

# A clustering framework for conditional extremes models

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**UK Research  
and Innovation**

# Introduction

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# Problem

- Often want to estimate

$$\mathbb{P}(X > x, Y > y) = \mathbb{P}(Y > y \mid X > x)\mathbb{P}(X > x)$$

for large  $x, y$

- “concomitant”/concurrent extreme events for random vector  $\mathbf{X}$  often particularly devastating
- Goal: identify trends by clustering sites with similar tail dependence

# Dependence Modelling

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# Asymptotic dependence

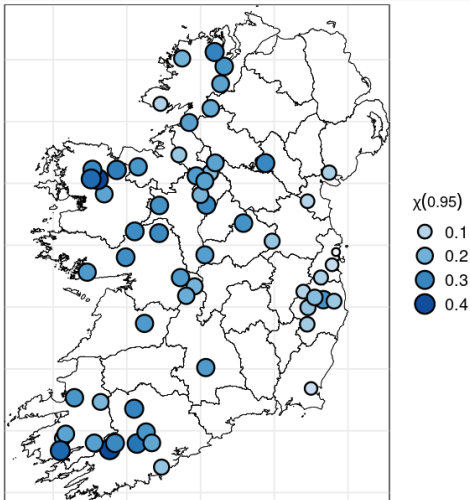
- Coefficient of extremal dependence  $\chi \in [0, 1]$ ,

$$\chi = \lim_{u \rightarrow 1} \mathbb{P}[F_1(X_1) > u \mid F_2(X_2) > u]$$

- (Increasingly strong) asymptotic dependence for  $\chi > 0$ .
- However,  $\chi$  only gives summary; inference requires **dependence model**.

# Ireland

- Precipitation<sup>1</sup> & wind speed<sup>2</sup> data for 59 sites across Ireland, Winter months (Oct-Mar) 1990-2020



<sup>1</sup> Met Éireann weekly aggregate

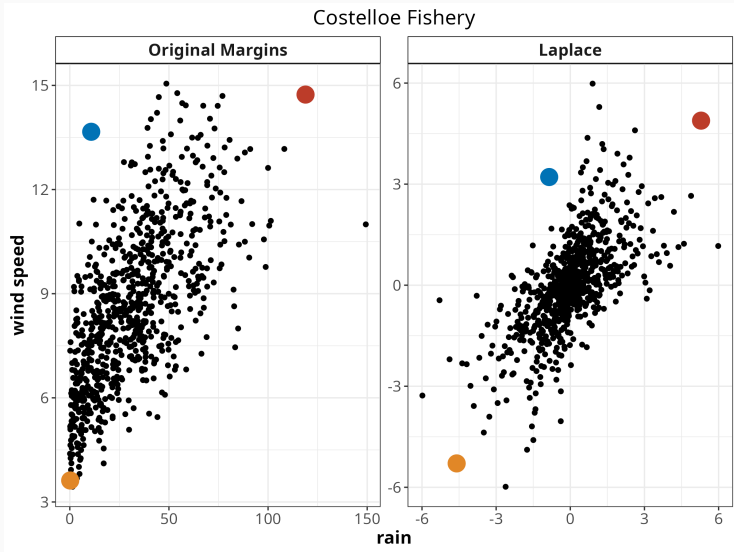
<sup>2</sup> ERA5 reanalysis weekly mean of daily maxima

## Conditional extremes

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# Marginal transformation



- Heteroskedastic regression dependence model:

$$(Y \mid X = x) = \alpha x + x^\beta Z, \text{ for } x > u$$

- slope parameter  $\alpha$  for  $Y$  given large  $X$ ,
- “spread” parameter  $\beta \in (-\infty, 1]$  controls stochasticity of relationship between  $Y$  and large  $X$ .

# Conditional extremes

- Heteroskedastic regression dependence model:

$$(Y_{-i} \mid Y_i = y_i) = \alpha_{ji} y_i + y_i^{\beta_{ji}} Z_{ji}, \text{ for } y_i > u_{Y_i}$$

- slope parameter  $\alpha_{ji} \in [-1, 1]$  for  $Y_j$  given large  $Y_i$ ,
- “spread” parameter  $\beta_{ji} \in (-\infty, 1]$  controls stochasticity of relationship between  $Y_j$  and large  $Y_i$ .

# Conditional extremes

- Heteroskedastic regression dependence model:

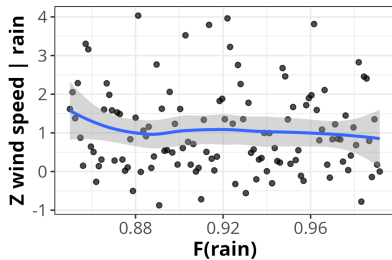
$$(Y_{-i} \mid Y_i = y_i) = \alpha_{|i} y_i + y_i^{\beta_{|i}} Z_{|i}, \text{ for } y_i > u_{Y_i}$$

- slope parameter  $\alpha_{j|i} \in [-1, 1]$  for  $Y_j$  given large  $Y_i$ ,
- “spread” parameter  $\beta_{j|i} \in (-\infty, 1]$  controls stochasticity of relationship between  $Y_j$  and large  $Y_i$ .
- Key assumptions:
  - Residuals  $Z_{|i} \sim N(\mu_{|i}, \Sigma_{|i})$
  - $Z_{|i}, Y_i$  conditionally independent for large  $Y_i$
- Special cases:
  - $\alpha_{|i} = 0, \beta_{|i} = 0 \implies Y_{-i}, Y_i$  independent,
  - $\alpha_{|i} = -1/1, \beta_{|i} = 0 \implies$  perfect positive/negative dependence,
  - $-1 < \alpha_{|i} < 1 \implies$  asymptotic independence

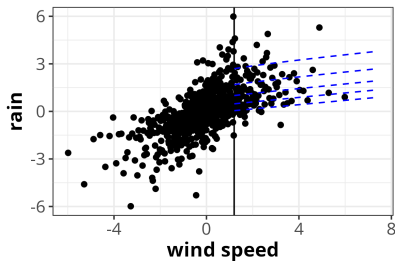
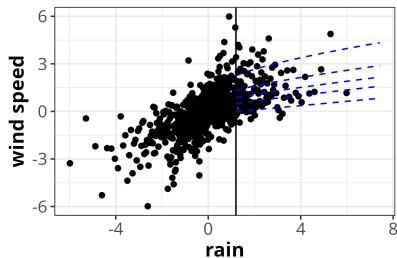
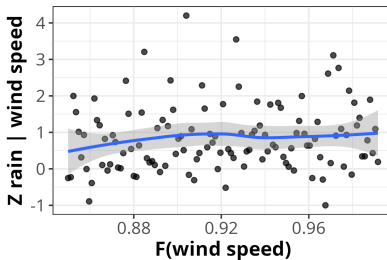
# Conditional extremes

## Costelloe Fishery

$a = 0.137, b = 0.052$



$a = 0.147, b = 0.243$



Inference assumes conditional distribution follows a multivariate Normal (MVN) distribution:

$$(Y_{-i} \mid Y_i = y_i) \sim N \left( \alpha_{|i} y_i + y_i^{\beta_i} \mu_{|i}, y_i^{\beta_i} \Sigma_{|i} \right), \text{ for } Y_i > u_{Y_i}$$

$\implies$  dependence structures at different sites can be compared using their MVN distributions

# Clustering

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