Combining spatial data derived from conventional research protocols and social media platforms

A story of two dolphin species

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[1]Giovanna Jona Lasinio, Daniela Silvia Pace, et al

Introduction

Introduction I

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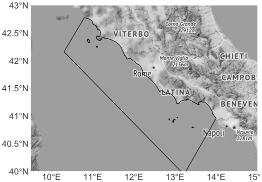

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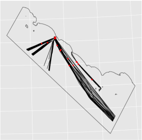

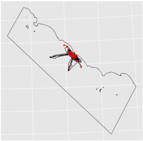

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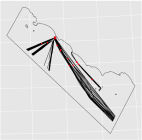

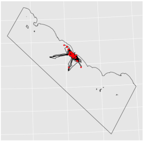

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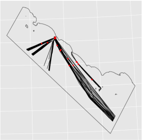

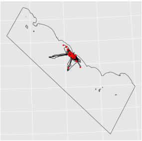

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  - We know the searching protocol...

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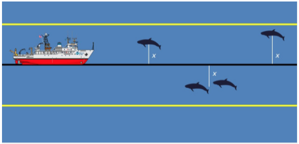

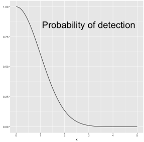

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- The observation process introduces a bias. . .
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  - ..we can correct for such bias
- There are more data available. . . .could we use them?

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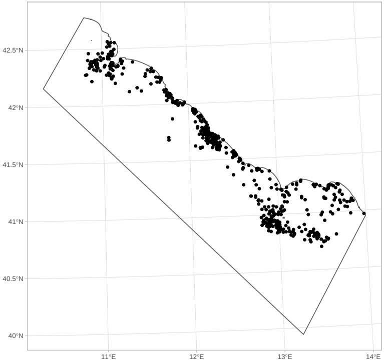

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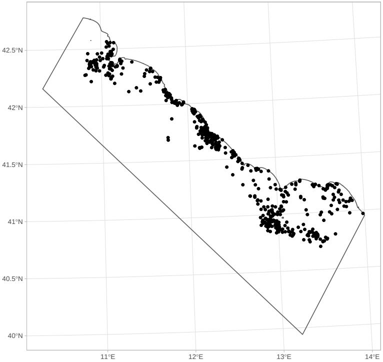

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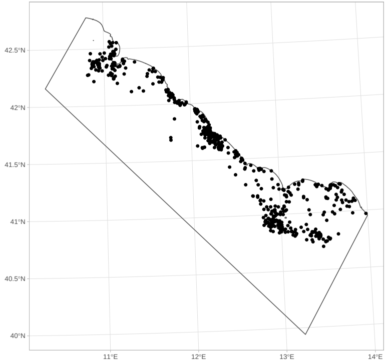
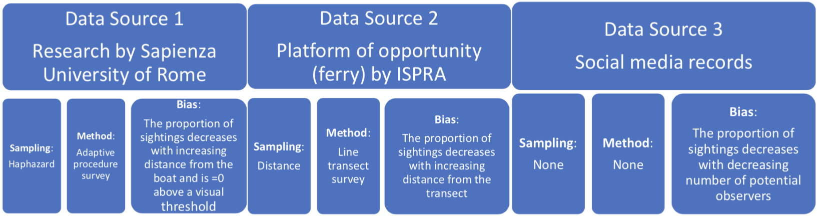


- …but there is no "searching protocol"
- How can we correct for the bias?



- All our data are presence-only
- We want to merge all data sources. . . .
- . . . accounting for each specific bias!

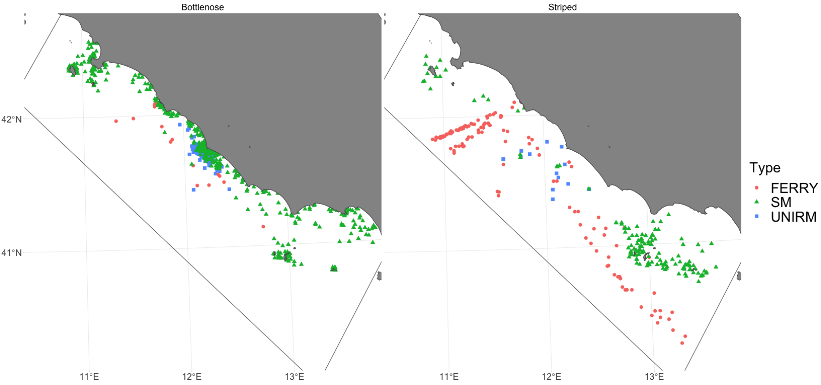
The Data

Data Type	Years	N.Campaigns	N.Sightings Stenella	N.Sightings Tursiope
FERRY	2007-2018	311	133	16
UNIRM	2017-2019	73	14	98
Social	2008-2019	??	136	465

Notes:

- We have many “Social media” data
- We have both a “Spatial” and a “Temporal” bias!!

Observations

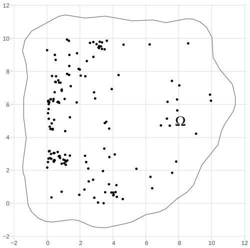


Statistical Tools

Statistical tools

- Log Gaussian Cox Processes (presence only data)
  - SPDE representation of Gaussian fields
  - Inference using INLA
- Thinned point process (observation bias)
  - Detection function
  - Needs more than just INLA $\longrightarrow$ **`inlabru`**
- Joint modeling (merging of all data sources)
  - Easy with INLA+**`inlabru`**

Log Gaussian Cox Processes



- We observe N points in the domain Ω.
- Given the intensity $\lambda(s)$ the likelihood is given by

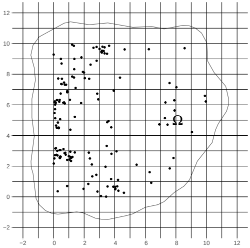
$$\pi(Y|\lambda) = \exp\left\{|\Omega| - \int_{\Omega} \lambda(s) ds\right\} \prod_{i=1}^{N} \lambda(s_i)$$

- The log-intensity is a Gaussian process

$$\log(\lambda(s)) = Z(s)$$

- Not analytically tractable

Implementation - Grid discretization

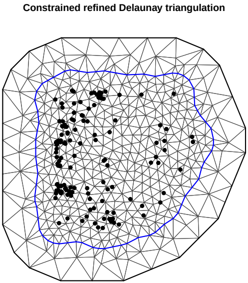


- Discretize the domain into a grid
- N_{ij} = # of observation in cell (i, j)
- $N_{ij} \sim \text{Pois}(\Lambda_{ij})$ where

$$\Lambda_{ij} = \int_{s_{ij}} \lambda(s) ds \approx |s_{ij}| \exp(z_{ij})$$

- Possible models for $Z(s)$:
  - Continuous GF $\longrightarrow$ dense covariance matrix
  - GMRF $\longrightarrow$ sparse covariance matrix
- The grid serves both to approximate the latent field and to approximate the likelihood

Implementation - SPDE Approach[2]



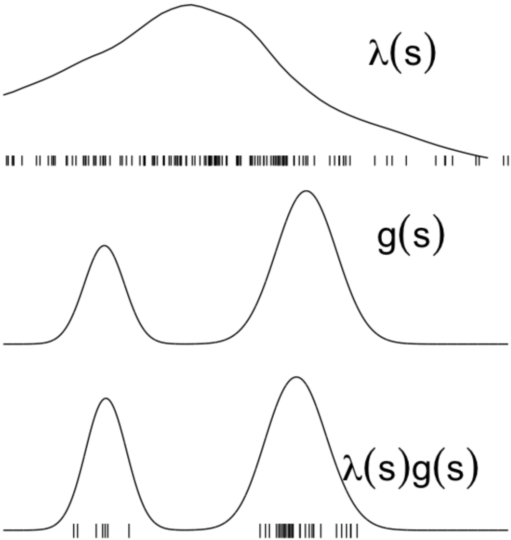
- Use the SPDE approach over a mesh to represent the GF

$$Z(s) = \sum_{i=1}^{n} z_i \phi_i(s)$$

- Approximate the GF
- Do not need to approximate the observation location
- Efficient computationally
- Use INLA

[2]in Going off grid: Computationally efficient inference for log-Gaussian Cox Processes, Simpson et al 2011

Thinned point process



Thinned point process

- "True" intensity: $\lambda(s)$
- Thinned intensity $\lambda^*(s) = \lambda(s)g(s)$
  - $g(s)$ is the thinning (detection) function
  - Unless $g(s)$ is log-linear in all parameters the INLA framework does not work!
  - `inlabru` is an extention of INLA that allowes for non linear terms

Modeling the intensity

Modeling the intensity

- The “true” (unthinned) intensity:

$$\lambda(s,t) = \beta_0 + \beta^T X(s,t) + \sum_k f_k(x_k(s,t)) + u(s)$$

  - $u(s)$ is a GRF with Matern correlation function
  - could be spatio-temporal but would need more data!

- The observed intensity:

$$\lambda_j(s,t) = t_j \ \lambda(s,t) \ g_j(s); \qquad j = 1, \dots, 4$$

where

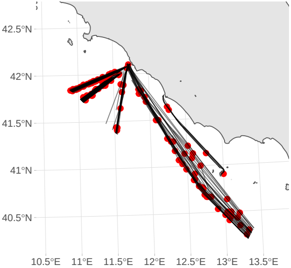
- $\lambda(s,t)$ is the true density
- $g_j(s)$ is the thinning function for observation process j
- t_j is the time-scaling factor (this is known for all observations processes except for the social data!)

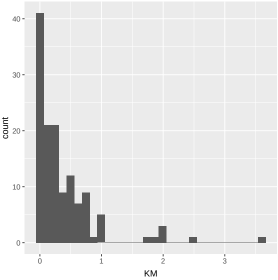
Accounting for spatial bias: detection functions

- For FERRY data

$$g_{\text{ferry}}(s) = \exp\left(-\frac{1}{\sigma^2_{\text{ferry}}} d(s)^2\right)$$

where $d(s)$ is the perpendicular distance to thetransect





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- How about the SOCIAL MEDIA data?

Modeling spatial bias for social data

- We assume that the sightings are biased towards area where there are more leisure boats. . . .

- Distance from the coastline
- Boat density data from EmodNET platform
- Use animal intensity as proxy for small boat intensiy

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Modeling spatial bias for social data

- We assume that the sightings are biased towards area where there are more leisure boats. . . .
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- Three different ideas:

- Distance from the coastline
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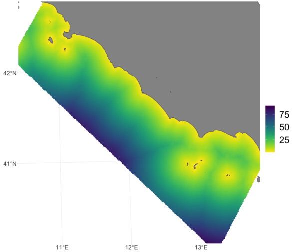
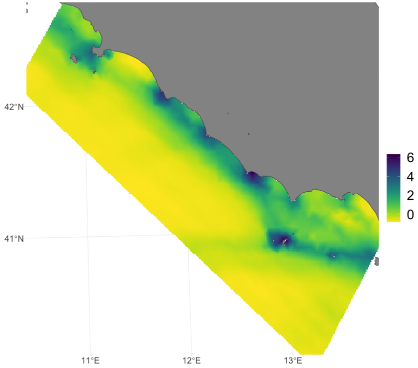
Distance from the coastline



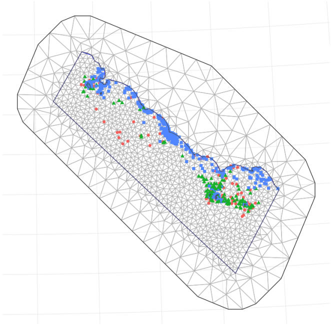
- Assume that the closer to the coast there are more small boats.... higher detection probability close to the coast
  - This in is not necessary true, people like islands
  - This is also a covariate often used to model species density

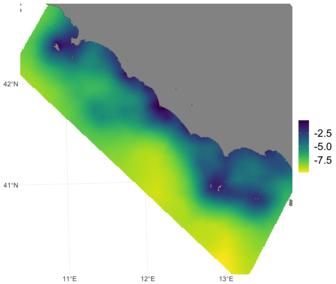
EMODnet data for boat density



- EmodNET (European Marine Observation and Data Network) records boats using AIS (Automatic Identification System, mandatory above 15m length)
- Detection probability is higher where boat intensity is higher
  - Does not consider small boats which are often those reporting sightings

Social data sightings for all species





- Use all sightings as a proxy for boat density
- Data include species with very different behavior
- Detection probability is higher where boat intensity is higher

Putting things togeter

- The "true" intensity:

$$\lambda(s) = \beta_0 + \beta X(s) + u(s);$$
$$u(s) \sim GRF(\rho, \sigma_u^2)$$

- The observed intensity:

$$\lambda_{FERRY}(s) = t_{FERRY}\ \lambda(s)\ g_{FERRY}(s);$$
$$\lambda_{UNIRM}(s) = t_{UNIRM}\ \lambda(s)\ g_{UNIRM}(s);$$
$$\lambda_{SOCIAL}(s) = t_{SOCIAL}\ \lambda(s)\ g_{SOCIAL}(s);$$

Four choices for $g_{SOCIAL}(s)$

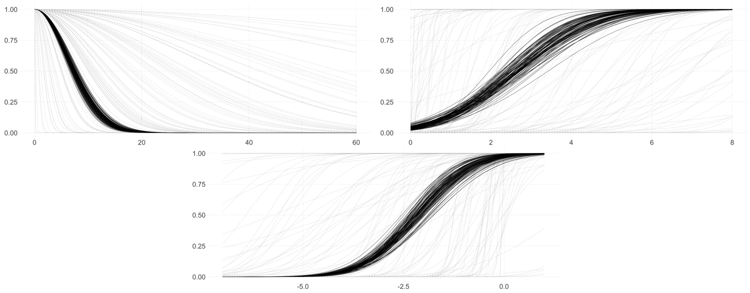
- No (constant) detection $g_{SOCIAL}(s) = 1$ (benchmark)
- Detection based on distance from the coastline
- Detection based on boat intensity
- Detection based on sightings intensity

Is the model identifiable?

-Low sigthings intensity can result from:

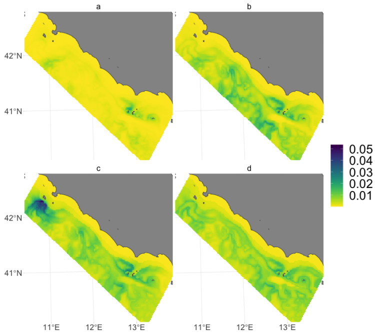
- There are no animals in the area
- There are no observer in the area
- How to solve this?
  - Gather information about the observation process
  - Use informative prior to “guide” inference

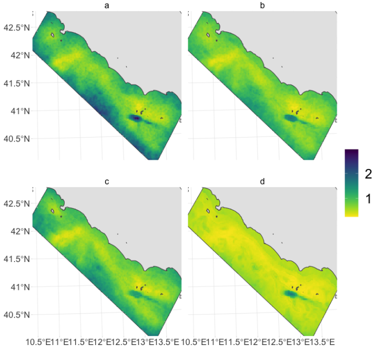
Prior for the parameters in the detection functions



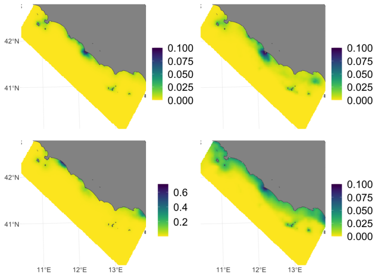
Results

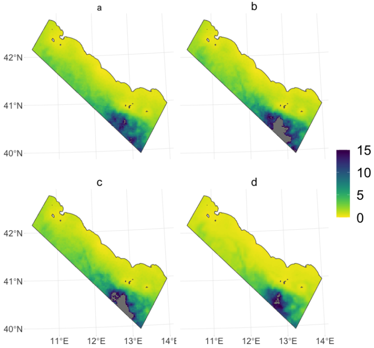
Reconstructed intensity surface (Stenella)





Reconstructed intensity surface (Tursiope)





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- INLA + `inlabru` give a huge model flexibility....with great power comes great responsibility!!!