Modeling Compound Wind/Precipitation Extremes Using a Large Climate Model Ensemble

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PACIFIC CLIMATE IMPACTS CONSORTIUM

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CANSSI INCASS

Plan for the (first) manuscript

1. Submit to *Extremes* on 6/15, special issue of climate/weather extremes
2. Tentative title: "Modeling Compound Wind/Precipitation Extremes Using the CanRCM4 Climate Model Large Ensemble"
3. Main ingredients:
   - Modeling multivariate (bivariate) extremes while considering/incorporating the timing information (event simultaneity)
   - Investigating the distributional properties of wind/precip compound extremes (spatial pattern, seasonality, climate change, ...) using the full ensemble
   - Using this Large Ensemble to assess the statistical performance of the proposed/existing methods when only one model run is available
4. Link to manuscript draft: https://www.overleaf.com/2534124115vwwbhpsvpfbb

Compound wind/precipitation extreme events

Source: www.standardmedia.co.ke

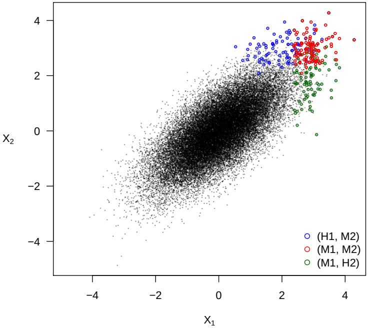
The problem

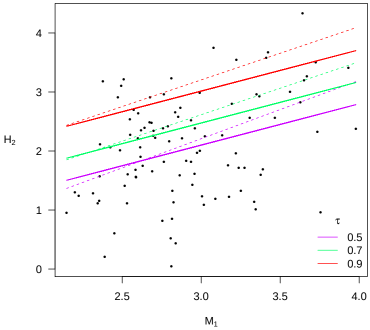
Consider $\boldsymbol{X} = (X_1, X_2)^T$, we are interested in estimating the "tail" distribution of $\boldsymbol{X}$

$$[X_1, X_2 \text{ large}] = \underbrace{[X_2 \text{ large}]}_{M_2}\underbrace{[X_1|X_2 \text{ large}]}_{H_1}$$

- M_2: Extreme value theory
- H_1: No general theory

A toy example





- Simulate "daily data" $(X_1, X_2)^\mathsf{T}$ from bivariate normal with mean 0 and $\rho = 0.7$. Extract $(M_1, M_2)^\mathsf{T}$ and $(M_1, H_2)^\mathsf{T}$, $(H_1, M_2)^\mathsf{T}$
- Under this setting, we know $[X_1 | M_2 = m_2] \sim$ N$(0.7m_2, 0.51)$ $\Rightarrow$ All the true quantile curves are linear functions

Methods for modeling compound extremes

- Classical bivariate EVT: Modeling (M_1, M_2) +: There are existing models (extreme-value marginals + copula) -: Ignore the event simultaneity

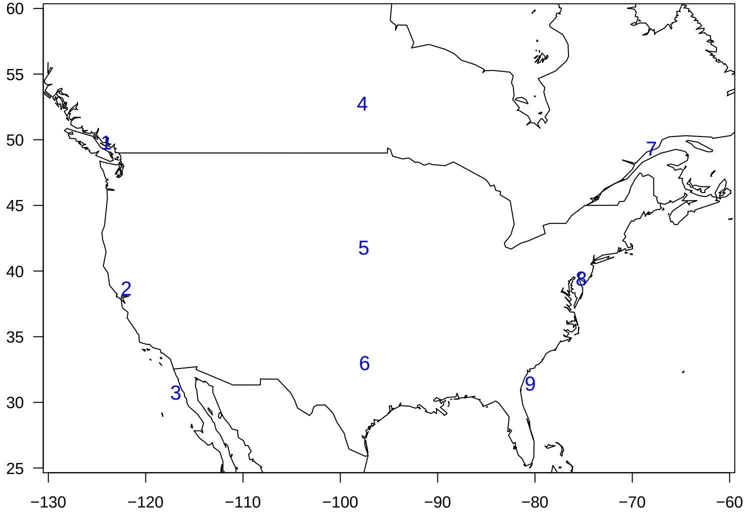
- Quantile regression to regress H_i on M_j +: Could give a quick idea on $[H_i]$ and how $[H_i]$ change with $[m_j]$. -: i) Not able handle extreme quantiles. ii) Could suffer from the issue of quantile crossing.

- Conditional Extremes [Heffernan and Tawn, 04, JRSSB]
  1. Marginals: GPD (ECDF) above (below) a chosen threshold. Transform to Laplace marginals (Y_1, Y_2)
  2. Dependence: $[Y_1 - u > y, (Y_2 - a(Y_1)) / (b(Y_1)) \leq z | Y_1 > u] \xrightarrow{u \to \infty}$ $\exp(-y)G(z)$, where $a(y) = \alpha y$ and $b(y) = y^{\beta}$, $\alpha \in [-1, 1]$, $\beta \in (-\infty, 1)$
  3. Conditionally on $Y_1 > u$, $[Y_1]$ and $[(Y_2 - a(Y_1)) / (b(Y_1))]$ are independent to each other

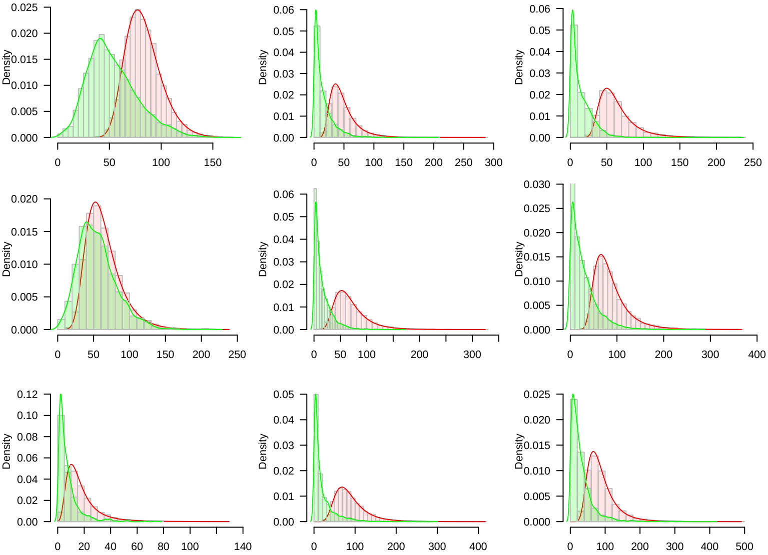
Data: CanRCM4 Large Ensemble Scinocca et al, 2016, J. Clim.

- From 1950 to 2100, driven by a member of the CanESM2 large ensemble (35 members)
- 1950 to 2005 using CMIP5 historical forcings and then to 2100 using RCP 8.5
- North American region, 0.44° horizontal grid resolution ($\sim$ 50 km)
- Focus on `pr` (Precipitation) and `sfcWind` (Near-Surface Wind Speed), 3 hourly, aggregated to daily level

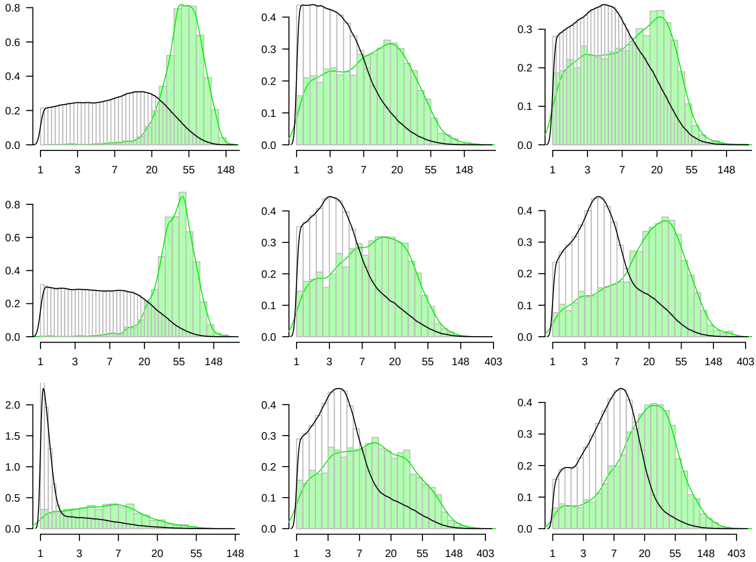
Selected locations from CanRCM4 Large Ensemble



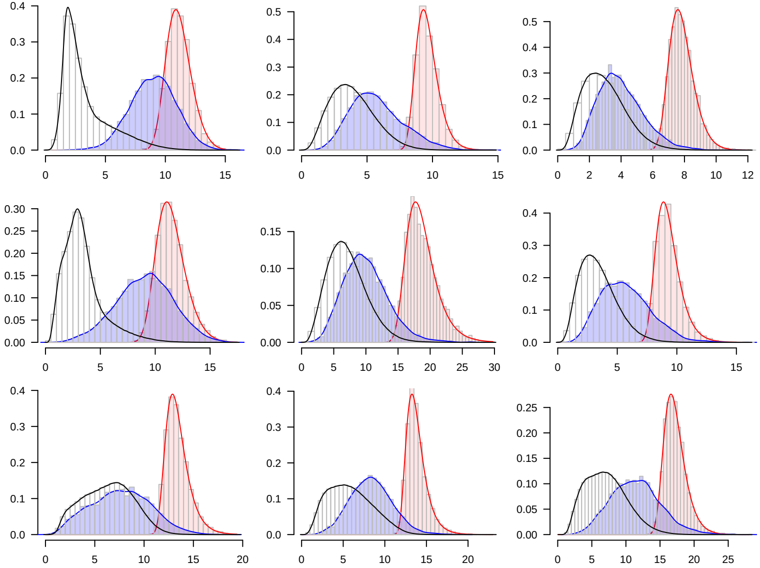
Marginals of daily precipitation : M_{pr}, H_{pr}



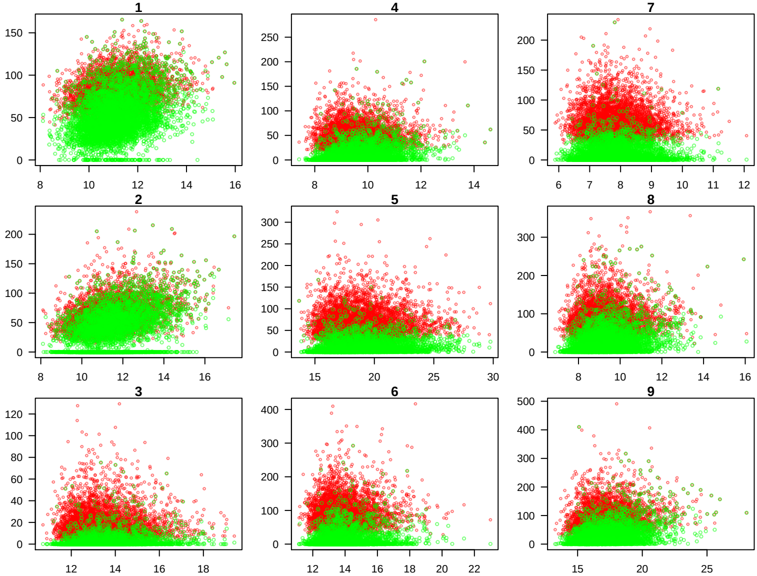
Marginals of daily precipitation (on log scale): H_{pr}, X_{pr}



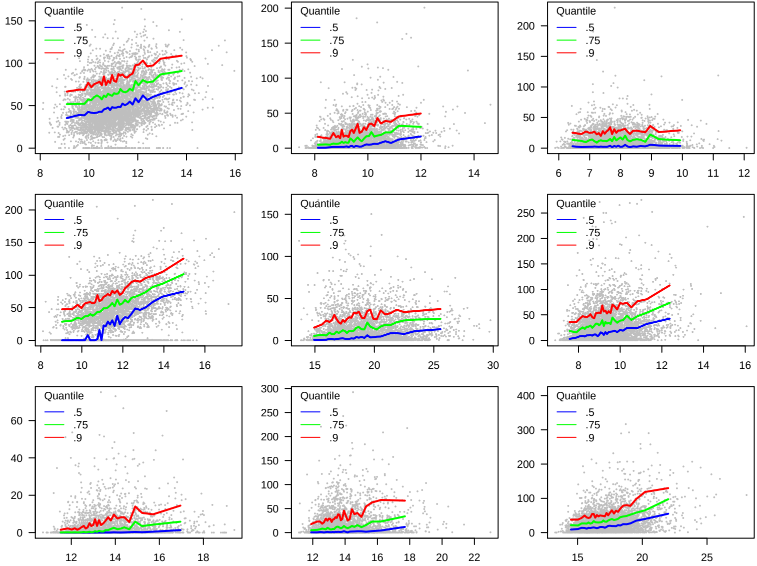
Marginals of wind speed: M_w, H_w, and X_w



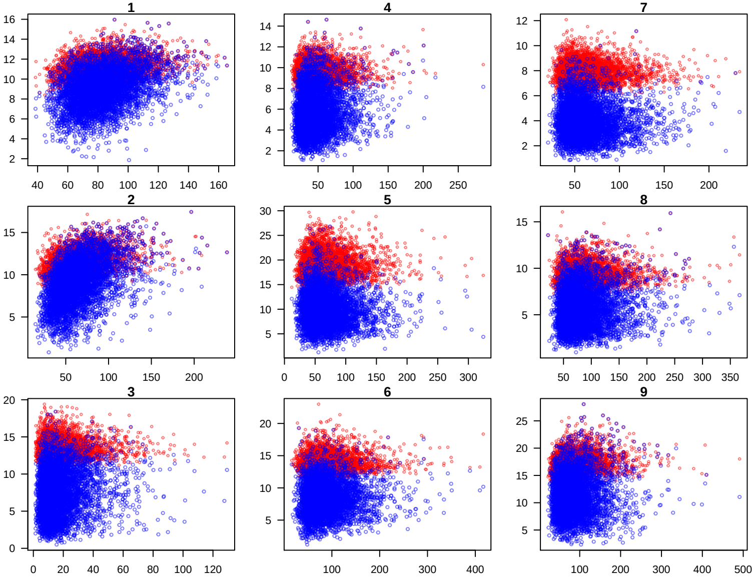
Dependence structures: (M_{pr}, M_w) and (H_{pr}, M_w)



"Non-parametric" quantile regression fits: H_{pr} vs. M_w



Dependence structures: (M_w, M_{pr}) and (H_w, M_{pr})



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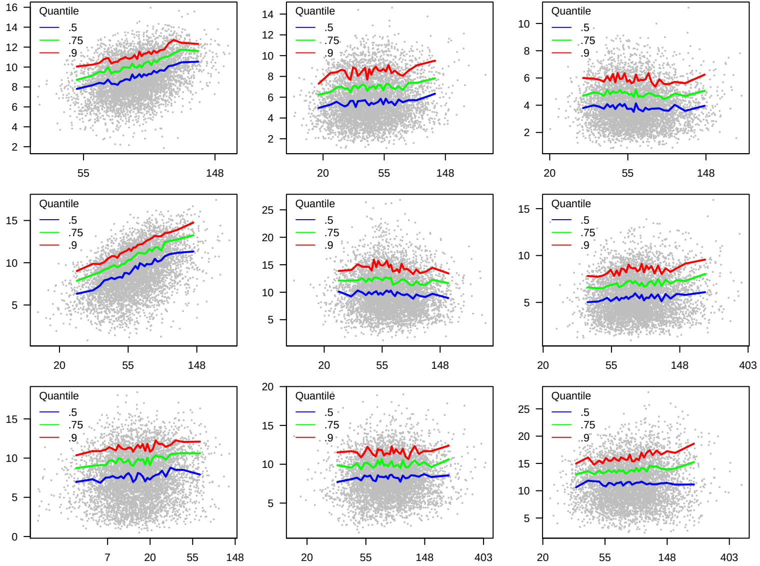
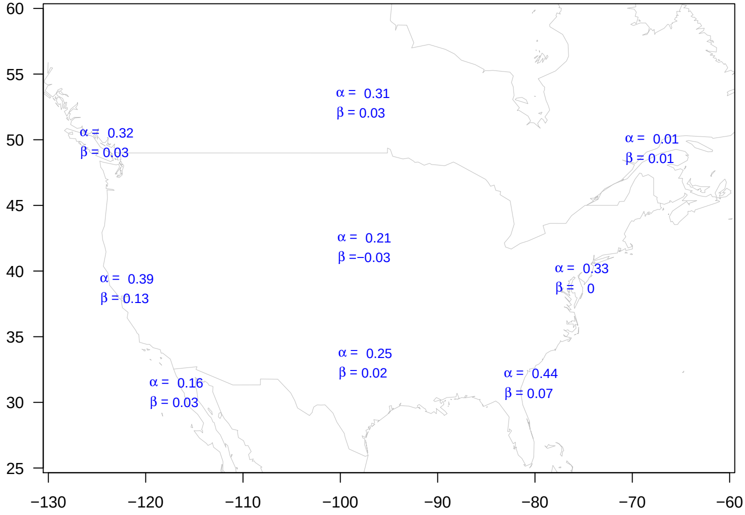


Conditional extreme value model fit (H_{pr}, M_w): $\hat{\alpha}$ and $\hat{\beta}$



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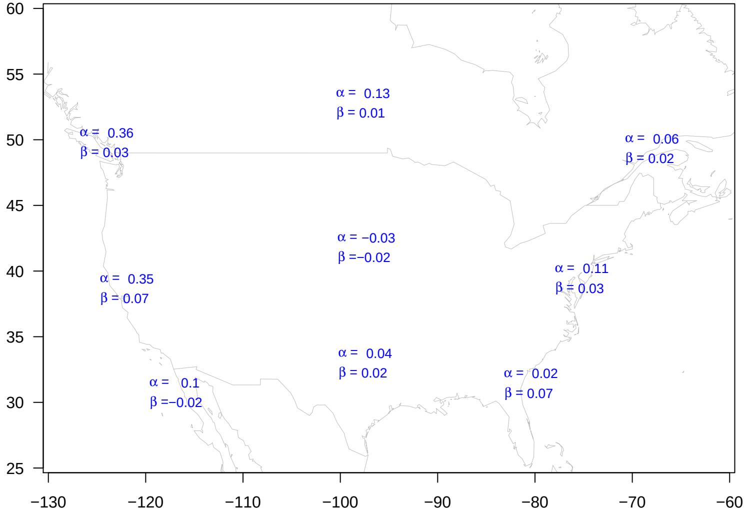
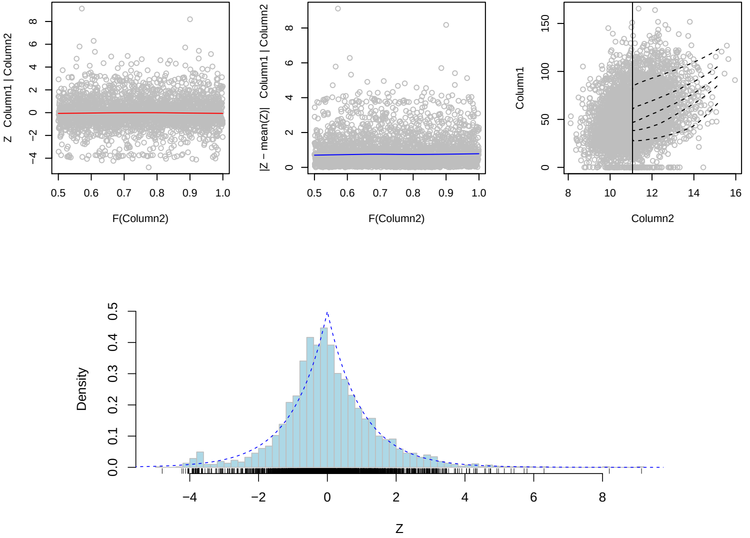
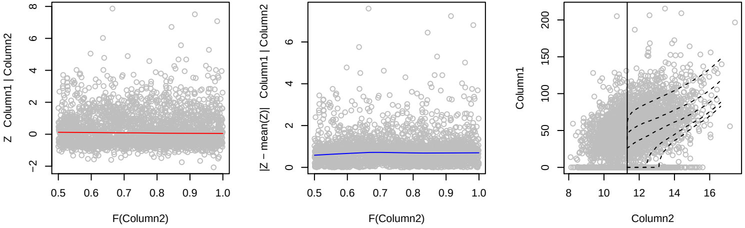
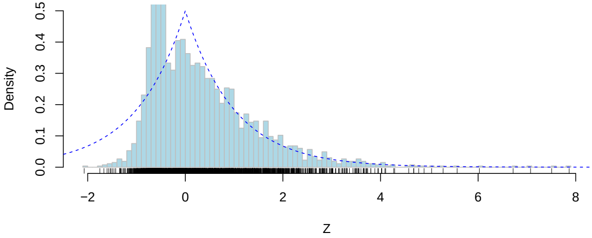


Conditional extreme value model fit (H_{pr}, M_w) at the "Victoria" grid point

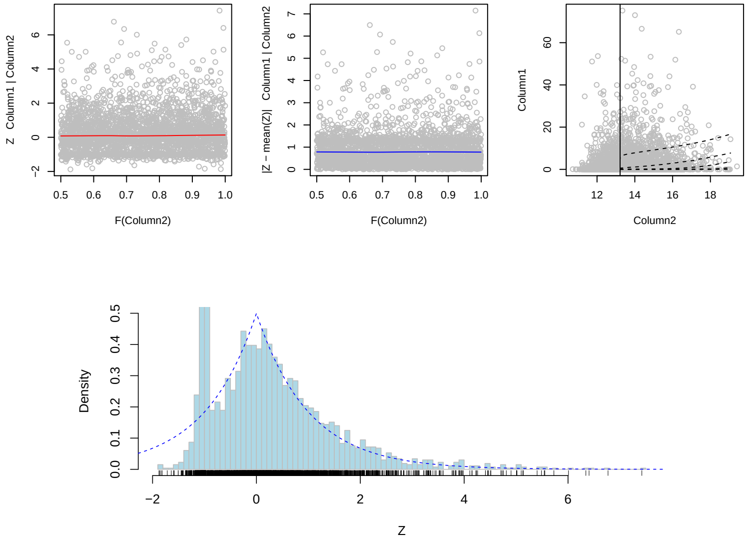


Conditional extreme value model fit (H_{pr}, M_w) at grid point 2

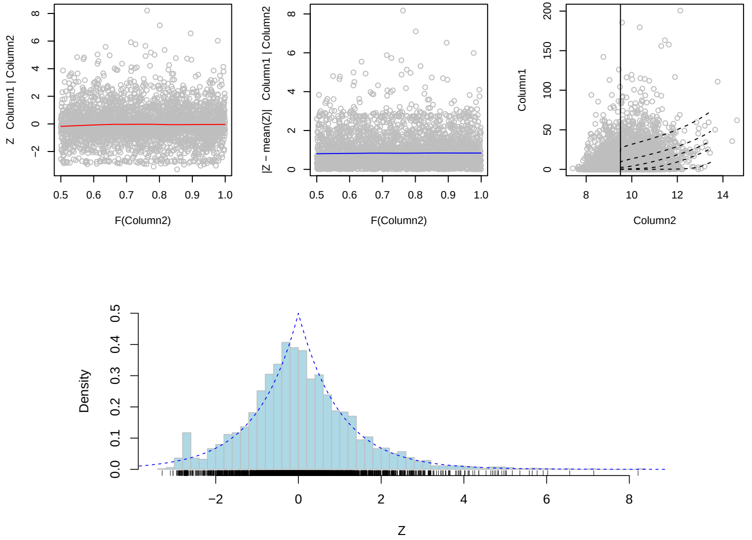




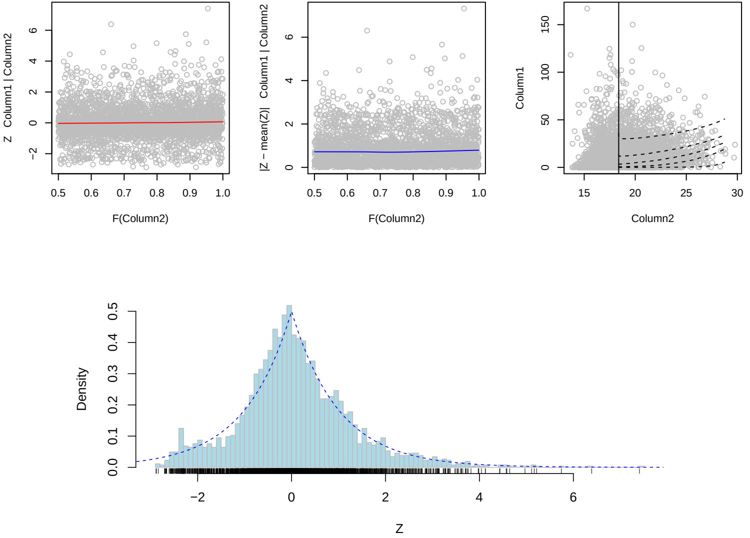
Conditional extreme value model fit (H_{pr}, M_w) at grid point 3



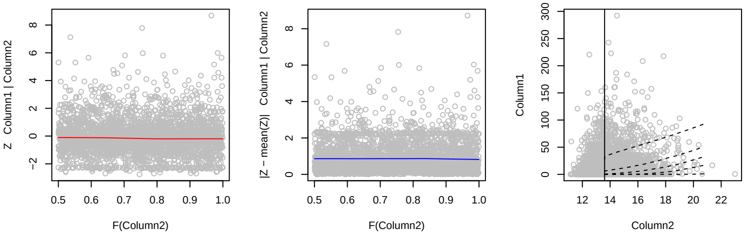
Conditional extreme value model fit (H_{pr}, M_w) at grid point 4

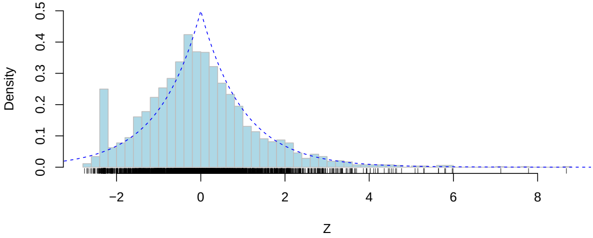


Conditional extreme value model fit (H_{pr}, M_w) at grid point 5

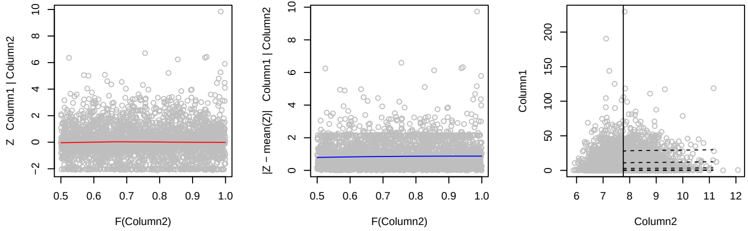


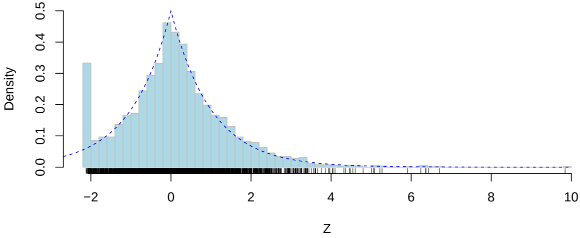
Conditional extreme value model fit (H_{pr}, M_w) at grid point 6



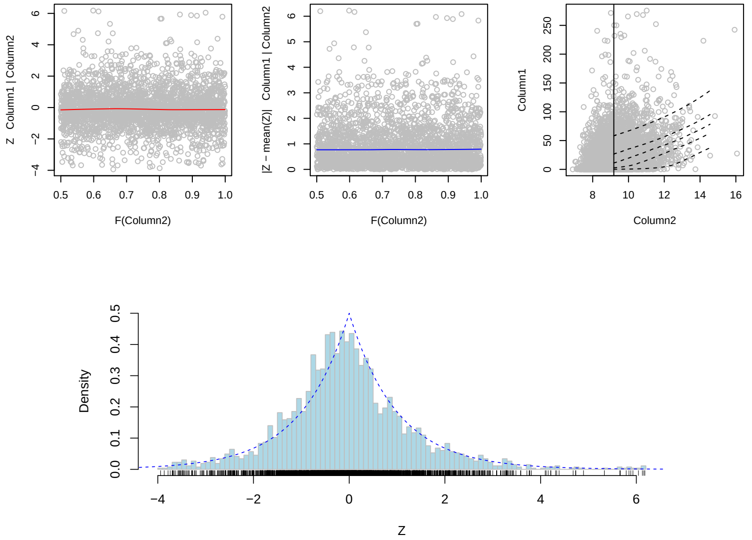


Conditional extreme value model fit (H_{pr}, M_w) at grid point 7

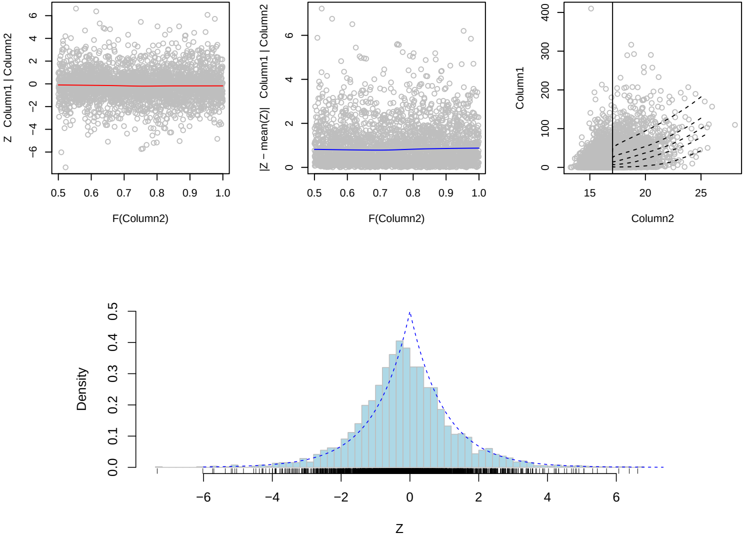




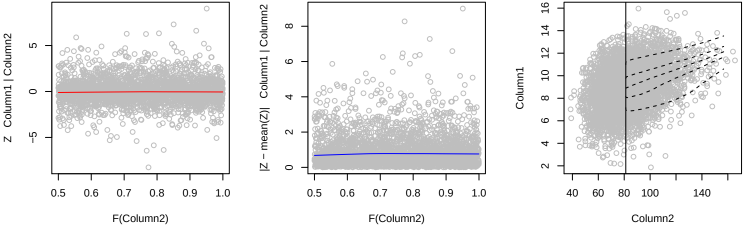
Conditional extreme value model fit (H_{pr}, M_w) at grid point 8

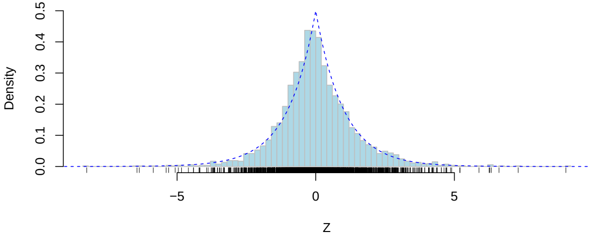


Conditional extreme value model fit (H_{pr}, M_w) at grid point 9

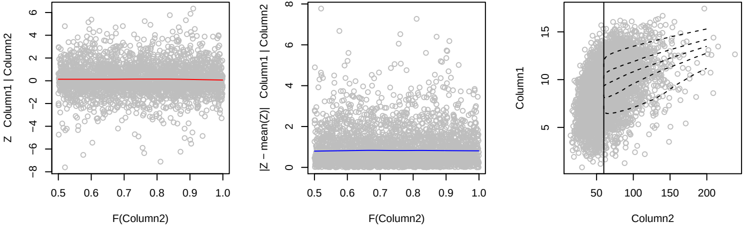


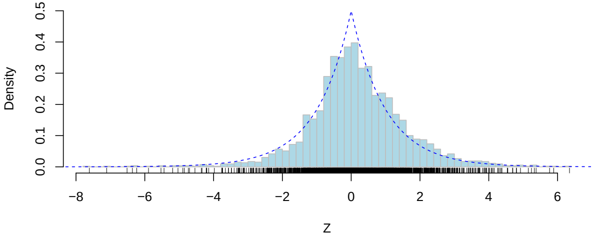
Conditional extreme value model fit (H_w, M_{pr}) at the "Victoria" grid point



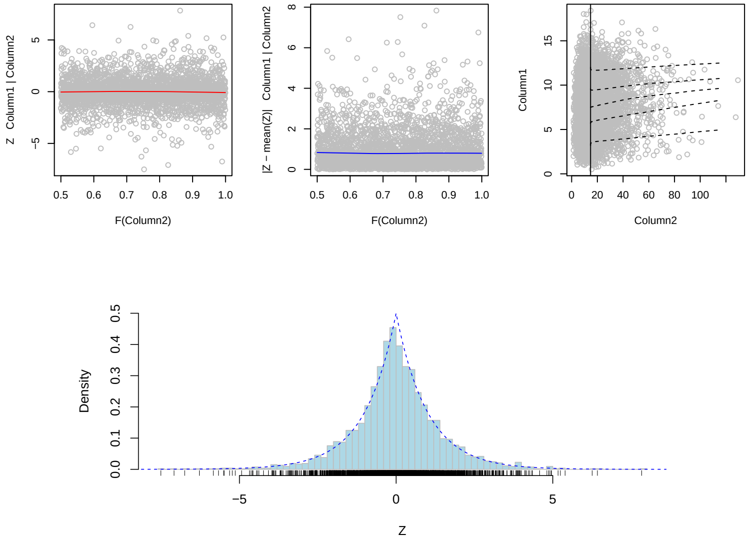


Conditional extreme value model fit (H_w, M_{pr}) at grid point 2

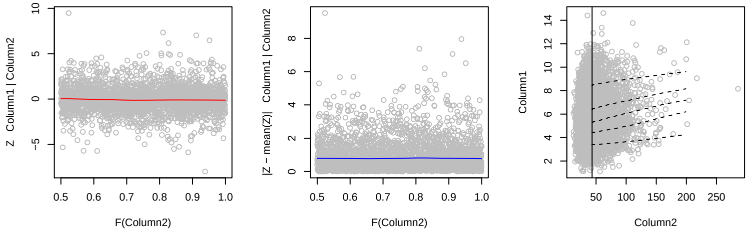


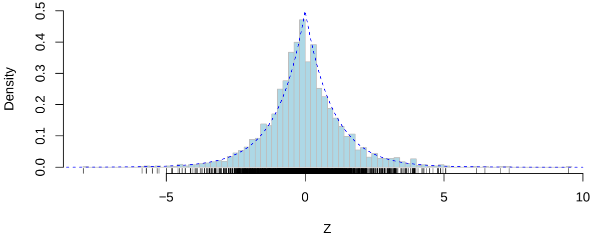


Conditional extreme value model fit (H_w, M_{pr}) at grid point 3

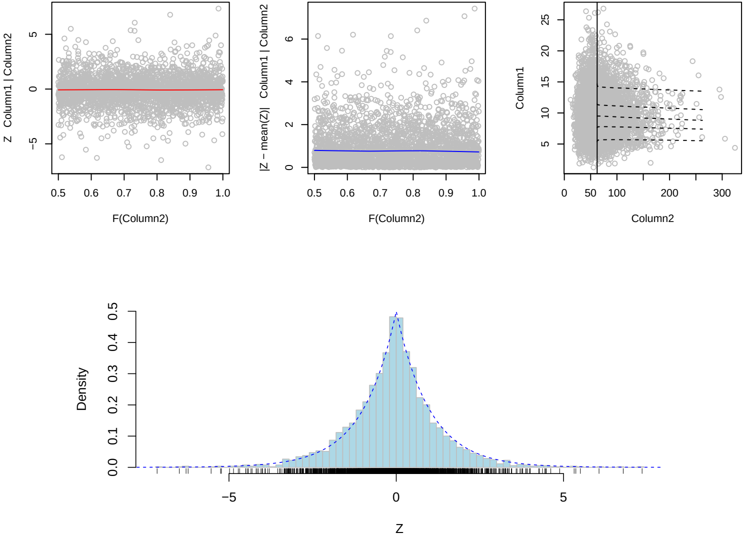


Conditional extreme value model fit (H_w, M_{pr}) at grid point 4

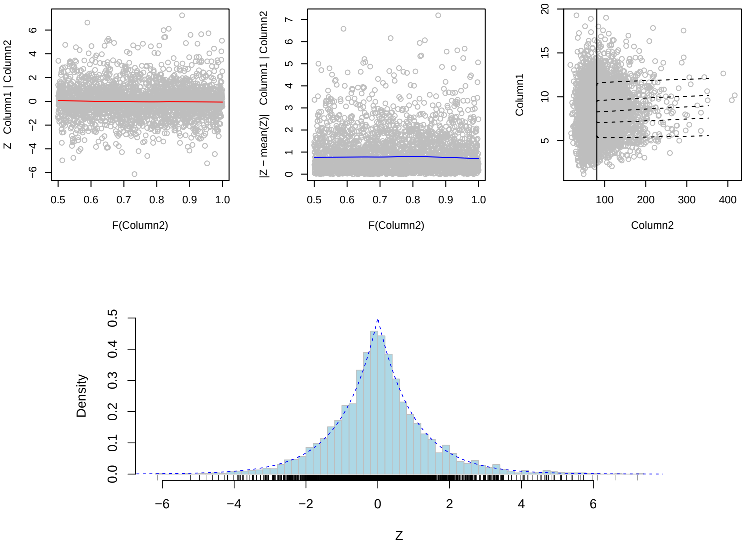




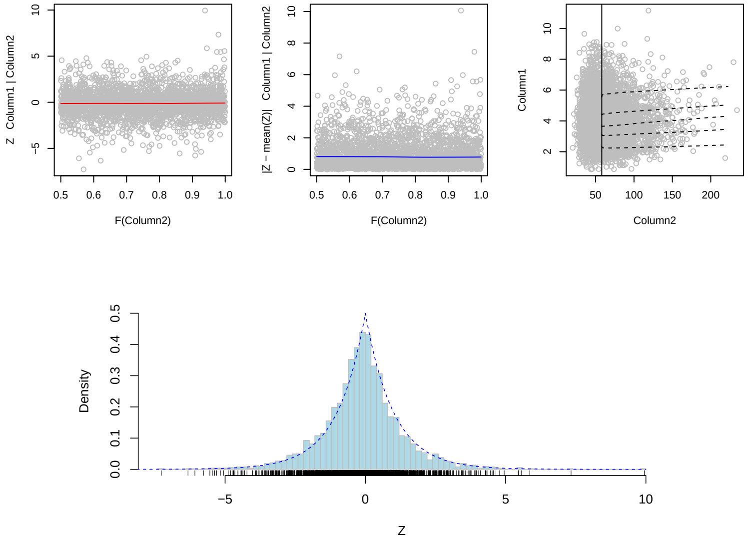
Conditional extreme value model fit (H_w, M_{pr}) at grid point 5



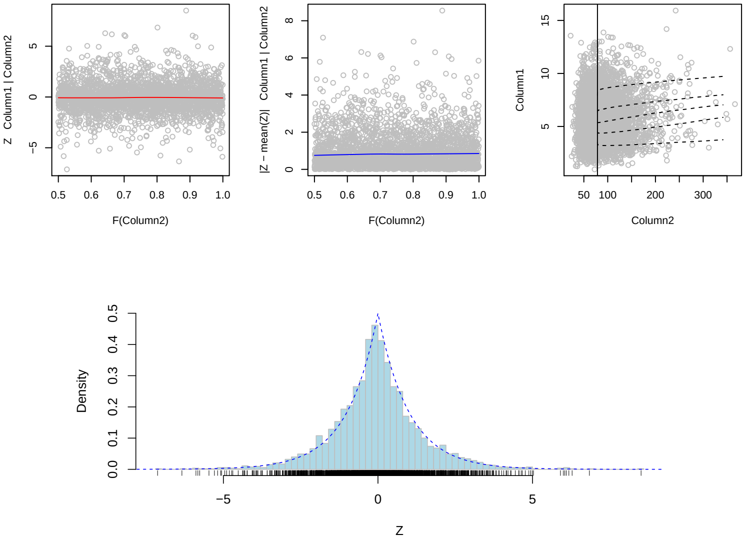
Conditional extreme value model fit (H_w, M_{pr}) at grid point 6



Conditional extreme value model fit (H_w, M_{pr}) at grid point 7



Conditional extreme value model fit (H_w, M_{pr}) at grid point 8



Conditional extreme value model fit (H_w, M_{pr}) at grid point 9