🌽	7
30363	2019	8	🐦🐦🪿🦜 🌧️ ❄️ 🌲	9
950294	2024	3	🪿 🪿 🐦🌧️🌡️🌲	?

In our example we say that the similarity only depend on the number of geese and the habitat:

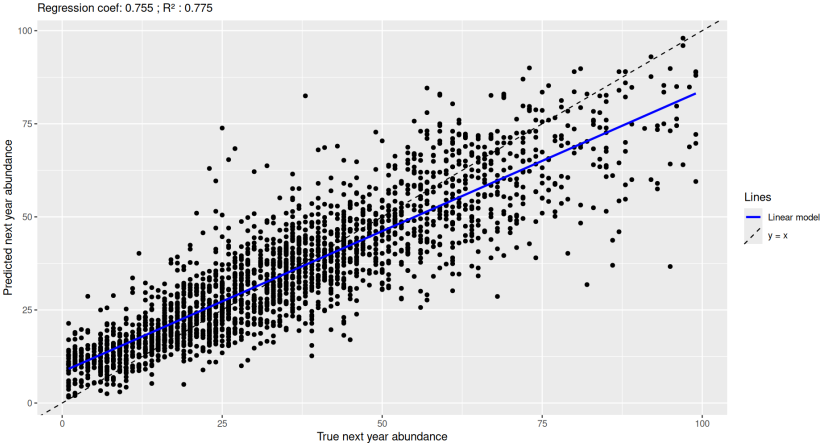
$$k(L_1, L_2) = \frac{1}{2}(\mathbb{1}_{\text{number of geese of } L_1 = \text{number of geese of } L_2} + \mathbb{1}_{\text{same habitat}})$$

Similarity matrix

Square	Year	Abundance	Environmental variables	Abundance next year	Similarity with square of interest
10295	2003	5	🦜🦜 🪿 🪿 🌡️☀️🌲	2	1
11158	2006	1	🪿 🪿 🌧️🌡️ 🌽	4	0.5
20204	2015	6	🐦🐦🐦☀️❄️ 🌽	7	0
30363	2019	8	🐦🐦🪿🦜 🌧️ ❄️ 🌲	9	0.5
950294	2024	3	🪿 🪿 🐦🌧️🌡️🌲	?	1

$$\hat{N} = \frac{2 \times 1 + 4 \times 0.5 + 7 \times 0 + 9 \times 0.5}{1 + 0.5 + 0 + 0.5 + 1}$$
$$= 2.125$$

Results with real data



Forest species

Some ideas on what can change bird's abundance

- Land use,
- climate,
- agricultural practices (land sharing vs land sparing),
- ...

Model

- We model bird counts using a **negative binomial regression model** to account for overdispersion.

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- The expected count $\lambda(s, t)$ is modeled as:

$$\log \lambda(s,t) = \beta_0 + \sum_k \beta_k X_k(s,t) + \sum_{i,j} \beta_{i,j} X_i(s,t) X_j(s,t) + w_{s,t}$$

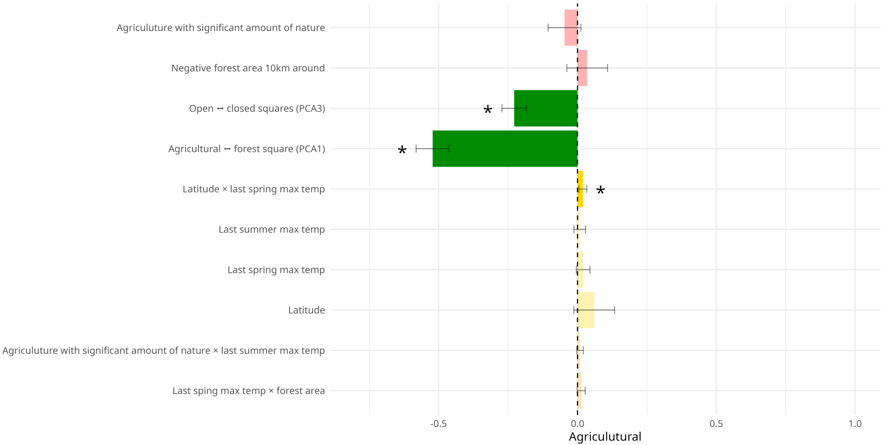
where:

- $X_k(s,t)$: environmental covariates (climate, land cover, etc.)
- $w_{s,t}$: spatio-temporal randomness

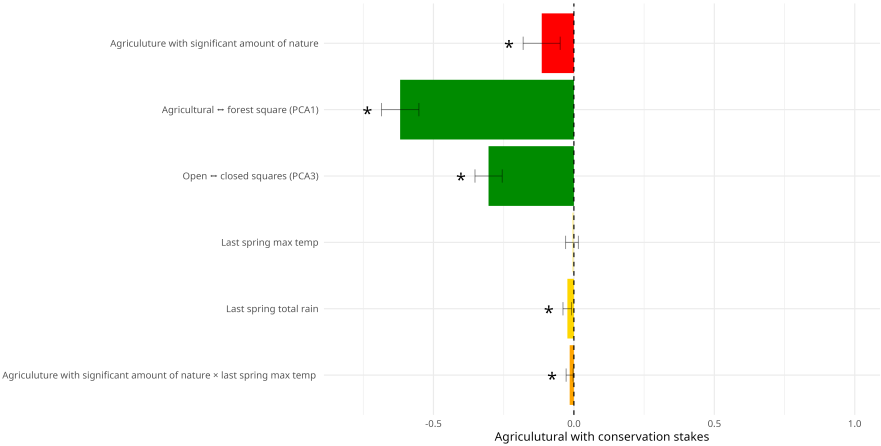
Bayesian inference with INLA Rue et al. 2009

- Deterministic approximations of the posterior law (Integrated Nested Laplace Approximation):
  - One for the latent field (β_i)
  - One for hyperparameters (spatial and time effects)
- Very fast but only for Latent Gaussian Model

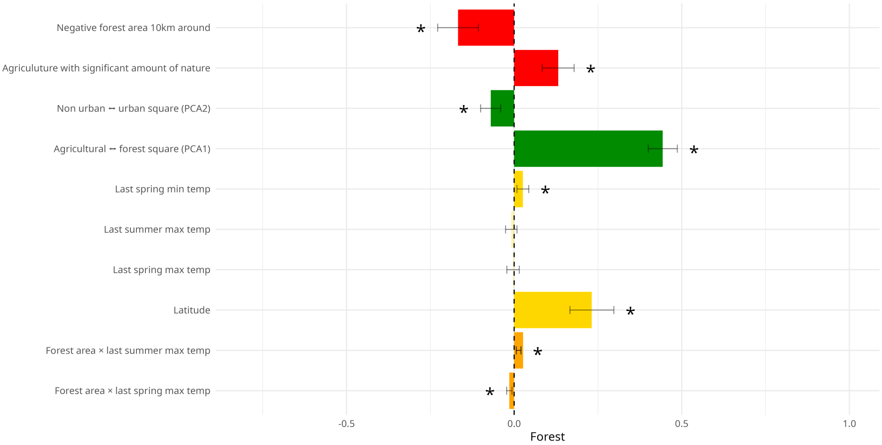
Results for agricultural birds



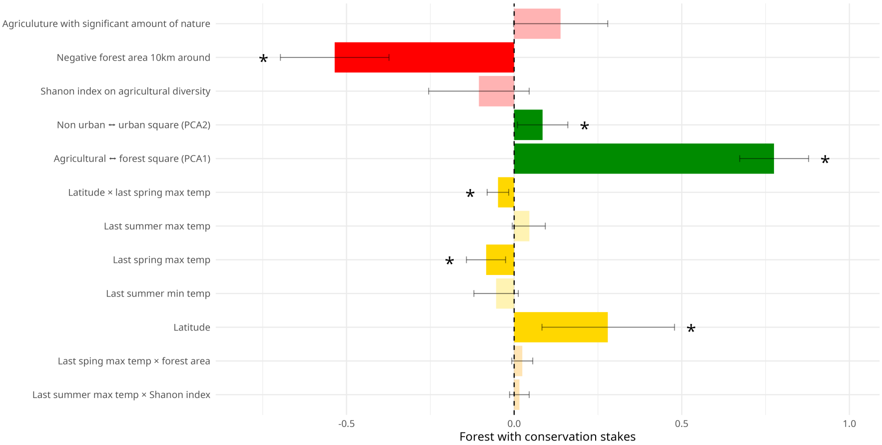
Results for agricultural birds with conservation stakes



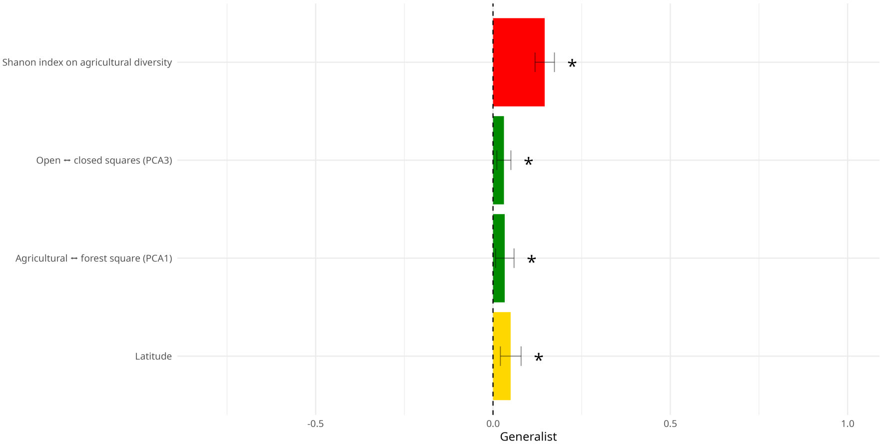
Results for forest birds



Results for forest birds with conservation stakes



Results for generalist birds



Thank you for your attention!