Modeling fine-scale abundance dynamics: a dual frequentist and Bayesian approach applied to common birds.

Adélie Erard, Ottmar Cronie, Raphaël Lachièze-Rey and Romain Lorrillière

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LABORATOIRE MAP5

CESCO Centre d'Écologie et des Sciences de la Conservation

Modélisation Mathématique et Biodiversité

Ecological context

Breeding Bird Surveys

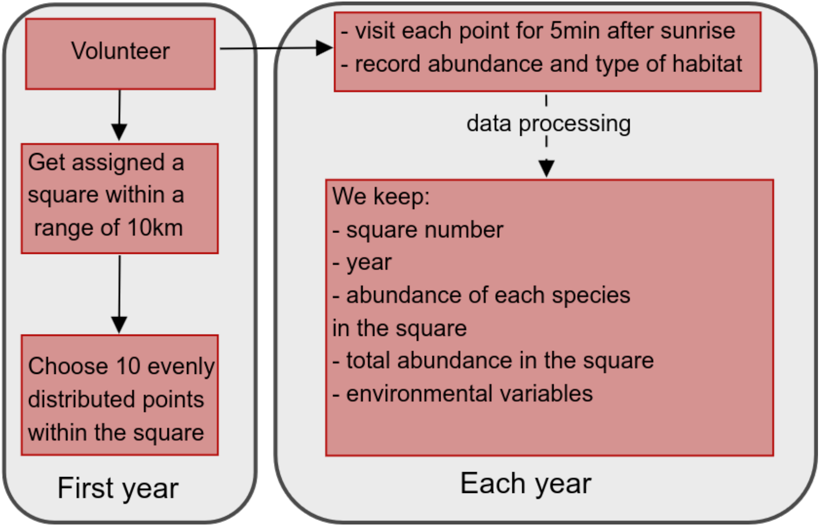
Meadow pipit (*Anthus pratensis*)

From Charles J. Sharp

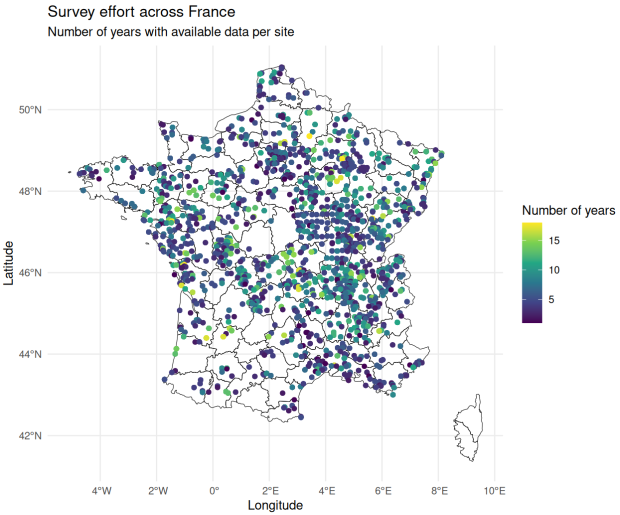
Breeding Bird Surveys (BBS) are long-term, large-scale, international avian monitoring programs designed to track the status and trends of bird populations.

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

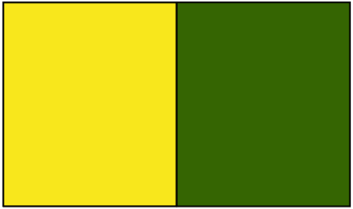
1. Find which agricultural practices are best.

2. Give a method to estimate the variation of abundance (or future abundance) at a local scale.

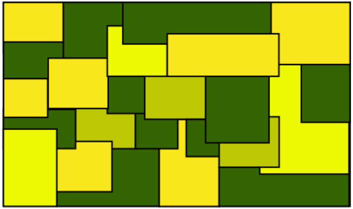
Land sharing or sparing? Implications for farmland birds of conservation concerns

Adélie Erard, Ottmar Cronie, Raphaël Lachièze-Rey, Romain Lorrillière

Land sharing and land sparing

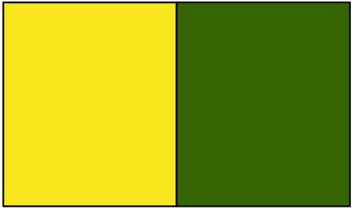


Land Sparing



Land Sharing

Land sharing and land sparing



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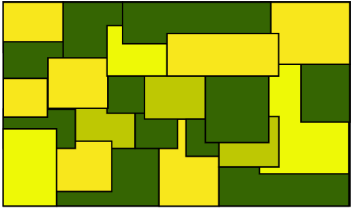
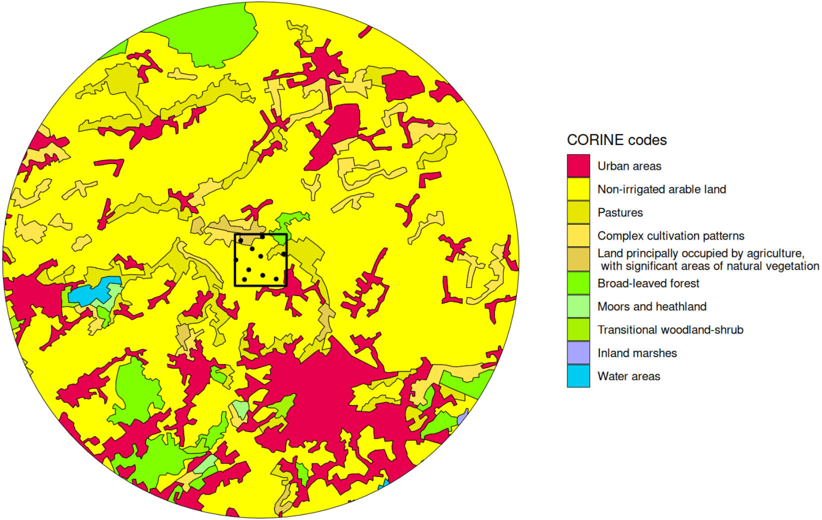


Land Sharing

What is the best agricultural practice to conserve farmland birds ?

Indicators of Land Sharing and Land Sparing



Model

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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 (land sharing and sparing indices, land cover of the square, climate)
- $w_{s,t}$: spatio-temporal randomness

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- Inference with `INLA` [Rue et al. 2009]

Model section

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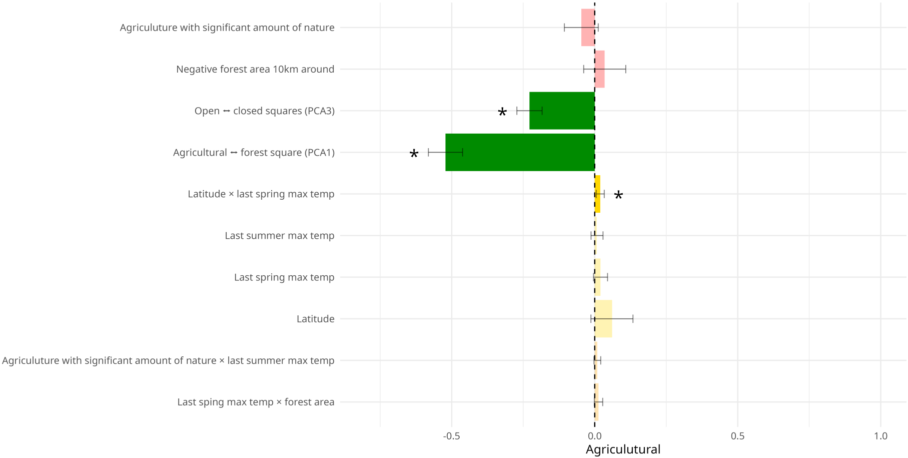
- land cover of the square: PCA on land use of each square - 3 variables
- climate: minimum and max temperature of last spring and summer, total rain of last spring
- interactions between climate and land sharing and sparing variables

Results for agricultural birds



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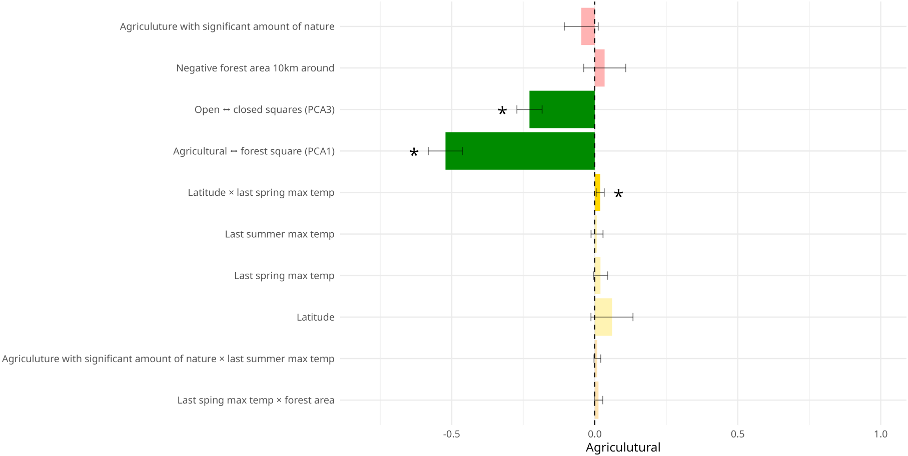
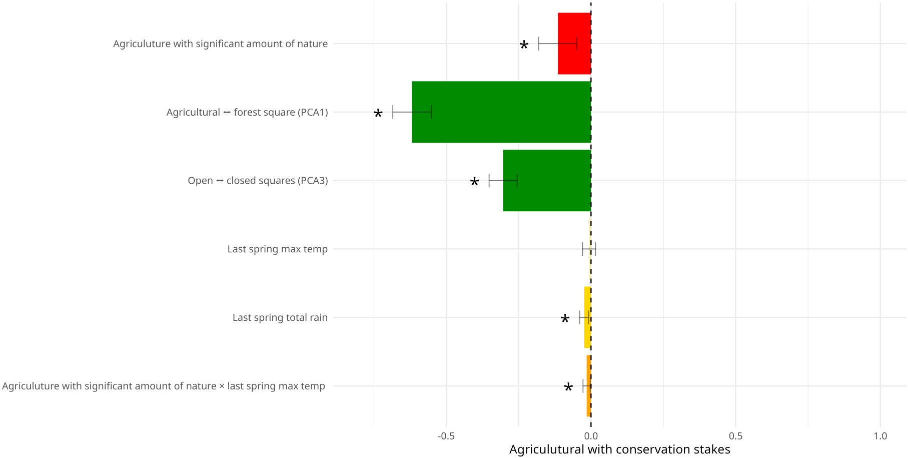


Land sparing is preferred

Results for agricultural birds with conservation concern



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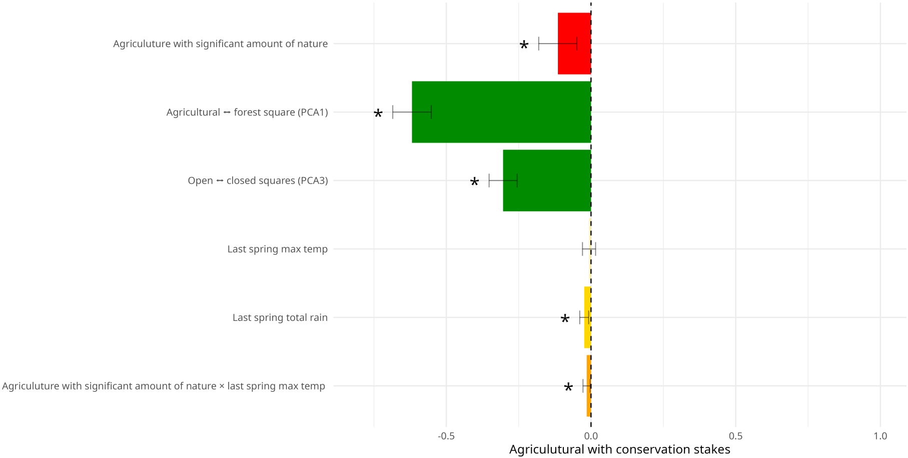

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- they nest on the ground so hedges and bushes are not improving survival

BUT studies showed that farmland birds are in decline because of agriculture intensification and pesticides use.

What we need is big open fields with low intensity agriculture.

Asymptotic properties of estimators for partially observed dependent spatial processes in a random environment.

Adélie Erard, Raphaël Lachièze-Rey, Romain Lorrillière

Birth and death model

Individuals at a time are represented as a point process $\mathcal{P}$:

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Field of covariates: $\theta := (\theta(x), x \in \mathbb{R}^2)$

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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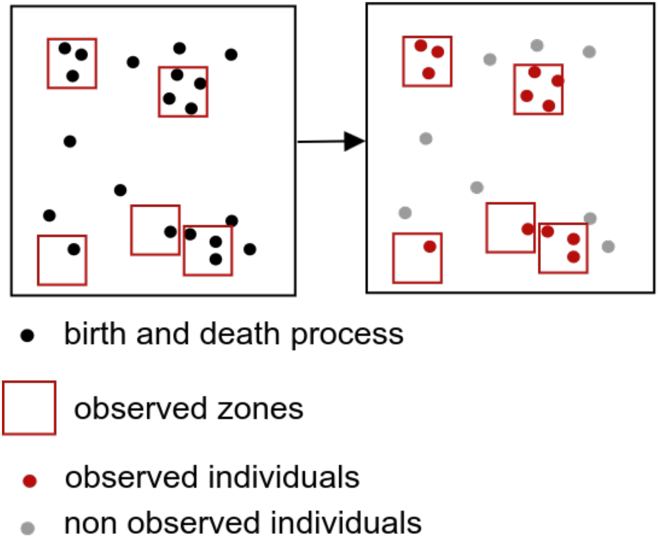
Example

$E_0 = \bigcup_e B(e, \rho)$ 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
- Not in an high density limit
- We assume our process to be spatially homogeneous

What do we want to predict?

Given a population $\mathcal{P}_0$ and covariates $\theta = (\theta(x), x \in \mathbb{R}^2)$.

What will be the new state $\mathcal{P}_1$ of the population around a point x at the next observation time?

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Two possible observables:

- Next year abundance around x: $N_1(x) = \#\{\mathcal{P}_1 \cap B(x, \rho)\}$
- Variation of abundance between the two states at x: $\Delta(x) = N_1(x) - N_0(x)$

Construction of $\hat{N}$

Let $(\theta', \mathcal{C})$ be a deterministic configuration of interest - somewhere where we have data at the initial state and want the abundance at the next state.

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Construction of $\hat{N}$

Let $(\theta', \mathcal{C})$ be a deterministic configuration of interest - somewhere where we have data at the initial state and want the abundance at the next state.

How do we construct our estimator?

1. Construct a similarity function to compare two contexts.
2. Calculate similarity between $(\theta', \mathcal{C})$ and know contexts (from the data).
3. Do a weighted mean to have an estimation of next year abundance (or variation of abundance).

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 $\mathcal{P}_n := \mathcal{P} \cap [-n/2, n/2]^2$

A central limit thorem

Theorem

Under some conditions:

1. *on the process $\mathcal{P}$ (exponential mixing);*
2. *on the covariate field θ (exponential mixing);*
3. *on the similarity function k (stabilization).*

We have:

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Under some conditions:

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We have:

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

Proof with a theorem from BYY 2025

Exponential mixing

Mixing properties

The point process of interest should have fast decaying spatial correlations. Intuitively, it means that observations far apart in space are nearly independent of each other. This should hold for the process $\mathcal{P}$ as well as for the covariate field θ.

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

For example, we can take $r(x-y) = \exp(-\beta|x-y|)$ as the covariance function of the Gaussian field.

Stabilization

Range and stabilization

Let $(\theta', \mathcal{C})$ be an observation. A finite range assumption means that there is some $R > 0$ such that $k((\theta, \mathcal{P}), (\theta', \mathcal{C}))$ only depends on $\{\theta(x); x \in B(0, R)\}$ and $\mathcal{P} \cap B(0, R)$.

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An example of a similarity function is:

$$k(x,y) = \frac{\sum_n \min(x_n, y_n)}{\sum_n \max(x_n, y_n)}$$

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

What with real data?

1. Divide into train and test datasets.
2. Similarity calculations:

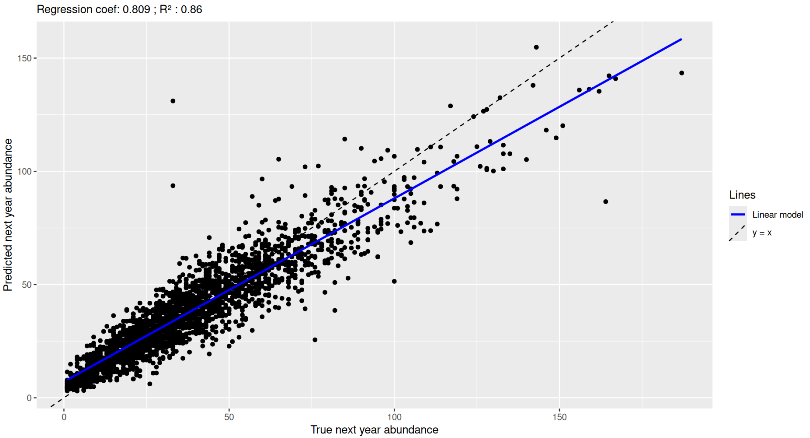
$$K(L_i, L_j) = \mathbb{1}_{k(L_1,L_2)\geq\alpha}$$
$$k(L_i, L_j) = \frac{\sum_n \min(L_i^n, L_j^n)}{\sum_n \max(L_i^n, L_j^n)}$$

with L_i in the train set and L_j in the test set and α a threshold.

3. Apply estimator for each line in the test set:

$$\hat{N}^{L_j} = \frac{1}{\sum_{L_i} k(L_i, L_j)} \sum_{L_i} N(L_i) k(L_i, L_j)$$

Results with real data



Forest species, $\alpha = 0.8$

What's next ?

- Show mixing properties for other processes (some Gibbs, cluster processes, ...)
- Find other similarity functions that work
- Simulation study

Meadow pipit (*Anthus pratensis*)

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Thank you !