PROJECT 2.4: PHYSICAL-STATISTICAL MODELLING OF EXTREME CLIMATE EVENTS

Principal Investigators

Eddy Campbell, CSIRO Mathematical and Information Sciences, Private Bag 5, Wembley WA 6913. (Ph: 08 9333 6203; Email: Eddy.Campbell@csiro.au)

Deborah Abbs, CSIRO Marine and Atmospheric Research**,** Private Bag 1, Aspendale VIC 3195. (Ph: 03 9239 4660; Email: Deborah.Abbs@csiro.au)

Objectives

- To identify the key climate drivers of extreme rainfall events at key spatial scales using observed data and climate models, providing a basis for forecasting on short time scales and scenario planning on long time scales.
- Using the above information and Version 2 of CSIRO's spatial extremes model, update rainfall intensity-frequency-duration characteristics and assess their historical variability over time.
- To develop and test a statistical model for the magnitude, frequency and duration of extreme heat events.
- Using the above capability, investigate the potential skill in forecasting extreme heat events.
- To produce climate change scenarios for rainfall intensity-frequency-duration characteristics and extreme heat events that are suitable for use in impact and vulnerability assessments.

Key Research Findings

- Recording rain gauge ('pluviometer') data has been obtained from both the Bureau of Meteorology and the Department of Water for sites in the North-West and South-West, and the time periods covered by these records assessed.

- Data from the NCEP/NCAR Reanalysis project have been downloaded for a number of atmospheric variables that are pertinent to the study of weather extremes.
- Initial results obtained from the use of a sparse regression method known as RaVE (**R**apid **Va**riable **E**limination) indicate that it can generate parsimonious atmospheric predictor sets for downscaling models that are both sensible and interpretable. Unlike conventional approaches to predictor selection, RaVE simultaneously indicates the locations of important grid points in Reanalysis datasets as well as key atmospheric predictors.
- The results of a parallel preliminary study indicate that RaVE is also a useful methodology for linking the parameters of the probability distributions of weather extremes to atmospheric variables.
- A hierarchical Bayesian spatial model for extreme rainfall (over varying intensities) has been developed. The model will be used to update rainfall intensity-frequency-duration and depth-area characteristics, to assess their historical variability over time and to identify key climate drivers.
- Two approaches for modelling runs of rainfall and temperature extremes (*extreme value and near-extreme theory and aggregated continuous-time Markov chains)* have been identified and formulated. They are judged as worthy of further development.
- A new monsoon index for the North-West describing the regional atmospheric circulation and its linkage to regional rainfall has been developed. Results show that the index has a significant positive correlation with summer (December-March) rainfall (r = 0.81).

MILESTONE 2.4.1 REPORT ON SELECTION OF HIGH QUALITY WEATHER RECORDING STATIONS

Principal Investigators

Eddy Campbell, CSIRO Mathematical and Information Sciences, Private Bag 5, Wembley WA 6913. (Ph: 08 9333 6203; Email: Eddy.Campbell@csiro.au)

Senior Investigator

Mark Palmer, CSIRO Mathematical and Information Sciences, Private Bag 5, Wembley WA 6913. (Ph: 08 9333 6293; Email: Mark.Palmer@csiro.au)

Background

Objective

To document the available data that is suitable for studying rainfall and temperature extremes and their spatial and temporal patterns.

Technical Details

Pluviometer ('pluvio') data has been obtained from both the BoM and the WA Department of Water for sites in both the northwest (NW) and southwest (SW) of Western Australia (Figure 2.4.1). Figure 2.4.2 displays a graphical summation of the periods of time covered by these stations.

Daily rainfall data for stations in the SW for the period 1953-2003 has been used in IOCI 2 and is available for these projects. However BoM is reviewing the quality of their daily rainfall data as part of Project 1.4, and it is acknowledged that our SW data sets may need future revision. The Year 1 report for Project 2.3 (see above) has further discussion of daily rainfall sites and data for the northwest.

We plan to use data from the NCEP/NCAR Reanalysis project (Kistler et al., 2001). Data are available from 1948 onwards, however, the earliest decade is generally considered less reliable due to a scarcity of upper-air observations in the southern hemisphere, so we will focus on the period 1958 to 2007/8.

A new gridded (0.25°×0.25°) daily rainfall and temperature data set has been provided by the Bureau of Meteorology; for details see:

http://www.bom.gov.au/silo/products/cli_var/further_info.shtml

http://www.bom.gov.au/climate/change/about/rain_timeseries.shtml

http://www.bom.gov.au/climate/change/about/temp_timeseries.shtml

Lo et al. (2007) provides comprehensive information on this data set, and is also a good reference on the North Australia wet season.

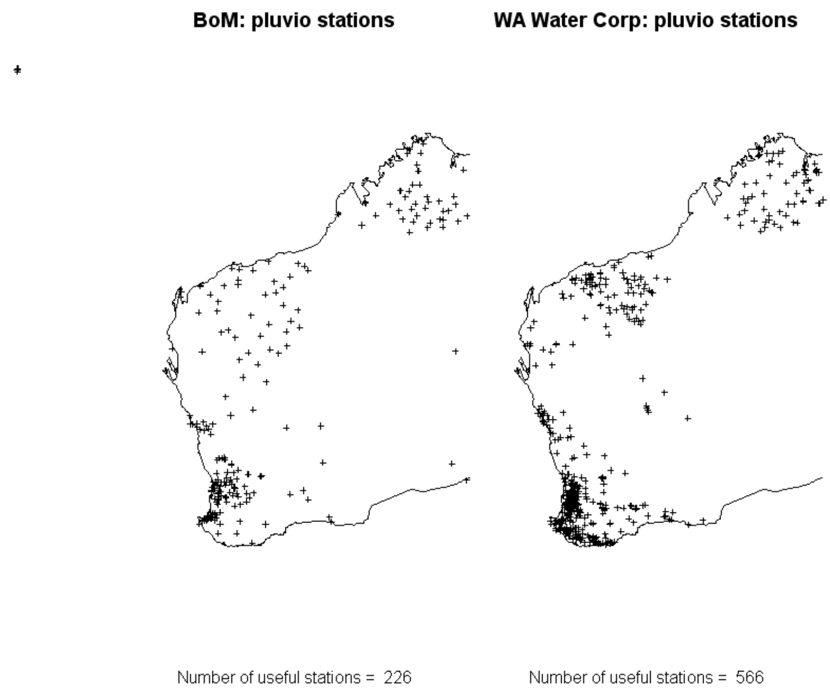


Figure 2.4.1: Locations of pluviometer (pluvio) stations in Western Australia.

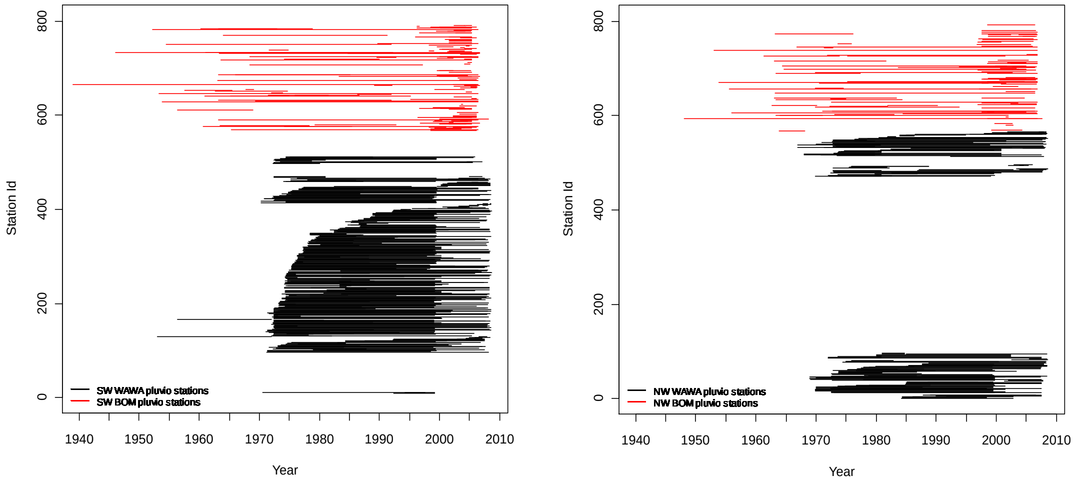


Figure 2.4.2: Periods covered by Northwest and Southwest pluvio stations.

References

Kistler, R., and Coauthors (2001), The NCEP-NCAR 50-year reanalysis: Monthly means CD-ROM and Documentation, *Bull. Amer. Meteor. Soc.*, *82*, 247-267.

Lo, F., M.C. Wheeler, H. Meinke, and A. Donald, 2007: Probabilistic forecasts of the onset of the north Australian wet season. *Mon. Wea. Rev.*, 135, 3506-3520.

MILESTONE 2.4.2: REPORT ON AVAILABILITY OF MODELLED DATA THAT COULD BE INTEGRATED WITH OBSERVED RECORDS TO IN-FILL GAPS.

Senior Investigators

Mark Palmer, CSIRO Mathematical and Information Sciences, Private Bag 5, Wembley WA 6913. (Ph: 08 9333 6293; Email: Mark.Palmer@csiro.au)

Yun Li, CSIRO Mathematical and Information Sciences, Private Bag 5, Wembley WA 6913 (Ph: 08 9333 6184; Email: Yun.Li@csiro.au)

Background

Objective

To identify the key climate drivers of extreme rainfall events at key spatial scales using observed data and climate models, providing a basis for forecasting on short time scales and scenario planning on long time scales.

Technical Details

As noted above, data from the NCEP/NCAR Reanalysis project are available from 1948 onwards (and many of these data sets have been downloaded), however, the earliest decade is generally considered less reliable due to a scarcity of upper-air observations in the southern hemisphere, so we will be focused on the period 1958 to 2007/8.

Data for the following variables have been obtained from the URL http://www.cdc.noaa.gov/cdc/reanalysis/reanalysis.shtml :

1. Mean sea level pressure
2. Geopotential height at two pressure levels (850 and 700 hPa)
3. Air temperature at four pressure levels (850, 700, 600 and 500 hPa)
5. Relative humidity at four pressure levels (850, 700, 600 and 500 hPa)

6. Cloud thickness

From which have been calculated

1. Dew point temperature at 850, 700, 600 and 500 hPa levels
2. Total totals from the air temperatures and relative humidity data

MILESTONE 2.4.3: REPORT ON PREDICTOR SELECTION METHODOLOGIES AND THEIR APPLICATION

Senior Investigators

Aloke Phatak, CSIRO Mathematical and Information Sciences, Private Bag 5, Wembley WA 6913 (Ph: 08 9333 6184; Email: Aloke.Phatak@csiro.au)

Background

This on-going research on the development of predictor selection methodologies is being undertaken in support of Projects 2.3, 2.4, 3.1, and 3.2 in particular.

Station selection for the northwest and southwest WA study regions was on-going activity throughout Year 1 of IOIC 3. Consequently, we focused initially on previous studies in other regions as a means of trialling new predictor selection procedures. If these trials were successful, our aim during Years 2 and 3 of the Initiative would be to apply these procedures to the stations selected for the IOCI 3 regions.

Objective

To develop predictor methodologies that will assist in identifying and understanding atmospheric and other predictors of extreme climate events.

Technical Details

We adopted a staged approach, and have investigated two aspects of predictor selection in climatology:

1. The use of implicit variable selection methods such as L1-norm and related methods (Tibshirani, 1996; Kiiveri, 2008) for identifying predictors in statistical downscaling applications; and
2. The use of such methods for modelling non-stationary sequences of extreme events.

During this trial phase, we focused our effort on predictor selection for statistical downscaling of daily rainfall occurrence and annual maximum series of daily rainfall amounts.

Daily rainfall occurrence

Predictor selection

We used a sparse variable selection method known as RaVE (**R**apid **Va**riable **E**limination, Kiiveri, 2008) to generate parsimonious predictor sets that are both sensible and interpretable. These sets were then used to construct sparse logistic regression models of half-year (MJJASO) rainfall occurrence at 20 stations from the Eyre Peninsula in South Australia. The models were constructed on data from 1986–2006 and tested on data from 1958–1985. The results were compared to those obtained from existing downscaling methods such as non-homogeneous hidden Markov models (Hughes *et al.*, 1999).

The pool of potential predictors consisted of atmospheric variables from the NCEP-NCAR reanalysis data set. The variables included mean sea-level pressure (SLP), and geopotential height (HGT) and dew-point temperature depression (DTD) at 500, 700, and 850 hPa over a total of 56 (7 x 8) grid points.

Figure 2.4.3 shows the grid points at which atmospheric variables were obtained, along with the variables selected for one particular station. Out of a total of 392 (7 x 8 x 7) possible atmospheric variable/grid point combinations, only 16 were selected. Of these 16 variables, there are 10 locations at which DTD is selected, four for HGT, and two for SLP. The locations at which DTD was selected lie in a north-west to south-east direction, likely reflecting the north-west to south-east cloudbands that are an important driver of rainfall in South Australia.

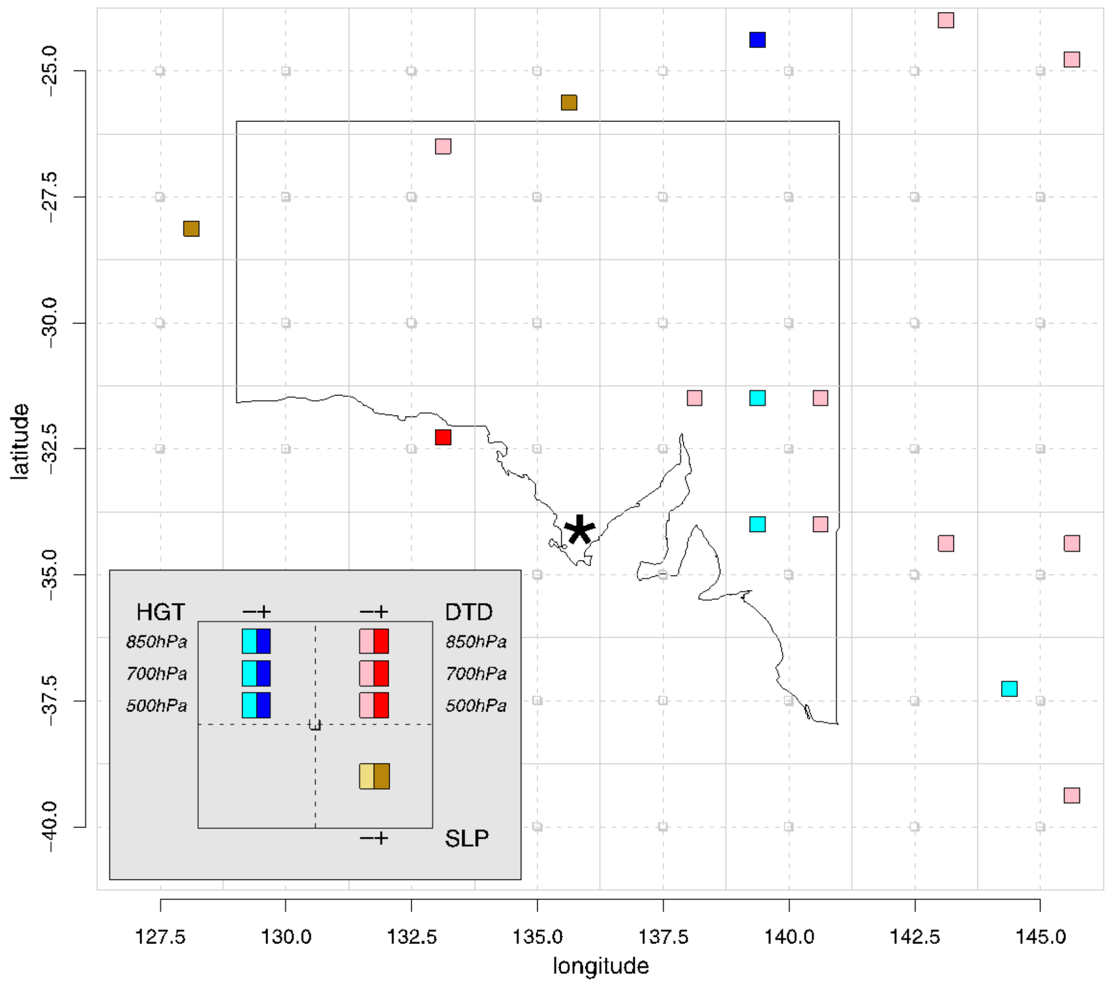
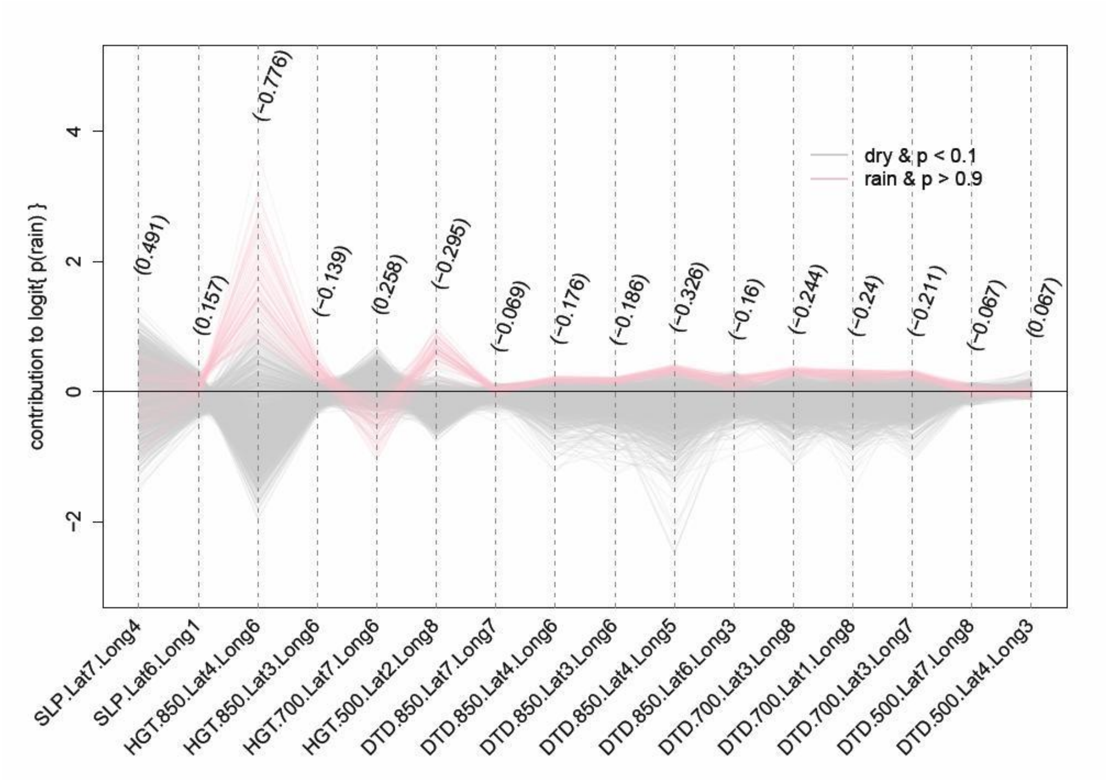


Figure 2.4.3: Atmospheric variables selected for the station marked by the asterisk. The location and colour of a box within a grid indicates which variable was selected as a predictor of rainfall occurrence, and is summarized in the legend.

Predictor interpretation



We evaluated the performance of the sparse downscaling models using several metrics (Phatak *et al.*, 2009b), and also compared their results to those obtained by an NHMM fitted to the same data. For all stations, the sparse regression models gave similar results to the NHMM in terms of wet-day frequencies and downscaled wet- and dry-spell lengths

Figure 2.4.4).

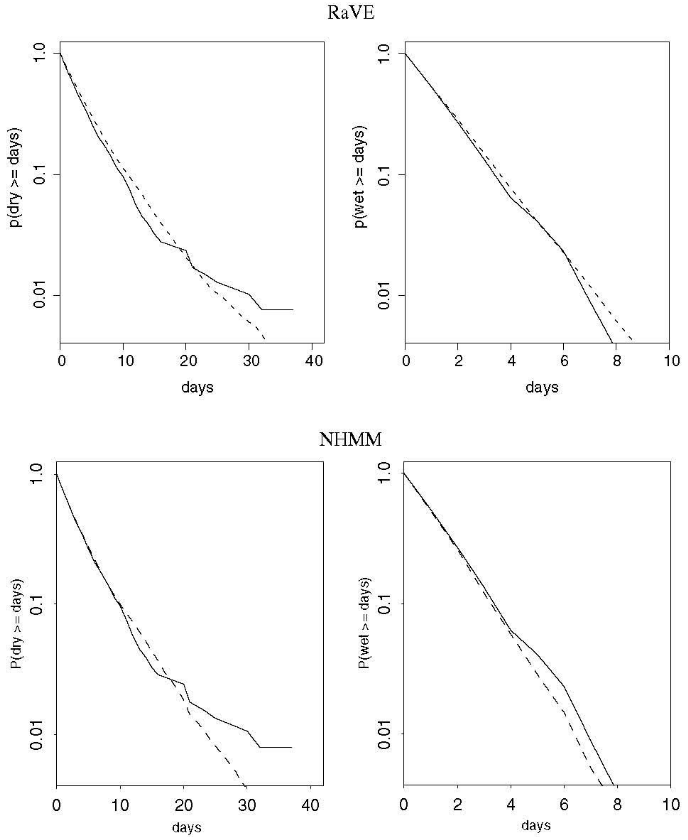


Figure 2.4.4: Observed versus downscaled winter spell lengths for the station in Figure 2.4.1 for the test period (1958–1985) from RaVE (top) and an NHMM (bottom). The solid line indicates the observed spell lengths, the dashed line shows downscaled spell lengths.

Predictor interpretation

<u>Sparse Regression for Extreme Events</u>

Extreme events, such as rainfall or temperature extremes, are often modelled using the generalized extreme value (GEV) distribution, which has three parameters: location, scale, and shape. Our test data consist of yearly maximum rainfall amounts between 1953 and 1991 at a single station in NSW and associated mean sea level pressures on a 14 x 11 grid. The locations of the station and the grid points are shown in Figure 2.4.5. To assess the usefulness of RaVE for extremes, we modelled the location parameter (μ) as a function of a linear predictor ($\boldsymbol{x}'\boldsymbol{\beta}$), where the vector of coefficients is subject to a sparsity (variable selection) constraint. Using RaVE, only eight variables (mean sea-level pressure at eight grid point locations 2 with a northwestsoutheast orientation) are selected (Figure 2.4.5). This example serves as 'proof-in-principle' that sparse regression using RaVE can be used for modelling the location and scale parameters of a GEV distribution (Phatak, 2009a).

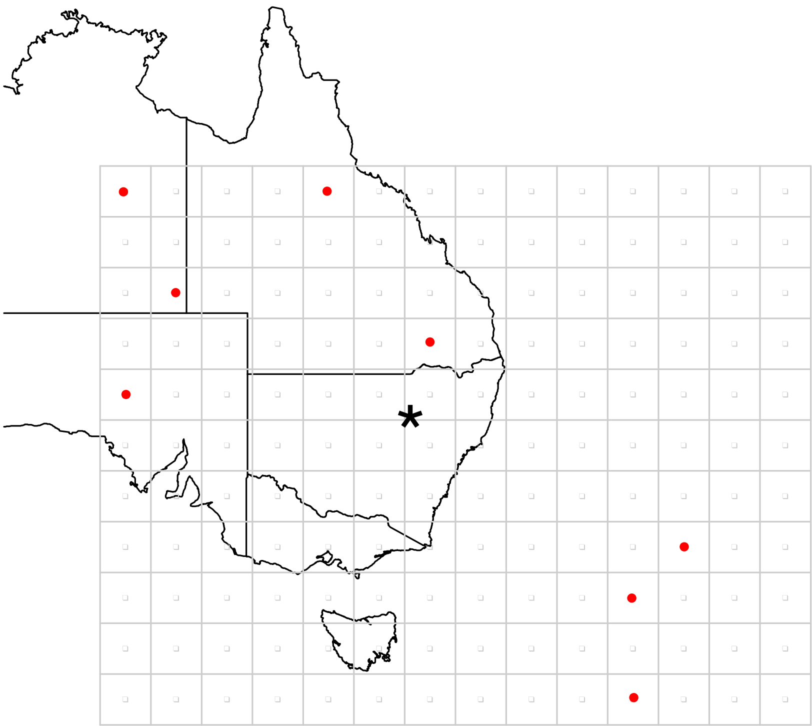


Figure 2.4.5. Location of station (asterisk) at which annual maximum rainfall was modelled as a function of a linear predictor subject to a sparsity (variable selection) constraint. The locations at which mean sea-level pressure was selected are shown as red filled circles.

Future Work

During Year 1 we have demonstrated 'proof-in-principle' use of a sparse regression method known as RaVE for modelling extremes. First, the method was applied to predictor selection for downscaling of rainfall occurrence, and then it was adapted to modelling the location parameter of a sequence of yearly maximum rainfall values that were modelled using a generalized extreme value distribution with covariates consisting of mean-sea level pressure measured at points on a grid. Three aspects of this methodology will be investigated in the next phase of this work:

1. *Numerical stability*. When modelling extremes, the algorithm underlying RaVE occasionally fails to converge; it may be that an alternative optimization algorithm is required.
2. *Spatial smoothness*. The grid points that are chosen by RaVE are not generally adjacent to one another, though we might expect them to be so because of the smooth underlying spatial field. One way of enforcing smoothness of the selected coefficients is to add an additional constraint to the RaVE optimization criterion so that *groups* of spatially clustered grid points are selected, and this will be the subject of continuing research
3. *Extensions to other climate extremes*. Variable selection methods that are developed will also be extended to model extremes of temperature.

References

Kiiveri, H (2008). A general approach to simultaneous model fitting and variable elimination in response models for biological data with many more variables than observations. *BMC Bioinformatics*, **9** (1), 195.

Tibshirani, R. (1996). Regression shrinkage and selection via the Lasso. *Journal of the Royal Statistical Society*. Series B (Methodological). **58** (1), 267–288.

Publications

Phatak, A (2009a). Using GeneRaVE for Extremes: An Initial Attempt. CSIRO Mathematical and Information Sciences Technical Report, CMIS 09/96, June 2009.

Phatak, A, Charles, SP, and Bates, BC (2009b). Statistical downscaling using sparse variable selection methods. Submitted to *Environmental Modelling and Software*, July 2009.

IOCI-Related Presentations

Phatak, A, Charles SP, and Palmer, MJ (2009c) Selection of atmospheric predictors in statistical downscaling of rainfall occurrence, amounts, and extremes in South Australia. Poster presentation at Greenhouse 2009, Perth, WA, 23–26 March 2009.

MILESTONE 2.4.4 REPORT ON NEW STATISTICAL MODEL FOR EXTREME TEMPERATURE (AND RAINFALL) EVENTS

Senior Investigators

Yun Li, CSIRO Mathematical and Information Sciences, Private Bag 5, Wembley WA 6913 (Ph: 08 9333 6388; Email: Yun.Li@csiro.au)

Mark Palmer, CSIRO Mathematical and Information Sciences, Private Bag 5, Wembley WA 6913. (Ph: 08 9333 6293; Email: Mark.Palmer@csiro.au)

Background

Extreme and near-extreme weather events can have especially damaging impacts when they occur in clusters, resulting in floods and heat waves for example. A run of extremes is defined as a cluster of exceedances over a high threshold. Runs of extremes assume that exceedances belong to the same run if they are separated by less than a certain number of values below the threshold. A basic problem in modelling runs of extremes is that current methods typically require the identification of independent runs of exceedances over a high threshold.

Objectives

Rainfall

To develop and use version 2 of CSIRO's spatial extremes model to update rainfall intensity-frequency-duration and depth-area characteristics, and to assess their historical variability over time and identify key climate drivers.

Temperature

1. To understand the drivers of runs of extremes and explore potential predictability.
2. To develop a new methodology for statistical modelling of runs of extremes and their inter-arrival times, the intensity of extremes in each run and their linkage to climate predictors.

Technical Details

Rainfall

A hierarchical Bayesian spatial model for extreme rainfall (over varying intensities) has been developed. A manuscript (Palmer et al., 2009) has been submitted to *Water Resources Research* (currently under revision) describing this model and its application. Initial attempts to implement an approach to estimating depth-area curves within this framework have been technically challenging, and other approaches are being considered.

Temperature

The work against this milestone is technically complex and to date we have focused on forming an understanding of relevant material in the scientific literature. We have identified two feasible approaches that are worth developing further. In the first we seek to implement an approach based on conventional extreme value theory, which we term *near-extreme theory*. This has the benefit that the research risk is quite low, although the potential upside is reduced compared to the second approach, which we term *aggregated Markov chains.* The second approach has the advantage that we can more easily customise the development to the applications of interest. In practice we will manage the research risk by focusing on conventional approaches first.

Extreme value and near-extreme theory

This approach makes use of the developed methods from extreme value (e.g. Coles 2001; Li et. al 2005) and near-extreme theory (e.g. Li 1999; Li and Pakes 1998, 2001; Pakes and Li 1998). The objective is to develop new extreme value theory methods for the modelling of runs of the climate extremes in rainfall and temperature. It will focus on studying the asymptotic behaviour of times between two runs of extremes, the length of runs of extremes, and intensity of extreme events in each run at different locations and their linkage to the time-varying factors such as natural modes of variability (e.g. ENSO and SAM) and long-term climate change in the atmospheric and oceanic circulation climate systems.

The statistical development of this approach will based on the limiting distribution of the times between exceedances of a threshold u by the process $X_n \; _{n\geq 1}$, where $X_n \; _{n\geq 1}$ is assumed to be a stationary sequence of random variables (e.g. rainfall and temperature) with a marginal continuous distribution. The limiting distribution of the times between exceedances can be used to infer the size of extreme clusters (Hsing 1991; Ferro and Segers 2003).

This approach will also be depend on the limiting distribution of the first epoch of near-maximum defined by $T_n(a) = \min \; j \leq n : X_j \in (M_n - a, M_n]$ and the last epoch of near-maximum $L_n(a) = \max \; j : X_j \in (M_n - a, M_n]$, where $M_n = \max \; X_1, \ldots, X_n$ and a is a positive number. $T_n(a)$ and $L_n(a)$ provide information about the first and last occurrences of an observation near the maximum M_n, respectively. It provides a basis to infer the first time when an observation (rainfall and temperature) falls into the near maximum level and last time when an observation exists its near-maximum level. It will further contributes to infer the runs of an extreme cluster.

Aggregated continuous-time Markov chains

Given a time series $Y(t) : t \geq 0$ (e.g. rainfall or temperatures at a station), we can assume the series is from an irreducible homogeneous continuous-time Markov chain. Suppose that $Y(t)$ have state space $S = 1, 2, \ldots, m$ and transition rate matrix $\mathbf{Q} = \left[q_{ij} \right]$. Thus, for $i \neq j$, q_{ij} is the transition rate from state i to state j, and the diagonal elements satisfy $q_{ii} = -d_i$ where $d_i = \sum_{j \neq i} q_{ij}$. The state space is assumed to be rainfall/temperature magnitudes at different levels.

As we focus on rainfall and temperature extremes, the state space can be further *aggregated* by a partitioning into classes, so that it is possible each class may contain more than one state, and observe only which class the chain is in at any given time, and not the individual state. For the purpose of the present project, it is suffices to consider five classes {"Low", "below normal", "near normal", "above normal", "High"}, denoted by L, *B, N, A, H* having respectively n_L, n_B, n_N, n_A and $, n_H$ states, with $n_L + n_B + n_N + n_A + n_H = m$.

Under the Markovian assumption, sojourn times in a class of states have a distribution which is a linear combination of exponentials (unless two or more eigenvalues of the appropriate submatrix are equal). This provides a base for us to develop a new statistical methodology to infer the sojourn time in each class (e.g. Li et al., 2000; Yeo et al., 2003). Of particular interest is to infer the sojourn time of extreme classes (clusters). For example, it will help us extract to the length of extreme rainfall and heat wave events from the sojourn time in class *H*, and frost events in class *L*.

References

Coles, S. G., 2001: *An Introduction to Statistical Modelling of Extreme Values.* Springer-Verlag, London Limited

Ferro, C. and Segers (2003). Influence of clusters of extreme values. *J. R. Statist. Soc.* B 65, Part 2. 454-556.

Hsing, T. (1991) Estimating the parameters of rare events. Stochast. Process. Applic., 37, 117-139.

Li, Y., W. Cai, and E. P. Campbell (2005). Statistical modelling of extreme rainfall in southwest Western Australia, *Journal of Climate* 18, No. 6, 852-863.

Li, Y**.,** and A. G. Pakes (2001). On the number of near-maximum insurance claims. *Insurance: Mathematics and Economics*. 28, 309-323.

Li, Y., G. F. Yeo, R. K. Milne, B. W. Madsen, and R. O. Edeson (2000). Burst Behaviour of a Double-Barrelled Chloride Ion Channel *Mathematical Biosciences*. 166, 23-44.

Li, Y. (1999). A note on the number of records near the maximum**.** *Statistics & Probability Letters*, 43,153-185. Full

Pakes, A. G., and Y. Li (1998). Limit laws for the number of near-maxima via the Poisson approximation. *Statistics & Probability Letters*, 40, 395-401.

Palmer, M.J., Campbell, E., Aryal, S and Bates, B. A Bayesian Spatial Model for Intensity-Duration-Frequency Curves Derived from Extreme Rainfall (submitted to *Water Resources Research*).

Yeo, G., Robin K. Milne, Barry W. Madsen, Yun Li and Robert O. Edeson (2003) Markov modeling of burst behavior in ion channels. In *Handbook of Statistics-Stochastic Processes*: Modeling and Simulation, Vol. 21, Chapter 23, pp. 931-968. (Eds. D.N. Shanbhag and C.R. Rao) Elsevier, Amsterdam.

MILESTONE 2.4.5 REPORT ON KEY ATMOSPHERIC PREDICTORS FOR EXTREME TEMPERATURE (AND RAINFALL) EVENTS.

Senior Investigators

Yun Li, CSIRO Mathematical and Information Sciences, Private Bag 5, Wembley WA 6913 (Ph: 08 9333 6388; Email: Yun.Li@csiro.au)

Background

Objective

Identification of key climate predictors to drive understanding of mechanisms and potential predictability.

Technical Details

This work is at an early phase of its three year timeline, but we have some interesting findings to report on rainfall predictors from this and related work.

- A new monsoon index may explain a summer rainfall increase over Northwest Western Australia
- New gridded rainfall data (0.25°×0.25°) provided by the Australian Bureau of Meteorology has been tested to be suitable to study the summer rainfall increase over NWA. The rationale to use Bureau's gridded rainfall data is the lack of high-quality gauged rainfall data over NWA.
- We have has used the monsoon concept to describe regional circulation patterns influencing summer rainfall variations in NWA and explored the impacts of the Northwest Western Australia summer monsoon (NWASM) on climate in this region. A new NWASM index (based on dynamics of normalized seasonality index by Li and Zeng 2002) was developed to describe this circulation and its linkage to rainfall over NWA. Results show that the

NWASM has a significant positive correlation with NWA winter rainfall (r=0.81).

- Variation of the NWASM correlates with NWA summer rainfall on short to long timescales. The relationship between the NWASM index and NWA rainfall is robust, and largely independent of the influence of other large-scale circulations such as the SAM and ENSO. This index can also therefore be used to assess the output from GCMs.

We have used 0.25°×0.25° gridded rainfall data provided by the Australian Bureau of Meteorology due to the lack of high-quality gauged rainfall records in NWA. The primary dataset for other atmospheric fields is from the National Centers for Environmental Prediction-National Center for Atmospheric Research (NCEP-NCAR) reanalysis on a 2.5°×2.5° grid (Kalnay et al. 1996).

Figure 2.4.6 shows the annual total rainfall over Australia during 1948-2007. Blue colour shows rainfall increase and red indicates rainfall reduction. (mm/year). It is evident that Australian coast regions have become drier over the past decades except the wetting trends dominated in NWA regions. If this wetting trend keeps going into the future, it may be main water resources for Australia.

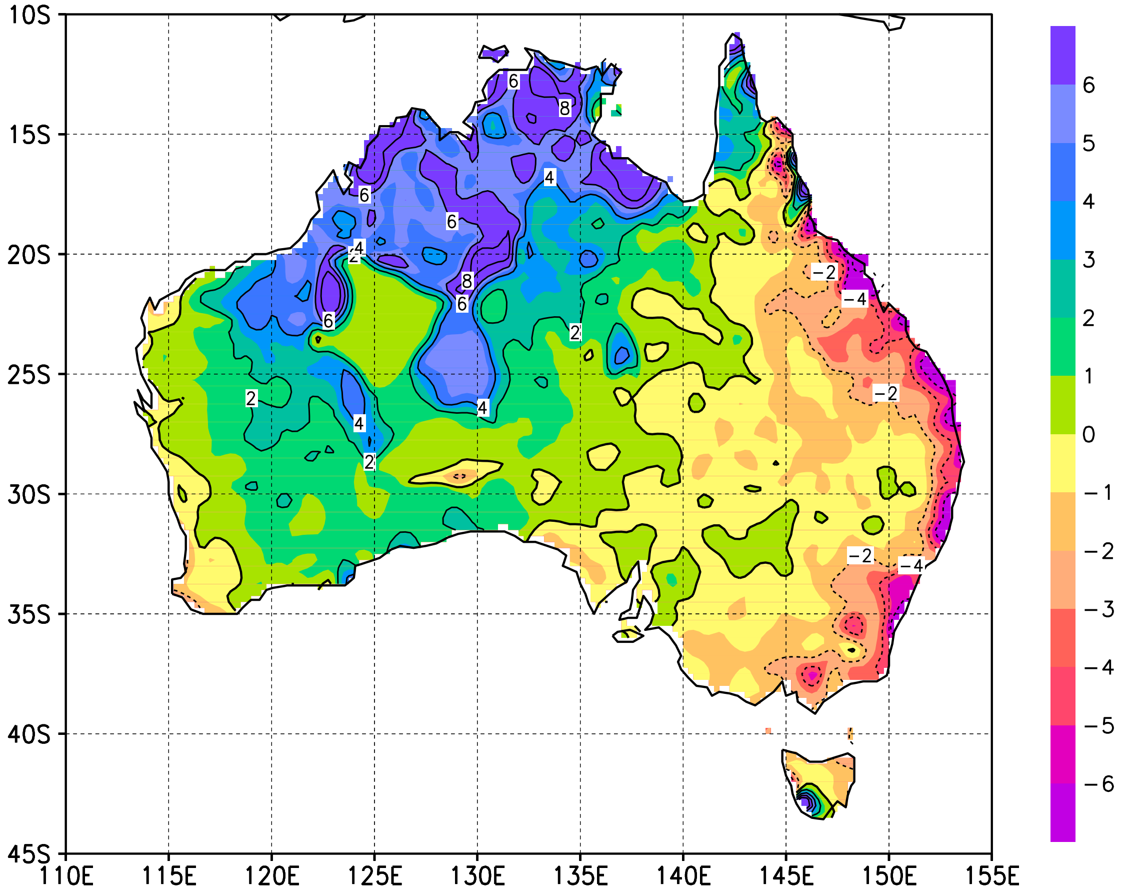


Figure 2.4.6: Annual total rainfall trend based on the ACC rainfall data over 1948-2007. Blue colour shows rainfall increase and red indicates rainfall reduction. (mm/year).

Figure 2.4.7 present the trend of summer (December-January-February-March, DJFM) over Australia. The structure of trend is comparable with that in Australian annual rainfall totals. Therefore, the Australian rainfall increase is more pronounced in summer rainfall over NWA region. This figure also shows a dipole structure (wetter in westward and drier eastward of 140°E) in summer rainfall over Northern Australia. This is consistent with previous studies by *Shi et al.* (2008).

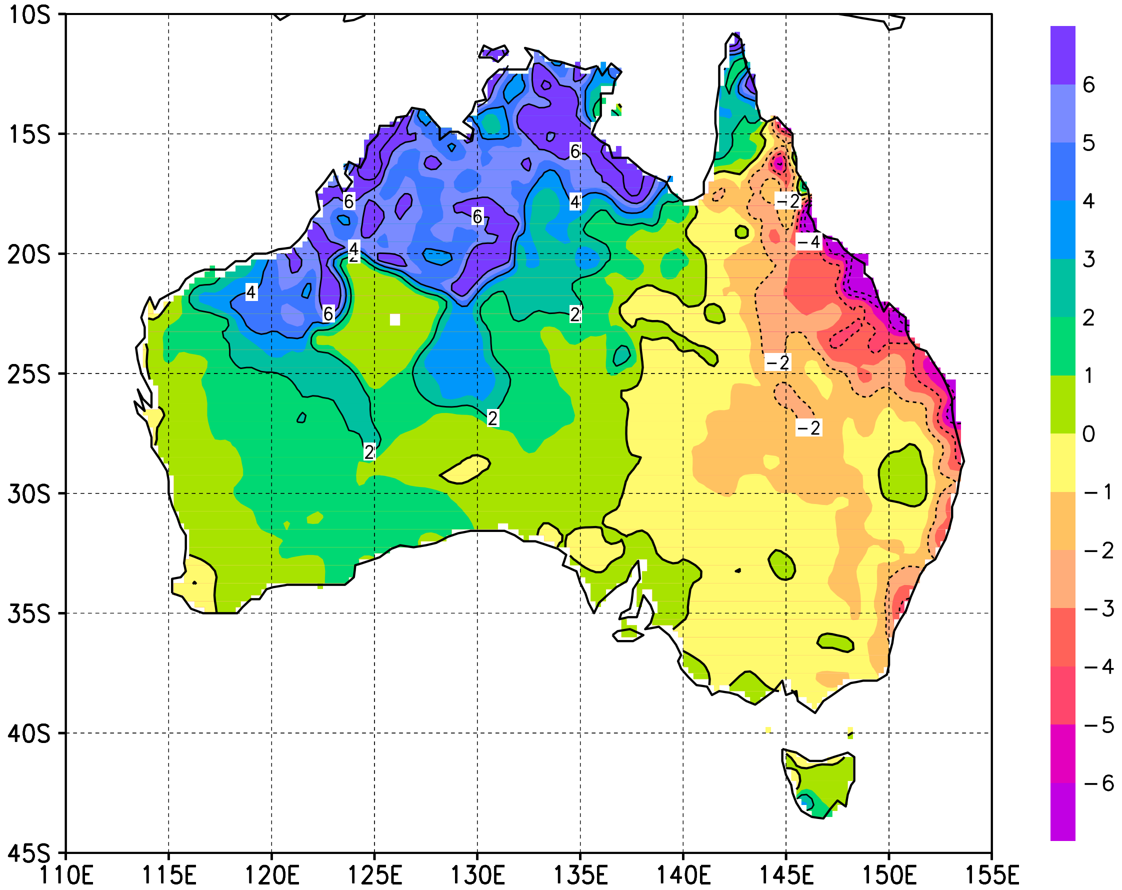


Figure 2.4.7: Summer total rainfall trend based on the ACC rainfall data over 1948-2006. The summer here refers to the period December-January-February-March (DJFM). (mm/year)

Figure 2.4.8 shows the monthly rainfall time series and their superimposed trends in summer (December, January, February and March) over NWA. It is evident that rainfall has increased over past decades since 1950. We have also explored NWA rainfall variability in other months. However, there is no clear trend in other months (figures not shown). So we will focus on investigating NWA DJFM rainfall under this project.

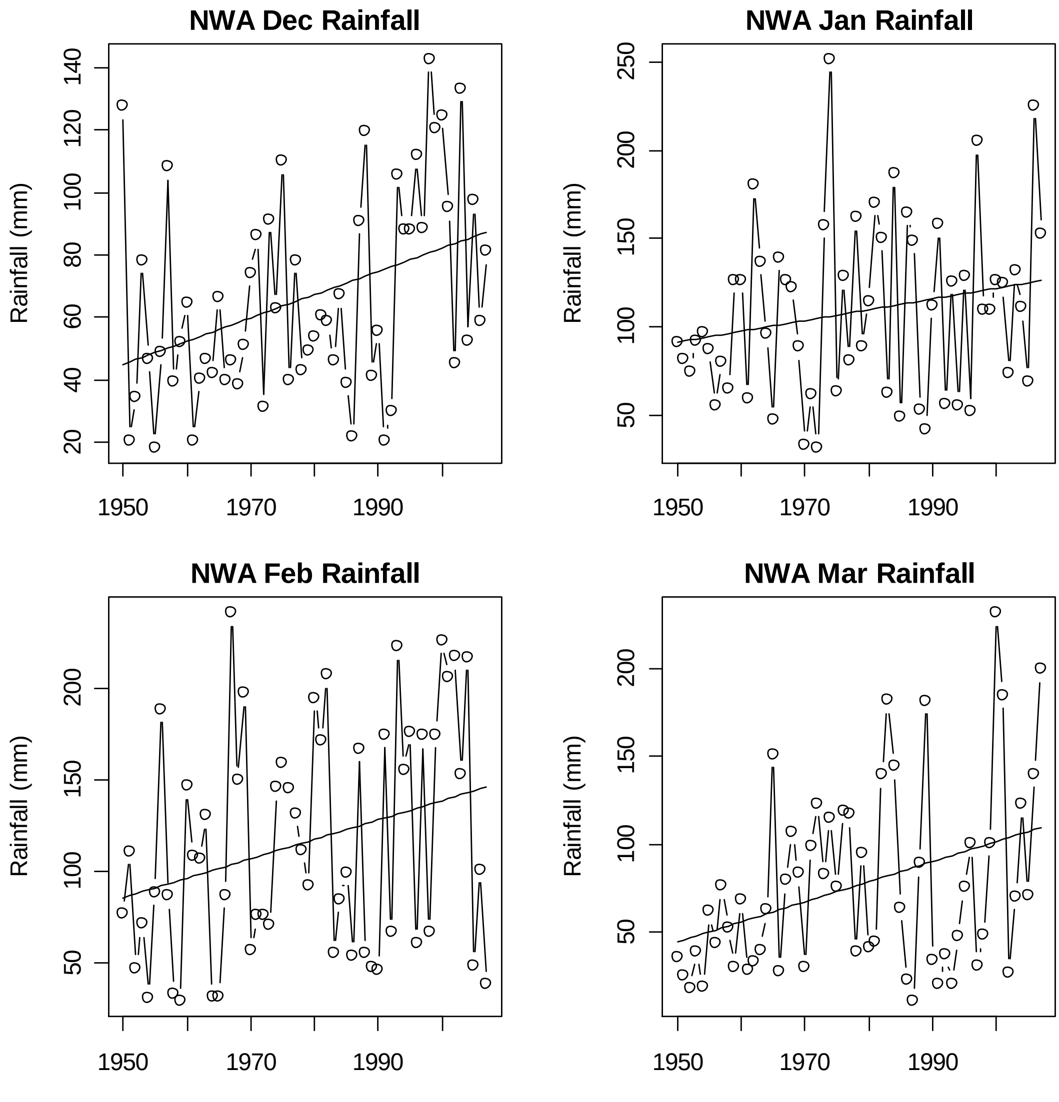


Figure 2.4.8: NWA summer month (Dec-Jan-Feb-Mar) rainfall and their trends in December (0.74mm/yr), January (0.61mm/yr), February (1.06mm/yr) and March (1.14mm/yr).

Figure 2.4.9 presents the time series and trend in NWA summer rainfall. Summer rainfall over NWA has increased with a trend 3.5mm/yr, significant at the 0.01 level. There is also a potential change point year around 1986 for rainfall drop to low beyond 250mm, and rainfall has increased again afterwards.

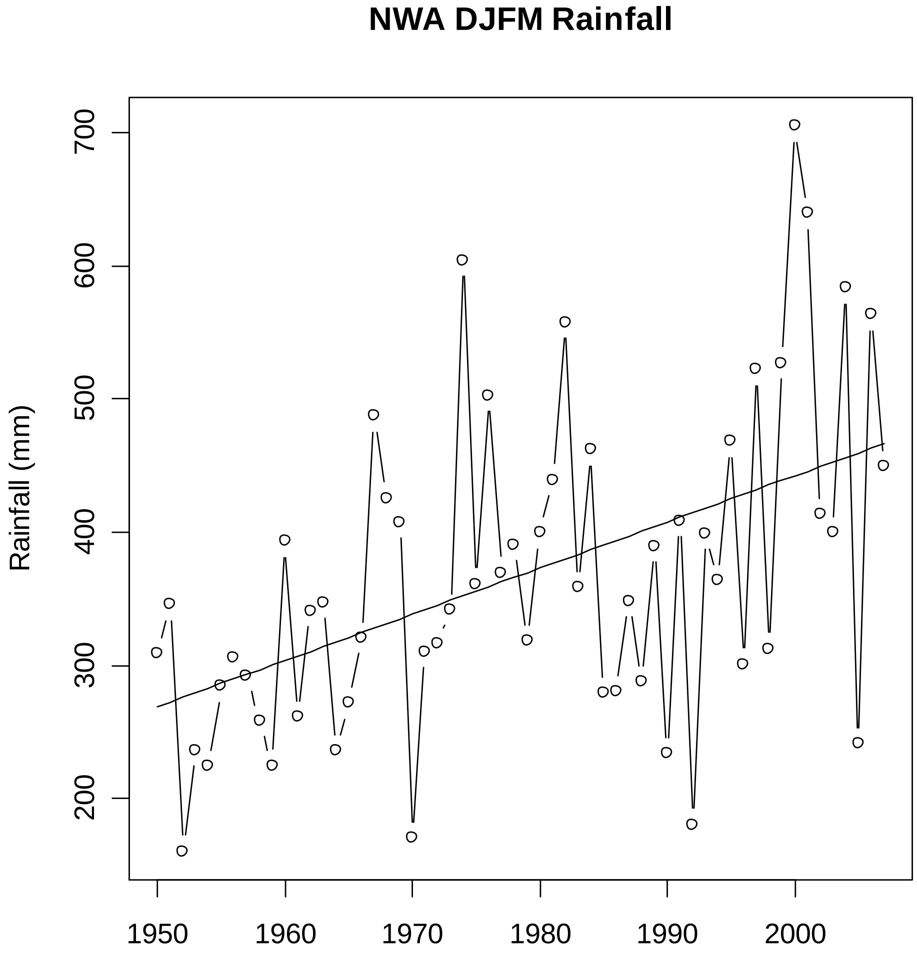


Figure 2.4.9: NWA summer (DJFM) rainfall and its trend 3.5mm/yr in 1950-2007.

The new NWASM index may explains the rainfall increase over NWA

We have developed a new NWASM index (MWASMI) using the dynamics of normalized seasonality index by Li and Zeng (2002) to describe NWASM and its linkage to summer rainfall over NWA.

Results show that the NWASM has a significant positive correlation with NWA winter rainfall (r=0.81). The NWASM not only influences the interannual variability of NWA summer rainfall, but also contributes to the long term increasing trend in NWA summer rainfall. The relationship between the NWASM index and NWA rainfall is robust, and largely independent of the influence of other large-scale circulations such as the SAM and ENSO.

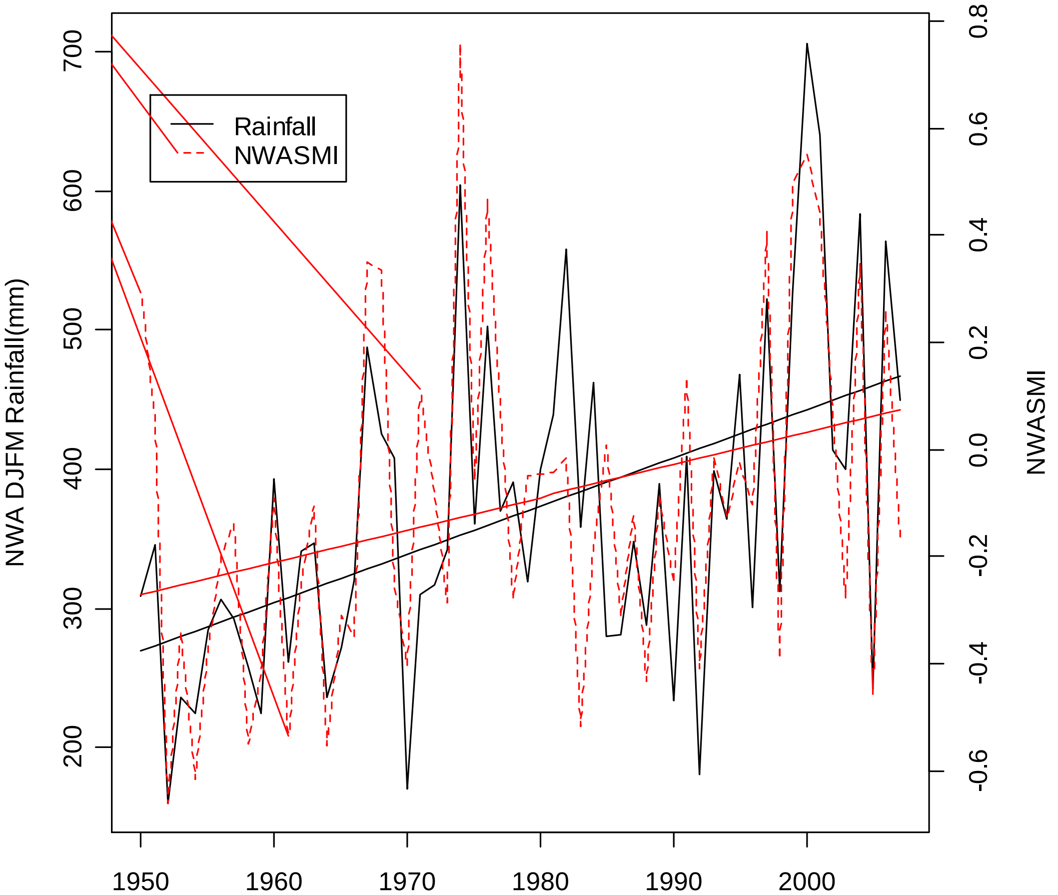


Figure 2.4.10: Time series of NWA DJFM Rainfall (black solid line) and NWASM index (red dash line). The NWASM domain is 95°-135°E and 25°-10°S. Correlation between NWA DJFM rainfall and NWAMI is 0.81, significant at the 0.01 level. The correlation between two detrended series is 0.79, also significant at the 0.01 level. Thus, the upward trend (red line) in NWASM may contribute to the summer rainfall increase in NWA.

Figure 2.4.10 presents correlation between the NWAMI and geopotential height at 925hPa for both original and detrended data. It shows the NWASM is associated with one cyclone over NWA region, and tripole structure with a cyclone centred over 70°E, 25°S, a anti-cyclone along the equatorial to subtropical Indian ocean and another anti-cyclone centred over southern Indian ocean near 100°E, 30°S. This cyclone structure implies when the NWASM is in its strong years, the cyclone centred over 70°E, 25°S brings more northwest winds along 10°-15°S and then enhanced by two anti-cyclones and NWA cyclone to bring more synoptic weather patterns to the NWA region which favours more rainfall. The opposite composition is true when the NWASM is in its weak years.

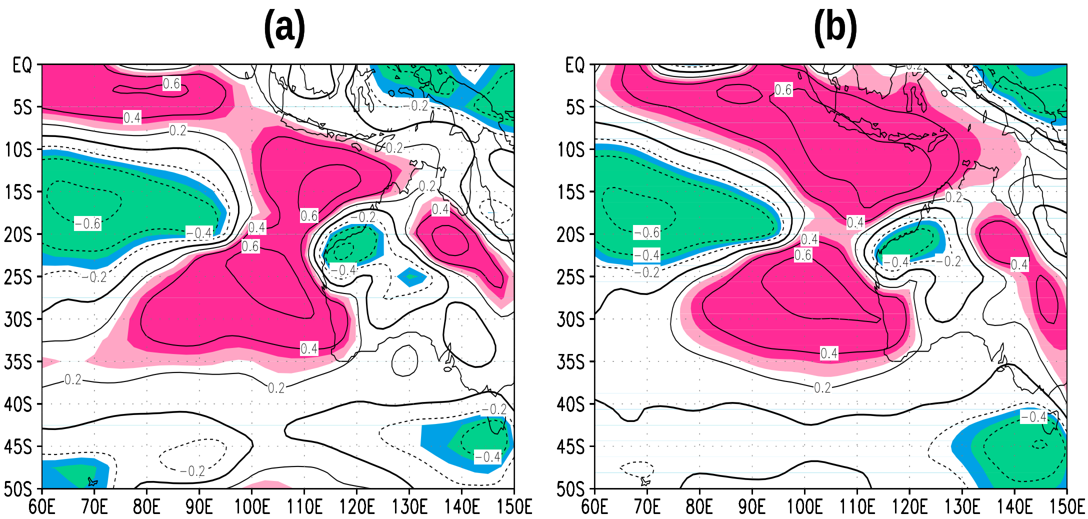


Figure 2.4.11 (a) correlation between the NWASMI and geopotential height at 925hPa; (b) same as (a), but for detrended data.

References

Kalnay, E., and Coauthors, 1996: The NCEP/NCAR 40-year reanalysis project. *Bulletin of the American Meteorological Society*, **77,** 437-471.

Li, J. P., and Q. C. Zeng, 2002: A unified monsoon index. *Geophysical Research Letters*, **29,** 1274.

Shi, G., W. J. Cai, T. Cowan, J. Ribbe, L. Rotstayn, and M. Dix, 2008: Variability and trend of North West Australia rainfall: Observations and coupled climate modeling. *Journal of Climate*, **21,** 2938-2959

LIST OF FIGURES