Spatio-temporal modelling of NEA mackerel: *Introducing estimates of uncertainty and going beyond ‘visual’ correlations*

**Nikolaos Nikolioudakis**, Hans J. Skaug, Jan Arge Jacobsen, Teunis Jansen, Leif Nøttestad, Guðmundur J. Óskarsson and Katja Enberg
EcoNorSe

Ecosystem dynamics in the Norwegian Sea: new methods for understanding recent changes

Visual diet analysis – Stable Isotopes – Genetics - Modelling
A very dynamic ecosystem with rather good survey coverage

NSSH NASC registrations during the IESSNS (July) (ICES 2016)

Distribution of catches during the IESSNS (July) (ICES 2016)

Figure 1. Spawning stock biomass of herring, mackerel, blue whiting and zooplankton biomass in the Norwegian Sea.
Mackerel is getting the blame for vanishing herring, puffin, ...

Climate change creates trouble for puffins

Klimaendringene skaper trobbel for lundefuglen

LUNDEFUGL

Hovestad et al. (2016) 

Average catch index (kg km^-2) for NEA mackerel in July–August 2007 and 2010–2014. (Nøttestad et al. 2016)
Mackerel is getting the blame for vanishing herring, puffin, ...

Climate change creates trouble for puffins

The results suggest that mackerel fed opportunistically on herring larvae, and that predation pressure therefore largely depends on the degree of overlap in time and space.

...mackerel and herring diets largely overlapped, with calanoid copepods being their main prey item, while the blue whiting diet consisted of larger prey items, particularly amphipods.
EU tackles Iceland over 'mackerel wars'

Island nation and Faroes face trade sanctions over rising catches of fish

Climate change prompts ‘mackerel wars’

Ocean warming expands habitat of a rich natural resource and benefits a national economy

Q&A: Mackerel wars explained
Mackerel Presence (○) / Absence (●)
Plankton dry biomass (mg/m²)
The rationale:
prey and abiotic variables should control mackerel distribution patterns

The questions:
1) Can inclusion of competition for prey improve the models?
2) Are the observed distribution patterns varying over space / time?
3) Can we derive uncertainty estimates from our fitted models?

The methodology:
Spatiotemporal Bayesian models using INLA

[Integrated Nested Laplace Approximation (Rue et al. 2009, Lindgren et al. 2011)]
The rationale:
prey and abiotic variables should control mackerel distribution patterns

The questions:
1) Can inclusion of competition for prey improve the models?
2) Are the observed distribution patterns varying over space / time?
3) Can we derive uncertainty estimates from our fitted models?

Spoiler: YES WE CAN!

The methodology:
Spatiotemporal Bayesian models using INLA

[ Integrated Nested Laplace Approximation (Rue et al. 2009, Lindgren et al. 2011) ]
**Response: Mackerel Presence / Absence**

\[ Y_{ti} \sim \text{Bernoulli}(P_{ti}) \]
\[ E(Y_{ti}) = P_{ti} \]
\[ \text{var}(Y_{ti}) = P_{ti} \times (1 - P_{ti}) \]

\[ \exp(\text{Intercept} + \text{Covariates}_{ti} + v_{ti}) \]
\[ P_{ti} = \frac{\exp(\text{Intercept} + \text{Covariates}_{ti} + v_{ti})}{1 + \exp(\text{Intercept} + \text{Covariates}_{ti} + v_{ti})} \]

, where:
\[ v_{ti} = \phi \times v_{t-1,i} + u_{ti} \]
\[ u_{ti} \sim \mathcal{N}(0, \text{SIGMA}) \]

**Covariates**

- Temperature (real time)
- Salinity (real time)
- Depth
- Mean SST (7 days mean)
- Mixed Layer thickness (7 days mean)
- Longitude / Latitude
- Herring Presence / Absence (catches)
- Zooplankton Dry Biomass (real time)
- Mackerel SSB
<table>
<thead>
<tr>
<th>Model</th>
<th>Random field</th>
<th>Herring</th>
<th>DIC*</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>NO</td>
<td>NO</td>
<td></td>
</tr>
<tr>
<td>I</td>
<td>NO</td>
<td>YES</td>
<td></td>
</tr>
<tr>
<td>II</td>
<td>SPATIAL</td>
<td>NO</td>
<td></td>
</tr>
<tr>
<td>II</td>
<td>SPATIAL</td>
<td>YES</td>
<td></td>
</tr>
<tr>
<td>III</td>
<td>SPATIOTEMPORAL</td>
<td>NO</td>
<td></td>
</tr>
<tr>
<td>III</td>
<td>SPATIOTEMPORAL</td>
<td>YES</td>
<td></td>
</tr>
</tbody>
</table>

**Why even bother?**

To take into account spatiotemporal autocorrelation and avoid pseudoreplication!!!
Important covariates: Plankton + Herring + mackerel SSB

The spatial correlation term therefore captures real spatial dependency but also unmeasured spatial covariates.

DIC* : metric of model goodness of fit (the lower the better)
Improvement of model fit?

Variogram of residuals indicates spatial dependency

Spatial dependency substantially reduced
Clustered large circles or triangles imply spatial correlation

NO spatial effect in the model
Substantial improvement of the model through inclusion of:

- the competing species (herring)
- the spatial autocorrelation

Clustered large circles or triangles imply spatial correlation.
...and the highlight!
Distribution of mackerel catches in 2006 (Uine et al. 2012)

‘Visual’ correlations
INLA pros:

- Estimates of uncertainty → trustworthy prediction
  - technical aspects: extremely fast (compared to MCMCs)
  - option for non-stationarity (correlation can vary with direction)
  - spatial fields are allowed to have temporal variation
- Not only models per se but also biomass/abundance estimates

INLA cons:

- ...not the easiest software to handle
Future plans:

- Model mackerel biomass distribution
  - herring and blue whiting inclusion BUT through using NASC

- Model herring biomass distribution in May

- Incorporate the spatial aspect into stock assessment
  - Better survey indices
  - Spatially explicit survey indices

Uncertainty introduction / reduction!!!

Better stock assessment (hopefully)
Thank you!

Project EcoNorSe

Ecosystem dynamics in the Norwegian Sea: new methods for understanding recent changes