

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

RBMR – September 10, 2026



Ecological context

Breeding Bird Surveys



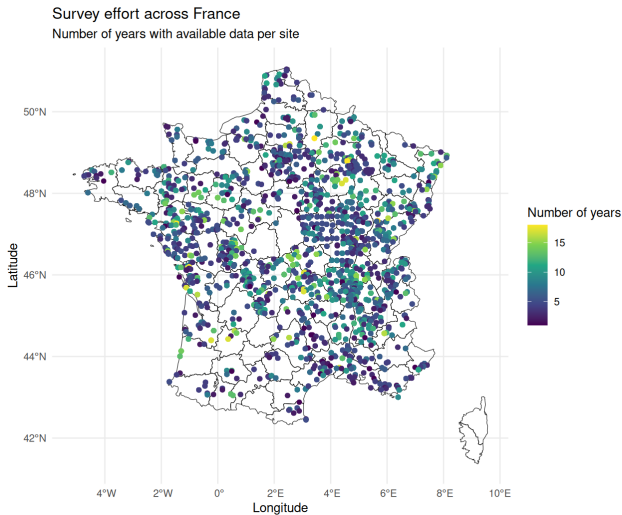
Meadow pipit (*Anthus pratensis*)

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.

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).

Goals

1. Give a method to predict the variation of abundance (or future abundance) at a local scale.
2. Find which agricultural practices are best.

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

Adélie Erard, Raphaël Lachièze-Rey, Romain Lorrillière

Model

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

$$\mathcal{P} := \sum_{x \in \mathcal{P}} \delta_x$$

Model

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

$$\mathcal{P} := \sum_{x \in \mathcal{P}} \delta_x$$

Field of covariates: $\Theta := (\Theta_x \in \mathbb{R}^m, x \in \mathbb{R}^d)$

Model

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

$$\mathcal{P} := \sum_{x \in \mathcal{P}} \delta_x$$

Field of covariates: $\Theta := (\Theta_x \in \mathbb{R}^m, x \in \mathbb{R}^d)$

Observed zone: $E = (E_x, x \in \mathbb{R}^d)$

Model

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

$$\mathcal{P} := \sum_{x \in \mathcal{P}} \delta_x$$

Field of covariates: $\Theta := (\Theta_x \in \mathbb{R}^m, x \in \mathbb{R}^d)$

Observed zone: $E = (E_x, x \in \mathbb{R}^d)$

We consider in the following the marked process

$$\bar{\mathcal{P}} := \sum_{x \in \bar{\mathcal{P}}} \delta_{\bar{x}}, \quad \bar{x} = (x, \Theta_x, E_x)$$

Hypothesis

Mixing properties

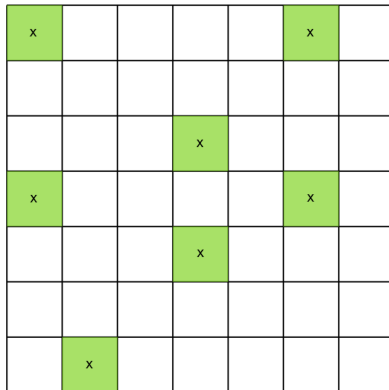
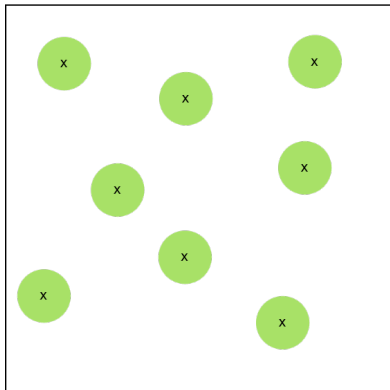
The point process of interest should have fast decaying spatial correlations. Intuitively, it means that observations far apart in space are nearly independent of each other. This should hold for the process $\mathcal{P}$ as well as for the covariate field Θ .

Example of process

Let G be a stationary Gaussian random field with covariance function of the form $\Gamma(x - y) = \exp(-\beta|x - y|)$ for some $b > 0$.

Let $\Lambda = \exp G$. The log-Gaussian Cox process $\mathcal{P}$ ($\mathcal{P} \mid \Lambda$ is a Poisson process) driven by Λ verifies the mixing properties.

Examples of effort process



Examples of covariates

- General random field (i.e. Gaussian random field) representing for example temperatures.
- Abundance (N_x) in the observed zone around.
- A custom mark to model competition:

$$\hat{f}(x) = \lambda + \sum_{y \text{ observed}} (N_y - \lambda) \exp(-\|x - y\|)$$

What do we want to predict?

Given a population $\mathcal{P}$ and covariates $\Theta = (\Theta_x, x \in \mathbb{R}^d)$.

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

What do we want to predict?

Given a population $\mathcal{P}$ and covariates $\Theta = (\Theta_x, x \in \mathbb{R}^d)$.

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

Two possible observables:

- Next year abundance around x : $N'_x = \#\{\mathcal{P}' \cap B(x, r_{\text{obs}})\}$
- Variation of abundance between the two states at x :
$$\Delta(x) = N'_x - N_x$$

Modelling transition

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

- an individual at location x gives birth to a new individual with probability $\mathcal{B}(\bar{x}, \bar{\mathcal{P}})$, the new location is chosen according to a random variable $X_{\text{disp}}(x) \in \mathbb{R}^d$ that is independent of $\mathcal{P}$ and Θ
- an individual at location x dies with probability $\mathcal{D}(\bar{x}, \bar{\mathcal{P}})$

$$\Delta(\bar{x}, \bar{\mathcal{P}}) = \begin{aligned} &\text{number of new individuals arrived around } x \\ &\quad - \text{number of individuals died around } x \end{aligned}$$

Hypothesis and example

Localization property

All functions we will consider $(\mathcal{B}, \mathcal{D}, \Delta)$ need to verify a localization property i.e. $|\xi(\bar{x}, \bar{\mathcal{P}}) - \xi(\bar{x}, \bar{\mathcal{P}} \cap B(x, r))|$ is fast decreasing to 0

$$\mathcal{B}(\bar{x}, \bar{\mathcal{P}}) = \frac{\#\mathcal{P} \cap B(x, R_{\text{comp}}) - 1}{\#\mathcal{P} \cap B(x, R_{\text{comp}})}$$

$$\mathcal{D}(\bar{x}, \bar{\mathcal{P}}) = \frac{\#\mathcal{P} \cap B(x, R_{\text{comp}})}{1 + \#\mathcal{P} \cap B(x, R_{\text{comp}})} \exp(-\Theta_x)$$

$$X_{\text{disp}}(x) \sim \mathcal{N}(x, \sigma Id)$$

Construction of $\hat{N}$

Let $\mathcal{C} \in \mathbb{R}^m$ 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?

Construction of $\hat{N}$

Let $\mathcal{C} \in \mathbb{R}^m$ 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 $\mathcal{C}$ 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 $\mathcal{C}$ be a deterministic configuration of interest.

$$\hat{N}_n^{\mathcal{C}} := \frac{1}{\sum_{x \in \mathcal{P}} k(\Theta_x, \mathcal{C}) \mathbb{1}_{\{E_x=1\}}} \sum_{x \in \mathcal{P}} N'_x k(\Theta_x, \mathcal{C}) \mathbb{1}_{\{E_x=1\}}$$

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

An example of a similarity function is:

$$k(x, y) = \frac{1}{\|x - y\|_2}$$

Limit theorems

Theorem

Under some conditions:

1. *on the process $\mathcal{P}$ (exponential mixing + stationarity);*
2. *on the covariate field Θ (exponential mixing);*
3. *on the transition functions (localization).*

We have:

Limit theorems

Theorem

Under some conditions:

1. *on the process $\mathcal{P}$ (exponential mixing + stationarity);*
2. *on the covariate field Θ (exponential mixing);*
3. *on the transition functions (localization).*

We have:

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

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

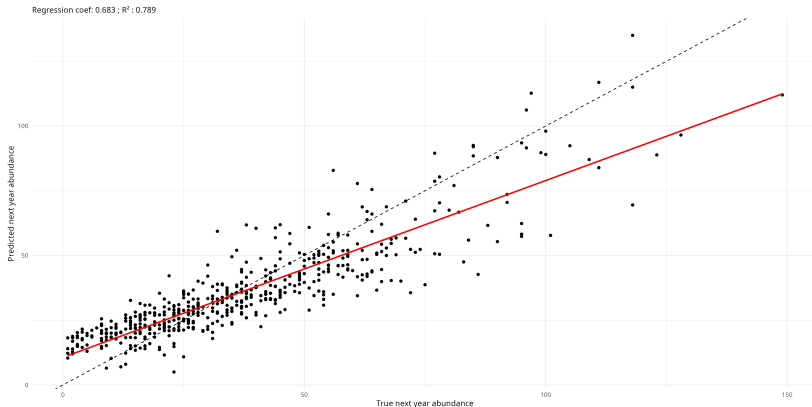
Square	Year	Abundance	Environmental variables	Abundance next year	Similarity with square of interest
10295	2003	5		2	1
11158	2006	1		4	0.5
20204	2015	6		7	0
30363	2019	8		9	0.5
950294	2024	3		?	1

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

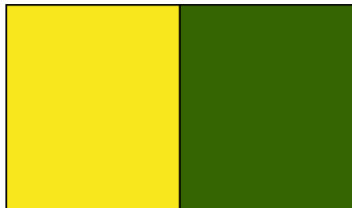


Forest species

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

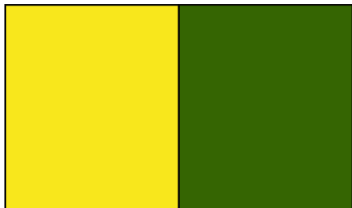


Land Sparing



Land Sharing

Land sharing and land sparing



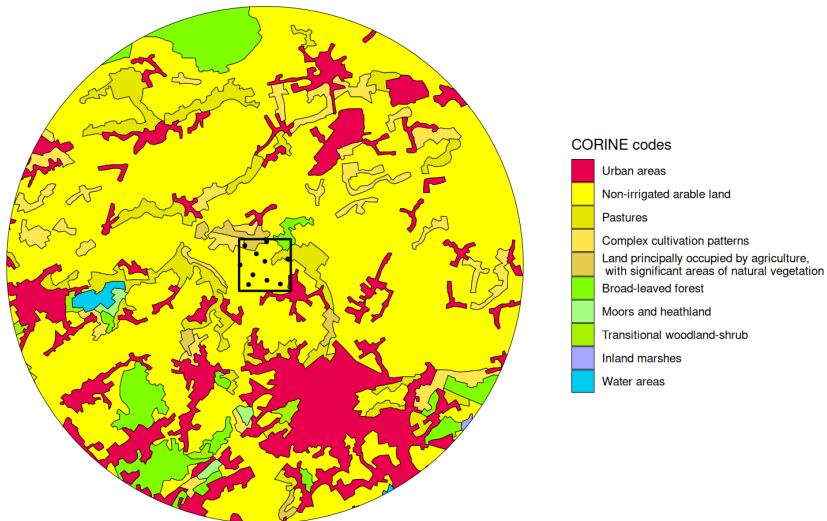
Land Sparing



Land Sharing

What is the best agricultural practice to conserve farmland birds ?

Indicators of Land Sharing and Land Sparing



Model

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

Model

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

Model

- We model bird counts using a **negative binomial regression model** to account for overdispersion.
- 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
- Inference with INLA [Rue et al. 2009]

Model section

Stepwise approach with the following variables:

Model section

Stepwise approach with the following variables:

- **land sharing and sparing indices**: Shanon index on agricultural patches, amount of forest and agriculture with a lot of nature

Model section

Stepwise approach with the following variables:

- **land sharing and sparing indices**: Shanon index on agricultural patches, amount of forest and agriculture with a lot of nature
- **land cover of the square**: PCA on land use of each square - 3 variables

Model section

Stepwise approach with the following variables:

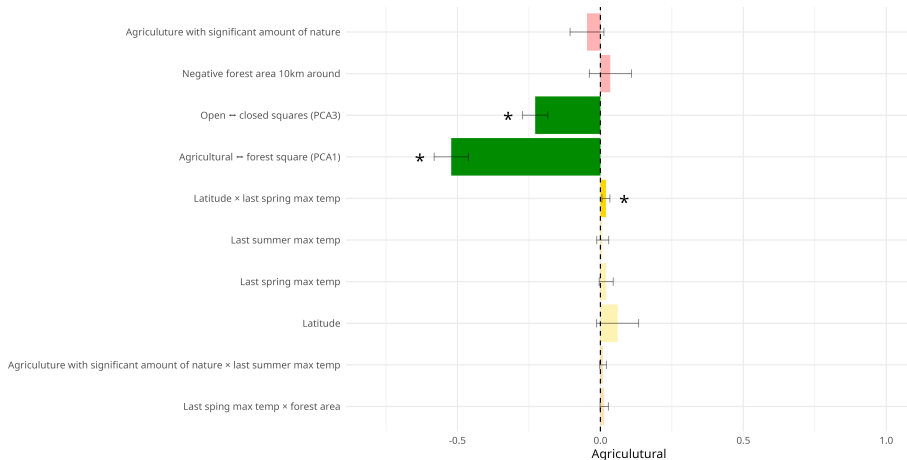
- **land sharing and sparing indices**: Shanon index on agricultural patches, amount of forest and agriculture with a lot of nature
- **land cover of the square**: PCA on land use of each square - 3 variables
- **climate**: minimum and max temperature of last spring and summer, total rain of last spring

Model section

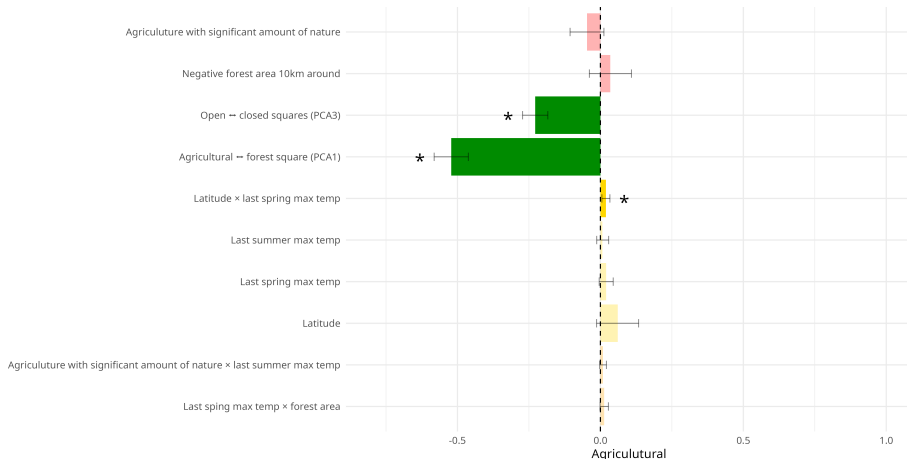
Stepwise approach with the following variables:

- **land sharing and sparing indices**: Shanon index on agricultural patches, amount of forest and agriculture with a lot of nature
- **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

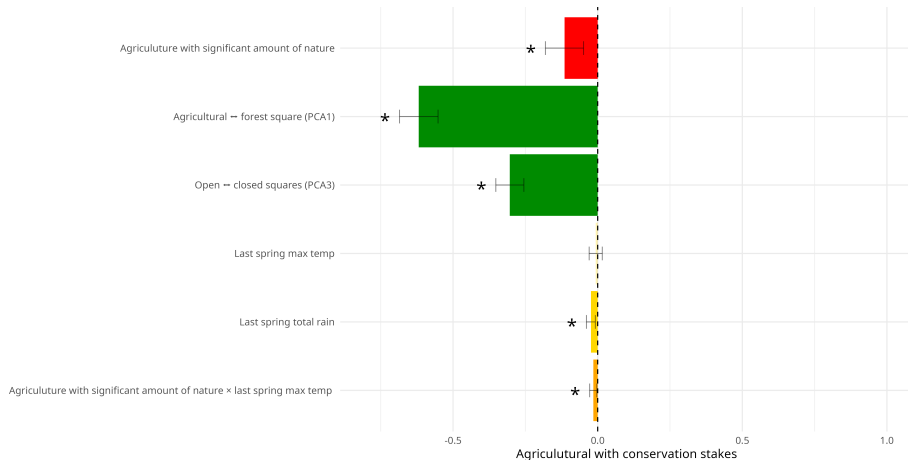


Results for agricultural birds

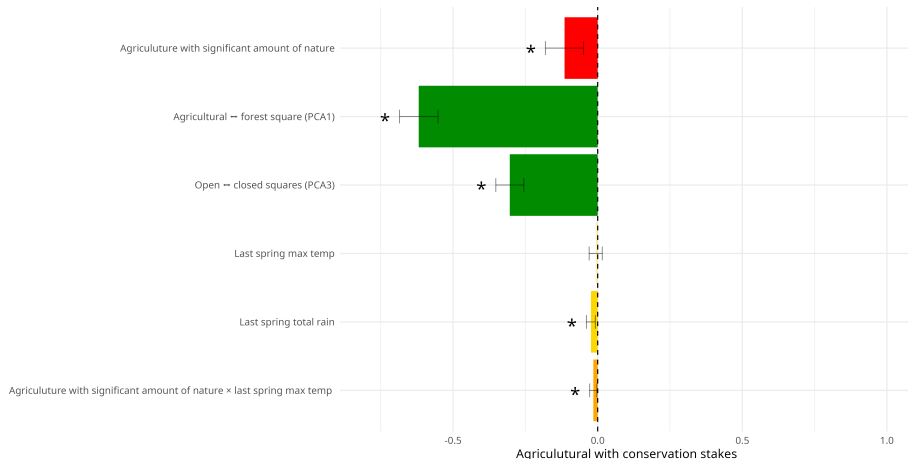


Land sparing is preferred

Results for agricultural birds with conservation concern



Results for agricultural birds with conservation concern



Land sparing is preferred

No, intensive agriculture is not to prefer

Land sparing is the practice to prefer for farmland birds because:

No, intensive agriculture is not to prefer

Land sparing is the practice to prefer for farmland birds because:

- they are adapted to big open area (such as the one with intensive agricultural practices);
- they nest on the ground so hedges and bushes are not improving survival

No, intensive agriculture is not to prefer

Land sparing is the practice to prefer for farmland birds because:

- they are adapted to big open area (such as the one with intensive agricultural practices);
- 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.



Meadow pipit (*Anthus pratensis*)

From Charles J. Sharp.

Thank you !

(I'm looking for a postdoc position starting early 2027 if you have any ideas)