

# The Extreme Team

## ITT 17

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- 1 Introduction
- 2 Data exploration + model fitting
- 3 BEAST - Mann Kendall test
- 4 Changing dependence
- 5 Future work

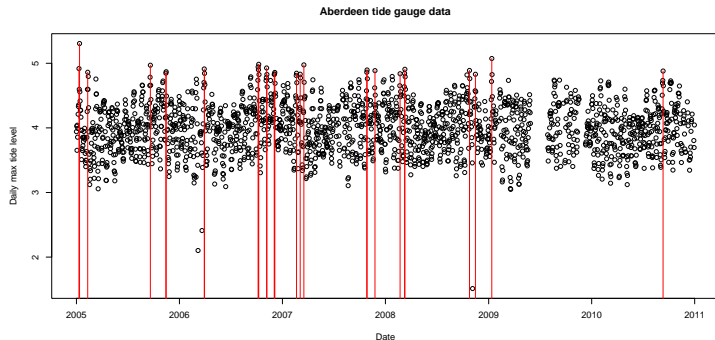
## Overview

- We are investigating extreme values in tidal levels
- Data: British Oceanographic Data Centre (BODC) coastal tidal gauge data
- What are we looking at
  - ▶ GEV (Generalised Extreme Value Distribution)
  - ▶ Detecting change-point, trend, and seasonality in monthly maxima
  - ▶ Spatial correlation between tide gauges

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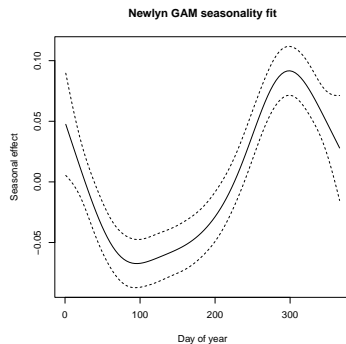
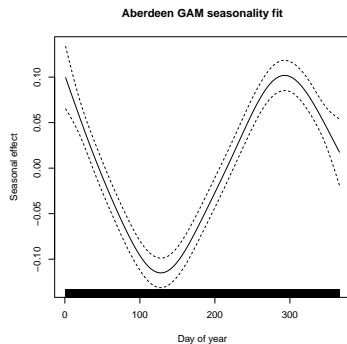
## BODC coastal tide gauge data

- The raw data from BODC contains data points marked with "T" (interpolated) or "M" (unlikely)
- We remove these data points and consider the daily maxima of the remaining data (to remove daily tidal effects)



Aberdeen daily maximum tide level, with values exceeding the 99% quantile marked in red.

## Removing seasonality using GAM

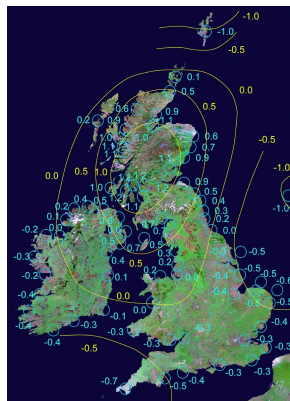


Fitting a GAM to the seasonal component of daily max tide gauge data.

- There is an effect on the mean daily maxima due to day of the year!

## Adjusting for land movement

- Land movement (rising/sinking) will affect tide gauge measurements since the tide level is measured relative to land
- For Aberdeen: 0.6mm/year (land rising!)
- For Newlyn: -0.6mm/year (land sinking!)



Land movement data <sup>a</sup>

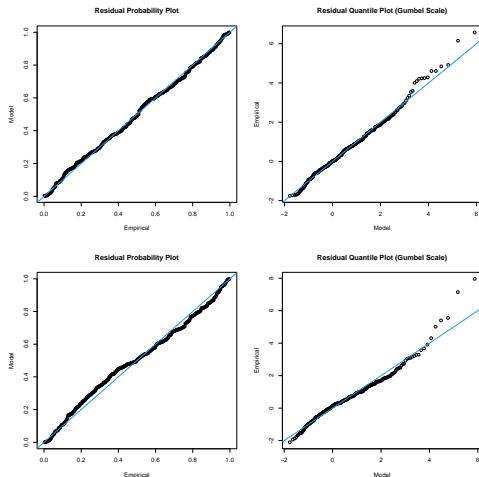
<sup>a</sup>See Shennan, Milne, and Bradley (2011)  
<https://doi.org/10.1002/jqs.1532>

## Fitting GEV model

- We remove the seasonal effect as fitted by the GAM model, and also adjust for land movement
- We calculate the monthly maxima of the daily data
- Then we can fit a Generalised Extreme Value (GEV) model:
  - ▶ Without trend:  $y_i \sim GEV(\mu, \sigma, \xi)$
  - ▶ With trend only in  $\mu$ :  $y_i \sim GEV(\mu_0 + \mu_1 x_i, \sigma, \xi)$
  - ▶ With trend only in  $\sigma$ :  $y_i \sim GEV(\mu_0, \sigma_0 + \sigma_1 x_i, \xi)$
  - ▶ With trend in both  $\mu$  and  $\sigma$ :  $y_i \sim GEV(\mu_0 + \mu_1 x_i, \sigma_0 + \sigma_1 x_i, \xi)$
- In the above,  $x$  is the time of an observation, expressed as the number of years after 1990



## Fitting GEV model



Diagnostic plots from fitting the best version of the GEV model in terms of AIC. **Top:** Newlyn - model with drift only in  $\mu$ . **Bottom:** Aberdeen - model with drift in both  $\mu$  and  $\sigma$ .

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## Let's deal with the BEAST

BEAST: Bayesian Estimator of Abrupt change, Seasonal change, and Trend.

We have data  $\mathcal{D} = \{(y_i, t_i)\}_{i=1}^n$ . Proposed model:

$$\hat{y}(t_i) = \underbrace{S(t_i)}_{\text{piecewise harmonic model}} + \underbrace{T(t_i)}_{\text{piecewise linear model}}$$

$$S(t_i) = \sum_{l=1}^{L_k} \left[ a_{k,l} \cdot \sin\left(\frac{2\pi l t_i}{P}\right) + b_{k,l} \cdot \cos\left(\frac{2\pi l t_i}{P}\right) \right]$$

$$T(t_i) = a_j + b_j t_i$$

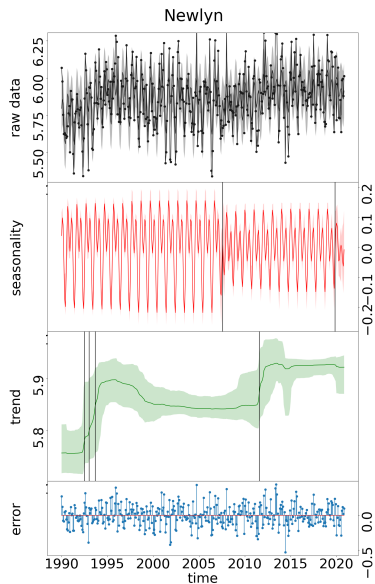
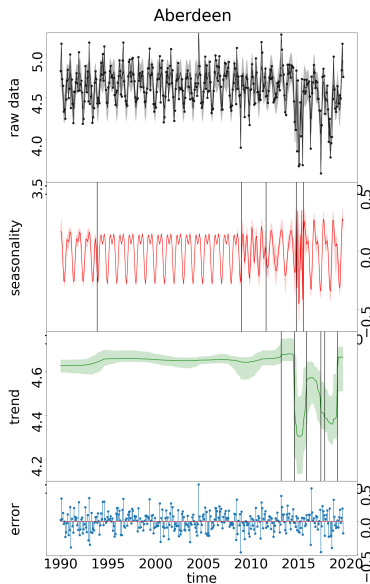
$$y_i = \hat{y}(t_i) + \underbrace{\epsilon_i}_{\mathcal{N}(0, \sigma^2)}$$

The posterior looks like this:

$$P(\Theta | \mathcal{D}) = P(\mathcal{D} | \Theta) \cdot \pi(\Theta) = \prod_{i=1}^n \mathcal{N}(y_i; \hat{y}(t_i; \Theta), \sigma^2) \cdot \pi(\Theta)$$

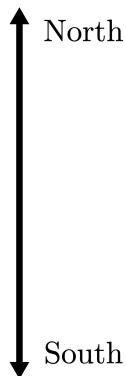
Bayesian model  $\rightarrow$  best values of parameters

## Let's deal with the BEAST



## Seasonal Mann Kendall test - Trends for different cities in the UK

City	Trend
Wick	-
Aberdeen	-
North Shields	-
Immingham	↓
Liverpool	-
Lowestoft	-
Portsmouth	↑
Bournemouth	-
Weymouth	-
Devonport	-
Newlyn	↑



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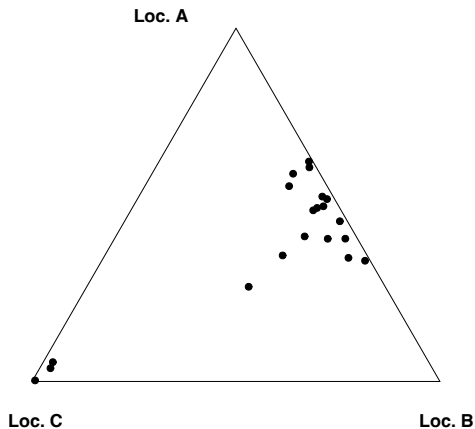
## Detecting changes in extremal dependence

"A changing climate leads to changes in frequency, severity [and] **spatial extent** . . . of climate extremes and can result in unprecedented extremes."

— IPCC 2018 report

- How are spatial patterns in UK flooding changing over time?
- What are the implications for flood risk mitigation?

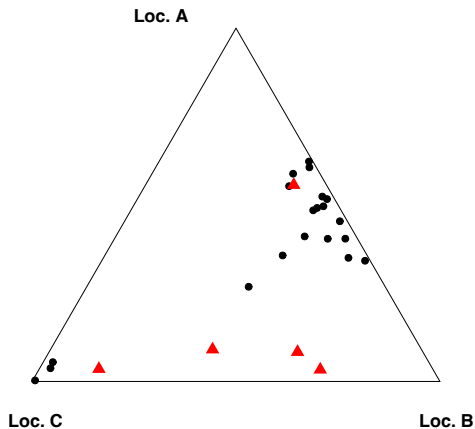
## What is a change in extremal dependence?



Historical data shows extremes hit A and B jointly, or C singly.



## What is a change in extremal dependence?



Newly observed events hit B and C jointly.

## What exists and what doesn't

- Hyp. test for non-constant dependence with  $d = 2$  locations (Drees 2022).
- DAMEX algorithm detects abnormal extremes, even for large  $d$  (Goix 2017).

**Develop an algorithm for modelling (high-dimensional) extremes with non-constant dependence.**

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## Directions for future work

- Further extend fitting of Generalised Extreme Value distribution – include additional covariates to improve model fit
- How to extrapolate to improve predictions on extreme events.
- How to include the Generalised Extreme Value distribution in the BEAST framework.
- Make predictions of e.g. Value at Risk and Expected Shortfall/Conditional Value at Risk using the GEV model, and test quality of predictions
- Spatial dependence - develop models that permit changing dependence structure; apply to UK coastal/river flooding data.

Thanks!  
Any Questions?