

# Functional Median Polish, with Climate Applications

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Based on joint work with Ying Sun

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# Functional Median Polish

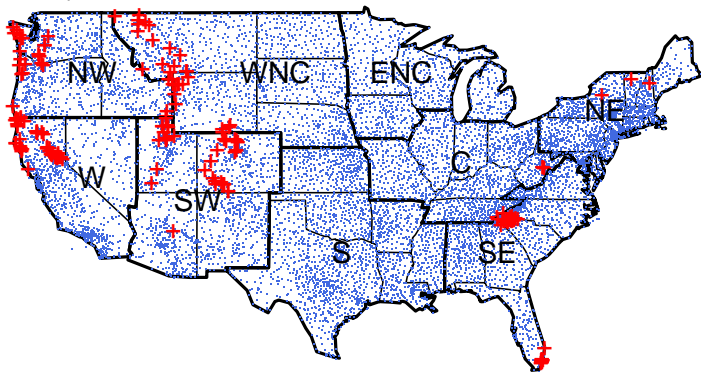
- 1 Motivation
- 2 Univariate ANOVA
- 3 Functional ANOVA
- 4 Simulation Studies
- 5 Applications
- 6 Discussion

# Observations and Climate Models

- Observations:
  - provide a corroborating source of information about physical processes being modeled.
  - have methodological and practical issues due to uncertainties.
- Climate Models:
  - numerically solve systems of differential equations representing physical relationships in the climate system.
  - have huge uncertainties and biases.
- Scientific Questions:
  - How do we compare sources of variability in observations or climate model outputs? i.e. quantification of uncertainties?

# Spatio-Temporal Precipitation Data

- Spatio-temporal precipitation data: annual total precipitation data for U.S. from 1895 to 1997 at 11,918 weather stations.
- Nine climatic regions for precipitation defined by National Climatic Data Center.
- Several areas of outliers detected by Sun and Genton (2011, 2012).



# Analysis of Variance

- Analysis of Variance (ANOVA):
  - An important technique for analyzing the effect of categorical factors on a response.
  - It decomposes the variability in the response variable among the different factors.
  - A two-way additive model: for  $i = 1, \dots, r, j = 1, \dots, c$ ,

$$y_{ij} = \mu + \alpha_i + \beta_j + \epsilon_{ij}.$$

- The ANOVA model can be fitted by arithmetic means (no outliers), or medians (robust).

## ANOVA Model Fitting

- Fitted by means:
  - $\hat{\mu} = \bar{y}$  (grand effect),
  - $\hat{\alpha}_i = \bar{y}_{i.} - \bar{y}$  (row effect),
  - $\hat{\beta}_j = \bar{y}_{.j} - \bar{y}$  (column effect).
- Fitted by medians:
  - Median polish (Tukey, 1970, 1977).
  - An iterative technique for extracting row and column effects in a two-way table using medians rather than means.
  - It stops when no more changes occur in the row and column effects, or changes are sufficiently small.

# Median Polish Example

- 1 Original table: find row medians.
- 2 1st iteration: subtract row medians, find column medians. Grand median in red, row effects in blue, column effects in green.
- 3 2nd iteration: subtract column medians, find row medians,

$$\begin{array}{ccc|c}
 6 & 3 & 11 & 6 \\
 3 & 2 & 4 & 3 \\
 9 & 0 & 0 & 0
 \end{array}
 \rightarrow
 \begin{array}{ccc|c}
 0 & -3 & 5 & 6 \\
 0 & -1 & 1 & 3 \\
 9 & 0 & 0 & 0 \\
 \hline
 0 & -1 & 1 & 3
 \end{array}
 \rightarrow
 \begin{array}{ccc|c}
 0 & -2 & 4 & 0 \\
 0 & 0 & 0 & 0 \\
 9 & 1 & -1 & 1 \\
 \hline
 0 & -1 & 1 & 0
 \end{array}
 \begin{array}{c}
 3 \\
 0 \\
 -3 \\
 3
 \end{array}
 \rightarrow$$

- 4 subtract new row medians, add their medians to the grand median, find column medians.
- 5 Polished table: new row and column medians are zero after two iterations.

$$\begin{array}{ccc|c}
 0 & -2 & 4 & 3 \\
 0 & 0 & 0 & 0 \\
 8 & 0 & -2 & -3 \\
 \hline
 0 & 0 & 0 & 0 \\
 \hline
 0 & -1 & 1 & 3+0
 \end{array}
 \rightarrow
 \begin{array}{ccc|c}
 0 & -2 & 4 & 3 \\
 0 & 0 & 0 & 0 \\
 8 & 0 & -2 & -3 \\
 \hline
 0 & -1 & 1 & 3
 \end{array}$$

# Functional Median Polish

- Observe functional data at each combination of two categorical factors.
- Examine their effects: functional row or column effects.
- $y_{ijk}(x) = \mu(x) + \alpha_i(x) + \beta_j(x) + \epsilon_{ijk}(x)$ , where  $i = 1, \dots, r$ ,  $j = 1, \dots, c$ ,  $k = 1, \dots, m_{ij}$ .
- Constraints:  $\text{median}_i\{\alpha_i(x)\} = 0$ ,  $\text{median}_j\{\beta_j(x)\} = 0$  and  $\text{median}_i\{\epsilon_{ijk}(x)\} = \text{median}_j\{\epsilon_{ijk}(x)\} = 0$  for all  $k$ .
- $x$  can be time for curves or spatial index for surfaces/images.
- Iterative procedure sweeping out column and row medians.
- One-way functional ANOVA can be done in a similar way.
- Need to order functional data.

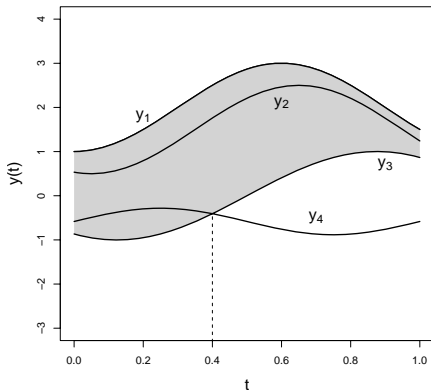


## Multivariate Ordering

- Basic ideas of depth in functional context
  - provides a method to order sample curves according to decreasing depth values,
  - $y_{[1]}$ : the deepest (most central or median) curve,
  - $y_{[n]}$ : the most outlying (least representative) curve,
  - $y_{[1]}, \dots, y_{[n]}$ : start from the center outwards.
- Usual order statistics: ordered from the smallest sample value to the largest.

# Band Depth for Functional Data

- López-Pintado and Romo (2009) introduced the band depth (BD) concept through a graph-based approach.
- Grey area: band determined by two curves,  $y_1$  and  $y_3$ .
- Contains the curve  $y_2$ , but does not contain  $y_4$ .



## Band Depth for Functional Data

- Population version of  $BD^{(2)}$ :

$$BD^{(2)}(y, P) = P\{G(y) \subset B(Y_1, Y_2)\}.$$

- $G(y)$ : graph of the curve  $y$ ,
  - $B(Y_1, Y_2)$ : band delimited by 2 random curves.
- The band could be delimited by more than 2 random curves,

$$BD_J(y, P) = \sum_{j=2}^J BD^{(j)}(y, P).$$

## Sample Band Depth

- Population level:  $BD^{(j)}(y, P)$  is a probability.
- Sample version of  $BD^{(j)}(y, P)$

$$BD_n^{(j)}(y) = \binom{n}{j}^{-1} \sum_{1 \leq i_1 < i_2 < \dots < i_j \leq n} I\{G(y) \subseteq B(y_{i_1}, \dots, y_{i_j})\},$$

- $I\{\cdot\}$ : the indicator function,
- fraction of the bands completely containing the curve  $y$ .
- Sample BD:  $BD_{n,J}(y) = \sum_{j=2}^J BD_n^{(j)}(y)$ .

## Modified Band Depth

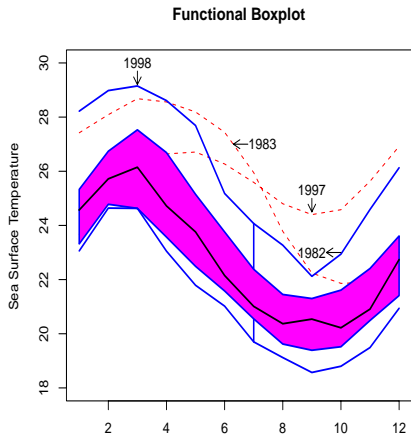
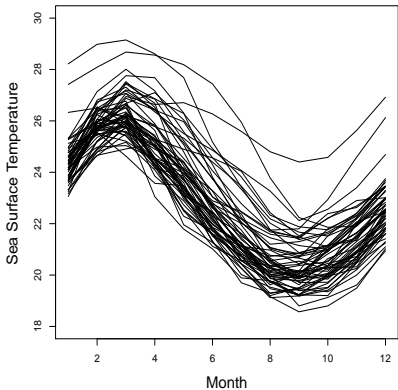
- López-Pintado and Romo (2009) also proposed a more flexible definition, the modified band depth (MBD).

$$BD_n^{(j)}(y) = \binom{n}{j}^{-1} \sum_{1 \leq i_1 < i_2 < \dots < i_j \leq n} I\{G(y) \subseteq B(y_{i_1}, \dots, y_{i_j})\},$$

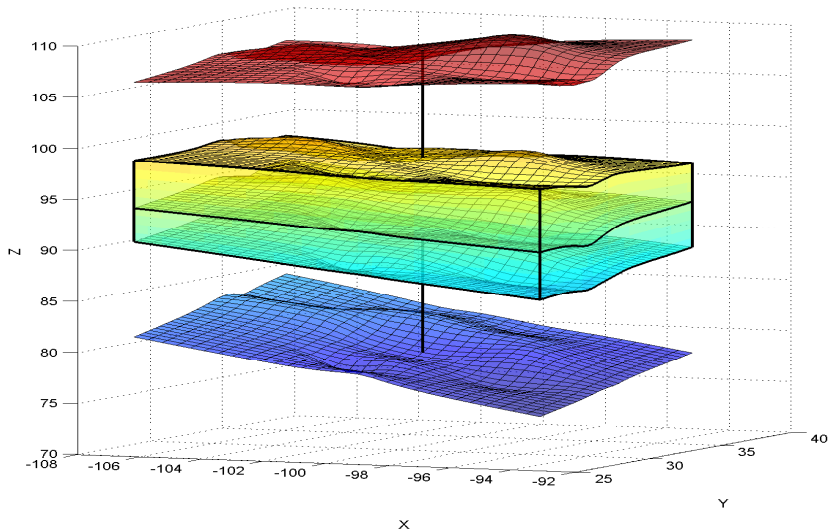
$$MBD_n^{(j)}(y) = \binom{n}{j}^{-1} \sum_{1 \leq i_1 < i_2 < \dots < i_j \leq n} \lambda_r\{A(y; y_{i_1}, \dots, y_{i_j})\}.$$

- $\lambda_r\{A(y; y_{i_1}, \dots, y_{i_j})\}$  measures the proportion of time that a curve  $y$  is in the band.

# Functional Boxplots (Sun and Genton, 2011, 2012)

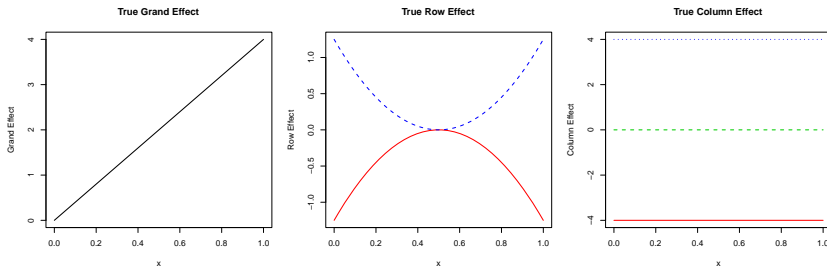


# Surface Boxplot



## True Model

- Generate data from a true model with  $r = 2$ ,  $c = 3$ , and  $m = 100$  curves in each cell at  $p = 50$  time points.

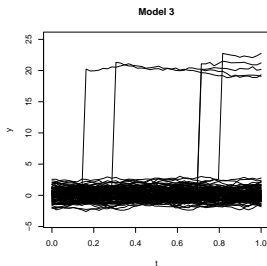
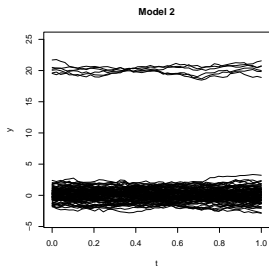
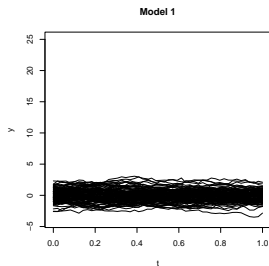


- Introduce outliers through a Gaussian process  $\epsilon_{ijk}(t)$ .
- Replications: 1,000.

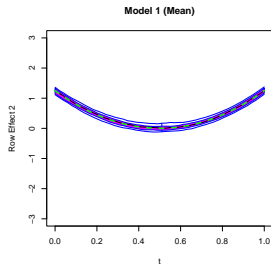
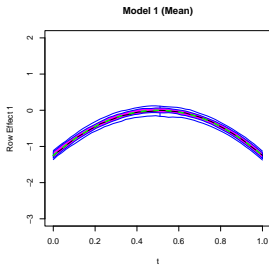
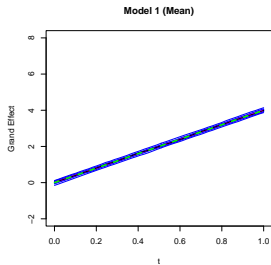
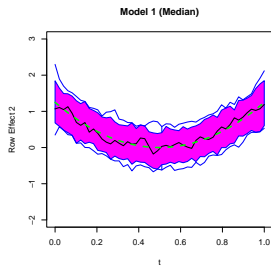
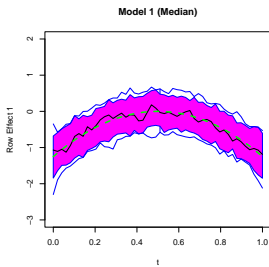
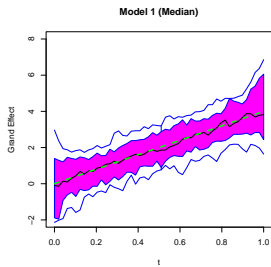


# Outlier Models

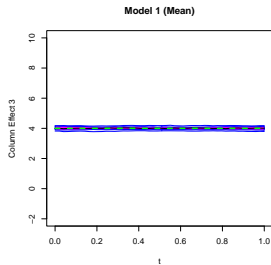
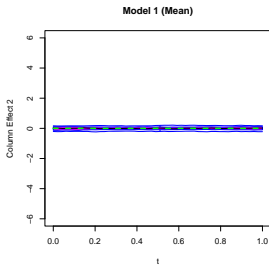
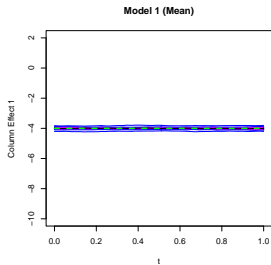
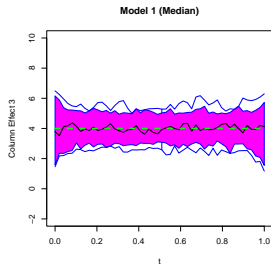
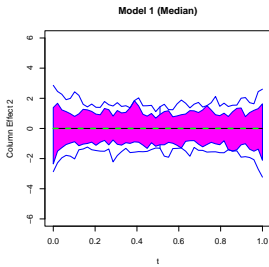
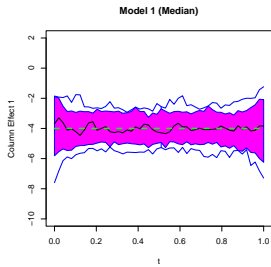
- Model 1:  $\epsilon_{ijk}(t) = e_{ijk}(t)$ , where  $e_{ijk}(t) \sim GP(0, \gamma)$  with  $\gamma(t_1, t_2) = \exp\{-|t_2 - t_1|\}$ .
- Model 2:  $\epsilon_{ijk}(t) = e_{ijk}(t) + c_{ijk}K$ , where  $c_{ijk}$  is 1 with prob  $q_{ij}$  and 0 with prob  $1 - q_{ij}$ ,  $q_{ij}$  is different for each cell.
- Model 3:  $\epsilon_{ijk}(t) = e_{ijk}(t) + c_{ijk}K$ , if  $t \geq T_{ijk}$  and  $\epsilon_{ijk}(t) = e_{ijk}(t)$ , if  $t < T_{ijk}$ , where  $T_{ijk} \sim U(0, 1)$ .



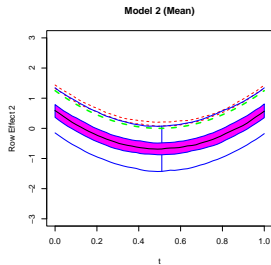
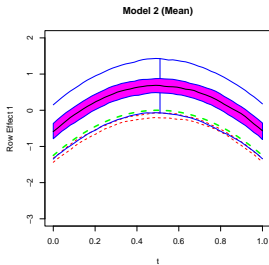
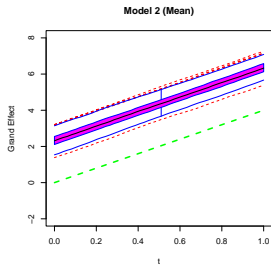
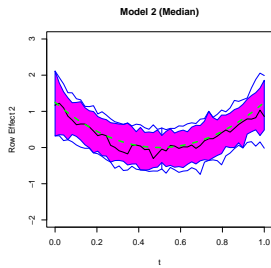
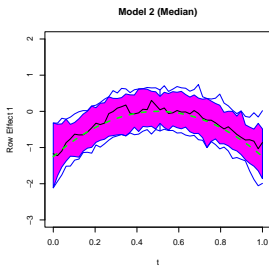
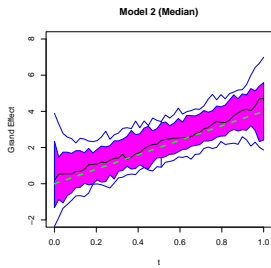
# Simulations: Model 1



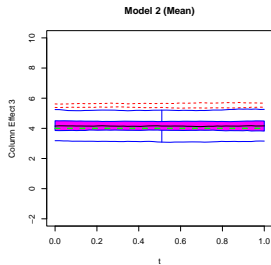
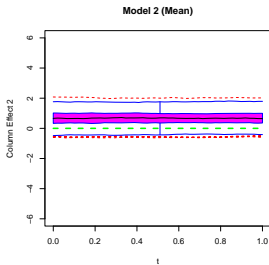
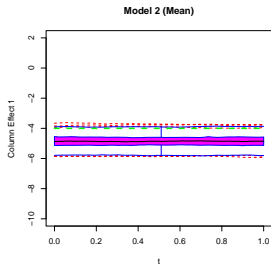
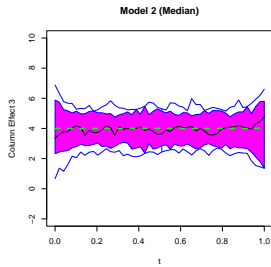
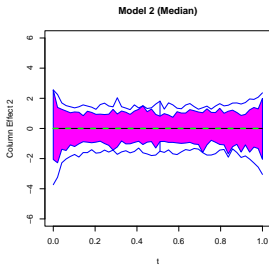
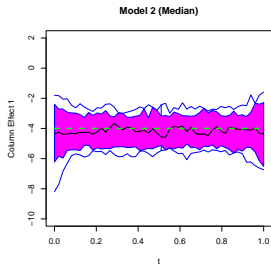
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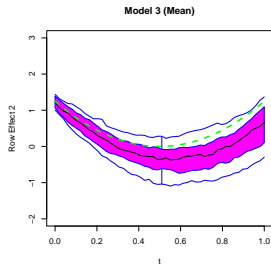
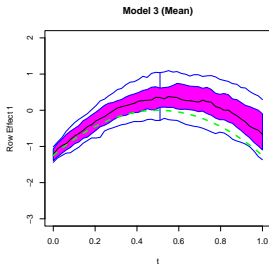
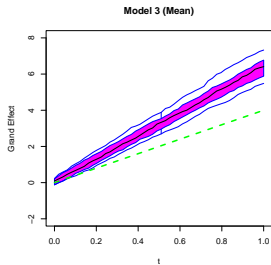
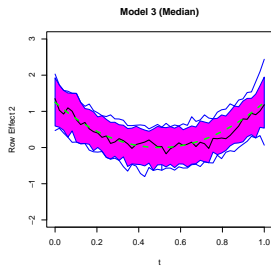
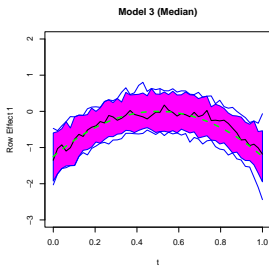
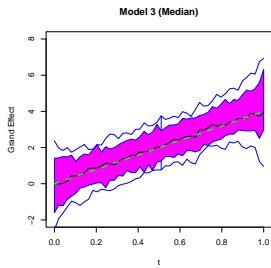
# Simulations: Model 2



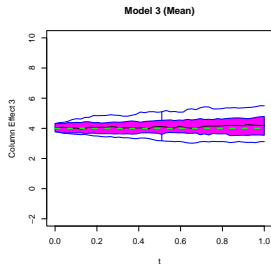
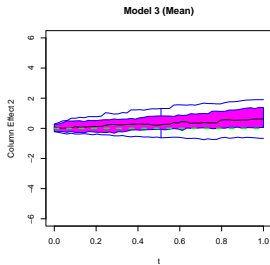
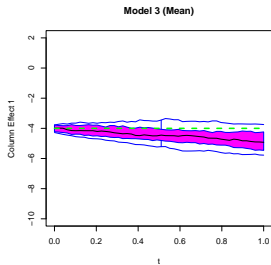
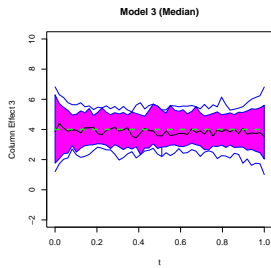
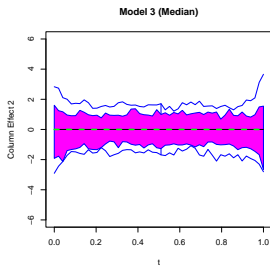
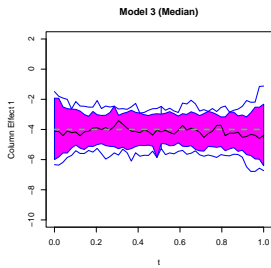
# Simulations: Model 2



# Simulations: Model 3

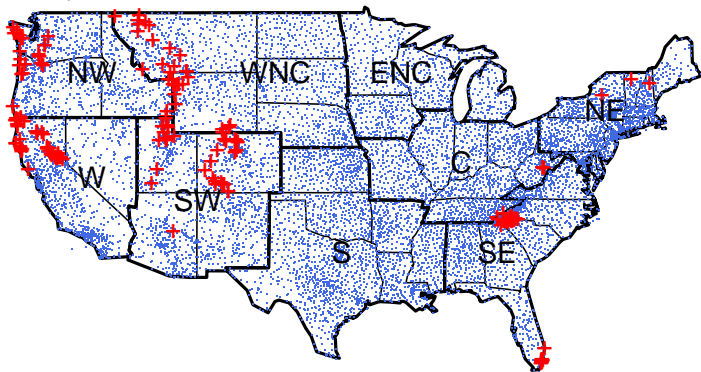


# Simulations: Model 3



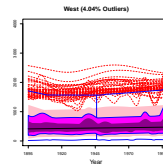
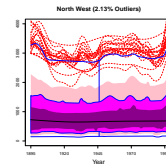
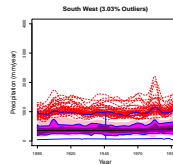
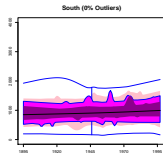
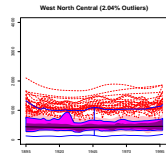
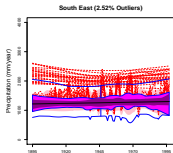
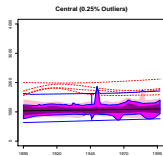
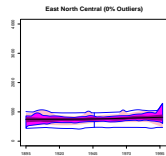
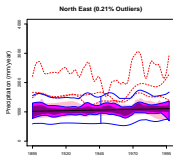
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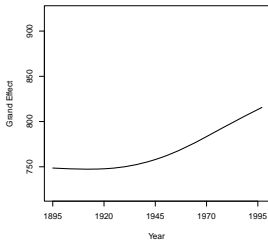


# Functional Boxplots for Nine Climatic Regions

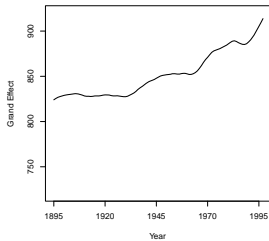


# Climatic Region Effects

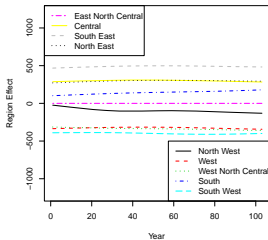
Weather Station (Median)



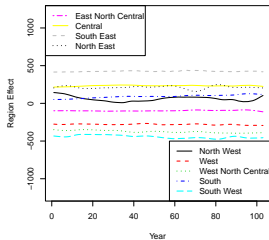
Weather Station (Mean)



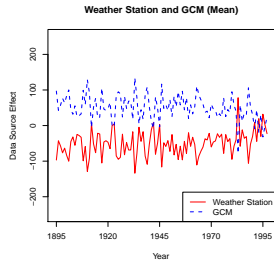
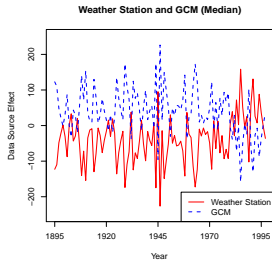
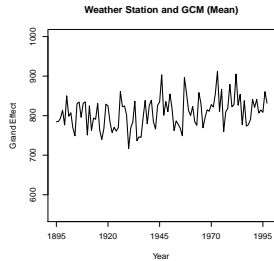
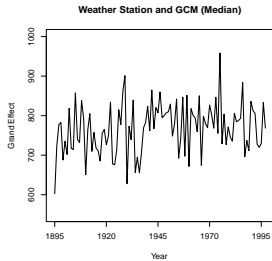
Weather Station (Median)



Weather Station (Mean)



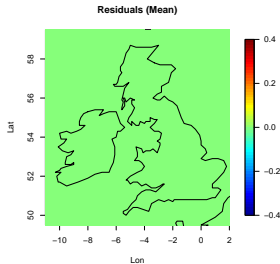
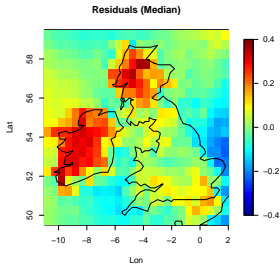
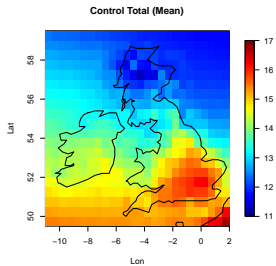
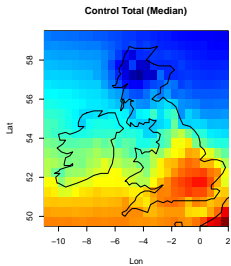
# Weather Station and GCM Effects



# UK and Ireland Temperatures

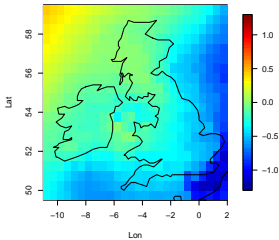
- Regional Climate Model (RCM): has higher resolution, covers a limited area of the globe.
- The boundaries of RCM are driven by variables output from a global climate model (GCM).
- Question: how much variability in the model output is from RCM and how much is due to the boundary conditions from GCM.
- Functional ANOVA: Kaufman and Sain (2010) proposed a mean-based Bayesian framework for spatial data.
- Data: PRUDENCE project (Christensen, Carter, and Giorgi 2002), consists of control runs (1961-1990).
- Two factors: RCM (HIRHAM and RCAO), GCM (ECHAM4 and HadAm3H).

# Grand Effect and Residuals

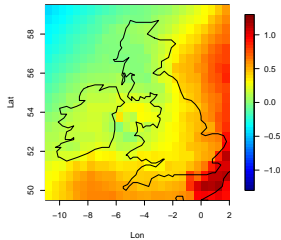


# GCM and RCM Effects

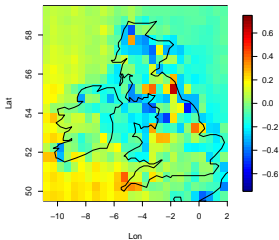
Control GCM: ECHAM4 (Median)



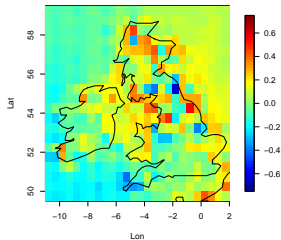
Control GCM: HadAM3H (Median)



Control RCM: HIRHAM (Median)



Control RCM: RCAO (Median)



## Discussion

- Functional Median Polish: robust functional ANOVA fitted by functional median.
- Band depth: graph-based nonparametric ordering for functional/image data (e.g. median image).
- The functional median polish algorithm does not guarantee to yield the least  $L_1$ -norm residuals.
- Fink (1988) proposed a rather complex modification of the classical procedure that converges to the least  $L_1$ -norm residuals.