Sea Ice: Data, Modelling and Uncertainty

Ben Robinson

University of Bath Postgraduate Seminar Series

February 25, 2016

Developing a model for sea ice

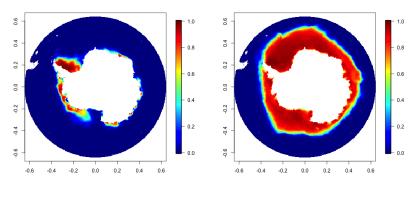


Developing a model for sea ice



The data

- Several data sources
- Most complete and reliable is data from satellites, collected by passive microwaves
- This is available from 1979-Present



(a) February mean

(b) August mean

The data

- Further back in time we only have observations of the ice edge
- Eventually only have point observations

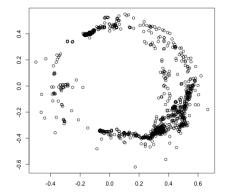


Figure: Ship observations from 1922-1953

Our aim is to develop a model for concentrations of sea ice, which can be used to reconstruct historical sea ice concentrations and quantify uncertainty.

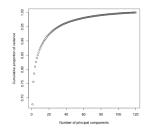
Our aim is to develop a model for concentrations of sea ice, which can be used to reconstruct historical sea ice concentrations and quantify uncertainty.

Challenges are:

- Multiple data sources, more sparse further back in time
- Need to account for
 - seasonality
 - long-time variation
 - spatial correlations
 - physical constratints
- Concentrations constrained between 0 and 1

Use singular value decomposition to identify main causes of variation around the mean:

- Columns of X contain ice concentrations for each month at all locations not on land, with row means subtracted
- Singular value decomposition is $X = U \Sigma V^T$
- Left singular vectors i.e. columns of U give principal components
- $\bullet\,$ Squares of diagonal entries of Σ are proportional to variance in direction of each principal component



Principal Component Analysis

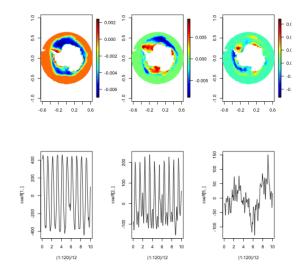


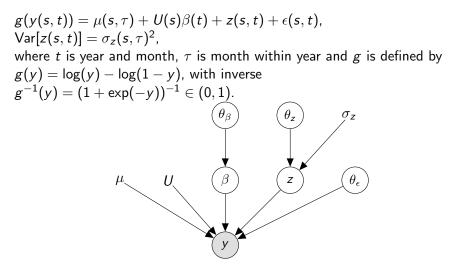
Figure: The first, second and fifth principal components.

$$g(y(s,t)) = \mu(s,\tau) + U(s)\beta(t) + z(s,t) + \epsilon(s,t),$$

$$g(y(s,t)) = \mu(s,\tau) + U(s)\beta(t) + z(s,t) + \epsilon(s,t),$$

Var[z(s,t)] = $\sigma_z(s,\tau)^2$,

$$\begin{split} g(y(s,t)) &= \mu(s,\tau) + U(s)\beta(t) + z(s,t) + \epsilon(s,t), \\ \text{Var}[z(s,t)] &= \sigma_z(s,\tau)^2, \\ \text{where } t \text{ is year and month, } \tau \text{ is month within year and } g \text{ is defined by} \\ g(y) &= \log(y) - \log(1-y), \text{ with inverse} \\ g^{-1}(y) &= (1 + \exp(-y))^{-1} \in (0,1). \end{split}$$



Observation level:

$$g(y)|\beta, z, \theta_{\varepsilon} \sim \mathcal{N}(\mu, \sigma_{z}\Sigma_{z} + \Sigma_{\varepsilon}).$$

Latent process level:

$$z| heta_z \sim \mathcal{N}(0, \Sigma_z).$$

- z is a Gaussian random field at any collection of points in space, distribution is jointly Gaussian
- Uniquely determined by mean and covariance functions
- Choose covariance to be:
 - Stationary only depends on relative position of two points
 - Isotropic only depends on Euclidean distance between two points

Gaussian Random Field

Simulate stationary isotropic gaussian random field, using SPDE model in INLA:

$$(\kappa^2 - \Delta)^{\frac{\alpha}{2}} z(u) = \mathcal{W}(u).$$

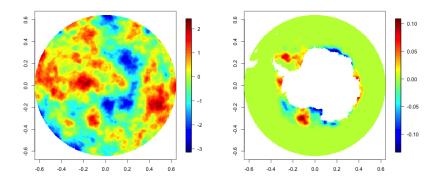
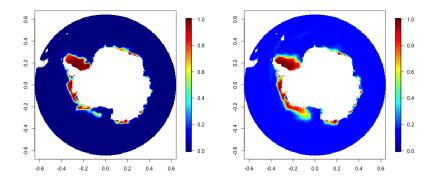


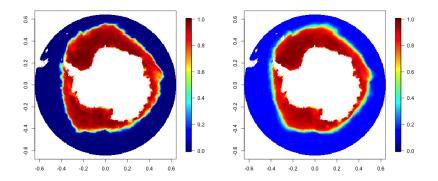
Figure: Stationary isotropic GRF (left) and GRF multiplied by standard deviation at each point in space (right)



(a) Observed sea ice concentrations February 1984.

(b) Simulated February sea ice concentrations.

Figure: Southern hemisphere sea ice concentrations for February.



(a) Observed sea ice concentrations August 1984.

(b) Simulated August sea ice concentrations.

Figure: Southern hemisphere sea ice concentrations for August.

- Current model is unable to predict changes in ice edge different from the data set
- Change what we model to concentration at a distance from coastline
- Express the distance from the coastline d as a function of the ice concentration c and the point on the coastline x; e.g. d(x, c) = sup{d : (ice concentration at the point x + d ⋅ n) ≥ c}.
- Coastline of Antarctica is not convex, so need to look at physical properties to determine direction

The Arctic

• Geographical features around the Arctic are more complicated:

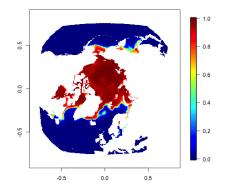
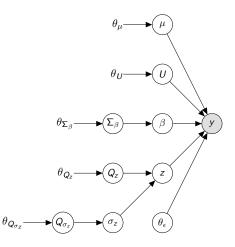


Figure: Observed ice concentrations in the northern hemisphere January 1981, where white space indicates land.

Improving the model



- Check model by using one decade of data to predict another, and vice versa
- Assign prior distributions to parameters and use Bayesian inference
- Model no longer jointly Gaussian means new computational challenges