Location estimation and track models

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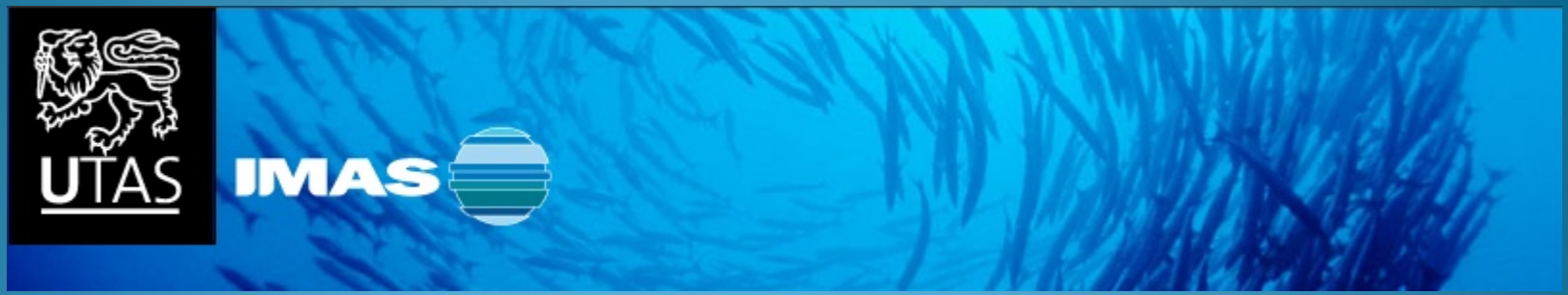

Summary

- General Bayesian framework for location estimation
- Track representation model
- Terrestrial light level geo-location example (Hoopoe)
- Location information from a 4D ocean model

Bayesian framework

- Flexible approach to track estimation
  - Prior knowledge
  - Tag data –Argos estimates or TDR light levels
  - Incorporate large environmental data sets
  - Integrated model for movement constraints
  - Full-path track representation model

- Sumner, Wotherspoon and Hindell (2009) Bayesian Estimation of Animal Movement from Archival and Satellite Tags. *PLoS ONE 4(10)*.
  - Software: http://www.r-project.org
  - *tripEstimation* package: Bayesian framework, MCMC estimation, spatial tools
  - *trip* package: "traditional" track analysis, filtering / time spent, GIS integration, sanity-checking for input to more complex models

Track representation model

- A: lines join points
- B: points have unknown error
- C: points as distributions (lines not enough)
- D: how to represent intermediates?
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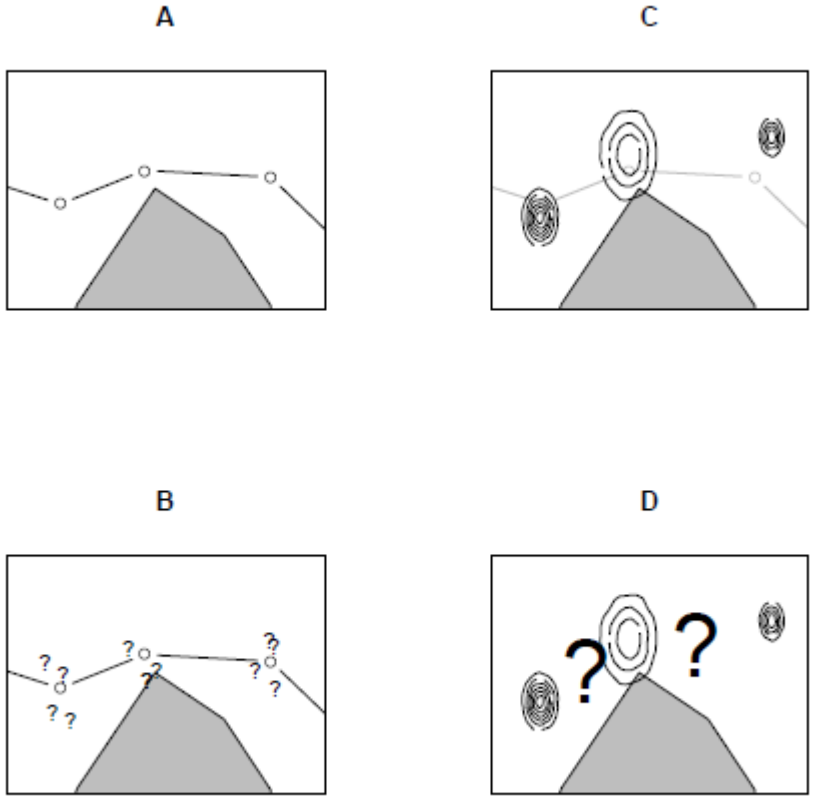
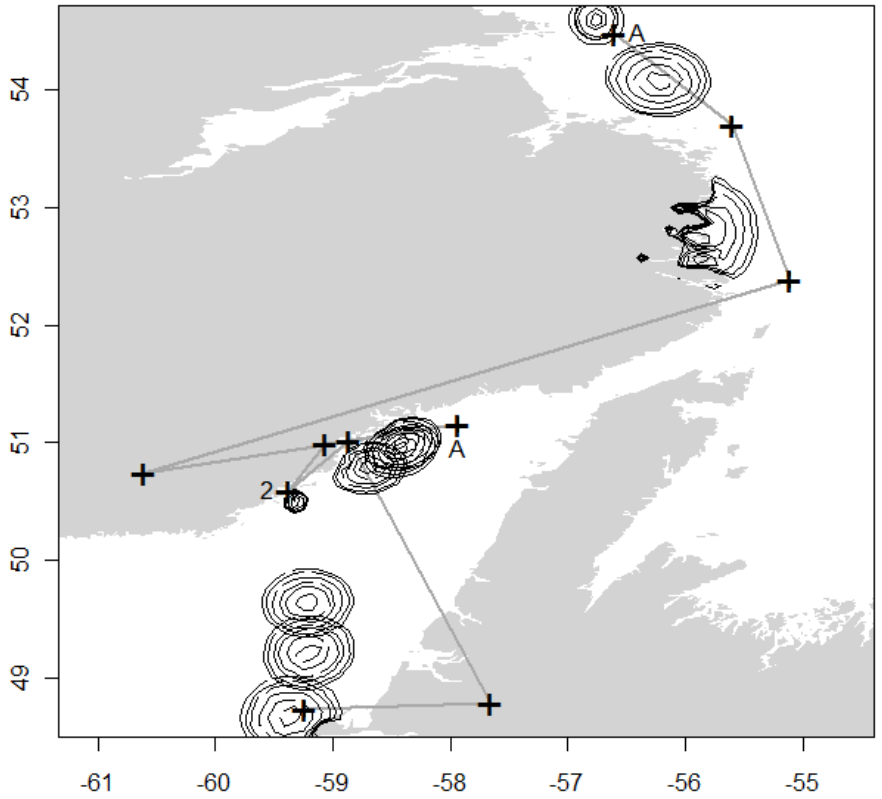
- Bayesian approach explicitly models the “full-path” range during intermediate times, as well as the “primary” locations.



Track representation model

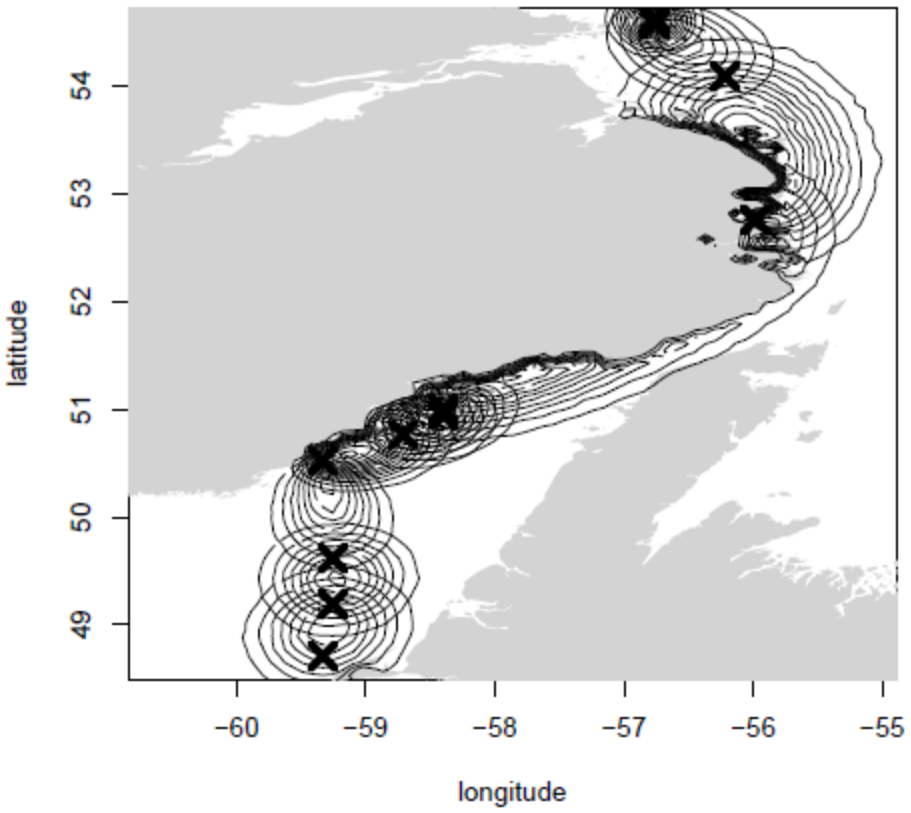
- Line joins Argos estimates
- Distributions represent modelled location estimates
- Modelled locations are discrete in time
- *Intermediates? Line segments are continuous, but not sufficient.*



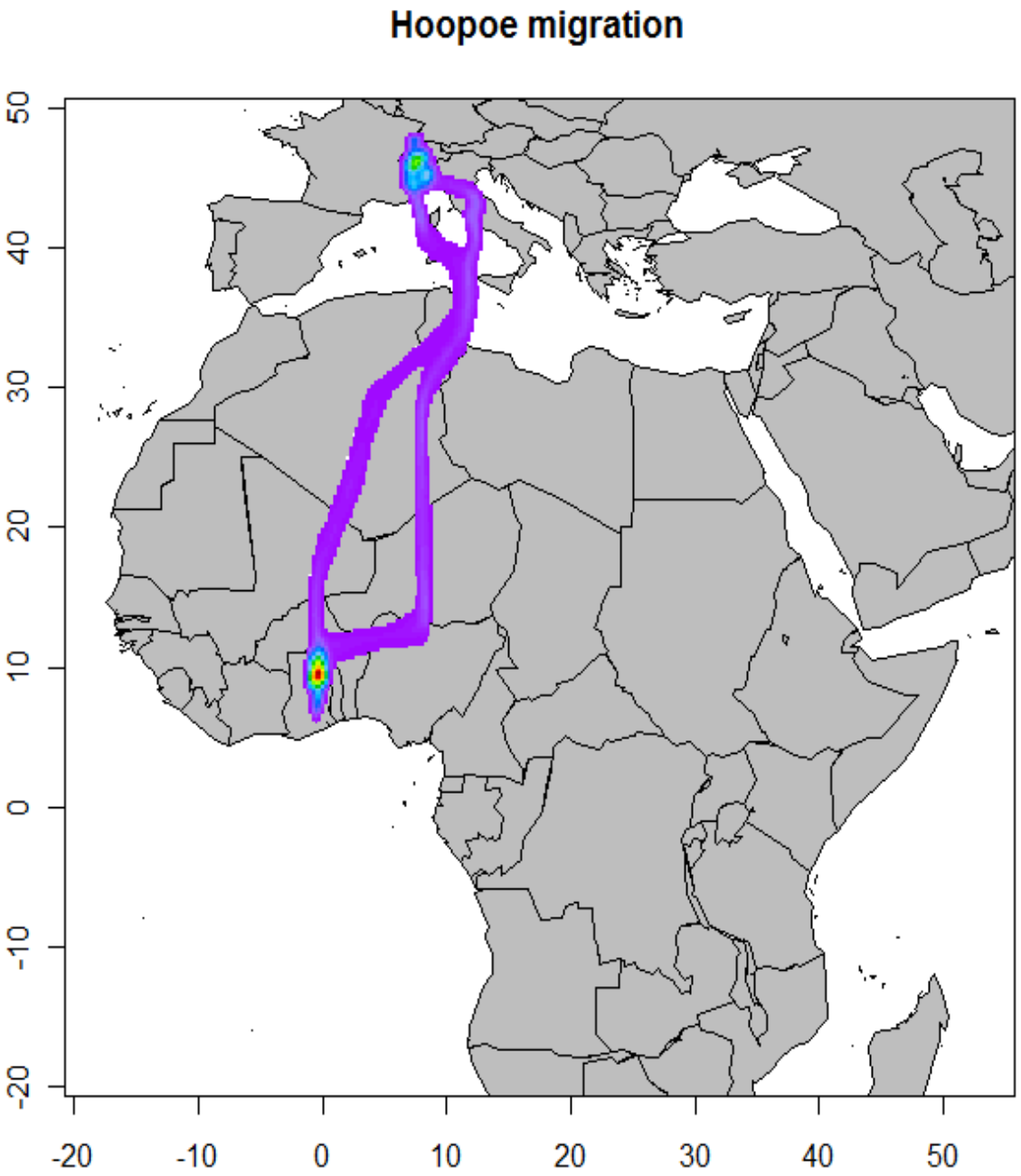
Argos ringed seal data from *diveMove* package, Sebastian Luque.

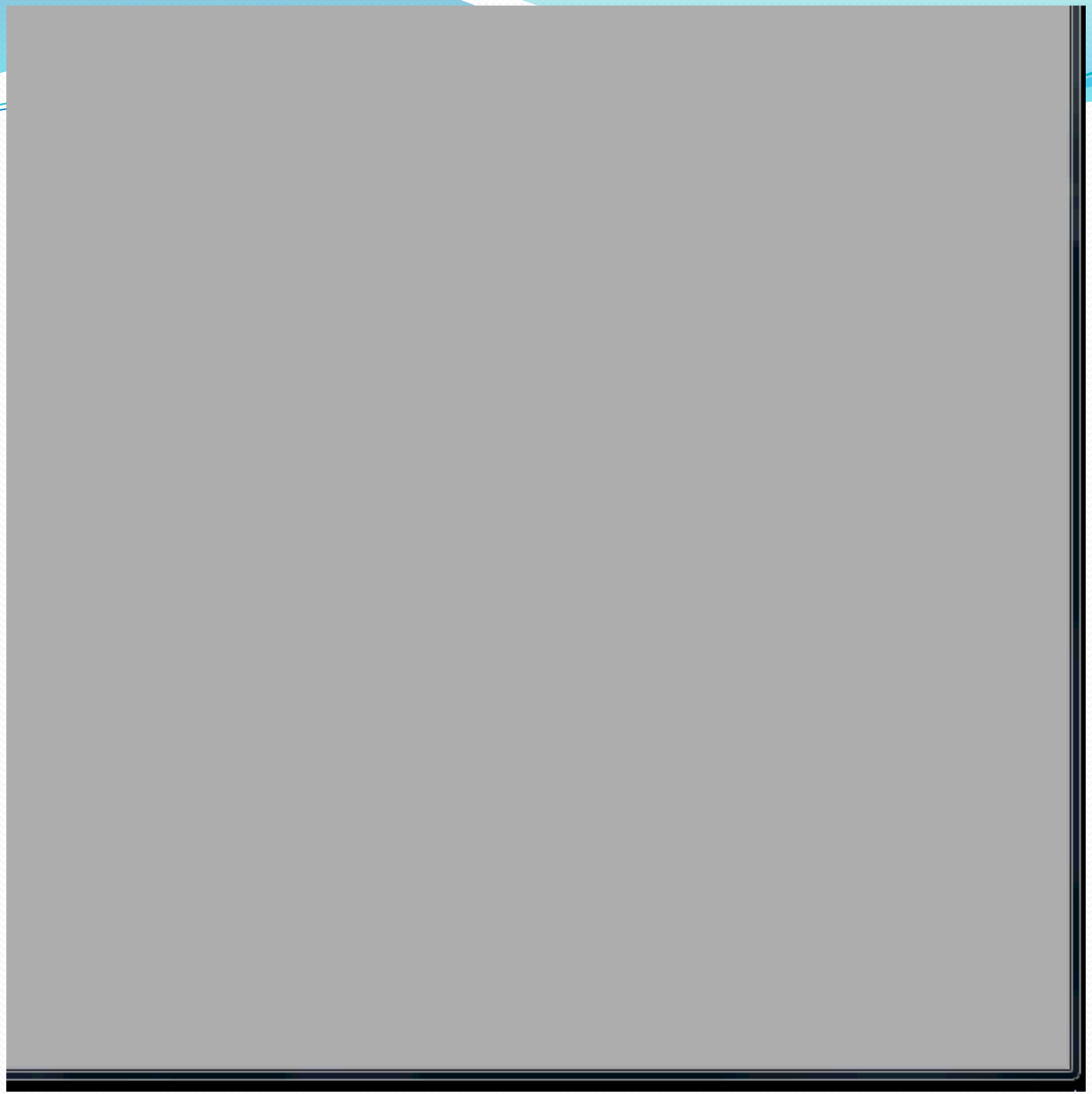
Track representation model

- Line joins Argos estimates
- Distributions represent modelled location estimates
- Modelled locations are discrete in time
- Modal primary locations **(X mode from posterior)**
- Intermediate locations represent interval between primary estimates **(contours from posterior)**



- Hoopoe light data from Felix Liechti and Steffen Hahn, The Swiss Ornithological Institute





Environmental data sets

Help pin down otherwise poor locations, but volumes can exceed available computing power.

Static in time

Polygon coastline – complicated computation

→ Raster masks (land vs. ocean) - simple

Changing in time, in 2 spatial dimensions

Time series of Sea Surface Temperature – large data volumes

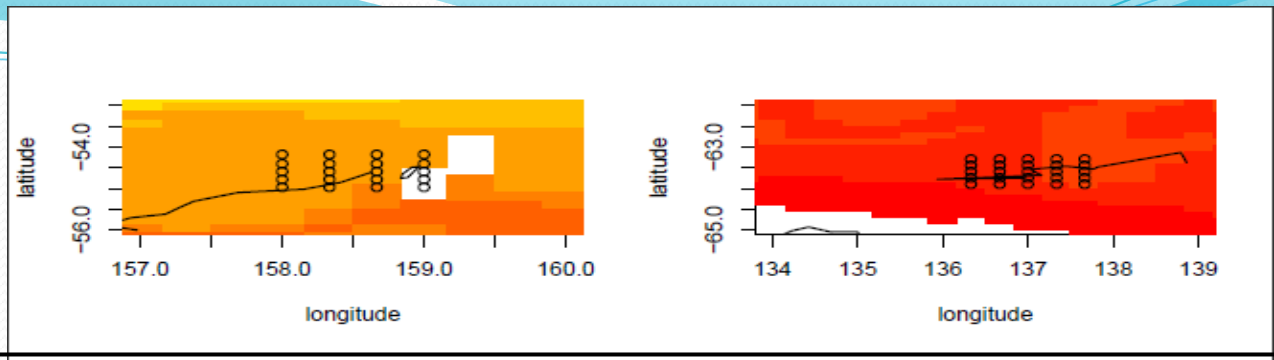
→ Raster masks, tricks for compression

Changing in time, in 3 spatial dimensions

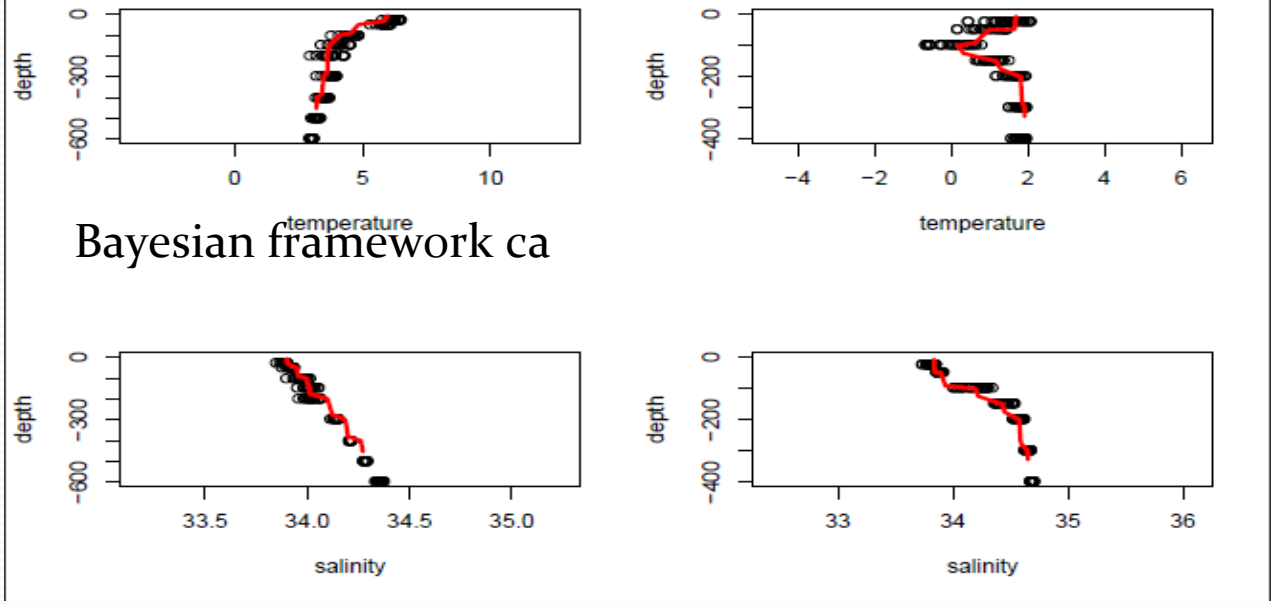
Time series of ocean circulation models – *really large data volumes*

→ *?? (powerful desktop computers, file-based memory tools,)*

Sample grid locations



- GEM samples
- Tag profile

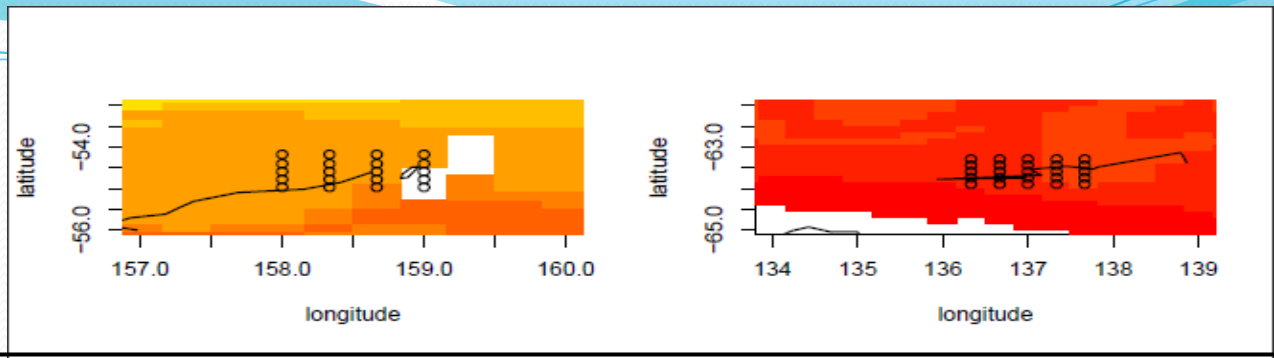


Bayesian framework ca

Bayesian framework can admit likelihood function for arbitrarily large environmental data sets. Randomly sampled locations used to generate profiles from GEM to compare with tag profiles.

Gravest Empirical Mode (GEM) Southern Ocean model (1992-2006): Andrew Meijers, CSIRO

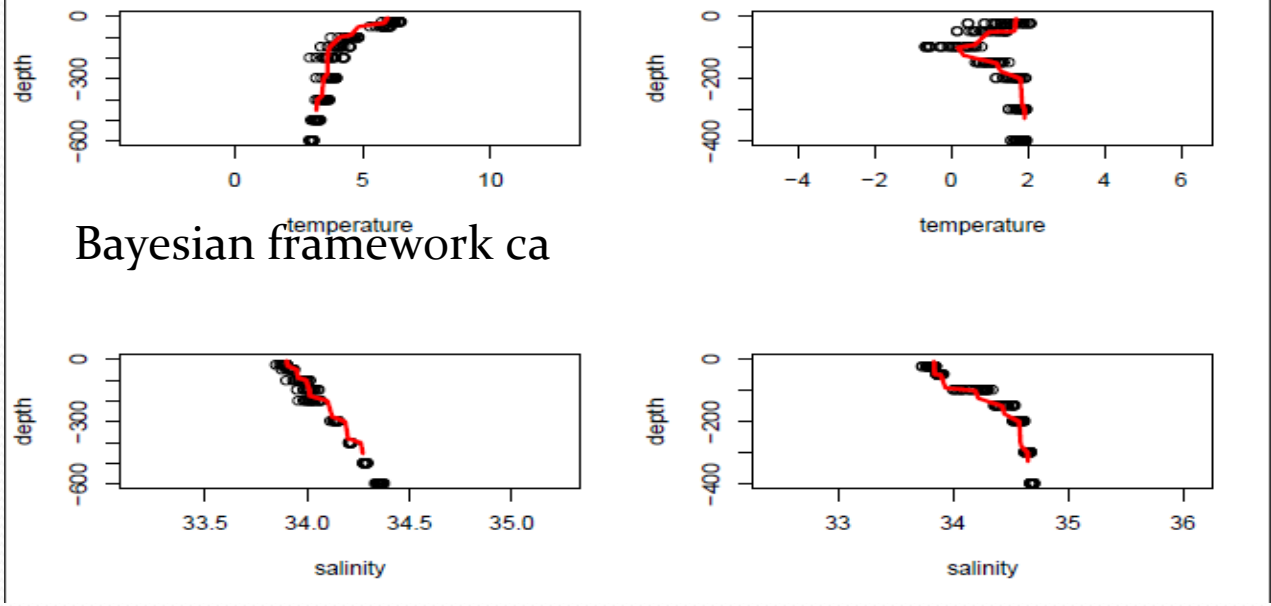
Sample grid locations



- GEM samples
- Tag profile

- Modelling attempts:
  - Profiles alone
  - Light data + profiles

Temperature looks promising, should be more informative in combination with salinity.



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