Spatial-Temporal Modelling of Extreme Rainfall

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Introduction

Extreme rainfall over two regions of Australia, the SW of Western Australia and the Sydney region of NSW, covering approximately the last fifty years, has been modelled using a Bayesian Hierarchical Model. A convolution kernel approach is used to derive Gaussian processes to model the spatial variability of the parameters of the Generalised Extreme Value distribution describing rainfall extremes. This is a flexible approach accommodating rainfall measured over different durations (from sub to super daily) and allowing for the possibility of linking the extremes to external drivers.

Australian Rainfall

Changes in rainfall patterns are of great concern in Australia. Two areas of concern (Figure 1) have been studied: the western region had been considered one of the most reliable rainfall areas for growing wheat in Australia and the other is centred on a large urban population. We are studying changes over the period 1953-2003.

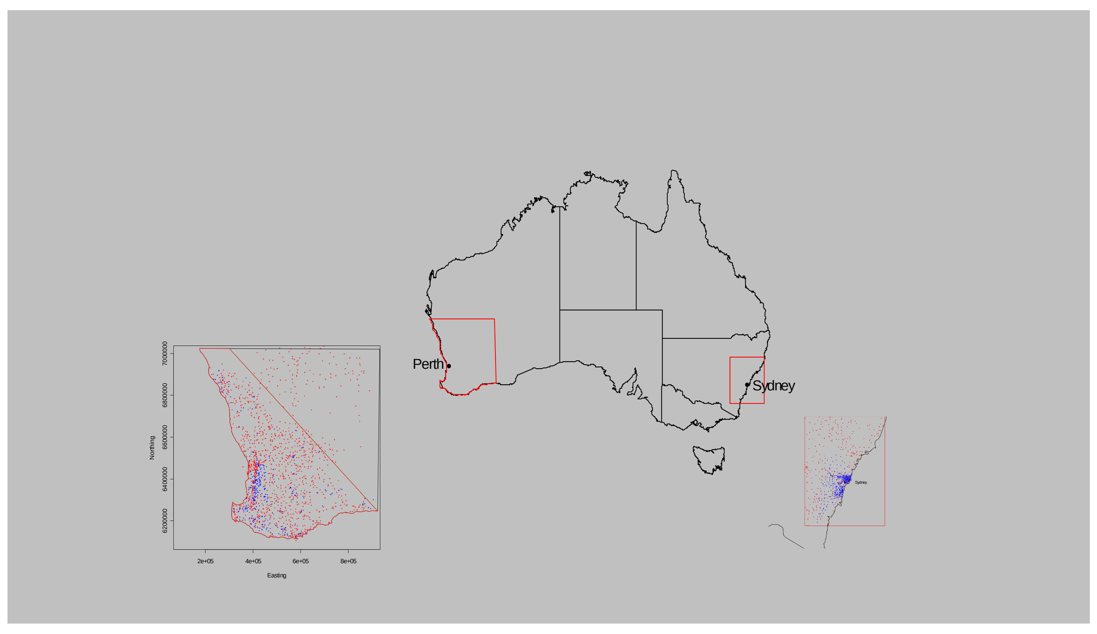

Figure 1: The study areas: The lower SW of Western Australia and mid New South Wales, showing daily rainfall stations (red) and pluvio stations (blue).

Both Daily and pluvio data (rainfall recorded over small time intervals, which one can aggregate) are available. It is important to utilise as much data as possible to develop accurate estimates. The data records for individual stations are not necessarily complete for the region of study, either spatially or temporally.

Spatial-Temporal Model

The parameters of the GEV, known as the location, scale and shape parameters, are modelled as Gaussian processes which allow them to vary smoothly through space.

A convolution kernel approach, based on convolving white noise with a suitable kernel, is used to derive these Gaussian processes. This is a very flexible approach to spatial modelling, able to cope with multivariate spatial correlation and non-stationarity, for example.

Covariates, such as ocean heat, are introduced to drive the parameters at a station through time, while other covariates such as height above sea level and distance from the coast model spatial trends in the parameters. Development of covariate selection procedures is currently being pursued.

Spatial-Temporal Model (contd)

This results in a Bayesian hierarchical model, Figure 2, when priors for the parameters in the model are introduced. MCMC techniques are used to estimate parameters and derive measures of variability.

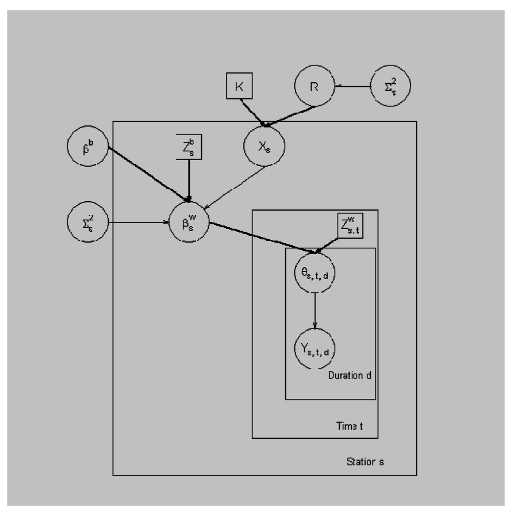

Figure 2: Di-graph representation of the Spatial-Temporal model of extreme rainfall

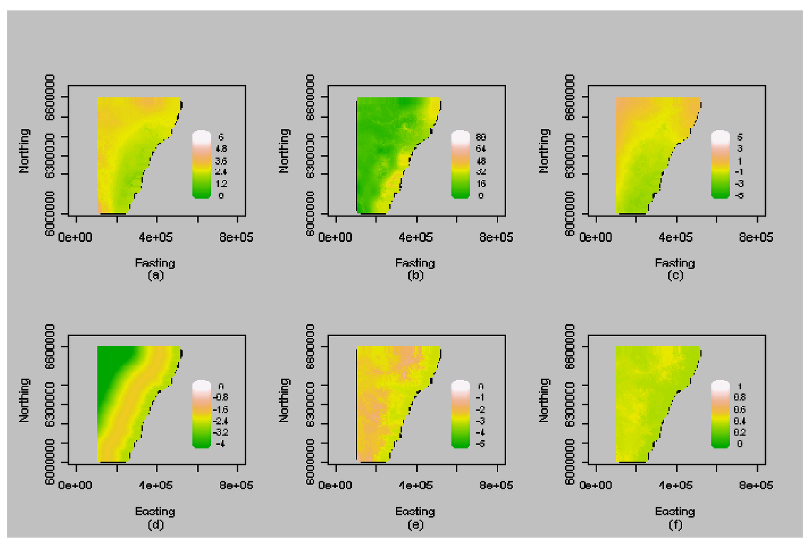

Figure 3: Fitted surfaces of GEV parameters from MCMC sampling; (a) location parameter, (b) scale (intercept) parameter, (c) linear ocean heat anomaly coefficient for modelling scale parameter, (d) shape parameter, (e) theta parameter, (f) eta parameter

Figure 3 shows the spatial patterns of estimates of the GEV parameters.

Conclusion

This model is very flexible in allowing us to incorporate an increased amount of data, and also for the incorporation of covariates. These covariates can be derived from other computer models and this then allows us to predict changes in extreme rainfall patterns under changing climate patterns. Figure 4 shows an increase in return levels close to the coast and a decrease further inland, when driven by ocean heat content.

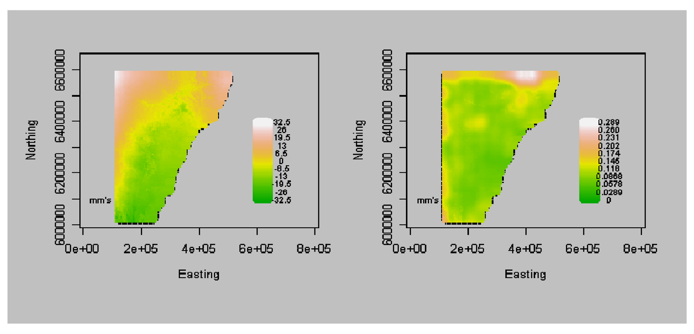

Figure 4: Differenced return levels surfaces (2003 – 1953) for a fifty year return period (a), and associated standard errors (b), driven by ocean heat.

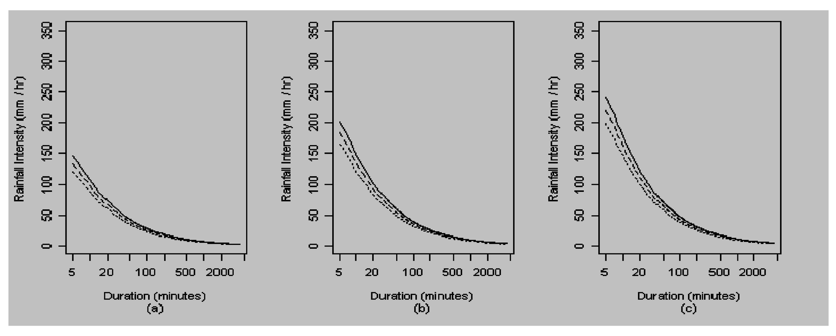

Figure 5: Estimated average IDF curves, for return periods of (a) 5 years, (b) 20 years and (c) 50 years. Each figure shows the IDF curves calculated using an ocean heat anomaly of -2.5, 0.0 and 2.5 respectively. Increasing values of the ocean heat anomaly lead to lower IDF curves within each figure.

From the model we can derive Intensity-Duration-Frequency curves, Figure 5, which are important tools in deriving engineering specifications for dams, culverts, road works etc. Importantly, because of the Bayesian approach, it is also possible to derive measures of variability associated with these curves.

A weakness of the model is its inability to simulate areal rainfall well, due to the assumption of site independence given the site parameters of the GEV. This problem is being addressed through an approach based on copulas, which will enable the statistics of extremes of areal rainfall to be investigated.

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National Research FLAGSHIPS Climate Adaptation

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