Efficient spatio-temporal modelling in practice

Janine Illian

University of Glasgow, Scotland

October 22, 2025

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introductions...

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spatial and spatio-temporal modelling:

focus on spatial point processes

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vision

development of methodology that is

- *practically relevant*
- *realistically complex and*
- *accessible*

approach:
develop **flexible**, computationally **efficient** models that are motivated by strongly **inter-disciplinary** communication, knowledge exchange and research

spatial point processes – what are they?

models of spatial patterns:

$\Rightarrow$ modelling **locations and properties (“marks”)** of objects, events, individuals in space and time

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  - plants or animals
  - earthquakes
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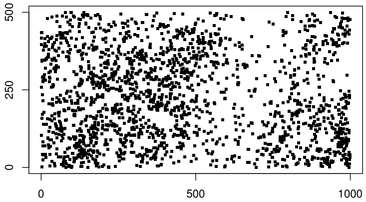

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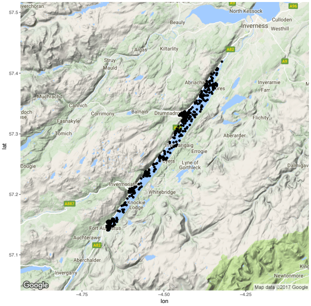

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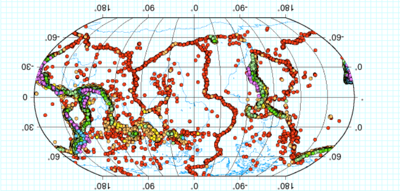

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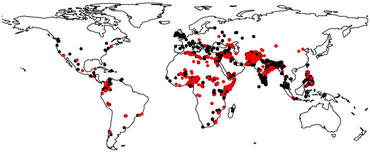

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- assigns a count of points to every subset in W; a **measure**; point process N is a **random (counting) measure**

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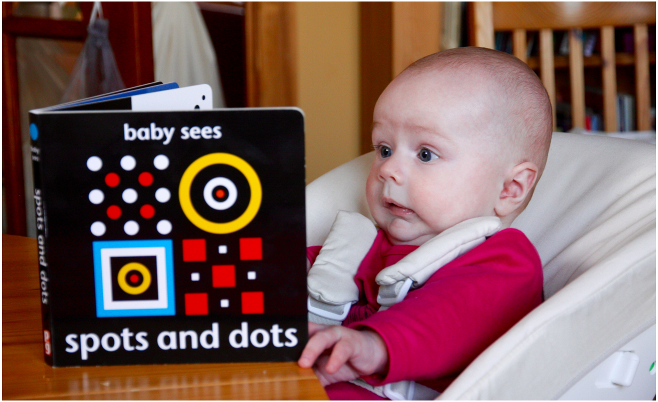

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$\rightsquigarrow$ making the very theoretic point processes relevant in practice

strategy ...

steps...

- development of models that are relevant in practice

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  $\rightsquigarrow$ `inlabru`
- work hard on the communicating these methods **and their results** to users...

in essence ...

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$\Rightarrow$ *wrapper around* `R-INLA`* $+$ *extra functionality:*

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observation process is an operation on the point pattern - e.g. a **thinning**

* R-INLA is the R-library implementation of integrated nested Laplace approximation (INLA)

benefits of INLA...

basing our approach on INLA allows us to:

- use computationally efficient model fitting approaches for many realistically complex models in space and time;

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- use all the functionality available in `R-INLA` – general context

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$\rightsquigarrow$ `inlabru` provides a general framework

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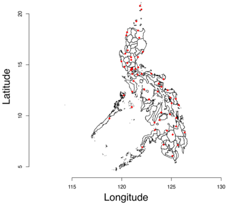
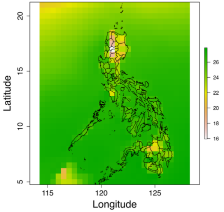


(a) Weather synoptic stations



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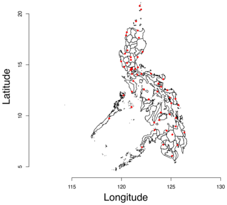

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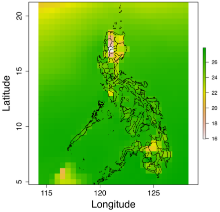

(b) Sample GSM outcomes

- weather stations: sparse but good quality
- weather model: good coverage, but not correct

$\rightsquigarrow$ model accounts for difference in data quality

joint modelling: climate data – England and Wales

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- Automatic Urban and Rural Network (AURN) in England and Wales; pollutants such as NO2, O3, PM10 and PM2.5l locations (a)

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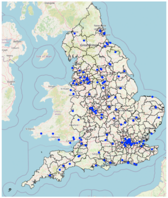
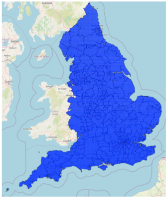
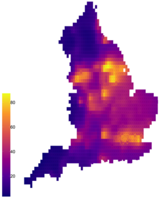


(a) Monitors in England and Wales



(b) AQUM data locations



(c) Sample AQUM Data

reintroduction of cranes into the UK – background


BIRDGUIDES FIRST FOR BIRD NEWS

Latest Sightings | Galleries | Species Guide | Sites | Listing | News | Reviews | Articles

News > British Crane Population Soars To New Heights

14/12/2018 Share

British crane population soars to new heights

Common Crane's remarkable British comeback continues, with a record-breaking 54 pairs counted across the country in 2018.

The total population is now believed to be in excess of 180 birds – the highest number since the species returned to Britain in 1979 after an absence of more than 400 years.

Standing at a height of 120 cm, Common Crane is the tallest bird found in Britain. Wild cranes were once widespread, but became extinct through hunting and the loss of their wetland habitat in the 1600s.

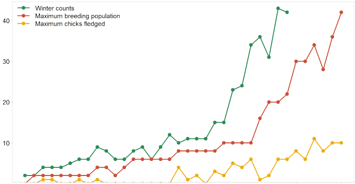
In 1979, a small number of wild cranes returned to East Anglia, establishing themselves in the Norfolk Broads. Thanks to conservation efforts, cranes have slowly spread to other areas of eastern England, with the species benefiting from work to improve habitat at RSPB reserves such as Lakenheath Fen and Nene Washes, as well as Natural England's Humberhead Peatlands.

- UK resident population extirpated in the 16th century
- re-established by a single breeding pair in 1979 through immigration from mainland Europe
- population boosted by further immigrants and a reintroduction project from 2010-2014

- only breed in wetlands...

Common Cranes numbers are at their highest level in Britain for 400 years (W Schulenburg).

modelling in fragmented habitat



- range expansion – which wetland habitats are likely to be colonised?
- looking at presence of the species in relation to environmental covariates alone could be misleading

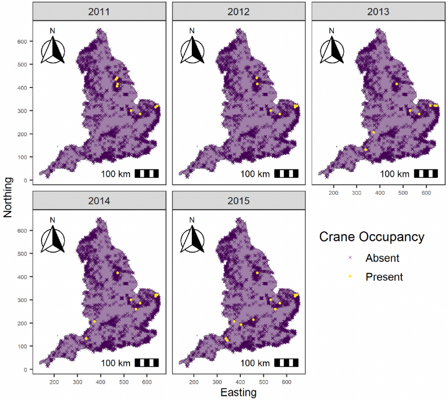
⇝ some habitats may be outside of the population's current range

⇝ cranes won't nest where there is no wetland

spatio-temporal marked point pattern model

- spatial point pattern: reflects wetland locations
- marks: occupancy (nesting/no nesting) over time (2010 - 2015)

$\rightsquigarrow$ point pattern reflects observation process



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joint model with two responses and likelihoods:

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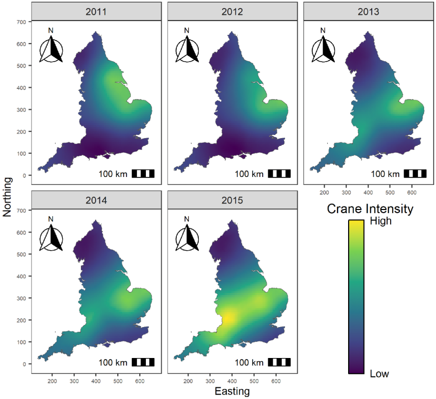
$\leadsto$ distinguishing between unfavourable habitat and favourable habitat not within reach yet

Soriano-Redondo et al. 2019, Laxton et al. 2023

reintroduction of cranes into the UK – some results

predictions in space and time...



joint modelling – some comments

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Supporting Louisiana's Whooping Crane Recovery Register for Oct. 30 webinar

Our Work Visit Learn SHOP DONATE

Asia

Breeding Eurasian Cranes in North East Scotland, United Kingdom

By Hywel Maggs, Conservation Officer, North East Scotland, Royal Society for the Protection of Birds

Old written records, artifacts and place names indicate our ancestors' familiarity with cranes, but definitive evidence of historical breeding in Scotland it is hard to come by. However, it seems inconceivable that cranes did not breed in many parts of Scotland up until at least some time in the Middle Ages.

SHARE

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- different quality of data – accounted for in models

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- model fitting fast – complex models can be fitted
- very general methodology and software

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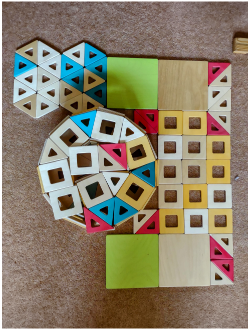
- these "building blocks" account for e.g. spatial autocorrelation
- **but:** also represent structures that reflect reflect processes, e.g. behaviour, dispersal limitation

background – building blocks

building blocks have a **role**

- a statistical role



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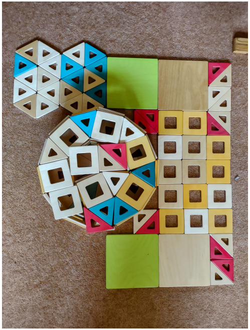

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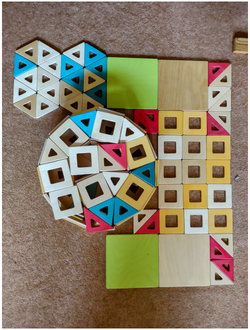
⇝ these need to be communicated



background – building blocks

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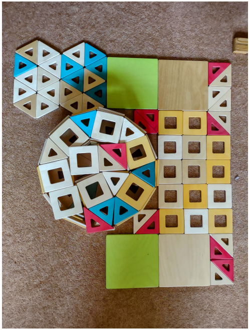

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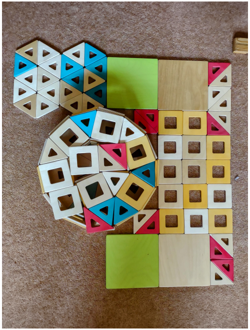

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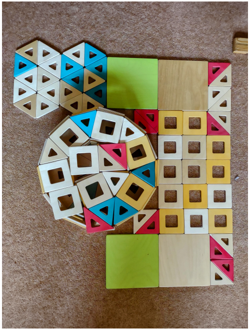

What properties of these building blocks do we want to interpret and represent – and how?

background – modelling approach

example: spatial point process models

- **log Gaussian Cox process**;
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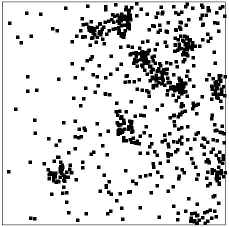
  $\Lambda(s) = \exp(X(s))$,



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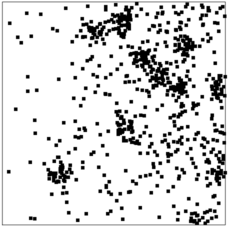

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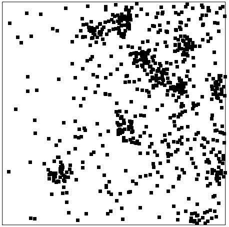

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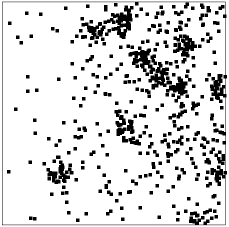

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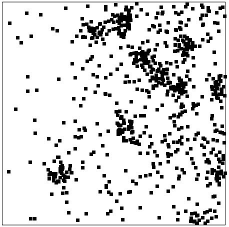

building blocks difficult explain...

background – role of the building blocks

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the approximated intensity and its properties play important ecological role

case study – Hawai'i 'akepa

study aim and data collection:

- bird conservation – estimating animal abundance of endangered and endemic bird species

case study – Hawai'i 'akepa

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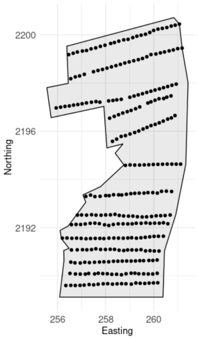

case study – Hawai'i 'akepa

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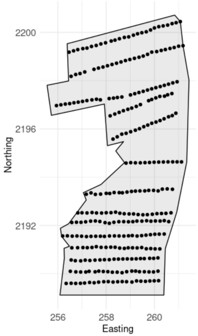

case study – Hawai'i 'akepa

visualizing the results, standard approach

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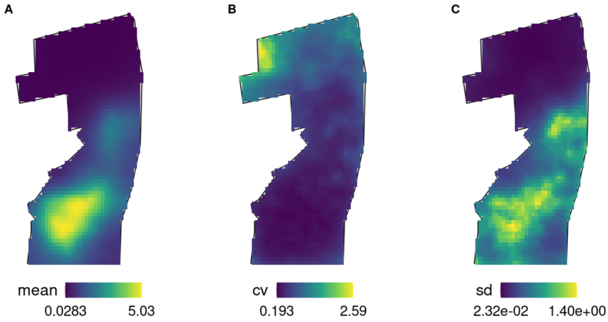

case study – Hawai'i 'akepa

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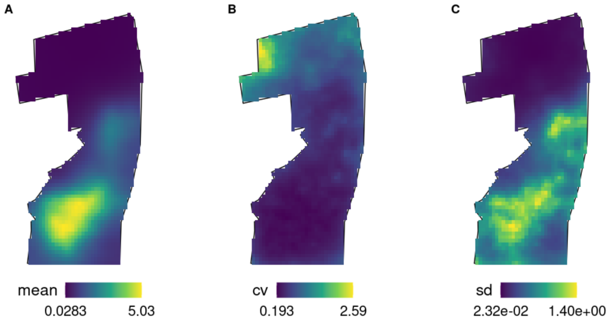

case study – Hawai'i 'akepa

visualizing the results, standard approach

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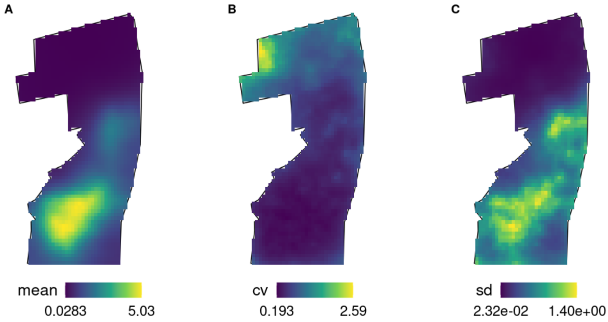

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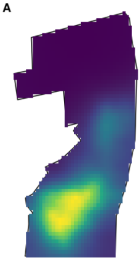

case study – Hawai'i 'akepa

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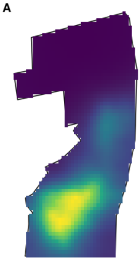

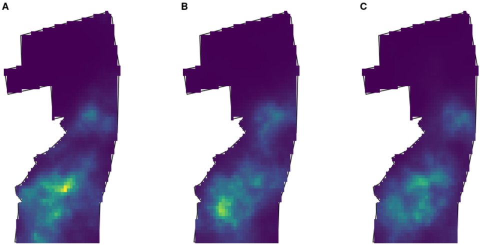

case study – Hawai'i 'akepa

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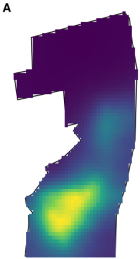

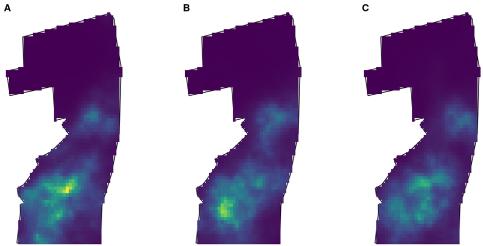

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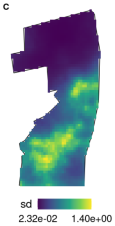

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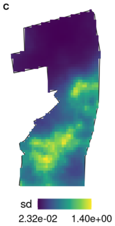

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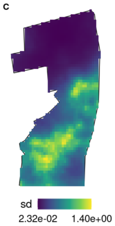

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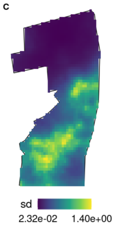

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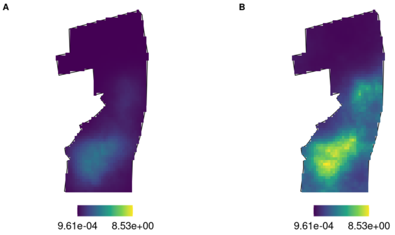

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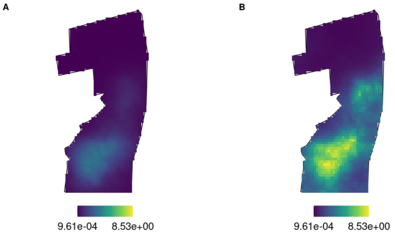

case study – Hawai'i 'akepa

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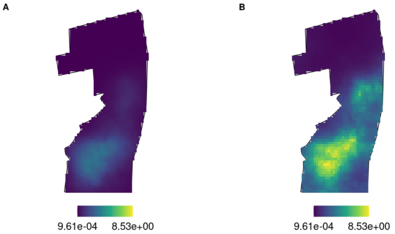

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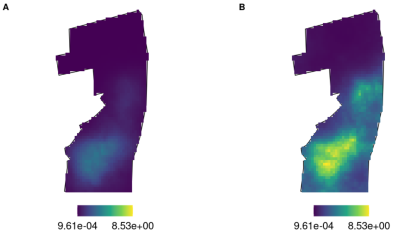

case study – Hawai'i 'akepa

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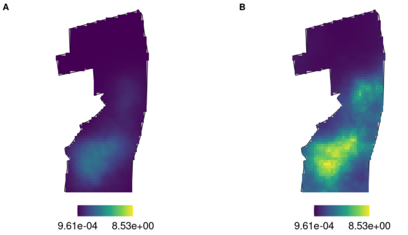

case study – Hawai'i 'akepa

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case study – Hawai'i 'akepa

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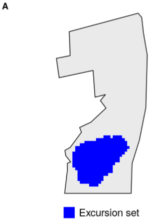

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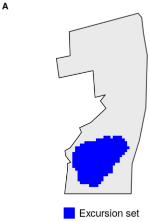

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$\leadsto$ effective visualisation requires effective communication and engagement with the (ecological) context

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- model development and presentation of outcomes not in isolation
- not all end-users are the same – e.g. quantitative ecologists vs. policy makers