

Regime-dependent modelling of extremes in the extra-tropical atmospheric circulation

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Workshop

*Non-equilibrium Statistical Mechanics
and the Theory of Extreme Events in Earth Science*
Isaac Newton Institute for Mathematical Sciences, Cambridge
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Outline

- 1 Introduction/Motivation
- 2 Statistics of extremes
- 3 Temporal clustering of extremes
- 4 Prediction of extreme events

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Extremes in the extra-tropical atmospheric circulation

- extremes of vorticity and wind speed
- hierarchy of scales in the atmosphere
- regime-dependent modelling, conditional on the large scales
- statistics, prediction and predictability of extremes
- data-driven methods from time series analysis and machine learning
- hierarchy of models of increasing complexity and realism

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Cluster-weighted modelling of threshold exceedances

Exceedance of a high threshold: $y = x - u$

Mixture of generalised Pareto distributions:

$$p(y|x > u, \mathbf{z}) = \sum_{i=1}^K g_i(\mathbf{z}) \text{GPD}_{\sigma_i, \xi_i}(y)$$

Clusters may be determined

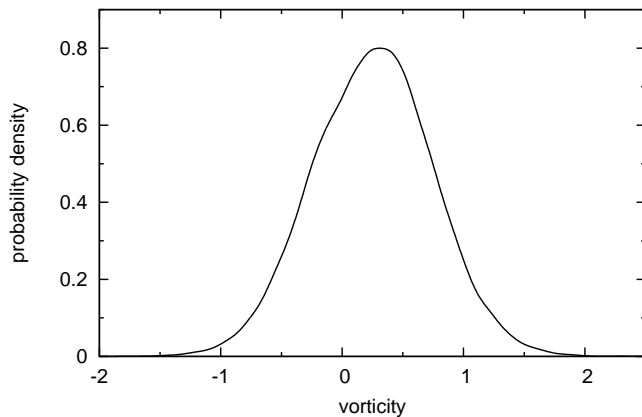
- separately using a Gaussian mixture model or hidden Markov model (persistent or metastable regimes)
- simultaneously with the extreme model

Parameter estimation via maximum likelihood with expectation-maximization (EM) algorithm

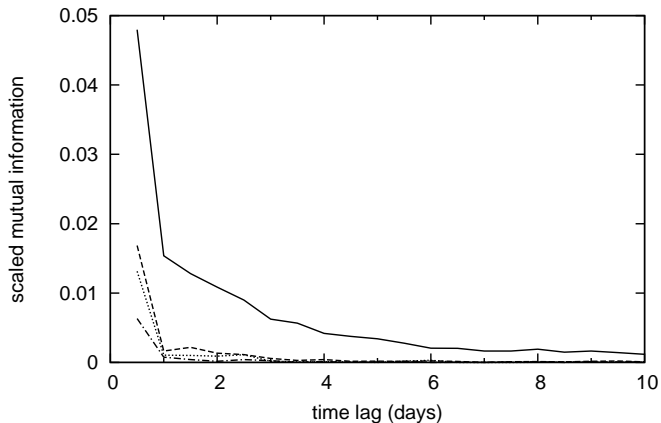
Intermediate-complexity atmospheric model

- Three-level quasi-geostrophic model on the Northern hemisphere
- Spectral truncation to T30
- Forcing determined from reanalysis data
- Realistic mean state and variability pattern
- Teleconnection patterns (PNA, NAO, ...)

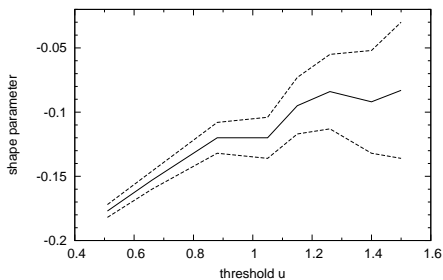
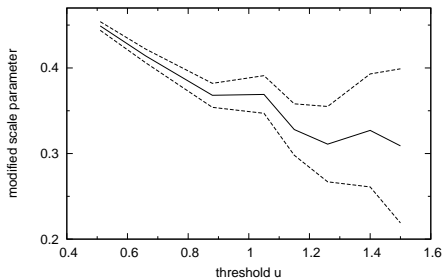
Vorticity at a grid point in the North Atlantic area



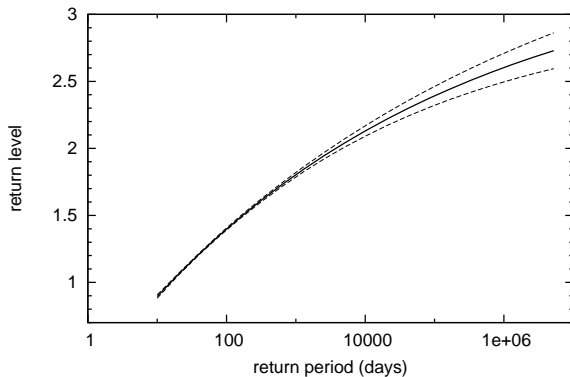
Temporal extremal dependence



GPD parameter estimation ($\sigma = 0.26$, $\xi = -0.10$)



Return level plot

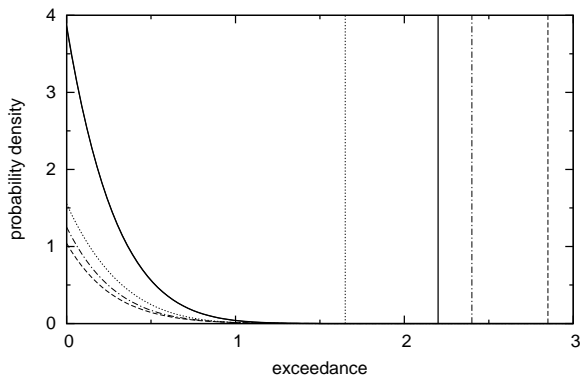


GPD for 3 clusters

$$\sigma_1 = 0.25, \xi_1 = -0.08$$

$$\sigma_2 = 0.25, \xi_2 = -0.11$$

$$\sigma_3 = 0.27, \xi_3 = -0.17$$

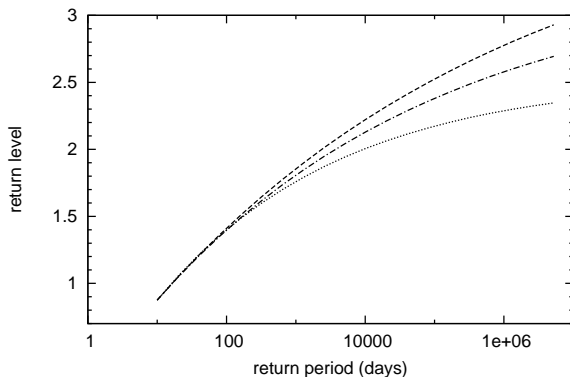


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Poisson process modelling of extremes

- extreme events often modelled as a Poisson process with rate parameter λ
- temporal clustering of extremes induced by
 - sampling variability
 - temporal variation in the rate parameter due to weather regimes
 - dependency between successive events
- inhomogeneous Poisson process whose rate parameter depends on large-scale flow variables

Cluster-weighted Bernoulli trial

Mixture of Bernoulli trial processes:

$$p(e = 1|\mathbf{z}) = \sum_{i=1}^K g_i(\mathbf{z}) \pi_i$$

As before, various options for determining the clusters.

Vorticity at a grid point / 3 clusters

π	π_1	π_2	π_3
0.050	0.083	0.062	0.027
0.020	0.047	0.022	0.009
0.010	0.025	0.008	0.003

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Regime-dependent prediction model for extremes

Predictive probability density:

$$p(e^\tau | \mathbf{z}^0) = \sum_{i=1}^K g_i(\mathbf{z}^0) p(e^\tau | \mathbf{z}^0, i)$$

with

$$g_i(\mathbf{z}^0) = p(i | \mathbf{z}^0) = \frac{w_i p(\mathbf{z}^0 | i)}{\sum_{j=1}^K w_j p(\mathbf{z}^0 | j)}$$

- prediction of individual extreme events at lead time τ
- relating to precursor patterns

Evaluation of forecasts

Characterisation

Utility:

$$R = \sum_{\alpha} f_{\alpha} \log(f_{\alpha}/b_{\alpha})$$

Probabilistic scores

Brier score:

$$\text{Br} = \sum_{\alpha} (f_{\alpha} - e_{\alpha})^2$$

Ignorance score:

$$\text{ign} = -\log f_{\alpha}$$

Extremes of energy in a barotropic atmospheric model

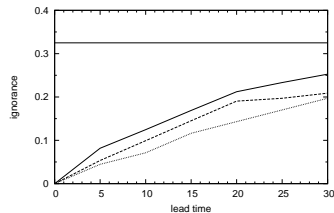
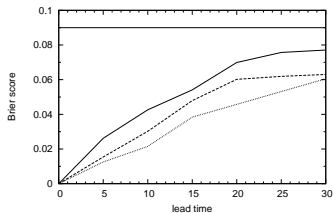
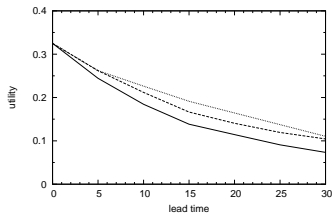
Gaussian clustering:

$$p(\mathbf{x}|i) \sim \mathcal{N}(\boldsymbol{\mu}_i, \boldsymbol{\Gamma}_i)$$

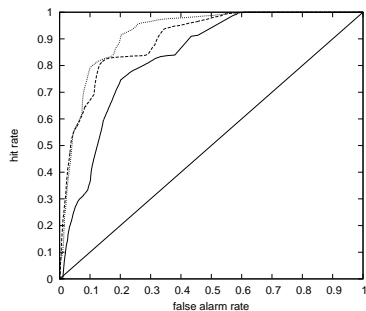
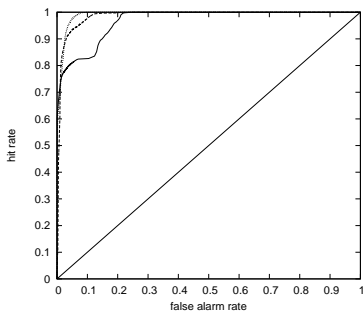
Locally constant predictive model:

$$p(e_1^\tau|i) = \rho_i$$

Utility, Brier score and ignorance score for $b = 0.1$



ROC curves for $b = 0.1$ and $\tau = 10, 30$



Model parameters

$b = 0.05$, $\tau = 25$, $K = 10$:

$$w_1 = 0.124, \rho_1 = 0.340$$

$$w_2 = 0.073, \rho_2 = 0.038$$

$$w_3 = 0.082, \rho_3 = 0.021$$

$$w_4 = 0.104, \rho_4 = 0.018$$

$$w_5 = 0.078, \rho_5 = 0.010$$

$$w_6 = 0.126, \rho_6 = 0.003$$

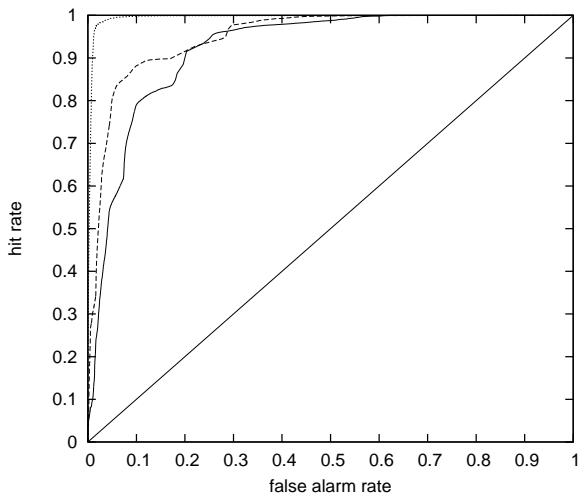
$$w_7 = 0.158, \rho_7 = 0.000$$

$$w_8 = 0.103, \rho_8 = 0.000$$

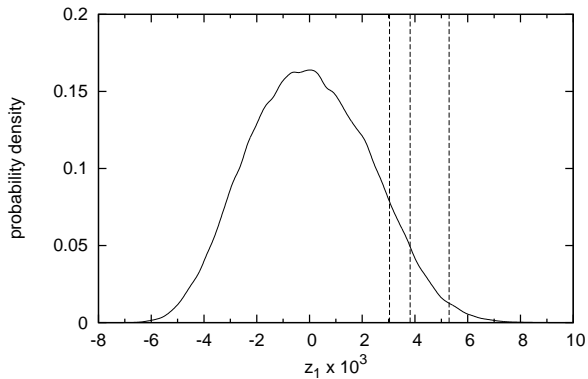
$$w_9 = 0.081, \rho_9 = 0.000$$

$$w_{10} = 0.072, \rho_{10} = 0.000$$

ROC curves for different event rarity; $\tau = 30$, $K = 15$



Large-scale extremes in a QG atmospheric model



Extreme model

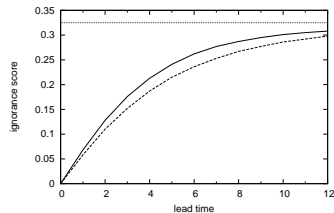
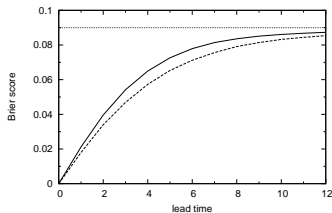
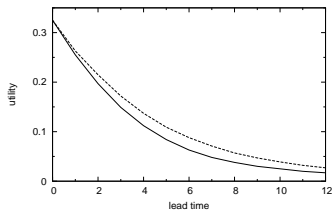
Gaussian clustering in EOF space:

$$p(\mathbf{z}|i) \sim \mathcal{N}(\boldsymbol{\mu}_i, \boldsymbol{\Gamma}_i)$$

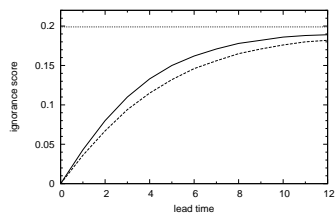
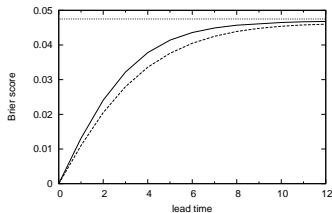
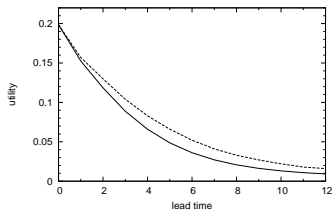
Logistic regression as predictive model:

$$p(e_1^T | \mathbf{z}, i) = \frac{1}{1 + \exp(-\sum_{m=1}^M \beta_{i,m} z_m)}$$

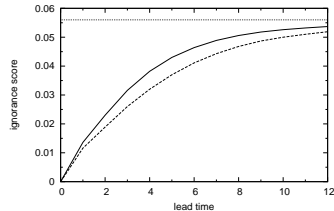
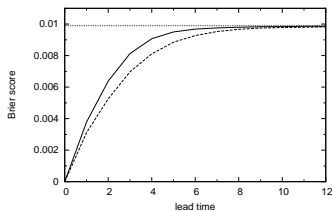
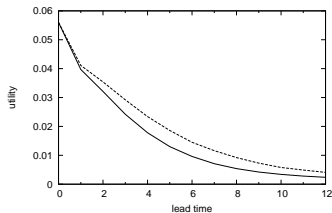
Utility, Brier score and ignorance score for $b = 0.1$



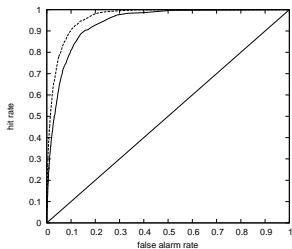
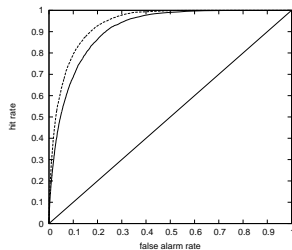
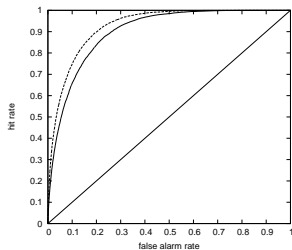
Utility, Brier score and ignorance score for $b = 0.05$



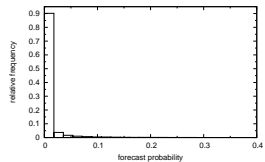
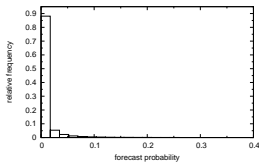
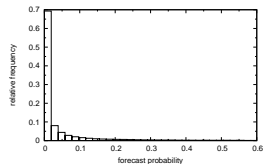
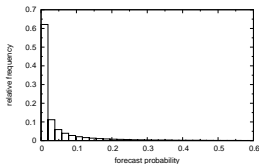
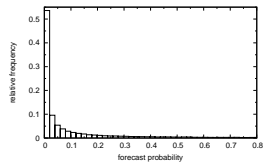
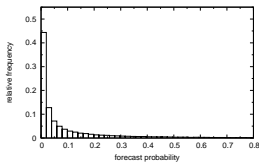
Utility, Brier score and ignorance score for $b = 0.01$



ROC curves for $b = 0.1$, $b = 0.05$ and $b = 0.01$



Distributions of forecasts



ROC curves for different event rarity; $b = 0.1$, $b = 0.05$ and $b = 0.01$

