Downscaling coarse observations to predict continuous species spatio-temporal distribution

Going from coarse landings data to fine scale fish distribution

Baptiste Alglave, Marie-Pierre Etienne, Kasper Kristensen, Youen Vermard, Mathieu Woillez, Etienne Rivot

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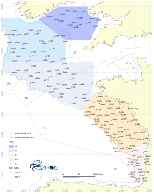
Spatial data in ecology

	Survey data	Citizen science data	Declaration data
+	Standardized sampling plan High quality data	Access to more data Exact locations available	Mandatory declaration Massive data
−	Small sample size	Opportunistic (or even preferential) sampling	Aggregated at the scale of administrative units
Examples			
	EVHOE data, Bay of Biscay (marine ecology)	Ebird application (ornithology)	Harvest data, Wisconsin (hunting)

How to integrate all these datasources?

(especially when they do not have the same spatial resolution)

Change of support

Common issue in statistical literature

"Modifiable areal unit" problem (MAUP): aggregation of data over increasingly larger geographic scales (e.g. data collected at point level but regrouped/declared at coarse level)

Several fields of application: climatology, health science, ecology

But mainly **standard observational data (Poisson, Gaussian)**, while data may be more complex in ecological applications (e.g. zero-inflated lognormal data)

➠ **Objective of our work:** provide an approach that suits for complex data

➠ Base our model on an existing framework in the context of fishery science:

Alglave Baptiste, Rivot Etienne, Etienne Marie-Pierre, Woillez Mathieu, Thorson James T, Vermard Youen (2022). ***Combining scientific survey and commercial catch data to map fish distribution.*** *ICES Journal of Marine Science IN PRESS. https://doi.org/10.1093/icesjms/fsac032*

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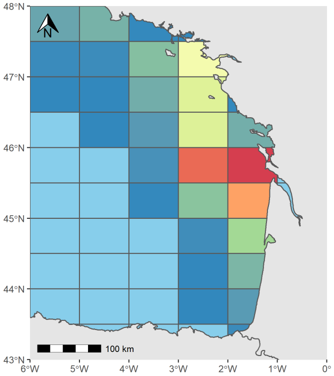
Commercial catch declarations data in fishery science

Logbook landings
(Sole, trawlers OTB-DEF, 2018)



Fishing locations (VMS)
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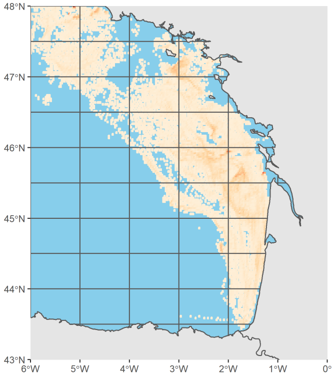

Spatial resolution

Catch are daily declared at the resolution of ICES rectangles

VMS pings are vessels GPS locations emitted each hour

➠ Refine landings spatial resolution

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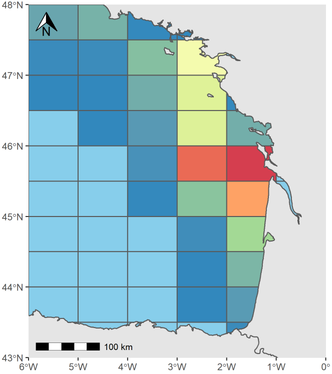

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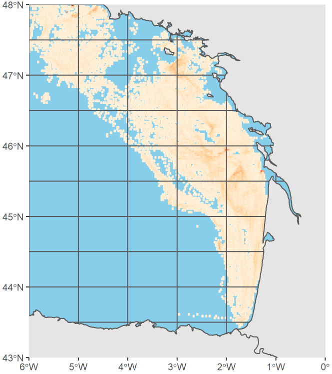

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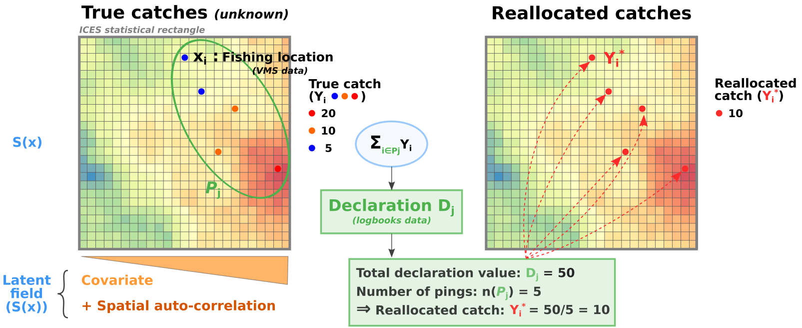
Two alternative procedures to reallocate catches



Current situation $Y_i | S(x_i), x_i \sim \mathcal{L}_Y(S(x_i), \xi, \sigma^2)$ $Y_i = \frac{D_j}{n(\mathcal{P}_j)} = Y_i^*$

Alternative solution $D_j = \sum_{i \in \mathcal{P}_j} Y_i$ $D_j | S_{\mathcal{P}_j}, \mathcal{P}_j \sim \mathcal{L}_D(S_{\mathcal{P}_j}, \xi, \sigma^2)$ ➠ Match $\mathcal{L}_D$ and $\mathcal{L}_Y$ moments

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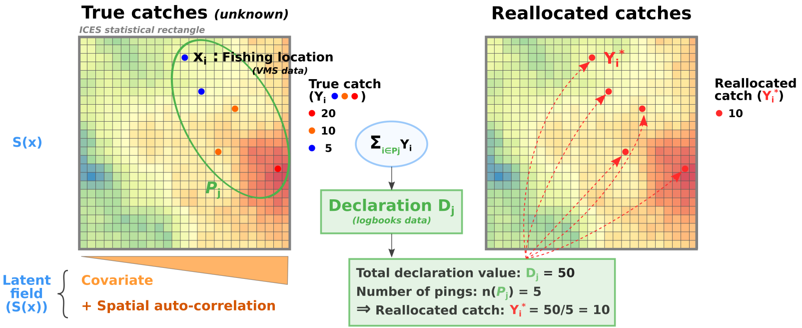

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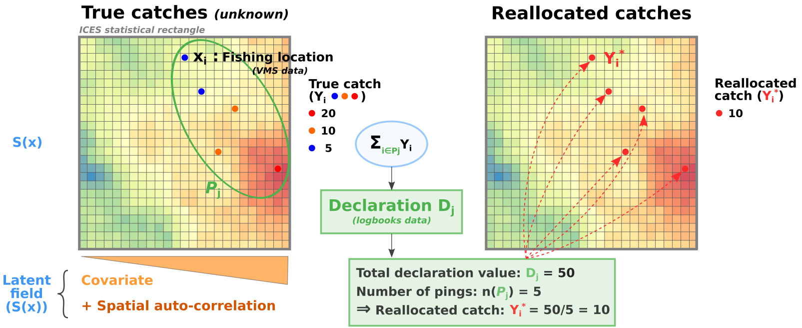

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Two alternative procedures to reallocate catches

Punctual observation model (Y_i)

$L(y, \mu, \sigma^2)$ is the lognormal likelihood for observation y, mean μ and variance σ^2
Y and D are supposed conditional on S and x

$$\mathrm{P}\left(Y_i = y_i\right) = \begin{cases} p_i & \text{if } y_i = 0 \\ (1-p_i) \cdot \mathrm{L}\left(y_i, \mu_i = \frac{S(x_i)}{(1-p_i)}, \sigma^2\right) & \text{if } y_i > 0 \end{cases}$$

$$p_i = \exp(-e^{\xi}.S(x_i))$$

Declaration model $(D_j = \sum_{i \in \mathcal{P}_j} Y_i)$

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Specifying $\mathrm{P}\left(D_j = d_j | d_j > 0\right)$

Compute the moments of $\mathbf{D_j|d_j > 0}$

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$$Var(D_j|d_j > 0) = \frac{\sum_{i \in \mathcal{P}_j} Var(Y_i)}{1 - \pi_j} - \frac{\pi_j}{(1 - \pi_j)^2} E(D_j)^2$$

$$Var(Y_i) = \frac{S(x_i)^2}{1 - p_i}(e^{\sigma^2} - (1 - p_i))$$

Consider $\mathbf{D_j|d_j > 0}$ is Lognormal too

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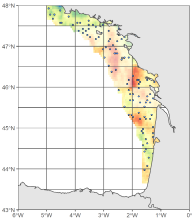
Simulation-estimation and case study

Simulation-estimation



Simulation

- **Latent field** (covariate + spatial random effect)
- **Commercial data** (3000 samples over 2/3 of the area)
- **Reallocation process** (10 locations per declaration)
- **Scientific data** (100 samples over the whole the area)

Model evaluation

1/ Mean square prediction error

$$MSPE = \frac{\sum_{x=1}^{n} (S(x) - \hat{S}(x))^2}{n}$$

2/ Covariate effect (or species-habitat relationship):

$$\beta_S = 2 \text{ versus } \hat{\beta}_S$$

Estimation

Comparison of 3 model configurations:

1/ Model fitted to scientific data only

2/ Integrated model (= scientific + commercial data) with commercial likelihood built on Y_i^*

3/ Integrated model with commercial likelihood built on D_j

Estimation realized through TMB (Template Model Builder)
100 runs of simulation-estimation

Case study: Sole in the Bay of Biscay

Survey data: Orhago
Commercial data: OTB-DEF trawlers (to ease convergence onboard observer data were integrated in the fit)
Fitted models: same as simulations
Covariate: substrate

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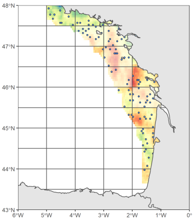

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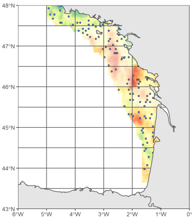

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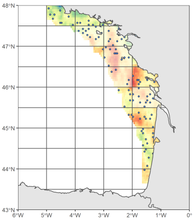

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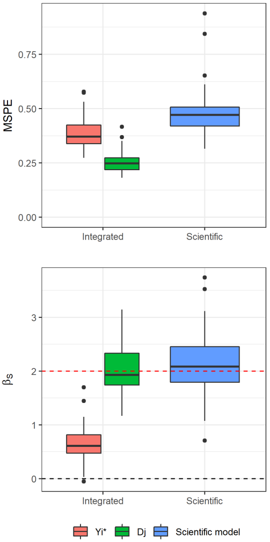

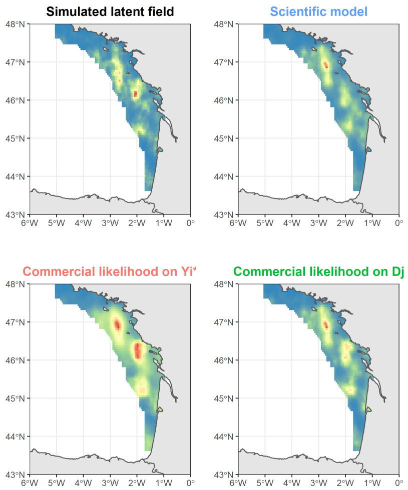

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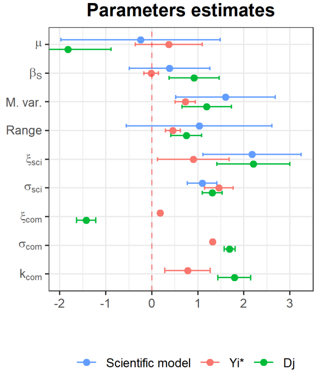

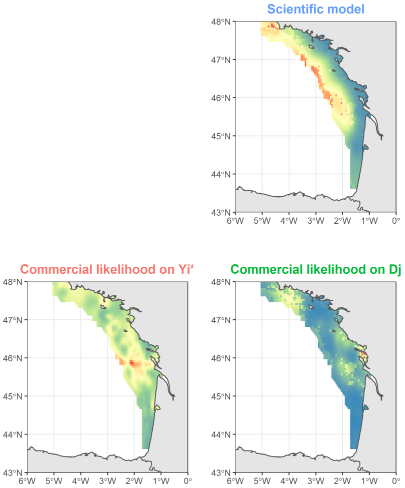

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- Modifies the **contrasts of the map**

(shape and intensity of the hotspots/coldspots)

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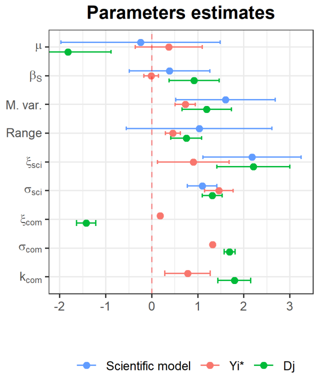

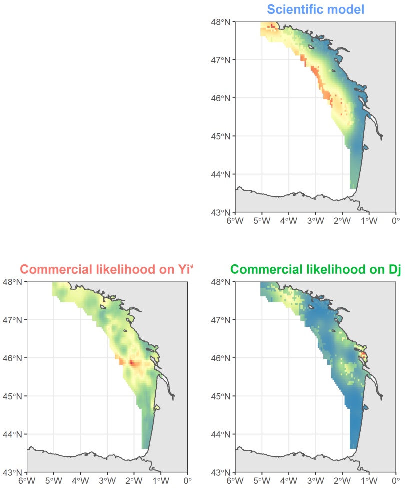

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  - ➠ Allows to estimate the **habitat effect** through commercial data
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- **Some limits:**
  - ➠ How to ease convergence ?
  - ➠ Need to make the hypothesis that fishing locations ($\mathcal{P}_j$) are known

- **Is it a generic framework ?**
  - ➠ The overall approach is,
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- **Moving to space-time ?**
  - ➠ Extending the observation model to account for **temporal misalignment**
  - ➠ Including spatio-**temporal covariance** in the latent field

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