spatial modelling for ecological surveys – contributions from and to point process modelling

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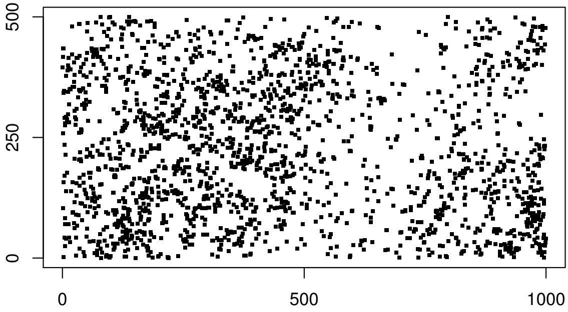
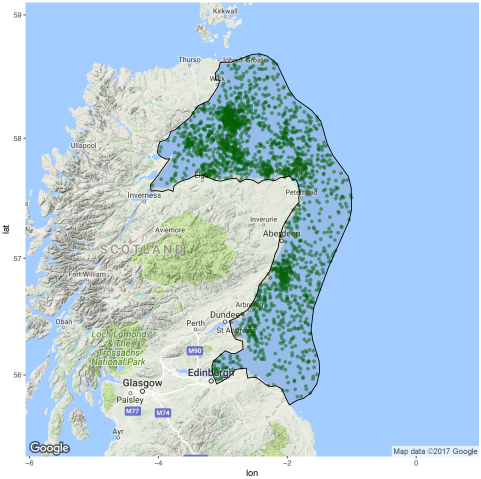
joint work with: David Borchers, Fabian Bachl, Yuan Yuan, Håvard Rue, Finn Lindgren, Daniel Simpson, Laura Williamson and others

an example:

Oenocarpus mapoura observed in a 50-ha study plot on Barro Colorado Island, Panama

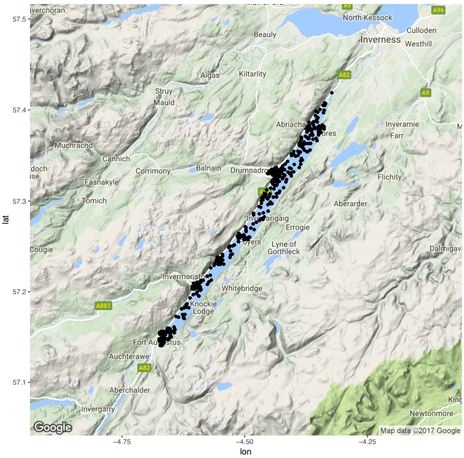


some more examples:



Locations of harbour porpoise sightings off the East Coast of Scotland.

some more examples:



Locations of reported sightings of the Loch Ness Monster, Loch Ness, Scotland.

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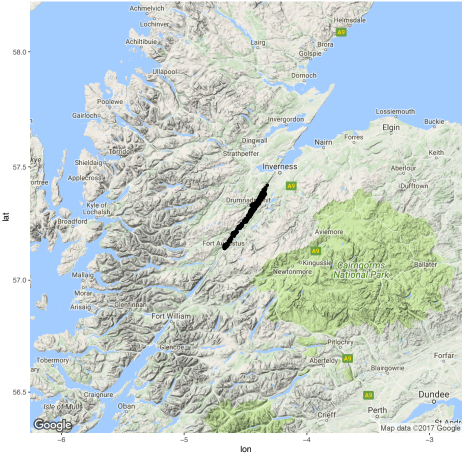

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spatial point processes in ecology

ecology – main interest:

- interactions among individual organisms and environment
- individuals exist – and interact – in space and time
- spatially explicit data increasingly available

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$\Rightarrow$ data: spatial (spatio-temporal) point patterns

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$\Rightarrow$ data: spatial (spatio-temporal) point patterns

$\Rightarrow$ **spatial point process methodology** should be highly relevant!

however...

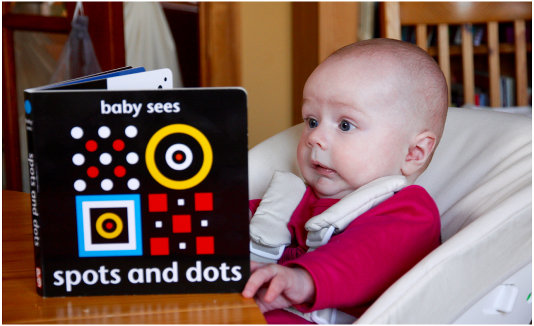
- few ecologists aware of spatial point process methodology
- e.g. models rarely used in practice

$\Rightarrow$ not part of the standard statistical toolbox

spatial point processes in ecology

WHY?

WHY?
In the end it's just a bunch of dots, isn't it?



but we have all these cool models...

with log Gaussian Cox processes and INLA+SPDE we can

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- flexibly account for remaining autocorrelation

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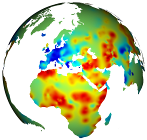
with log Gaussian Cox processes and INLA+SPDE we can

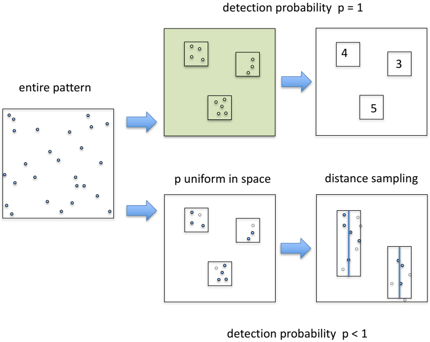
- flexibly account for remaining autocorrelation
- jointly model individuals' properties (*marks*) and spatial covariates with spatial pattern
- have point pattern reflect observation process: preferential sampling
- modelling on complex domains
  - the sphere = the earth
  - observation areas with barriers (islands, archipelagos...)



Illian et al., 2012 a+b, Simpson et al., 2016, Bakka et al., 2016, Ledo et al., 2016, Jones-Todd et al., 2017

ecological surveys...

Area of interest is too big to sample entirely.
thinned point process



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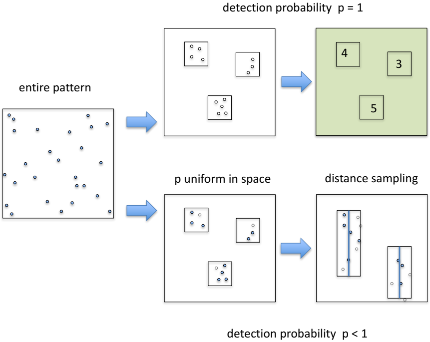

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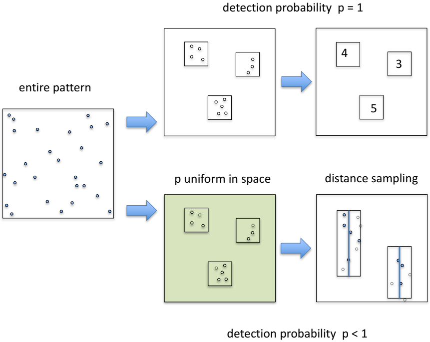

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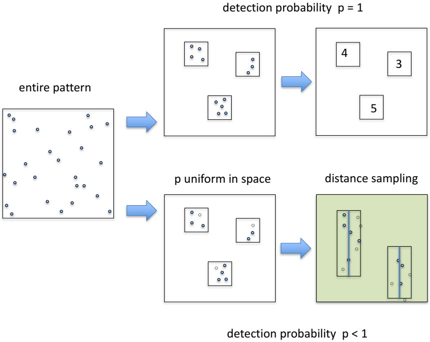

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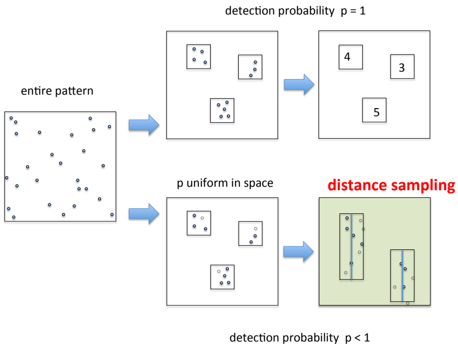
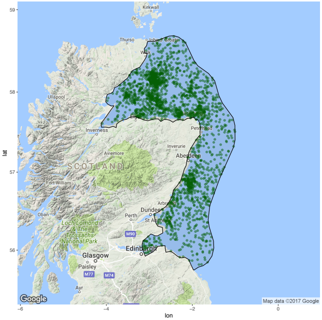


Examples... recall...



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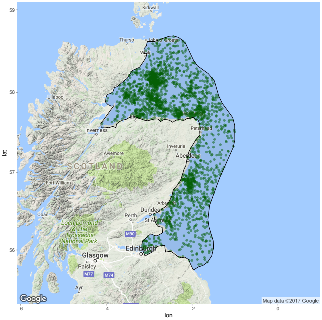
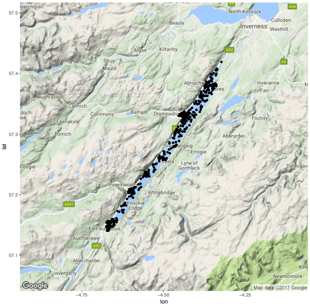
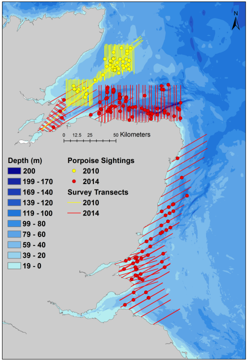




harbour porpoise study–video survey



video survey data

- conducted in August and September 2010 and 2014
- 5762 km survey effort
- 303 porpoises sighted

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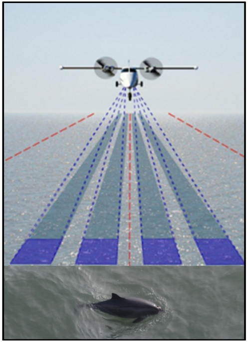

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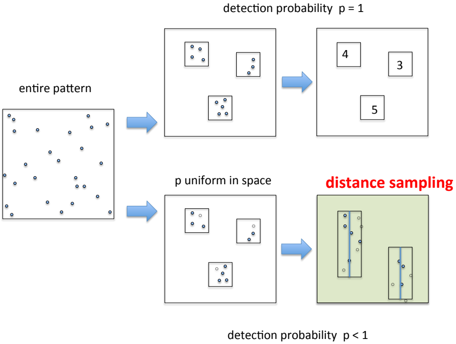
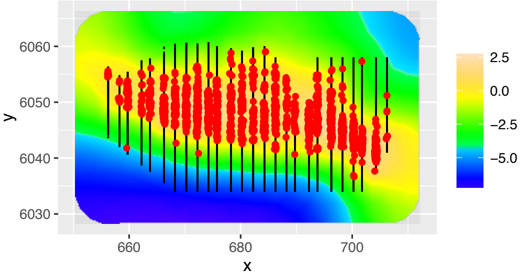
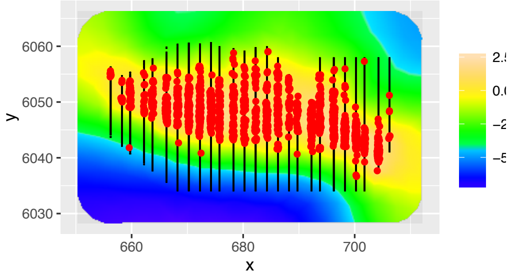


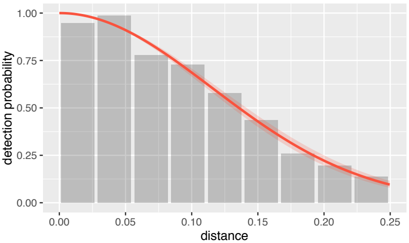
Scottish windfarm survey



distance sampling data

Scottish windfarm survey





[example data set in `inlabru`–more about this later...]

this talk

this talk

- spatial point process modelling and observation processes – in ecology
- `inlabru`

this talk

- spatial point process modelling and observation processes – in ecology
- `inlabru`
- Scottish drinks

observation processes...

ecological research – interested in individuals (in space and time)

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in practice:

- need to gain information on individuals – given practical limitations

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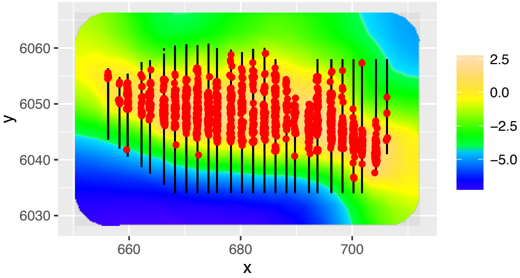
here:

- "think" in terms of the underlying structure, the point process
- observation process is operation on the underlying data structure

$\Rightarrow$ more general methodology and software

distance sampling data



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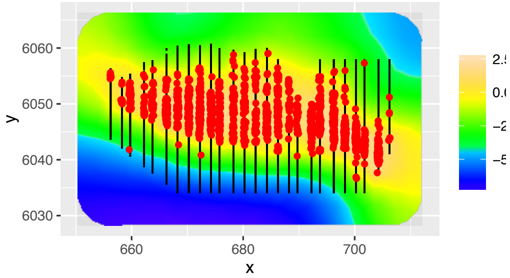
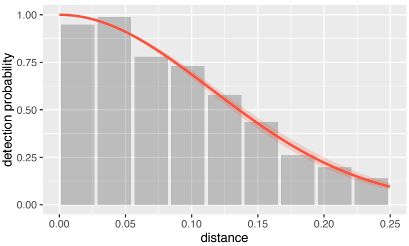
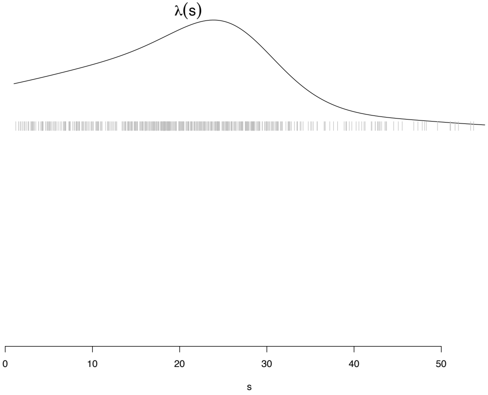




thinned point process!

distance sampling...

thinned point process



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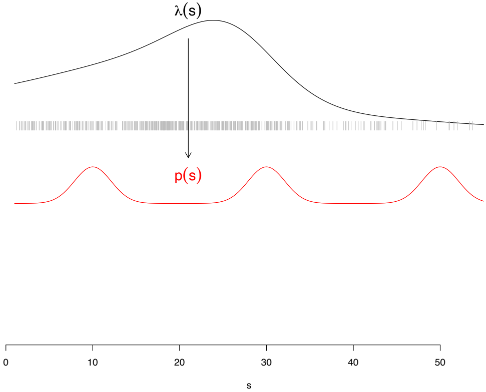

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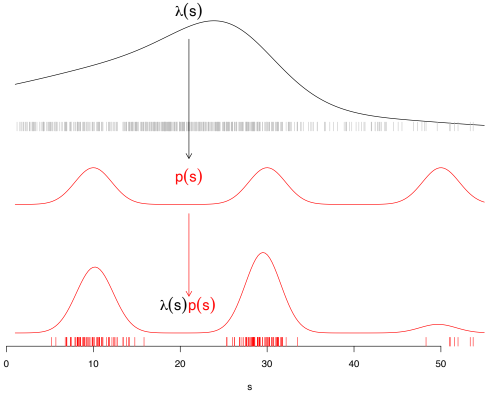

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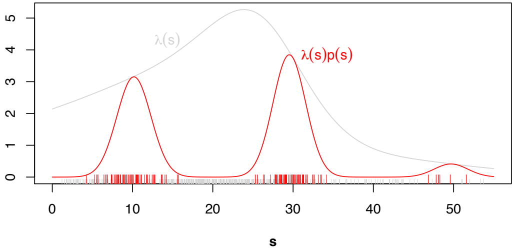

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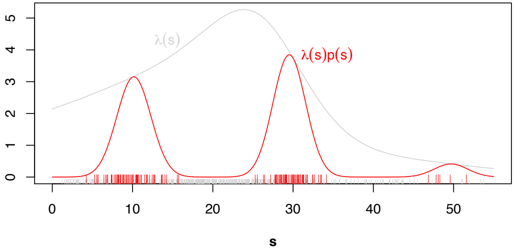

Observations are from a thinned Poisson process with intensity $\lambda(\boldsymbol{s})p(\boldsymbol{s})$

example...

- large scale line-transect cetacean survey in the eastern tropical Pacific Ocean (ETP) between 1986 and 2007
- area of 21.353 million square kilometers ($>$ twice the size of Europe!) was surveyed (transects)
- blue whale sightings

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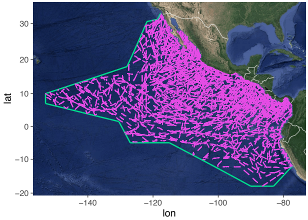
linear predictor depends on:

- (hazard rate) detection function
- (SPDE-based) model for animal intensity
- integration scheme accounts for observation process



Yuan et al. 2016, Bachl et al. in preparation

distance sampling... nice...

- spatio-temporal point process model

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- preserving sighting locations

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- spatio-temporal point process model
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- models the effect of covariates continuously in space
- models spatial structure that cannot be explained by covariates

distance sampling... nice...

- spatio-temporal point process model
- preserving sighting locations
- models the effect of covariates continuously in space
- models spatial structure that cannot be explained by covariates
- elegant, integrated approach
- implemented in *inlabru*

software...

inlabru

software...

`inlabru`

- *takes observation process into account*

software...

inlabru

- *takes observation process into account*
- *makes INLA more accessible*

software...

inlabru

- *takes observation process into account*
- *makes INLA more accessible*
- *wrapper around* `R-INLA` *+ extra functionality*

inlabru – what can it do?

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fit log Gaussian Cox processes using INLA

`inlabru` – what can it do?

fit log Gaussian Cox processes using INLA – **conveniently**

`inlabru` – what can it do?

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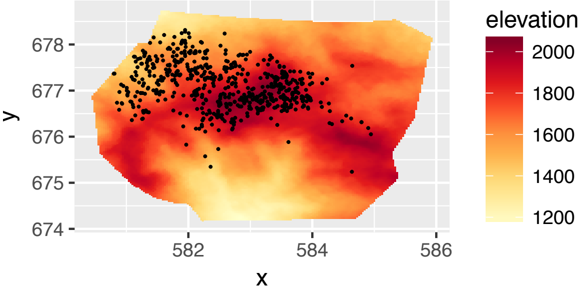
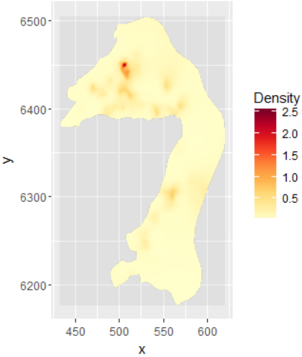
$\Rightarrow$ continuous space

fit log Gaussian Cox processes using INLA – **conveniently**

⇒ continuous space



harbour porpoise study



results

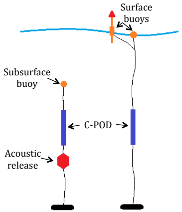
- fine scale clustering apparent
- suggests animals occur in groups

harbour porpoise study–c-pods

harbour porpoise study II

passive acoustic monitoring

- hydrophone detects cetacean vocalisation (place and time)
- harbour porpoise vocalise continuously – clicks and buzzes
- long time series data ($>$ 4 months)
- **not** point pattern data!



C-POD Mooring System

harbour porpoise study–c-pods

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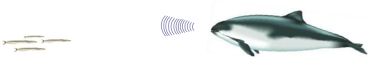

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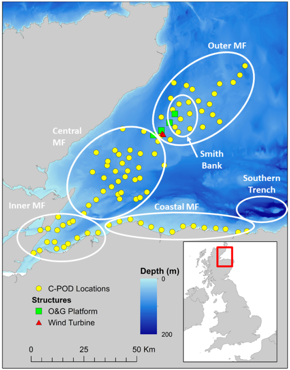


harbour porpoise study–c-pods

results

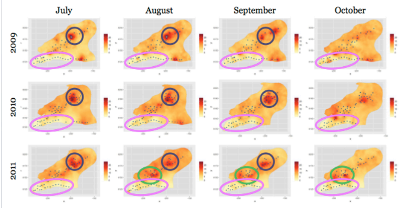
- detection positive hours – seasonal trends

⇒ changes in food availability/competition

- proportion of clicks that are buzzes

⇒ overall distribution different than that of foraging buzzes

⇒ changes in behaviour between different habitats



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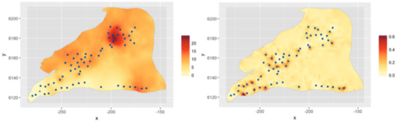

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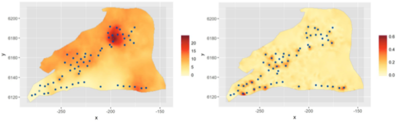

$\Rightarrow$ implications for Marine Protected Areas

distance sampling revisited...

Or: what I didn't tell you...

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$\Rightarrow$ larger groups are more easily detected

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distance sampling revisited...

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⇒ larger groups are more easily detected

- also: we used a really boring (non-flexible) detection function...

⇒ assumption that log intensity has to be linear in all latent terms no longer a good idea...

distance sampling revisited...

group size:

- detection function depends on group size (a "mark", m): $p(\boldsymbol{s}, m)$
- distribution of group sizes as function of space, $g(m|\boldsymbol{s})$
- joint point process intensity $\lambda(\boldsymbol{s})g(m|\boldsymbol{s})p(\boldsymbol{s}, m)$

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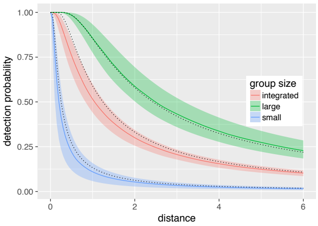
striped dolphins:



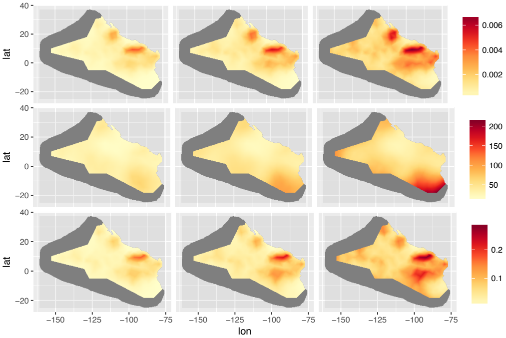
distance sampling revisited...

striped dolphins: groups size varies in space

distance sampling revisited...

striped dolphins: groups size varies in space

- dolphin group intensity (top row)
- expected group size (middle row)
- single animal intensity (bottom row)



left, middle and right column show the 2.5, 50 and 97.5 percent quantiles, respectively

ok...

for distance sampling we can now

- have flexible detection functions
- make detection dependent on marks

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BUT: what about if you are not interested in distance sampling...?

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- ecologists
- general applied users

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- make detection dependent on marks

BUT: what about if you are not interested in distance sampling...?

- ecologists
- general applied users
- INLA users
- point process people...

applied users

- convenient integrated fitting of distance sampling models

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- user-friendly software *inlabru*

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- other observation processes may be seen as different types of “thinnings”

$\Rightarrow$ unified approach, general software

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$\Rightarrow$ unified approach, general software

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spatial modellers

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- dropping linearity assumption – applicable in many contexts
- complex marked point processes

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- can interpret (univariate) function as one-dimensional LGCP

$\Rightarrow$ use *inlabru* for function estimation (detection function, pdfs, K-functions...)

inlabru, a friendlier INLA interface

R-INLA

```
A.data <- inla.spde.make.A(...)
A.pred <- inla.spde.make.A(...)
stack.data <- inla.stack(data=..., A=list(A.data, ...), effects=...)
stack.pred <- inla.stack(data=..., A=list(A.pred, ...), effects=...)
stack <- inla.stack(stack.data, stack.pred)
formula <- y ~ ... + f(field, model=spde)
result <- inla(...)
## Linear prediction:
prediction <- result$summary.fitted.values[some.indices, "mean"]
```

http://inlabru.org

```
components <- ~ ... + field(map=coordinates, model=spde)
formula <- y ~ ... + field
result <- bru(...)
result <- lgcp(...)
## Non-linear prediction (via direct posterior sampling)
prediction <- predict(..., cos(field))
## Extra: non-linear formulas and marked LGCP capabilities
formula <- y ~ field1 * exp(field2)
formula <- coordinates + size ~ field1 +
             dnorm(size, field2, sd=exp(theta), log=TRUE)
```

that Scottish drink...

that Scottish drink...

that Scottish drink...

that Scottish drink...