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

Sylvia Soltyk\textsuperscript{1,2}, Michael Leonard\textsuperscript{3}, Aloke Phatak\textsuperscript{2}, Eric Lehmann\textsuperscript{2}

\textsuperscript{1}Curtin University, Perth
\textsuperscript{2}CSIRO Computational Informatics, Perth
\textsuperscript{3}University of Adelaide
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

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

At site

Regional Growth Curve

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 $P(.)$ with different range parameters:
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

Gauged location

Ungauged location

BHM

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)
Contacts

Sylvia Soltyk, Alope Phatak, Eric Lehmann
CSIRO Computational Informatics
Perth, Australia

E-mail: firstname.lastname@csiro.au
Website: www.csiro.au

Michael Leonard
University of Adelaide
Adelaide, Australia

E-mail: michael.leonard@adelaide.edu.au
Website: www.adelaide.edu.au