Efficiently modelling non-stationarity in ecological spatial models

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Motivation

Characterising **species distributions** is a fundamental challenge in ecology. Understanding the effects of **changing environmental conditions** on species distributions is required for conservation efforts and spatial planning. However, mapping distributions are challenging for many species as they reside in **inaccessible terrain** such as marine environments and mountainous regions. To follow their movements, remote sensors can be attached to animals that record location, movement, physiological parameters, and environmental conditions, termed **telemetry data**. These data have intrinsic properties, such as strong **spatiotemporal autocorrelation** due to successively observed animal locations, and study areas defined by the animals themselves can range over wide geographical areas. We propose to develop statistical advances that accommodate complexities of such data to allow robust predictions of changes in species distributions.

Different Terrain Model

- Shown here is a successful example using this model.
- Studying smelt (*Osmeridae*) larvae in the Finnish Archipelago near Turku, where land is a barrier that fish cannot cross.
- Previous approaches use **stationary autocorrelation** fields, assuming dependence continues across boundaries homogenously, **'leaking' across barriers**.
- High correlation between points on the opposite sides of land (i.e. smooths over land).

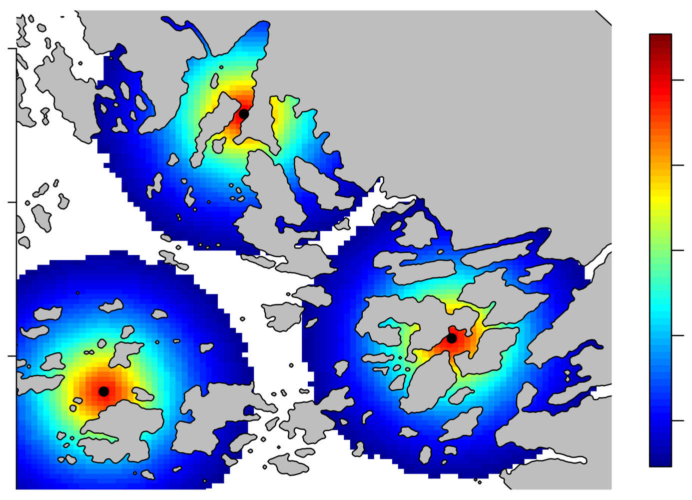

Figure 1: A priori stationary correlation structure

- Developed methodology uses a **flexible random effect** on autocorrelation.
- Stochastic partial differential equations (Lindgren *et al.* 2011) combined with Integrated nested Laplace approximation (INLA) (Rue *et al.* 2009), **adaptable range parameters** account for non-stationarity and boundary effects.
- The Different Terrain model estimate does not smooth over land.
- Covariate estimates change from stationary to DT model, although predictive performance was similar on these data.

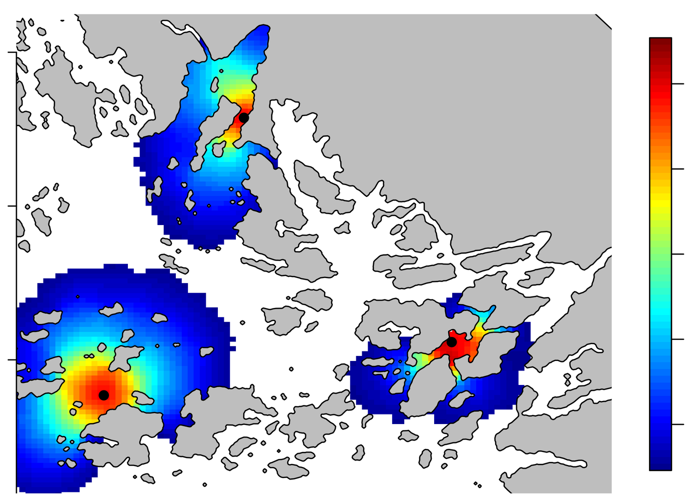

Figure 2: A priori non-stationary correlation

Theoretical construction

We used the SPDE approach by Lindgren *et al.* (2011), re-parametrised the equation, and used a separate range for different terrains (land and water).

$$u(s) - \nabla \cdot \frac{r^2}{8}\nabla u(s) = r\sqrt{\frac{\pi}{2}}\sigma_u \mathcal{W}(s),$$

Impact on inference results

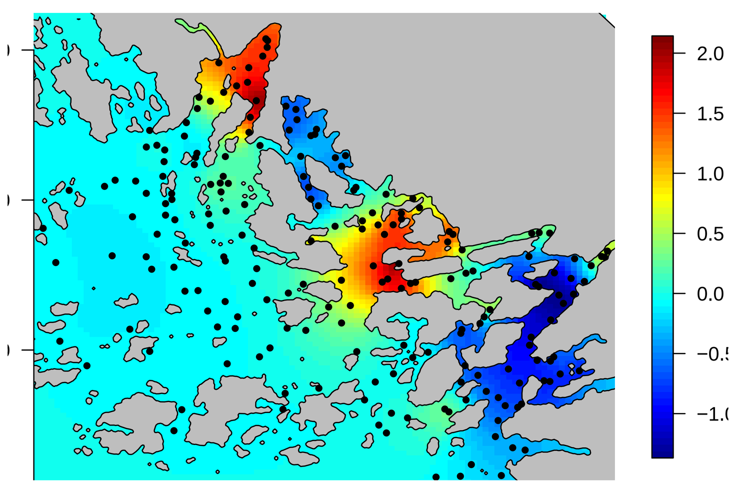

Figure 3: Estimate of the spatial field (posterior mean). Covariates are in addition to this.

Model	Estimate	2.5 %	97.5%
Stationary	-0.80	-1.82	0.30
DT model	-1.01	-2.02	-0.04

Table 1: Example of an estimated covariate (ShoreDens) in the model. Covariates can range from significant to not significant, or vice versa.

- If underlying autocorrelation within the movement data is not accounted for correctly, covariates can be falsely identified as being important (or unimportant) to a species' habitat use because uncertainty and parameter estimates are incorrect.
- If these covariates are used to suggest changes in space use under changing environmental conditions, those predictions may be misleading.
- When movement data are analysed as spatial point patterns, assuming stationarity is problematic because non-stationarities in the mean can be masked (analogous to unmodelled covariates).
- Area-dependent spatial autocorrelation allows important variation in movement behaviour can be described and animals' sensitivity to changes in the environment can be captured.
- For the fish larvae, the DT model results in higher uncertainty in inlets.

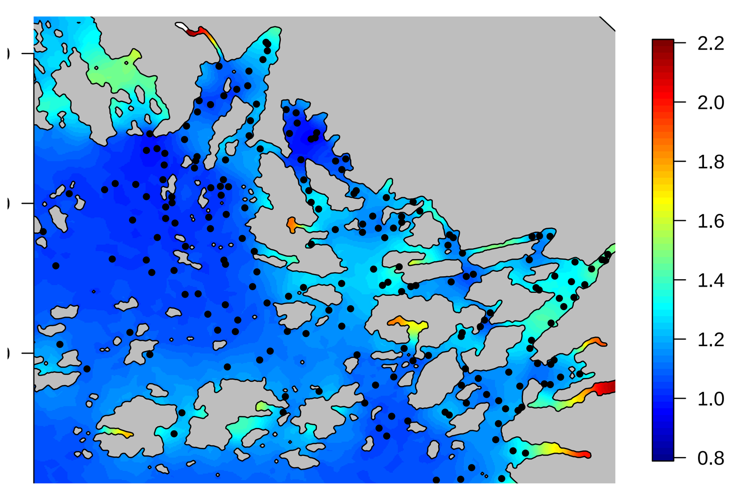

Figure 4: Spatial uncertainty (posterior standard deviation) for the spatial field.

References

[1] F. Lindgren, H. Rue, and J. Lindstrom. *J. R. Stat. Soc. Ser. B (Statistical Methodol.)*, 73(4):423–498, 2011.

[2] H. Rue, S. Martino, and N. Chopin. *J. R. Stat. Soc. Ser. B (Statistical Methodol.)*, 71(2):319–392, apr 2009.

Data

Grey seals (*Halichoerus grypus*)

- Telemetry data from grey seals tagged in the Netherlands will be analysed. They are central place foragers, travelling to their at-sea feeding grounds before returning to haul out on land.
- Foraging behaviour typically produces focused repetitive movements in a small area, whilst travelling behaviour can be demonstrated by directed movement over large distances.
- Such behaviours are often analysed using state-space models which are computationally intensive.
- Our new models will use **different spatial autocorrelation** structures in the **foraging** and **travelling** areas (based on informative priors).

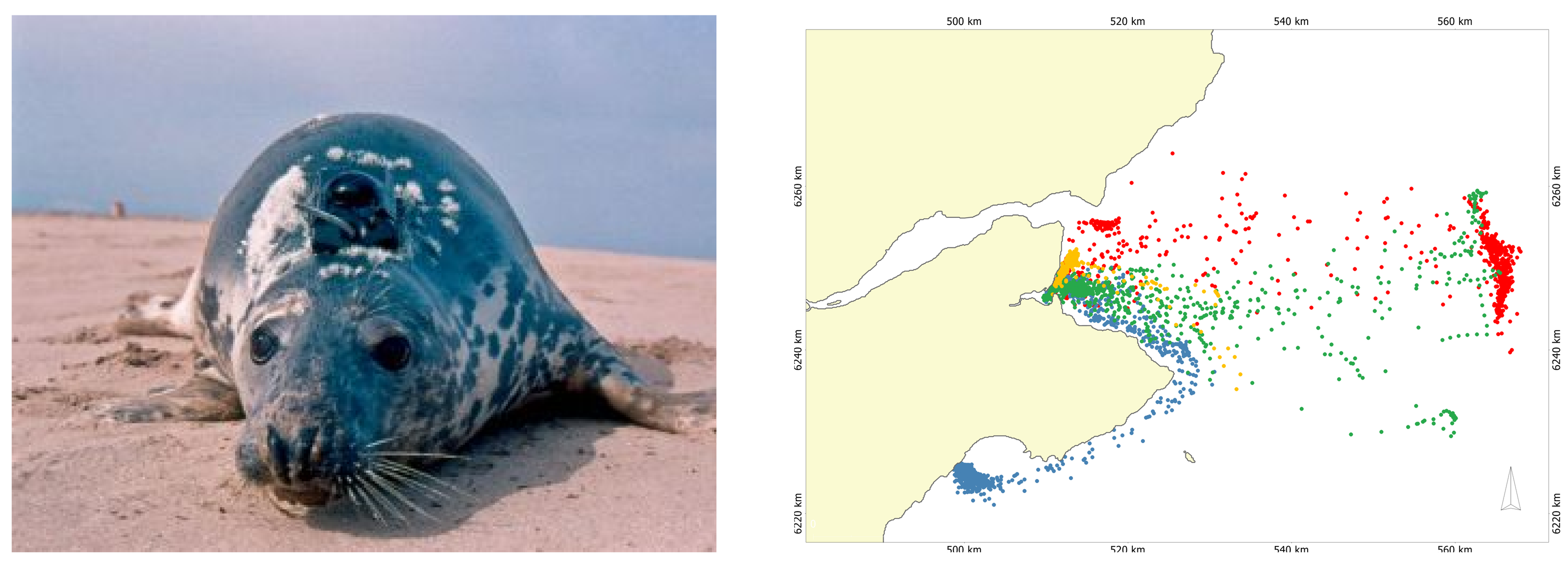

Figure 5: (a) Grey seal with telemetry tag (photo credit: SMRU), (b) telemetry locations of 4 animals tagged in east Scotland in 2011-12 by SMRU.

Black eagles (*Aquila verreauxii*)

- Like other large raptors, black eagles rely heavily on uplift for flight, generated either by thermal updrafts or the flow of air over steep slopes.
- Their movements inside (soaring) and outside updrafts are different and so fields of varying spatial autocorrelation will be implemented.
- To enable commercial developers, policy makers, and conservationists to work effectively tools must be developed to robustly analyse the vast amounts of data generated by remote sensing.

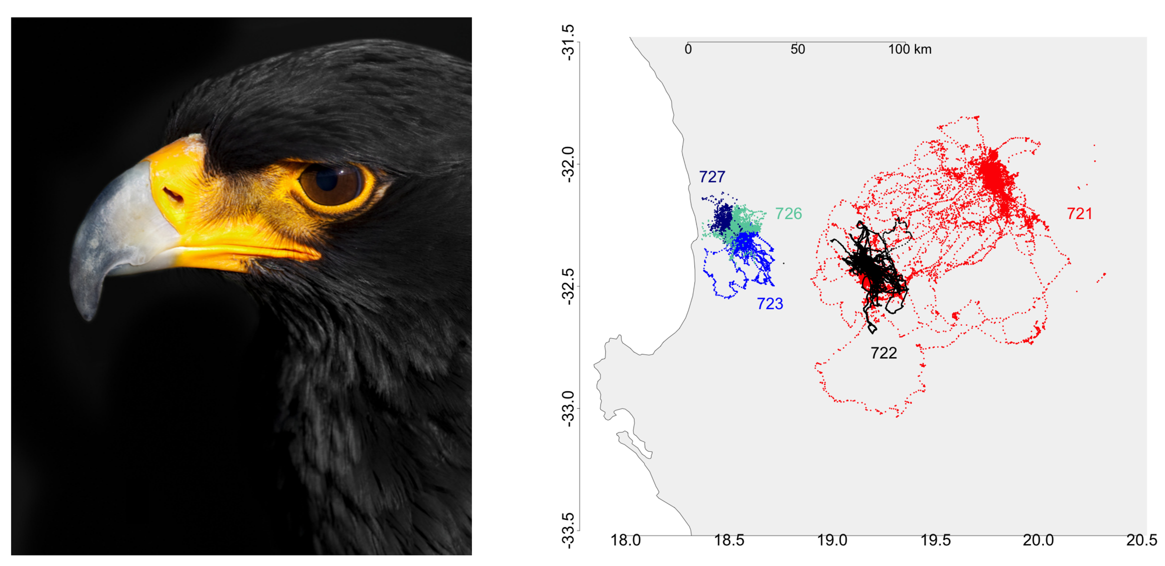

Figure 6: (a) Black eagle (photo credit: Mario Moreno), (b) telemetry locations of 5 eagles tagged in South Africa (provided by Theoni Photopoulou).

Outcomes

- The aim is to provide an integrated species distribution modelling framework.
- General methodology of non-stationary random fields will be implemented in existing R-INLA library.
- We will also develop a set of wrapper functions specific to movement modelling.
- These data examples will be used in R-INLA courses currently run by members of the research group.

Acknowledgements

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