

Statistical Modelling of Rainfall Intensity-Frequency-Duration Curves Using Regional Frequency Analysis and Bayesian Hierarchical Modelling

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IFD Curves and Climate Change

Methods for assessing how IFD curves may change under different emissions scenarios should:

- take into account **uncertainty** in the curves themselves
- be linked to **climate model outputs**, since models are the only tool we have to make future projections
- combine data **spatially** as well across **accumulation durations** in order to obtain more precise estimates of IFD curves

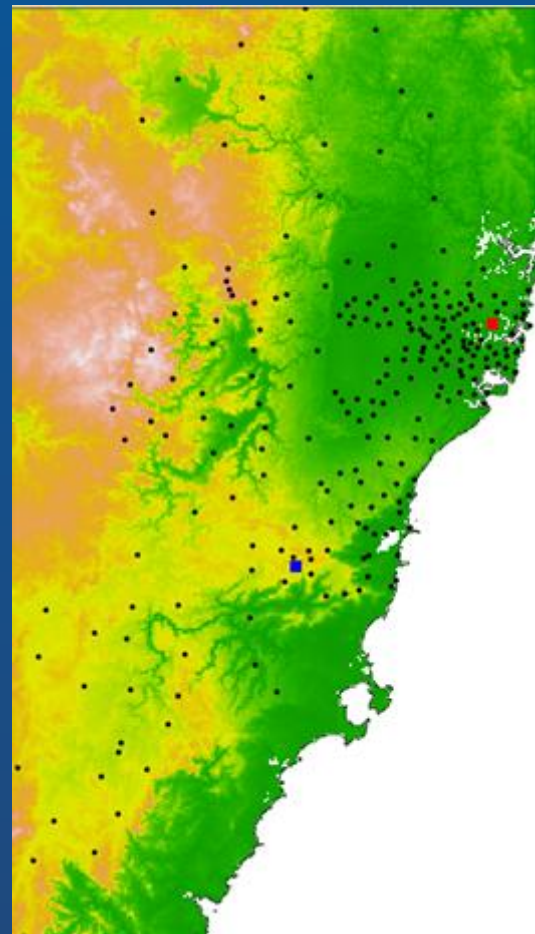
Objective: Develop a flexible framework for doing all of the above and compare with existing methods.

Data

- Greater Sydney Region (~160km x 340km)
- 242 pluviometer stations
- 1959 – 2002 period (7 – 41 year records)
- 5 min – 72 hour annual maxima extracted

■ Representative gauged location

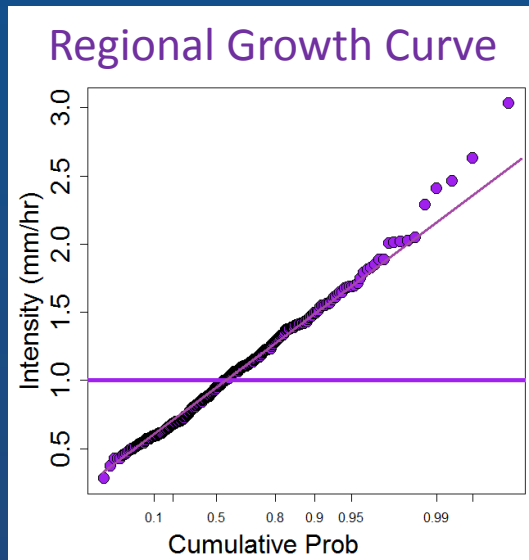
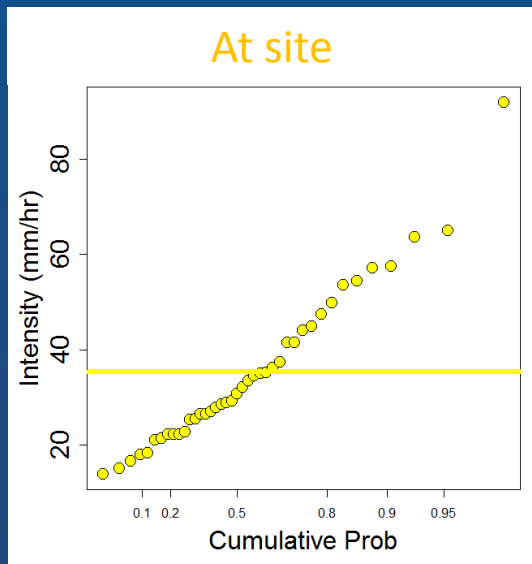
■ Representative ungauged location



Regional Frequency Analysis

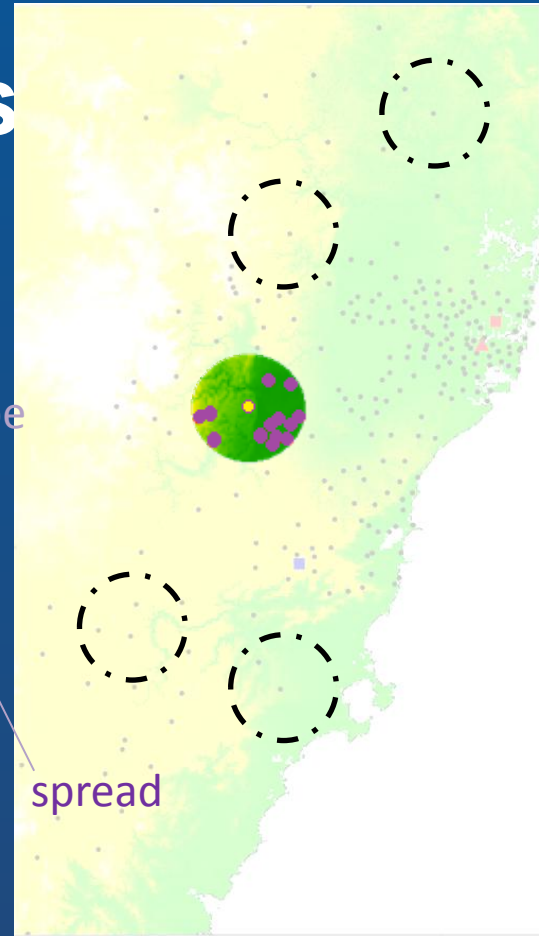
$$Y \sim \text{GEV}(\mu, \sigma, \xi) = \exp \left\{ - \left[1 + \xi \left(\frac{y - \mu}{\sigma} \right) \right]^{-1/\xi} \right\}, \xi \neq 0$$

mean



shape

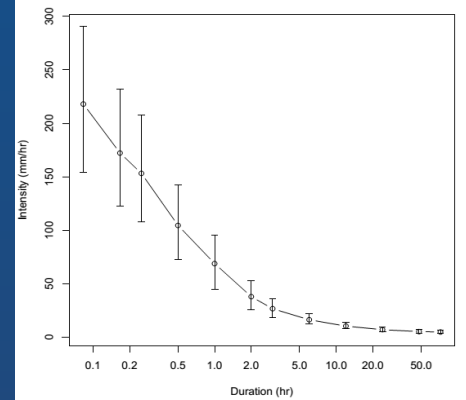
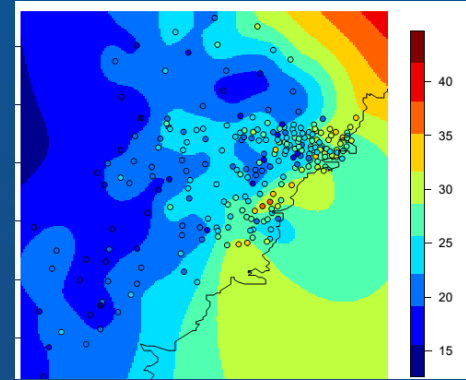
spread



Regional Frequency Analysis

Estimates at ungauged locations are obtained by spline interpolation

Traditional boot-strapped RFA estimates do not account for all sources of uncertainty



Bayesian Hierarchical Modelling

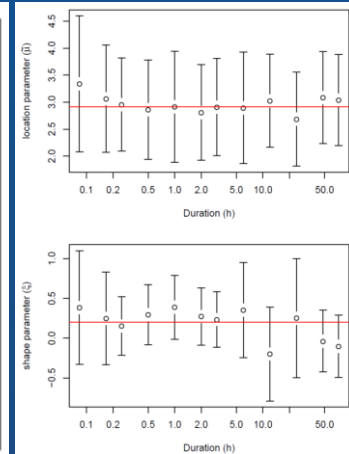
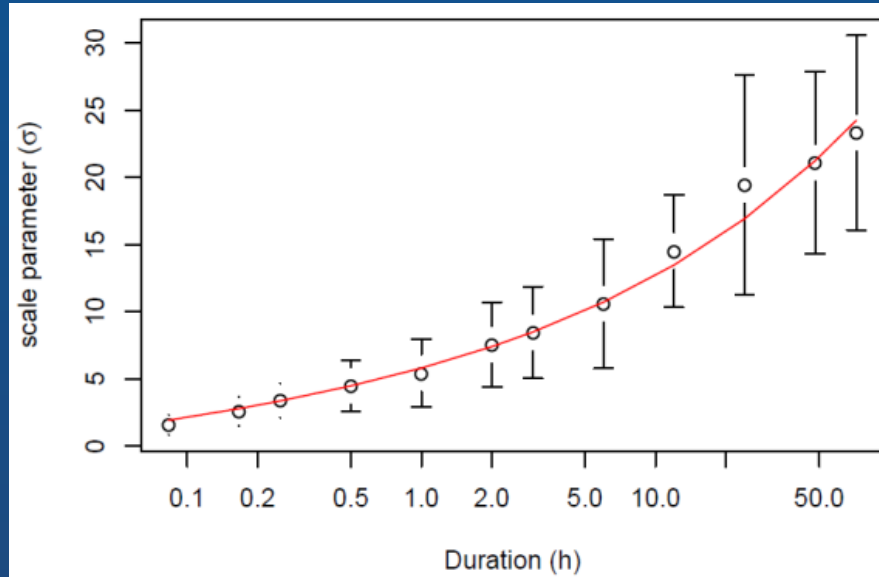
Data layer

Precipitation maxima Y are GEV distributed:

$$Y \sim \text{GEV}(\tilde{\mu}, \sigma_d, \xi)$$

Dependence on accumulation duration d (as per Koutsoyiannis *et al.*, 1998):

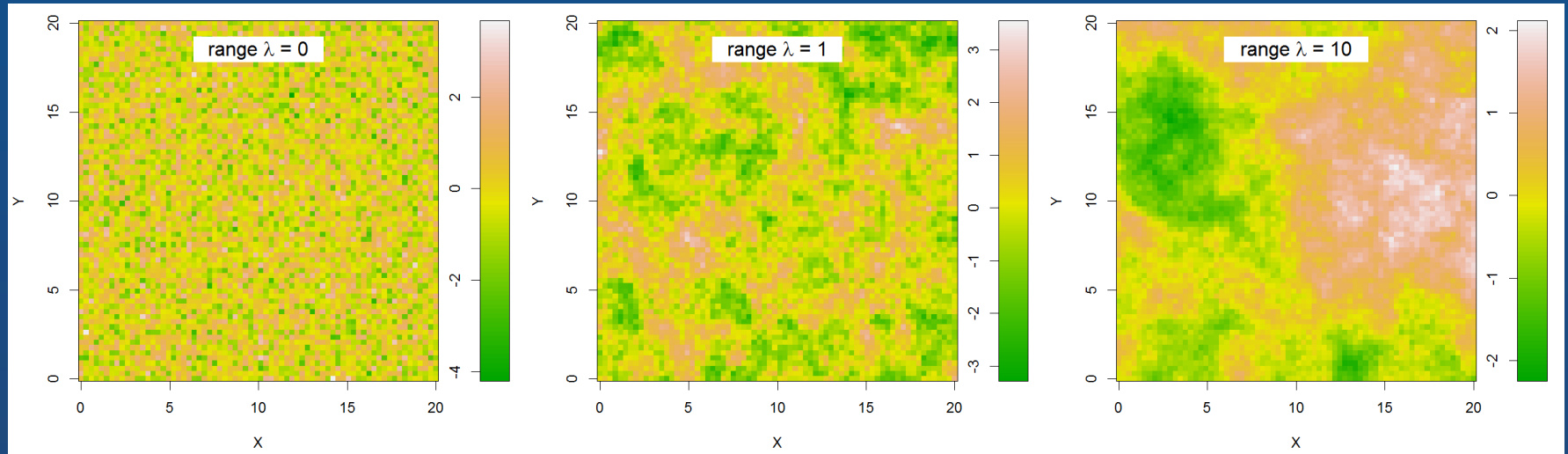
$$\sigma_d = \frac{\sigma \cdot d}{(d + \theta)^\eta}$$



Bayesian Hierarchical Modelling

Process model: $\xi = \beta_0 + \beta_1 \cdot \text{lat} + \beta_2 \cdot \text{lon} + P(\alpha_\xi, \lambda_\xi)$

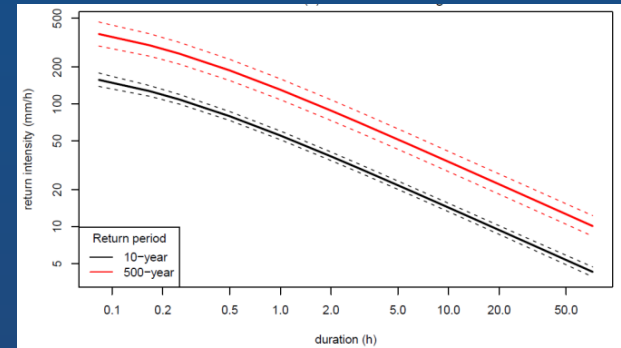
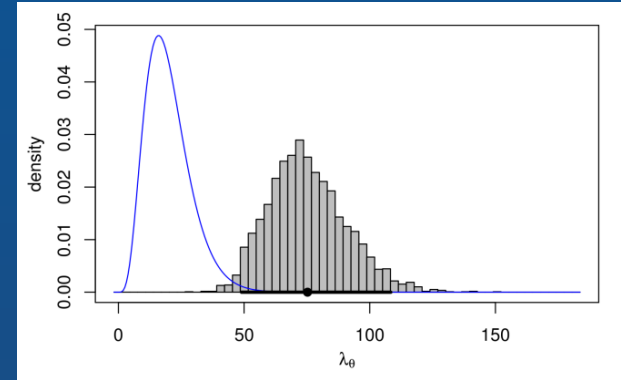
Examples of spatial process $P(\cdot)$ with different range parameters:



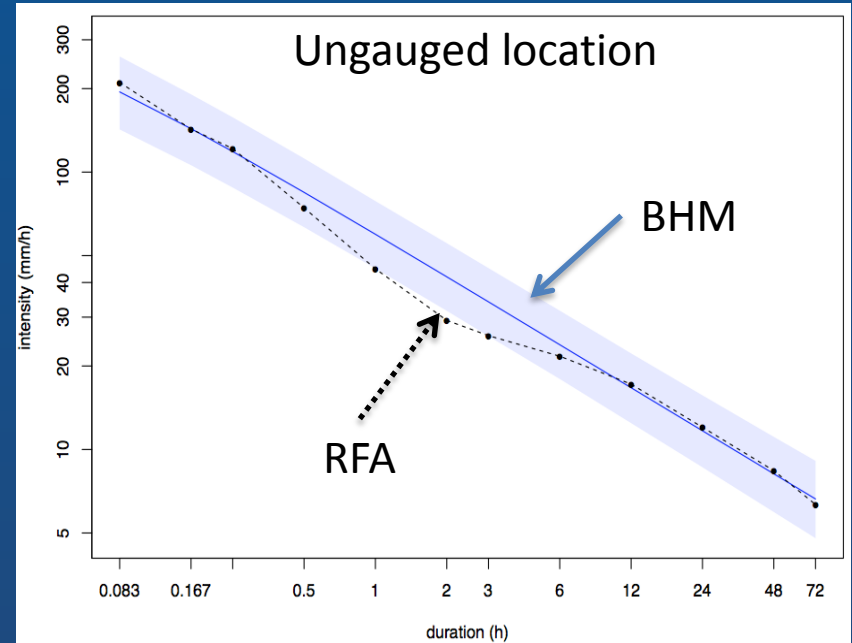
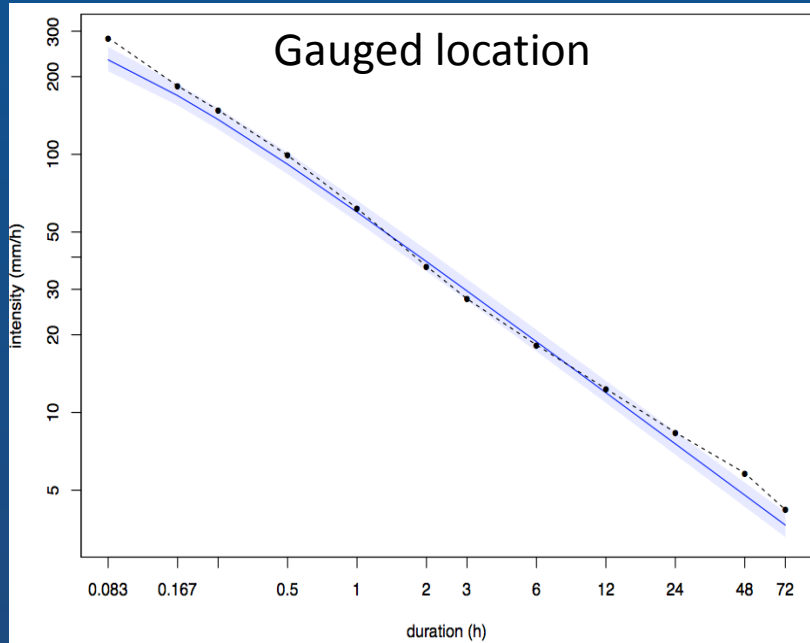
Bayesian Hierarchical Modelling

A unified and flexible statistical modelling framework:

- propagation of **uncertainty** from all layers to the posterior estimates of all variables (e.g. GEV parameters, IFD curves, etc.)
- **flexible framework**: easy to integrate covariates, dependence of parameters on accumulation duration, r -largest maxima, daily data, climate model outputs



Comparison of BHM and RFA

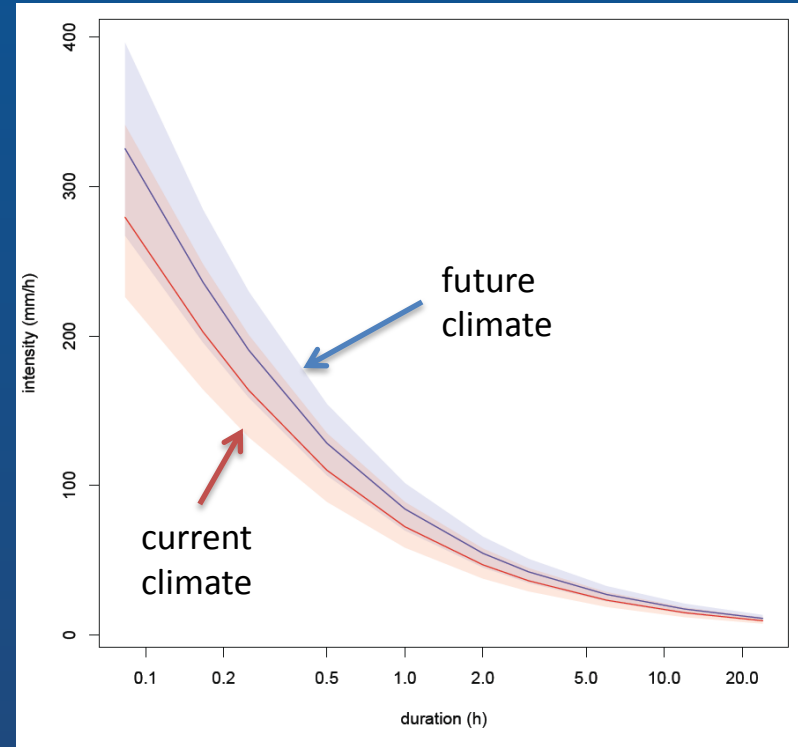


Bayesian Hierarchical Modelling

IFD curves under climate change

Integrate regional climate model (RCM) outputs as **predictors** of current extreme rainfall, then use **future projections** to model the future characteristics of extreme rainfall

$$\xi = \beta_0 + \beta_1 \cdot \text{lat} + \beta_2 \cdot \text{lon} + \beta_3 \cdot \xi_{\text{RCM}} + P(\alpha_\xi, \lambda_\xi)$$



Conclusion

- **Uncertainty** is an important aspect for assessing future IFD curves:
 - Bayesian hierarchical models provide a **coherent and flexible statistical framework** for estimating uncertainty
 - the uncertainty of IFD estimates varies with duration and location
- Some differences between RFA and BHM with current pluvio dataset, due to:
 - modelling of duration dependence in BHM
 - use of different spatial models and regions of influence
- Ongoing work:
 - further work on integration of climate models
 - use of “full” dataset (daily & pluvio)

Supported by



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